SENSING HUMAN ACTIVITY TO IMPROVE SEDENTARY LIFESTYLE

Simone T. Boerema

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CHAPTER 1

GENERAL INTRODUCTION

SEDENTARY BEHAVIOR & PUBLIC HEALTH

Recent public health campaigns often communicate the alarming phrase: “Sitting is the new smoking”. Sitting is related to all-cause mortality, cardiovascular disease, type 2 diabetes, and metabolic syndrome as shown by a recent overview of systematic reviews [1]. Sedentary behavior is generally understood as “sitting or reclining while expending ≤1.5 metabolic equivalents” [2]. The interesting aspect of sedentary behavior is that it is a modifiable health risk [3]. The health risk can be reduced if a person changes his or her behavior towards a more healthy one; to sit less and to become more physically active. However, it is unknown when sitting becomes unhealthy [1]. Moreover, studies indicate that the pattern of sedentary behavior during the day is an independent health risk; independent of physical inactivity and total sedentary time. Prolonged sedentary time affects cardio-metabolic and inflammatory biomarkers, independent of the total sedentary time [4, 5].

Sedentary behavior research is rapidly developing and emerging and strengthening its knowledge base. Nevertheless, the current health guidelines on sedentary behavior are not as well-developed as their counterparts on physical activity. Translating the current knowledge on sedentary behavior into meaningful clinical guidelines or protocols is not straightforward. This is reflected in the global recommendations on Physical Activity for Health (2010) [6] from the World Health Organization (WHO). These recommendations state rather detailed recommendations on physical activity regarding duration and intensity per week for various target groups such as children, adults and older adults. But they lack recommendations on sedentary behavior, only stating that “the scientific knowledge being accumulated in areas such as sedentary behaviors, will necessitate a review of these recommendations by the year 2015” [6]. However, this review has not yet taken place. Some nations did implement sedentary behavior in their current physical activity and sedentary behavior guidelines. For example, Australia has two recommendations for adults (2014) [7]: 1) “minimize the amount of time spent in prolonged sitting.” and 2) to “break up long periods of sitting as often as possible.”, reflecting both independent health risks of sedentary behavior. The Netherlands (2017) (Dutch: Beweegrichtlijnen) [8] very recently updated their physical activity recommendations for (older) adults, without being very specific regarding sedentary behavior: “minimize the amount of time spent sitting.” (Dutch: Voorkom veel stilzitten).

ACTIVITY SENSORS IN SEDENTARY BEHAVIOR RESEARCH

Research focusing on patterns of sedentary behavior has taken a flight since the rise of both wearable technologies and activity sensors. They provide opportunities for uncovering sedentary patterns within the context of daily life. As a consequence, the field moved forward from the predominant usage of self-reported measures on sedentary behavior, such as questionnaires and diaries (methods that inherently contain recall and normative biases) towards fine-grained, objective monitoring of sedentary behavior in free-living conditions for substantial time frames [9]. This change towards the use of objective measurement is now also included in health policies. For example, the Dutch physical activity recommendations (2017) [8] indicate that future research should shift from questionnaire-based towards activity-sensor-based population research.

Current wearable activity sensors are, however, not flawless in measuring sedentary behavior. One should be aware that the translation of activity into sedentary behavior measurement is not straightforward. Both are the opposite ends of the activity continuum, requiring different measurement strengths. It is therefore important to understand the effects of possible measurement bias in sedentary behavior, in order to deal with it in the best way [9–13]. Additionally, there is no consensus yet among researchers on the representation of objectively measured sedentary behavior: which outcome measures represent the pattern of sedentary behavior during the day the best? This makes the current body of knowledge on sedentary patterns, fragmented, contra dictionary and difficult to build upon.

ACTIVITY SENSORS IN SEDENTARY BEHAVIOR INTERVENTIONS

People are often unaware of their sedentary behavior, making it difficult to change the behavior. mHealth interventions can improve awareness and trigger behavior change by providing direct feedback and coaching on physical activity and sedentary behavior [14–16]. Increased awareness can help to overcome barriers in our daily context, such as work environments (e.g., deskwork) and the ‘luxury’ of the modern world such as cars and TV that promote sedentary behavior. mHealth interventions benefit from real-time information on the context and activity pattern of users to tailor the intervention. Among other information sources, activity sensors are very suitable for this, as this information is objective and can be available in real-time.

Sedentary behavior is more difficult to communicate, than for example the number of steps, which is general measure of physical activity. Total sedentary time in hours per day or as percentage of total time is commonly used, but one can question whether this is an easy to understand variable for an average user. This becomes even more difficult when one intends to communicate daily sedentary pattern.

INCLUDING CONTEXT IN PERSUASIVE SEDENTARY BEHAVIOR INTERVENTIONS

Adoption and effect of mHealth interventions can be improved when they address the 'world of the user' and the goals he or she values [17]. mHealth interventions should become context-aware by integrating information about the users' preferences, environment, tasks, agenda and what he or she is doing or feeling [18]. This can be done by integrating relevant data sources, such as the agenda of meetings during office hours. Or by posing questions about the here-and-now by a wearable device; the Experience Sampling Method (ESM) [19, 20].

Context-awareness can optimize timing and content of encouraging messages towards physical activity. A message advising to "take a short walk to break-up a prolonged sedentary period", while the user is in the middle of a meeting can then be avoided. Tailoring by including context-awareness can improve adherence to an intervention and improve the physical activity behavior [21, 22]. Targeting real needs of individuals will further increase acceptance. Eliciting values, and barriers and facilitators to these values, can contribute to the design of interventions. A value-based approach offers a close look into the lives of users, thereby opening up a wide range of innovation possibilities that better fit actual needs [17].

OUTLINE AND SCOPE OF THIS THESIS

The aim of this thesis is to determine how wearable activity sensors can be applied successfully in health interventions focused on sedentary behavior.

The first part of this thesis focuses on measuring sedentary behavior and its patterns by means of wearable activity sensors. Here, we distinguish the sensing method, the use of the sensor, data processing methods and the application of relevant outcome measures. The second part of this thesis focuses on the development and evaluation of mHealth interventions that utilize wearable activity sensors. The chapters of this thesis follows an expanding scope by increasing the context, from the level of activity sensor until the level of public health, see Figure 1.

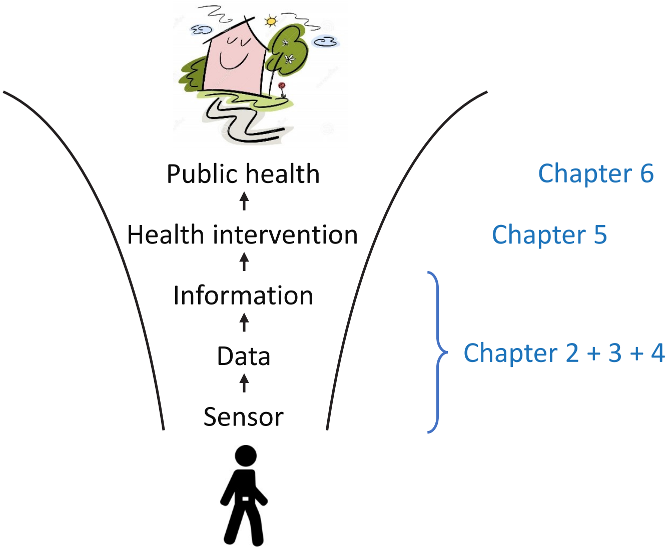

Figure 1 Outline of the thesis, funneling out from wearable activity sensor to contribution to Public Health.

In Chapter 2, we review the current state of the art on outcome measures that describe a sedentary pattern. We will look into the diversity of sensing methods, data processing steps and measurement protocols and the effects of these on the comparability of outcome measures. We aim at providing useful recommendations on which measures to report in studies and provide an overview of findings in the literature.

In Chapter 3, we study the effect of sensor placement around the hip on the assessment of physical activity in laboratory conditions. We will determine which position on the waist belt is the least sensitive to interference and which method of sensor mounting – connection to the body – provides the most reliable data.

In Chapter 4, we study the consequences of applying different cut-points for sedentary behavior classification to various commonly used pattern measures in an office setting. Sedentary pattern measures should be sensitive to change in behavior and robust to differences in data processing steps.

In Chapter 5, we combine the knowledge on sensor use, data processing steps and outcome measures with context-aware technology in an intervention for older office workers towards less sitting and breaking up sitting time. We study the effect of this intervention on the actual sedentary behavior pattern and the change in awareness of the personal behavior.

Chapter 6 finally, describes the methods and application of value-based design. In this study we focus on older adults' difficulties related to their reduced mobility – meaning difficulty with walking, biking, and/or activities of daily living. Their values in life, and the barriers and facilitators to these values are gathered in in-depth interviews, to gain rich information on individuals and serve as input for designers. In this chapter the designers focus on mobility aids. However, mobility is related to physical capacity and not being sedentary. In-depth understanding of the values of life to be mobile, can therefore directly inspire designers focused on mobility aids. This understanding can as well tap into the context and personal goals needed to tailor health interventions on sedentary behavior.

CHAPTER 2

PATTERN MEASURES OF SEDENTARY BEHAVIOR IN ADULTS: A LITERATURE REVIEW.

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ABSTRACT

Background: The interest in sedentary behavior and its objective measurement, via wearable devices, has rapidly increased over the last years. This is partly due to the increased ability of sensors to assess sitting behavior during the day. However, there is, as of yet, no consensus among researchers on the best outcome measures for representing the accumulation of sedentary time during the day.

Methods: In this systematic review, we analyzed the pattern measures of sedentary behavior. Articles reporting patterns measures in adults, in which behavior data was collected with a sensor were included. We discuss the strengths and weaknesses of the pattern measures of sedentary behavior and provide recommendations for choosing objective measures of sedentary behavior.

Results: Most studies report the number of sitting bouts during the day. Others focus on the number of breaks and/or periods of physical activity. Simple measures of sedentary behavior were most popular, like the number of bouts, the medium or median bout length. More complex pattern measures, such as the GINI index or the W50 were reported sparsely. The sedentary patterns, reported in the various studies, were difficult to compare, due to the differences among measurement devices, data analysis protocols and a lack of basic outcome parameters such as total wear-time and total sedentary time.

Conclusions: Objective sedentary measures can be grouped into simple and complex measures of sedentary time accumulation during the day. These measures serve different goals, varying from a quick overview to in-depth analysis and prediction of behavior. The answer to which measures are most suitable to report, is therefore strongly dependent on the research question. We have shown that the reported measures were dependent on 1) the sensing method, 2) the classification method, 3) the experimental and data cleaning protocol, and 4) the applied definitions of bouts and breaks. We recommend to always report total wear-time, total sedentary time, number of bouts and at least one measure describing the diversity of bout lengths in the sedentary behavior such as the W50. Additionally, we recommend to report the measurement conditions and data processing steps.

BACKGROUND

High amounts of sedentary behavior are associated with increased risk for chronic diseases and poor health outcomes [3, 23]. This risk is unrelated to the amounts of moderate- to vigorous-intensive physical activity a person achieves during the day [3, 23–25]. Moreover, there is little association between the time spent in sedentary behavior and the time spent in moderate- to vigorous-intensive physical activity in the course of a day [26], meaning that an individual can be simultaneously very sedentary, while being sufficiently physically active [27]. The focus of assessing sedentary behavior has shifted over the last years from a focus on total sedentary time during a day towards approaches that focus on the pattern of accumulation of sedentary behavior. In which a pattern is a regular and intelligible form or sequence discernible in the way in which sedentary behavior happens [28]. Studies that apply these pattern measures indicate that the breaking up of sedentary time may be beneficial for cardiovascular disease risk. The prolonged sedentary time affects cardio-metabolic and inflammatory biomarkers, independent of the total sedentary time [4, 5]. In other words, sitting for many hours is a health risk, and the sedentary pattern affects this health risk.

Sedentary behavior research has, until recently, predominantly relied on self-reported measures for determining total sitting time per day, for example by means of questionnaires and diaries. However, self-reported measures do not provide detailed information on the pattern of accumulation of sedentary behavior, as they are hindered by recall and normative biases. The introduction of wearable activity sensors has radically expanded the range of measurement instruments, as sensors are very capable of recording data at a very high level of granularity suitable for uncovering the patterns of accumulation.

Wearable activity sensors are predominantly based on two different inertial sensing techniques: accelerometry and inclinometry. These two types of sensing techniques are reflected in the most widely adopted definition of sedentary behavior: “sitting or reclining while expending ≤1.5 metabolic equivalents” [2], as the strength of accelerometry is measuring intensity of movement, while the strength of inclinometry is measuring posture [29]. Accelerometry-based sensors often use the intensity of accelerations to estimate energy expenditure during daily life. For this, accelerometer-based sensors use cut-points to distinguish intensity levels, which are most sensitive for moderate- to vigorous physical activity [30]. Inclinometry-based sensors measure inclination of body part(s) to estimate postural information such as standing, sitting, lying and walking. These types of sensors are very accurate in distinguishing sitting and lying from standing and stepping. Both sensing types have their strengths at the opposite ends of the activity spectrum. Where the whole spectrum of activities from sitting to high intensity physical activity is relevant, the choice for the best sensor type less evident.

Properly measuring and interpreting sedentary behavior will help developing health and clinical guidelines on sedentary behavior [31]. In this literature review, we assess **which pattern measures have been used to capture daily sedentary behavior (patterns)** and determine how these measures **disclose information on the accumulation of sedentary behavior**. This review will help researchers to understand the differences between the various pattern measures, as well as their strengths and weaknesses. We will provide general recommendations for the use of sedentary pattern measures in scientific research and clinical practice.

METHODS

Search strategy and selection. Articles reporting sedentary behavior patterns in adults measured with wearable sensors, were included in this systematic review. Literature searches were conducted using ISI Web of Knowledge and Scopus (See Additional file 1. Search strategy, conducted at 8 June 2016). Combinations of the following key terms were used to search the databases: Sedentary behavior terms (sedentary behavior, sitting, sedentary time, sedentary lifestyle, and physical inactivity); Pattern terms (pattern, bout, behavior); sensor terms (sensor, accelerometer, pedometer, Actigraph, ActivPal); and objective measures terms (objective, monitor, measure, classification, pattern, accumulation). We applied the PRISMA guidelines to report our findings.

Screening. Two authors (STB an LV) individually screened the search results and identified studies based on 1) the study title and 2) the abstract. Studies were included if they described sedentary behavior pattern measures within the timeframe of a day, based on wearable sensor data in adults (age ≥18 years) and were peer reviewed journal articles, letters, or conference proceedings. Studies were excluded if they described ambient sensing techniques (i.e., not on-body), provided graphical representations of sedentary patterns only, were not in English, were review articles or were published before 1989 (as modern wearable sensors were yet not available back then). If the authors did not agree, they discussed their arguments until agreement was reached.

Data extraction and synthesis. From each article, information about the type of sedentary behavior pattern measures, specification and validation of the measure were extracted and synthesized. These measures were complemented with information about the study design, sample characteristics, sample size, sensor type, data cleaning, activity classification, and analysis methods. Principal summary measures of this review are the number of times a specific pattern measure is reported and its implications for data analysis and interpretation. Results are summarized on total wear-time, bouts, breaks and composite measures.

RESULTS

A total of 868 unique titles were identified and screened for inclusion. Full-text analysis was done on 144 records, from which 64 described pattern measures of sedentary behavior. (See Figure 2).

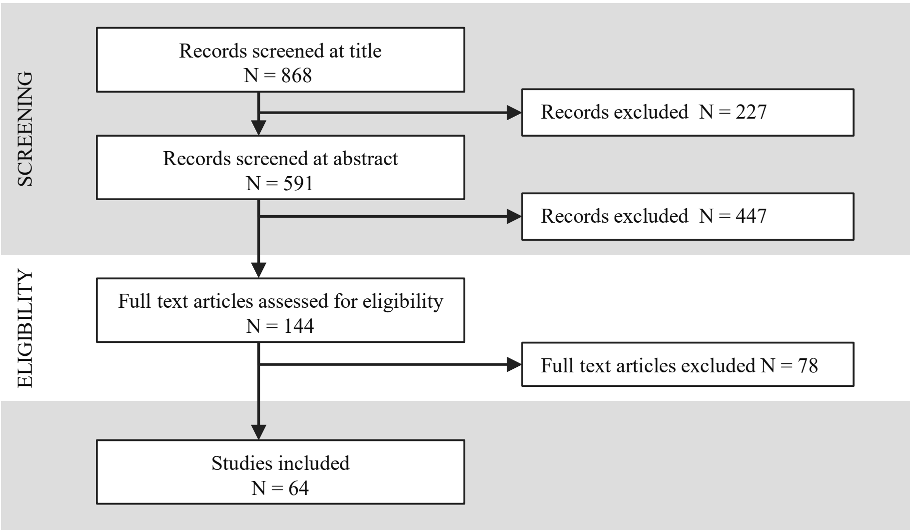

Figure 2 Flow diagram of numbers of studies screened, assessed for eligibility, and included in the review.

To review the pattern measures of sedentary behavior from activity sensors, we first need to introduce the general approach of data analysis. We identify three levels of data aggregation to describe sedentary behavior measures, as shown in Figure 3:

A. The most basic information level of sedentary behavior is **total sedentary time**. To interpret this measure it is best accompanied by the **total wear-time.** Relevant questions here are: Are results also considering sleep time or only waking time? How many hours is the behavior measured during waking time? Does it include evenings, for example watching television?

B. The total sedentary time is accumulated in sedentary **bouts** (periods of sitting and/or lying) which are interrupted by **breaks** (physically active periods). Outcome measures at this level describe, for example, the number of bouts during waking hours and the mean bout length.

C. Finally, we discern composite measures of sedentary behavior. These measures are composed of bout or breaks relative to another measure. This can be either 1) *relative to another sedentary pattern measure*, such as total sedentary time; or 2) relative to its timing, describing the *temporal aspects of sedentary behavior*; or 3) relative to the order of bouts and breaks, describing the *sequential aspects of sedentary behavior*.

Our results will be described following these three levels of data aggregation. For each level we will discuss the general data processing steps, the most reported outcome measures, the various levels of detail, generalizability and complexity and challenges with these measures. Details of the described measures are reported in Additional file 2. Detailed results table.

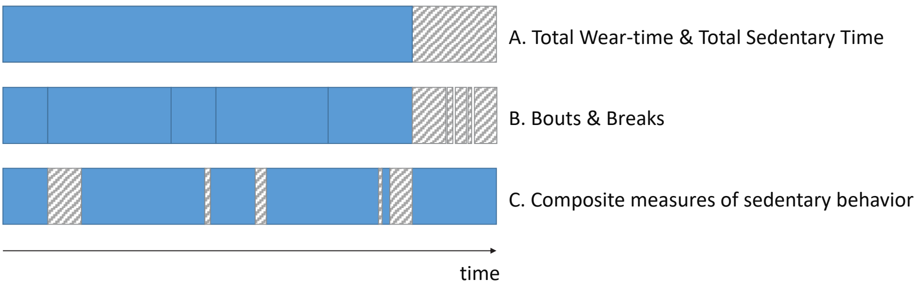

Figure 3 Three levels of data aggregation for sedentary pattern measures.

A. Total sedentary time, total wear-time & sensor type

Total sedentary time was often reported as the sum of all sedentary minutes during the measurement day or as a percentage of wear-time. 62 of the 64 included studies reported **total sedentary time**; **total wear-time** was reported by 34 studies.

The 64 studies reporting sedentary pattern measures most often used the Actigraph (n=43) or ActivPal (n=14) activity sensor. Other sensors were the Actical, Actiheart, Active stylePro, ASUR, SenseWear Pro3 Armband, Stepwatch, Promove3D, and research devices. These various sensors are either accelerometry-based sensors or inclinometry-based sensors, see Table 1. These two sensing methods have their own specific limitations in measuring sedentary behavior. These differences affect all the outcome measures, making it difficult to compare for example total sedentary time of various studies.

The most important advantage of accelerometry-based sensors is that they are predominantly worn on the clothes, such as on the waist belt or the wrist, which is convenient for users, can be self-applied and is therefore a more practical option for large scale, longitudinal studies. These sensors are predominantly applied in protocols measuring sedentary behavior during waking hours, with a minimum wear-time or minimum valid data of at least 10 hours/day (n=42). The most important disadvantage of accelerometery-based sensors is the vast variety of classification methods applied in literature, which are listed in Table 1. This means that identical behavior of sedentary and active time can be classified differently, resulting in differences in total sedentary time and the pattern measures that are derived from this. For example Kim et al. [12] found that the performance of the Actigraph sensor for the assessment of sedentary behavior improved when applying the Sojourn classification method or by applying a cutpoint of <150 cpm (counts per minute). This cutpoint classifies more minutes as being active than the most commonly applied cutpoint (100cpm) in literature, likely resulting in less sedentary time.

Inclinometry-based sensors are often attached to the skin of the upper leg with adhesive tape for 24 hours per day for several days. The proprietary ActivPAL software that classifies the postures, lying, sitting, standing and walking, is overall more accurate in distinguishing standing and walking from sitting and lying than accelerometry-based classification **[32, 33]**. Nevertheless, distinguishing sitting from lying remains a challenge and is often deduced from the behavior preceding and succeeding the sitting or lying. This limitation is reflected in the applied definitions of sedentary behavior when using the ActivPAL. Most of these studies define sedentary behavior as the posture sitting (n=6) while others sum sitting and lying (n=9), see Table 1. This difference in definition can affect the sedentary measures significantly if during waking hours subjects lay down more, for example in patient-groups suffering from fatigue. Moreover, if sleeping at night is included in the sedentary behavior, subjects will be sedentary for many more hours **[34]**. However, in general only waking hours are analyzed (n=7).

The essential differences in sensing methods are reflected by the findings of articles that studied validity or sensitivity of accelerometry- and inclinometry-based sensors in measuring sedentary behavior. ActivPAL was found to be more accurate than Actigraph and Actiheart for most measures of sedentary behavior [33, 35–37]. Nevertheless, the performance of the Actigraph improved when only studying prolonged sedentary bouts [33]. The cutpoint in accelometry-based sensors can be either too low or too high, as Actigraph overestimated, and Actiheart underestimated the total sedentary time [37]. Nevertheless, the number of breaks was overestimated by both Actigraph and Actiheart [35, 37]. The sensitivity to behavior change in an intervention varied with the intervention and behavior of a population [36]. Chastin et al. [36] found that ActivPAL was in general more sensitive, but not consistently for all measures and intervention designs. And they conclude that "the instrument of choice should also take into consideration accuracy and validity characteristics." [36]

Table 1 Overview of sensor types, the classification methods of sedentary behavior and number of studies in which the sensor was reported.

Sensing method	Output unit	Sensors	Classification of sedentary behavior	n
Accelerometry-based sensors 	Acceleration intensity	Actigraph	Cut-points: <100 cpm; ≤50 cpm; ≤150 cpm; 8 counts per 10 seconds. Classification algorithms: ActiLife [38]; Soj-1x and Soj-3x by Lyden et al. (2014) [39]	43
		Actical	<100 cpm; ≤100 cpm; <91 cpm; <50 cpm	5
		Promove3D	≤1.660 $m \cdot s^{-2}$	1
	Activity Intensity	Actiheart	<1.5 MET	1
		Active stylePro	≤1.5 MET	1
		SenseWear Pro3 (Armband)	≤1.8 MET	1
	Number of steps	Stepwatch	0 steps	1
Inclinometry-based sensors 	Posture; Inclination	ActivPAL	Sitting; Sitting + Lying	14
		ASUR	Sitting + Lying	1
		Research devices	Sitting + Lying	1
		Actigraph*	Inclination >45°; Sitting by Acti4 classification software	2

n = number of studies reporting the specific sensor, cpm = counts per minute. MET = Metabolic Equivalent of Task. *The Actigraph was attached to the upper leg and or trunk. Icons were created by S.T. Boerema based on Freepik from www.flaticon.com.

B1. Bouts

A continuous period of sedentary time is called a (sedentary) **bout** and has most often a length in minutes. In general, a bout ends when a higher intensity activity is measured. However, there are some differences in definitions regarding the minimum duration and allowed minutes of higher intensity activity within a bout. An example of such a restriction is that a bout should last at least two minutes. The definitions applied in the included studies are listed in Additional file 2. Detailed results table.

Bouts are the most reported measure of sedentary behavior that describes a pattern (n=33). Bouts were reported by direct measures such as the **number of bouts**, the **bout length** (its duration) or these measures stratified by **bins of bout length** of 1, 5, 10, 20, 30 or 60 minutes. 'Prolonged bouts' of lengths of 20 and 30 minutes [40] were reported more frequently, as they have been found to mitigate health effects. For example, Dunstan et al. (2012) [6] showed that breaking up sedentary time every 20 minutes can confer health benefits as it lowers postprandial glucose and insulin levels in overweight/obese adults.

A number of measures capture the diversity of bout lengths during a day. The **distribution of bout lengths** are reported in various measures such as the coefficient of variation (CoV = standard deviation of bout length / mean lognormal transformed bout length) of bout length [41] and the cumulative distribution of bout lengths (α) [42]. The CoV is high when the bout length shows much within subject-variability. A low α indicates a larger proportion of long sedentary bouts. For example Chastin et al. [42] found that "the sedentary time of subjects with chronic diseases and sedentary occupation is made up of a larger proportion of long sedentary periods [low α] compared to healthy subjects with active occupation." Chastin et al. linked this effect to a low ability to adapt to random challenges during the day regulated by either their occupation or the medical condition, rather than the individual freewill.

Single outcome measures, such as number of bouts and bout lengths, may hinder full understanding of the behavior pattern. One method to overcome this is by **visualization** of the outcome measures and their relation [31, 43].

Table 2 Sedentary pattern measures based on Sedentary Bouts.

Pattern measure	Unit	References
Bout length	Mean	[30, 41, 44–50]
	Median	[30, 36, 42, 45, 48, 50–52]
	Log mean	[41]
	Mean – stratified*	[53]
	Median – stratified*	[54]
	Total sedentary time, accumulated in bouts of specific bout lengths	[55–57]
	Longest bout length	[38, 48]
Number of bouts	Mean	[33, 36, 41, 44, 48, 54, 58–60]
	Day-part (morning, afternoon, evening)	[58]
	Mean – stratified*	[33, 45–47, 49, 53, 54, 57, 59, 61–65]
Diversity of bout lengths	coefficient of variation	[41]
	Distribution of bout lengths**	[36, 42, 54, 66–68]
	Burstiness parameter	[69]
	Memory parameter	[69]

* = Reported for various bout lengths; ** = various measures.

B2. BREAKS

Breaks from sedentary behavior were reported in 27 articles. They are a relevant part of the sedentary behavior pattern and we encountered various units in which breaks were reported in our review.

The period between two bouts is called a **break**. A break in sedentary time was often defined as the moment a data point was above the cut-point for sedentary behavior or any instance where a sedentary behavior was followed by a non-sedentary behavior. Most studies classify each interruption in sedentary time as a break, which can be as short as 1 minute. Sometimes a break should have a minimum duration, for example at least 3 minutes [40]. This difference affects the number of breaks as well as the number of bouts.

The most reported aspects of breaks are the **number of breaks** (n=24) and their **duration** (n=8). Additionally, **break intensities** are sometimes reported to discuss the relation between sedentary and specific active behavior. For example Straker et al. (2014) [31] found that prolonged sedentary bouts (≥30 minutes) and short light intensity breaks (0-5 minutes) were sensitive to differences between small groups, “suggesting adequate sensitivity for use in intervention studies”. [31]

Table 3 Sedentary pattern measures based on Breaks from sedentary time.

Pattern measure	Unit	References
Break length	Mean	[4, 46, 51, 58, 70]
	Median	[51, 71]
	Log mean	[36]
	Burstiness parameter	[69]
	Memory parameter	[69]
Number of breaks	Mean	[4, 34, 35, 37, 39, 46, 55, 58, 61, 65, 70, 72–83]
	Median	[71]
Break intensity	Mean	[58, 70]

C. Composite measures of sedentary behavior

Finally, we report on the composite measures that we encountered in our review. These measures are composed of bouts or breaks, relative to another measure and provide the most detail of sedentary patterns.

Composite measures – related to total sedentary time

32 studies reported composite measures, related to total wear time, see Table 4. A common approach in this is reporting the **contribution of specific bout lengths to the total sedentary time** per day. For example Shiroma et al [54] reported that “most of the sedentary time is accumulated in bouts of less than 10 minutes.” Reporting the percentage of total sedentary time accumulated in prolonged bouts is also common, for example in bouts of ≥30 min. A more universal measure to report bout length related to total sedentary time is the **half-life bout duration** (W_{50}), which is the bout length at which 50% of the total sedentary time is accumulated. Chastin et al. [36] found that “measures of sedentary time accumulation, in particular $W_{50\%}$, were consistently more sensitive than total sedentary time [to changes in sedentary behavior in intervention studies]”. And they recommend that for sedentary behavior interventions, measures of accumulation should be considered as outcomes.

Bout-rate is a composite measure from total sedentary time and the number of bouts and is also called the **fragmentation of bouts** (F= number of bouts / Total sitting time [min]) [41] [52]. This approximates the **break-rate**, when one assumes that each bout is followed by a break (which depends on the definition of a break). A higher fragmentation index indicates that the sedentary time is more fragmented with shorter bouts. Blikman et al. (2015) [41] describe the sedentary pattern as follows: "There was a tendency for persons with multiple sclerosis to have a less fragmented pattern of sedentary behavior". These relative measures have the advantage of being less dependent on total wear-time or total sedentary time, improving the comparability of studies. However, Break-rate is a composite measure from total sedentary time and number of breaks and therefore depended on biases in both measures that can have independent sources of variability. Lyden et al. [32] states that "[…] using a composite measure such as break rate also has limitations. Change in break-rate will indicate sedentary behavior has changed, but this metric will provide no indication if the change was in total amount of sedentary time, how sedentary time is broken up, or both. When we measure total sedentary time and the number of breaks independently, we can use statistical adjustment to evaluate the independent effects. Break-rate cannot be statistically adjusted for because this would result in variables being entered in the model twice."

2

Other studies provided a visual representation of the relation between bout length and total sedentary time, by showing the accumulation graph of total sedentary time for increasing bout length, see for example Figure 4. This graphical representation provides a more intuitive feel for the distribution of bout length and its corresponding sitting pattern during the day than measures such as the bout-rate or fragmentation index. However, to make such a graphical representation suitable for statistical analysis, often specific points on the accumulation graph were analyzed, such as: the bout lengths corresponding to 10%, 50% and 90% of total sitting time and the proportion of total sedentary time accumulated in bouts longer than 30 and 60 minutes [81].

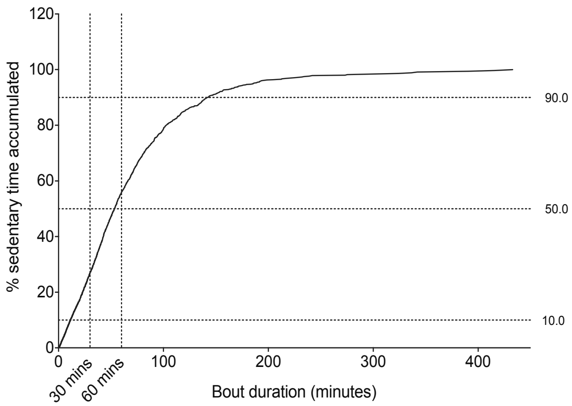

Figure 4 Accumulation of total sedentary time versus increasing bout length. Reprinted with permission from Reid et al. (2013) [81]

One of the solutions to bridge the gap between the accumulation graph and the wish for a single value is the **Gini index** (G). This is a composite measure that captures a relation between bout length and accumulation of total sedentary time [42]. The Gini index appeared to be suitable for comparing diagnosis groups and healthy subjects. Chastin et al. state that "The very high *G* index for chronic fatigue syndrome and low back pain groups suggest that these subjects seem to adopt a boom-bust behavior with sedentary time mostly made of very long rest periods." [42] However, comparing *G* indexes between studies should be done with great care: the study protocol highly affects the pattern measure. Blikman et al (2015) [41] discussed that differences in reported G indexes may appear because of the inclusion of night as sedentary time. Finally, it is important to realize that the *G* index is a measure of bout length distribution and not of bout length itself. For this reason Ortlieb et al. [50] additionally report measures like the mean and median bout length and the percentage of time spent in bouts longer than the median bout length to provide a more complete overview of the sedentary behavior pattern.

Composite measures – temporal & sequential patterns of sedentary behavior

Composite measures that describe temporal and sequential patterns were reported in four studies, see Table 4. These measures capture the most detailed aspects of the sedentary behavior, can predict behavior and are capable of distinguishing healthy subjects from patient groups.

The **temporal diversity of bouts** described by Lord et al. [74] quantifies how many different lengths of bouts are present in the sedentary pattern and how regularly they are used. This calculation is based on Hill numbers, which are common in literature describing diversity in species. A high value indicates that sedentary bouts are spaced at irregular intervals.

Detrended fluctuation analysis and **fano factor analysis** are both methods to describe the randomness of succeeding bout and break lengths. Both methods show in the studies that healthy subjects show a more random sedentary pattern than patient groups. Paraschiv et al. [68], for example, found a larger value of fluctuation in the sedentary pattern of chronic pain patients. They also suggested that "activity-to-rest transitions are randomly spread over time with pain patients as opposed to organized in healthy people". This bursty nature of (healthy) human behavior was further analyzed in a later publication [69].

Cavanaugh et al. [84] used **Entropy rate** and **Approximate entropy** to quantify the amount of uncertainty associated with whether step activity was recorded in any given minute. “Greater uncertainty implied that the ordering of active versus inactive minutes contained a greater amount of information, and, therefore, greater complexity.” [84] Cavanaugh et al. showed that the successive activity-rest pattern recorded from highly active participants was more complex than of less active participants. In other words: there was relatively more uncertainty about whether or not activity occurred in any given minute. The behavior is less predictable.

A similar approach for predicting the sedentary behavior was described by Paraschiv et al. [68]. The **symbolic sequence of successive rest-activity-rest periods** is a binary code of ones and zeros for each break depending on the length of the preceding and successive bout. Paraschiv et al. [68] found that the probability of ‘long activity followed by short rest’ was significantly greater for the healthy control than for the chronic pain group.

Table 4 Composite measures of sedentary behavior.

Pattern measure	Unit	References
Measures related to total wear-time	Percentage of wear-time – stratified*	[85]
	Break-rate	[31]
Measures related to total sedentary time	Mean Bout length (at specific % of sedentary time)	[86]
	W50	[30, 36, 38, 48]
	Percentage of sedentary time – stratified*	[36, 40, 43, 45, 48, 50, 52, 59, 61, 63, 71, 84, 86, 87, 87–91]
	Bout-rate	[36, 41, 52, 58]
	Break-rate	[39, 40, 43, 59, 61, 72, 77, 82, 87, 92]
	Gini index (G)	[41, 42, 50, 66, 74]
	Sedentary time per day-part	[93]
Temporal pattern measures	Temporal diversity of sedentary bouts	[74]
	Detrended fluctuation analysis	[68, 84]
	(Approximate) Entropy	[69, 84]
Sequential pattern measures	Fano factor analysis	[68, 69]
	Probability of specific sequences	[68]

* = Reported for various bout lengths.

DISCUSSION

This review has shown that objective sedentary measures can be grouped into simple and complex measures of sedentary time accumulation during the day. These measures serve different goals, varying from a quick overview of the total behavior to in-depth analysis of sedentary time accumulation and prediction of behavior. The answer to which measures are most suitable to report, is therefore strongly dependent on the research question. The measures of sedentary behavior patterns we identified in the literature are difficult, if not impossible, to compare, making the current body of knowledge fragmented, contra dictionary and difficult to build upon. We suggest to always report total wear-time, total sedentary time, number of bouts and one of the measures describing the diversity of bout lengths in the sedentary behavior. The half-life bout duration (W50) seems very suitable here, as it is sensitive to changes in behavior and is relatively easy to calculate. Additionally, we suggest to report measurement conditions (the sensor used and measurement protocol) and the data processing steps (valid days, non-wear, classification method).

Reporting these measures does not solve the problem of incomparability of different studies. We identified various sources of errors, especially in the first steps of data processing, that can have significant effects on the results. The sensing method – accelerometry-based versus inclinometry-based sensors – and the classification method, have the strongest effect on the measured sedentary behavior patterns. Second, the succeeding data processing steps can strongly affect the results, such as the inclusion of sleep in the sedentary behavior. Finally, some measures have multiple sources of biases. For example, a change in the break-rate does not clarify which aspect of the sedentary behavior changed: the total sedentary time or the number of breaks. Most importantly, one should always consider the whole picture of sensor, protocol, classification, data processing and sensitivity of the outcome measure.

Limitations

We have seen that because sedentary behavior pattern analysis is a new and fast emerging field of research, relevant pattern measures find their origin in other disciplines. Our search terms may have not been comprehensive, omitting relevant sedentary pattern measures from other domains. However, we have checked all references in the records and did not find any evidence in such direction.

The rapid increase of commercial activity trackers such as the Fitbit, are not reflected in this study. They are not commonly applied in current scientific research. However, we do expect them to become adopted by the field both as applied sensing method as well as valuable data source resulting from to the consumer, quantified-self domain. As free-living, self-tracking of behavior is becoming more and more common.

CONCLUSIONS

Sedentary behavior research is a fast emerging field of study. Many sedentary pattern measures already show how they developed towards more robust, general measures and this development will probably continue in the upcoming years as has happened to physical activity measures.

This review has shown that objective sedentary measures described in literature are strongly dependent on 1) the sensing method (accelerometry-based or inclinometry-based sensors), 2) the method of classifying sedentary behaviour, 3) the experimental and data cleaning protocol, and 4) the applied definitions of bouts and breaks. Differences in one or more of these steps makes it difficult or even impossible to compare reported sedentary pattern measures.

Nevertheless, the sedentary behaviour patterns studied in this review learn us that the sedentary pattern can be best described by providing both general outcome measures and measure of bout length distribution.

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ADDITIONAL FILES

Additional file 1. Search Strategy for ISI Web of Knowledge and Scopus. This file contains the search terms used in this review, the databases that were searched and the hit rates for search terms.

Additional file 2. Detailed results table. This file contains the results table of all included records. It provide details on the population, sensor & settings, data cleaning, sedentary behaviour classification, pattern measure, unit and sedentary pattern values of each study.

APPENDICES CHAPTER 2

ADDITIONAL FILE 1 SEARCH STRATEGY

Search conducted at 8 June 2016.

Scopus

((TITLE ("sedentary behavior" OR "sedentary pattern" OR "sitting behavior" OR "sedentary bout" OR "sedentary variable" OR "sedentary time" OR "sedentary lifestyle" OR (("physical activity" OR "physical inactivity") AND (pattern OR bout)) OR "physical activity level" OR "free-living behaviour" OR "physical behaviour" OR “activity pattern”)) AND (TITLE-ABS-KEY(sensor* OR acceleromet* OR inclinomet* OR pedomet* OR actigraph OR activpal OR directlife OR actical OR promove OR fitbit OR dynaport OR geneactive OR actometer OR GT1M OR GT3X OR stepcount))) AND (TITLE-ABS-KEY(objectiv* OR monitor* OR measur* OR assess* OR determine OR defin* OR classif* OR pattern OR bout OR qualif* OR accumulat* OR accrue*)) AND (PUBYEAR > 1989) AND NOT TITLE(child* OR adolesc* OR boy* OR girl*) AND NOT TITLE(question* OR interview) AND (LIMIT-TO(LANGUAGE, "English")) AND (LIMIT-TO(LANGUAGE, "English")) AND (EXCLUDE(DOCTYPE, "re"))

ISI Web of Knowledge

TITLE "sedentary behavior" OR "sedentary pattern" OR "sitting behavior" OR "sedentary bout" OR "sedentary variable" OR "sedentary time" OR "sedentary lifestyle" OR "physical activity" OR "physical inactivity"

AND TITLE pattern OR bout OR "physical activity level" OR "free-living behaviour" OR "physical behaviour" OR “activity pattern”

AND TOPIC sensor* OR acceleromet* OR inclinomet* OR pedomet* OR actigraph OR activpal OR directlife OR actical OR promove OR fitbit OR dynaport OR geneactive OR actometer OR GT1M OR GT3X OR stepcount

AND TOPIC: objectiv* OR monitor* OR measur* OR assess* OR determine OR defin* OR classif* OR pattern OR bout OR qualif* OR accumulat* OR accrue*

NOT TITLE: child* OR adolesc* OR boy* OR girl*

NOT TOPIC: question* OR interview

Refined by: [excluding] DOCUMENT TYPES: (REVIEW) AND LANGUAGES: (ENGLISH)
Timespan: 1989-2016.
Search language=Auto

2

ADDITIONAL FILE 2 RESULTS TABLE

Table 5 Legend of Sedentary behavior pattern measures overview table.

General	
CI	Confidence Interval
SH	Sedentary Hour
DO	Direct Observation
IQR	Interquartile range from the 1st and 3rd quartile
Classification	Method of classifying sedentary behavior
S	Sitting
S+R	Sitting or Reclining
S+L	Sitting or Lying
S+S+L	Sitting or Standing or Lying
S→S	sit-to-stand transition
Pattern measure	Sedentary behavior pattern measure
Data cleaning	
*	Number of times across the entire wear time (≥5 days).
Excessive values were removed, if either …	
Excessive values / artefacts	1) excessively high counts were removed, or 2) days with excessively high counts (>20 000 cpm) were excluded, or 3) days containing spuriously high values were removed
Non-wear was removed, if …	
≥10 min zeros	at least 10 min of continuous zeros
≥20 min zeros	at least 20 min of continuous zeros
≥20 min zeros, with gap (2min)	at least 20 min of continuous zeros, with allowance for 1 to 2 min of counts >0 cpm
≥60 min zeros	at least 60 min of continuous zeros
≥60 min zeros, with gap (2min)	at least 60 min of continuous zeros, with allowance for 1 to 2 min of counts >0 cpm
≥60 min zeros, with gap (2min <150 cpm)	at least 60 min of continuous zeros, with allowance for 1 to 2 min of counts 0-150 cpm
≥60 min zeros, with gap (2min <100 cpm)	at least 60 min of continuous zeros, with allowance for 1 to 2 min of counts 0-100 cpm
≥60 min zeros, with gap (2min <50 cpm)	at least 60 min of continuous zeros, with allowance for 1 to 2 min of counts 0-50 cpm
≥60 min <1.0 METs, with gap (2min ≥1.0 METs)	at least 60 consecutive minutes of no activity (i.e., estimated activity intensity < 1.0 METs), with allowance for 2 minutes of activities where intensity rose up to 1.0 METs
≥90 min zeros	at least 90 min of continuous zeros
≥90 min zeros, with gap (2min if ≥30 min before and after)	at least ≥90 consecutive minutes of zero counts to allow for movement of the unworn device, two minutes with movement (counts > 0) were permitted as long as ≥30 minutes of non-movement were observed before and after it.
≥90 min zeros vertical, with gap (2min if ≥30 min before and after)	at least ≥90 consecutive minutes of zero counts on the vertical axis; to allow for movement of the unworn device, two minutes with movement (counts > 0) were permitted as long as ≥30 minutes of non-movement were observed before and after it.
>100 min zeros	at least 101 min of continuous zeros (more than 100 minutes)
≥120 min zeros	at least 120 min of continuous zeros
>120 min zeros	at least 121 min of continuous zeros
≥150 min zeros	at least 150 min of continuous zeros
≥180 min zeros	at least 180 min of continuous zeros
Diary	non-wear was logged in a diary or logbook e.g. self-reported sleeping or removal of the sensor (e.g. during water activities).

Table 6 Sedentary behavior pattern measures

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
	N (Mean ± SD) *Men/Women* *Age(Mean ± SD)* *Health status*	*Sensor brand/type* *Settings (e.g. epoch length; type of filter)*	*Non-wear* *Day/night* *Ouliers* *Minimum wear time*	*< 100 cpm* *MLT* *L+S* *L+S+S*	*Wear-time* *Total SB* *Bouts* *Breaks* *Law exponent* *Gini index*		
(Barber, Forster, & Birch, 2015) [53]	N = 28 Age: 82.1 ± 9.2 Care home residents	ActiGraph GTX-3 Epoch: 15s Elastic belt to be worn over the right hip.	≥5d ≥10h Waking hours Non-wear (≥120 min zeros)	< 100 cpm	Wear-time	All subjects (hours)	12.78 ± 1.90
					Total SB	(hours) (mean ± SD)	
						All subjects	10.12 ± 2.18
						< 85 yrs	10.22 ± 2.48
						≥ 85 yrs	10.02 ± 1.92
						Men	9.68 ± 2.13
						Women	10.32 ± 2.23
						FAC 0-2	11.27 ± 1.33
						FAC 3-5	9.73 ± 2.30
						BI ≤ 11	10.97 ± 1.53
						BI >11	8.78 ± 2.43
						Outside in last month YES	11.35 ± 1.60
						Outside in last month NO	9.83 ± 2.23
						Fallen in last 6 months YES	8.95 ± 2.30
						Fallen in last 6 months NO	11.12 ± 1.55
						MMSE ≤ 24	11.13 ± 1.48
						MMSE > 24	8.52 ± 2.12
						% of waking time	
						All subjects	79
						< 85 yrs	75.3 ± 12.2
						≥ 85 yrs	83.3 ± 13.3
						Men	76.7 ± 16
						Women	80.6 ± 11.9
						FAC 0-2	88.2 ± 6.6
						FAC 3-5	76.4 ± 13.6
						BI ≤ 11	84.1 ± 7.8
						BI >11	71.9 ± 16.5
						Outside in last month YES	90.2 ± 5.4
						Outside in last month NO	77.0 ± 13.2
						Fallen in last 6 months YES	73.5 ± 16.5
						Fallen in last 6 months NO	84.4 ± 6.6
						MMSE ≤ 24	85.4 ± 6.9

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						MMSE > 24	69.1 ± 14.3
					Bouts	Number(n): BL: ≥ 60 min	
						All subjects	3.3 ± 1.3
						< 85 yrs	3.5 ± 1.6
						≥ 85 yrs	3.1 ± 1
						Men	2.8 ± 1.5
						Women	3.5 ± 1.2
						FAC 0-2	2.8 ± 3.4
						FAC 3-5	1.3 ± 1.3
						BI ≤ 11	3.6 ± 1.3
						BI >11	2.7 ± 1.3
						Outside in last month YES	2.5 ± 1.1
						Outside in last month NO	3.4 ± 1.4
						Fallen in last 6 months YES	3 ± 1.4
						Fallen in last 6 months NO	3.5 ± 1.2
						MMSE ≤ 24	3.6 ± 1.2
						MMSE > 24	2.3 ± 1.3
						BL (min) (of bouts BL ≥ 60 min)	
						All subjects	167 ± 211
						< 85 yrs	107 ± 45
						≥ 85 yrs	228 ± 287
						Men	248 ± 364
						Women	129 ± 52
						FAC 0-2	345 ± 382
						FAC 3-5	108 ± 36
						BI ≤ 11	195 ± 265
						BI >11	124 ± 63
						Outside in last month YES	396 ± 452
						Outside in last month NO	118 ± 52
						Fallen in last 6 months YES	102 ± 35
						Fallen in last 6 months NO	224 ± 278
						MMSE ≤ 24	213 ± 262
						MMSE > 24	96.2 ± 38.6
(Barreira, Zderic, Schuna, Hamilton, & Tudor-Locke, 2015) [35]	N = 15 Age = 27.5 ± 2.5yrs	ActiGraph GT3X+ Epoch: 1 min	07:00 – 22:00h	<100cpm → ≥100cpm	Breaks	Number (n/day)	74 ± 4.1
		ActivPAL Epoch: 1 min	07:00 – 22:00h	Sit → Stand	Breaks	Number (n/day)	39 ± 3.1

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
(Baruth, Sharpe, Hutto, Wilcox, & Warren, 2013) [94]	N = 197 Age: 39.3 ± 7.6 Women	Actigraph GT1M Epoch: 1 min	≥ 4d ≥ 10h/d Waking hours Non-wear (≥60 min zeros) Daypart analysis: Morning (06:00 – 12:00) Afternoon (12:00 – 18:00) Evening (18:00 – 24:00)	< 100 cpm	Total SB	Hours (h) Hours (h) in the morning Hours (h) in the afternoon Hours (h) in the evening	9.07 ± 1.79 2.51 ± 0.74 3.75 ± 0.59 2.55 ± 0.95
						% of wear time (%) % of morning % of afternoon % of evening	64.1 ± 8.7 61.8 ± 10.7 63.9 ± 9.5 65.8 ± 10.0
					Bouts	Number per SB hour (n/SH) BL: ≥1 min BL: ≥10 min BL: ≥30 min BL: ≥60 min	 10.5 ± 2.8 1.6 ± 0.2 0.3 ± 0.1 0.1 ± 0.04
						BL (min) BL: ≥1 min BL: ≥10 min BL: ≥30 min BL: ≥60 min	 6.4 ± 1.7 21.4 ± 3.5 46.3 ± 7.1 79.9 ± 17.9
						Number (n) in the morning Number (n) in the afternoon Number (n) in the evening	11.5 ± 3.8 10.9 ± 3.1 10.2 ± 3.4
					Breaks	Number (n) Intensity (cpm) Duration (min)	90.9 ± 16.0 484.3 ± 75.2 3.3 ± 0.8
(Bellettiere e.a., 2015) [48]	N = 307 Age = 83.6 ± 6.4	ActiGraph GT3X+ 30Hz, low freq. extension. Epoch: 1 minute Only vertical axis	≥10h/day 4 days Non-wear (≥90 min zeros vertical; with gap (2min if ≥30 min before and after))	<100cpm	Wear-time	(hours)	13.5 ± 1.3
					Total SB	(hours) All subjects	 9.73 ± 1.27
					Bouts	Number (n) All subjects; BL ≥1min	 70.6 ± 13.7
						% of total SB (%) All subjects BL: >1 min BL: ≥5 min BL: ≥10 min BL: ≥20 min	 100.0 86.0 74.1 57.5

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						BL: ≥30 min	45.5
						BL: ≥40 min	35.9
						BL: ≥50 min	28.3
						BL: ≥60 min	21.2
						BL: ≥90 min	7.5
						BL: ≥120 min	3.1
						Men	
						BL: >1 min	100.0
						BL: ≥5 min	88.6
						BL: ≥10 min	78.1
						BL: ≥20 min	62.5
						BL: ≥30 min	50.1
						BL: ≥40 min	39.9
						BL: ≥50 min	31.7
						BL: ≥60 min	23.8
						BL: ≥90 min	8.1
						BL: ≥120 min	3.3
						Women	
						BL: >1 min	100.0
						BL: ≥5 min	84.9
						BL: ≥10 min	72.5
						BL: ≥20 min	55.4
						BL: ≥30 min	43.6
						BL: ≥40 min	34.2
						BL: ≥50 min	26.9
						BL: ≥60 min	20.0
						BL: ≥90 min	7.3
						BL: ≥120 min	3.0
						65-79yrs	
						BL: >1 min	100.0
						BL: ≥5 min	85.5
						BL: ≥10 min	73.1
						BL: ≥20 min	55.6
						BL: ≥30 min	43.6
						BL: ≥40 min	33.7
						BL: ≥50 min	26.8
						BL: ≥60 min	19.8
						BL: ≥90 min	6.9
						BL: ≥120 min	2.6

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						80-89yrs	
						BL: >1 min	100.0
						BL: ≥5 min	86.0
						BL: ≥10 min	74.0
						BL: ≥20 min	57.3
						BL: ≥30 min	45.1
						BL: ≥40 min	35.4
						BL: ≥50 min	27.7
						BL: ≥60 min	20.5
						BL: ≥90 min	7.5
						BL: ≥120 min	3.0
						90+yrs	
						BL: >1 min	100.0
						BL: ≥5 min	86.5
						BL: ≥10 min	75.4
						BL: ≥20 min	60.3
						BL: ≥30 min	48.8
						BL: ≥40 min	39.4
						BL: ≥50 min	31.7
						BL: ≥60 min	24.4
						BL: ≥90 min	8.6
						BL: ≥120 min	4.0
						BL (min) (median (se))	
						All subjects	2.9 (0.1)
						Men	3.3 (0.1)
						Women	2.8 (0.1)
						65-79yrs	3.0 (0.1)
						80-89yrs	2.9 (0.1)
						90+yrs	2.8 (0.1)
						Longest BL (min) (mean (se))	
						All subjects	81.9 (16.8)
						Men	85.1 (2.6)
						Women	80.6 (1.7)
						65-79yrs	80.1 (2.7)
						80-89yrs	81.4 (2.0)
						90+yrs	85.4 (3.4)
						W_{50} (min) (mean (s.e.)	

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						All subjects	17.0 ± 0.1
						Men	19.8 ± 0.1
						Women	16.0 ± 0.4
						65-79yrs	19.8 ± 0.7
						80-89yrs	16.8 ± 0.5
						90+yrs	18.4 ± 0.8
(Blikman e.a., 2015) [41]	N = 23 + 23 Age: 45.7 ± 10.2 Groups: 1) Multiple Sclerosis (MS) 2) Control	ActiGraph GT3X+ 30Hz Epoch: 10 sec Low-frequency extension enabled VMU	≥11 h/d ≥5d Non-wear (≥180 min zeros)	≤150 cpm	Wear-time	Hours (h) MS patients Control group	 15.12 ± 1.4 15.72 ± 0.85
					Total SB	% of wear-time MS patients Control group	 63.2 ± 9.0 57.5 ± 9.4
					SB Bouts	Number(n) MS patients Control group	 799 ± 200 823 ± 168
						BL (min) ('log-mean') MS patients Control group	 2.62 ± 0.55 2.40 ± 0.33
						Variation of BL (CoV_{sed}) MS patients Control group	 16.1 ± 1.6 15.2 ± 1.4
						Fragmentation of sedentary bouts (F_{sed}) = bouts per SB hour (n/SH) MS patients Control group	 0.26 ± 0.07 0.30 ± 0.06
						Gini index (G) MS patients Control group	 0.50 ± 0.05 0.47 ± 0.05
(Boerema, Essink, Tönis, van Velsen, & Hermens, 2015) [95]	N = 27 Age = 37.9 ± 13.5 Office workers	Promove 3D 40Hz; Epoch: 1 min. IMA	Waking hours 5d	≤ 1.660 $m \cdot s^{-2}$	Wear-time	Hours (h)	13.3 ± 2.55
					Total SB	% of wear-time	85.66
					SB Bouts	BL (mean) BL (median)	17.34 5.09
						% of total SB (%) BL: 54.78 min ($W_{50\%}$)	 50.0

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Gini index	0.67
(Carson e.a., 2014) [96]	N = 4935 Age: 45.9 ± 15.1	Actical Worn on right hip on an elasticized belt. Epoch: 1min	≥ 4d (incl. Sat. or Sun.) ≥ 10h/d Waking hours Non-wear (≥60 min zeros, with gap (2min <100 cpm))	<100 cpm	Wear-time	Hours (h)	14.73 ± 1.49
					Total SB	Hours (h)	10.76 ± 2.03
					Bouts	Duration (min); BL: ≥20 min	331.6 ± 126.5
					Breaks	Number (n)	83.2 ± 18.3
(Cavanaugh, Kochi, & Stergiou, 2010) 84]	N = 157 Age: 80.1 ± 5.8 community-dwelling older adults: 1) high (≥10,000 steps/d) 2) moderate (5,000-10,000 steps/day) 3) inactive (<5,000)	StepWatch Attachted to the ankle using Velcro closures. During data processing, stride counts are doubled to reflect steps accumulated by both legs. Epoch: 1 min	14d 24h/d (Except when bathing, showering or swimming and to refrain from aerobic exercise other than walking or jogging)	0 steps	Total SB	% of wear time (%) Highly active elderly Moderately active elderly Inactive elderly	 72.2±2.1 79.2±1.6 86.9±1.0
					Sequence of activity-rest periods	Detrended Fluctuation Analysis (DFA) scaling component (α) Highly active elderly Moderately active elderly Inactive elderly	 0.88±0.11 0.82±0.08 0.72±0.07
						Entropy Rate (ER) Highly active elderly Moderately active elderly Inactive elderly	 3.94±0.39 3.61±0.55 2.89±0.57
(Chapman, Fraser, Brown, & Burton, 2015) [71]	N=75 Age= 42yrs Adults with mental illness	ActiGraph GT3X Right hip Vertical axis Epoch: 1 min	24h/day → Waking hours 7 days → ≥ 4d with 90% of waking hours Non-wear (≥60 min zeros + diary)	≤100cpm	Wear-time	Hours (h) (median)	14.15
					Total SB	% of wear-time (median) (IQR)	65 (58 – 72)
					Bouts	% of Total SB (IQR) BL ≥20 min	 34 (25 – 42)
					Breaks	Number (n) (median) (IQR) Break Length (min) (median) (IQR)	87 (77 – 102) 3.3 (2.7 – 3.9)
(S. F. . Chastin e.a., 2010) [66]	N = 34 Age: 55.4 ± 9.5 Groups: 1) Parkinson (PD) 2) Control	ActivPAL Sf = 10 Hz;	7d 24h/d	S+L	Total SB	% of wear time (24h) (%) PD Control	 76.7 ± 10.6 71.5 ± 9.4
					Bouts	% of Total SB (%) PD: BL: < 3.5h Control: BL < 2h	 60 60
						Distribution of bout lengths (α) PD Control	 1.32 ± 0.05 1.49 ± 0.07

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Gini index (G)	
						PD	0.84 ± 0.06
						Control	0.75 ± 0.05
(S.F.M. Chastin & Granat, 2010) [42]	N = 126 Age: 49.7 Groups: 1) Healthy active (Ha); 2) Healthy sedentary (Hs); 3) Chronic low back pain (BLP); 4) Chronic fatigue syndrome (CFS).	ActivPAL	24h/d	S+L	Total SB	% of wear time (24h) (min, max)	75% (41%, 92%)
					Bouts	Duration (min) (median)	
						Ha	17.3
						Hs	20.7
						LBP	23.8
						CFS	24.9
						% of Total SB (%)	
						Ha: BL: >17.3 min	71.5
						Hs: BL: >20.7 min	76.1
						LBP: BL: >23.8 min	92.7
						CFS: BL: >24.9 min	95.4
						Distribution of bout lengths (α)	
						Ha	2.27
						Hs	1.95
						LBP	1.80
						CFS	1.76
						Gini index (G)	
						Ha	0.35
						Hs	0.40
						LBP	0.74
						CFS	0.77
(S. F. M. . Chastin, Mandrichenko, Helbostadt, & Skelton, 2014) [44]	N = 2635 Age: 47 (median)	Actigraph 7164 Epoch: 1 min	≥ 5d (incl. Sat. or Sun.) ≥ 10h/d Waking hours Non-wear (≥60 min zeros, with gap (2min <50 cpm)) Excessive values	< 100 cpm *The values were normalized to total wear time.*	Total SB	% of wear time	
						Men 22-29	52.4 ± 13.8
						Men 30-39	54.0 ± 13.4
						Men 40-49	53.3 ± 12.3
						Men 50-59	58.2 ± 11.9
						Men 60-69	60.6 ± 11.1
						Men 70-79	68.3 ± 10.5
						Men 80+	72.5 ± 11.0
						Women 22-29	56.6 ± 9.3
						Women 30-39	55.6 ± 10.5
						Women 40-49	55.0 ± 10.5
						Women 50-59	57.9 ± 9.9
						Women 60-69	60.4 ± 11.7

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Women 70-79	65.0 ± 11.9
						Women 80+	71.1 ± 10.4
					Bouts	Number (n)	
						Men 22-29	92.5 ± 19.8
						Men 30-39	94.3 ± 18.5
						Men 40-49	96.6 ± 17.4
						Men 50-59	94.3 ± 19.3
						Men 60-69	88.3 ± 19.2
						Men 70-79	80.9 ± 17.4
						Men 80+	77.5 ± 19.5
						Women 22-29	98.4 ± 15.6
						Women 30-39	99.9 ± 16.3
						Women 40-49	99.5 ± 16.2
						Women 50-59	97.9 ± 16.7
						Women 60-69	91.9 ± 17.3
						Women 70-79	89.5 ± 18.2
						Women 80+	84.4 ± 19.3
						Bout Length (min)	
						Men 22-29	4.89 ± 1.76
						Men 30-39	5.15 ± 2.02
						Men 40-49	4.89 ± 1.47
						Men 50-59	5.69 ± 2.02
						Men 60-69	6.15 ± 2.04
						Men 70-79	7.24 ± 2.63
						Men 80+	9.07 ± 4.37
						Women 22-29	4.80 ± 1.14
						Women 30-39	4.82 ± 1.48
						Women 40-49	4.83 ± 1.30
						Women 50-59	5.23 ± 1.50
						Women 60-69	5.82 ± 2.14
						Women 70-79	6.79 ± 3.50
						Women 80+	7.58 ± 2.71
(Sebastien F. M. Chastin e.a., 2015) [36]	N=53 Age = 73.7 ± 8.8 Older adults	ActiGraph GT1M Epoch: 1 min	≥10h/d ≥3d PRE-intervention ≥3d POST-intervention Only baseline period	<100 cpm	Total SB	% of wear-time	68.0 ± 10.1
					Bouts	Number (n)	35.5 ± 7.2
						BL (min) (median)	5.12 ± 1.03
						% of Total SB BL: 19.8 ± 6.4($W_{50\%}$)	50.0

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						α (slope of the frequency distribution of bout duration)	1.93 ± 0.15
						Fragmentation of sedentary bouts (F_{sed}) = bouts per SB hour (n/SH)	10.7 ± 2.4
					Breaks	Break Length ('period') (min) (log-mean)	14.4 ± 2.6
	N=36 Age = 43.0 ± 10.3 Office workers Groups: - Intervention - Control	ActiGraph GT3X+ Epoch: 1 min	≥10h/d ≥3d PRE-intervention ≥3d POST-intervention Only baseline period	< 100 cpm	Total SB	% of wear-time	63.9 ± 9.4
					Bouts	Number (n)	26.6 ± 11.8
						BL (min) (median)	8.22 ± 9.1
						% of Total SB BL: 27.1 ± 18.5 ($W_{50\%}$)	50.0
						α (slope of the frequency distribution of bout duration)	1.39 ± 0.14
						Fragmentation of sedentary bouts (F_{sed}) = bouts per SB hour (n/SH)	5.72 ± 3.79
					Breaks	Break Length ('period') (min) (log-mean)	5.11 ± 4.1
		ActivPAL	≥10h/d ≥3d PRE-intervention ≥3d POST-intervention Only baseline period	S	Total SB	% of wear-time	69.4 ± 9.1
					Bouts	Number (n)	33.0 ± 10.4
						BL (min) (median)	6.86 ± 3.0
						% of Total SB BL: 21.9 ± 7.7 ($W_{50\%}$)	50.0
						α (slope of the frequency distribution of bout duration)	1.37 ± 0.03
						Fragmentation of sedentary bouts (F_{sed}) = bouts per SB hour (n/SH)	6.0 ± 2.7
					Breaks	Break Length ('period') (min) (log-mean)	4.92 ± 1.7
(Chen e.a., 2016) [76]	N = 1634 Age = 73.3 ± 6.0 Older adults	Active stylePro HJA-350IT Epoch: 1 minute	≥10h/d (waking hours) ≥4d	≤ 1.5 METs	Wear-time	Hours (h) All subjects Disability in IADL YES Disability in IADL NO	 14.0 ± 1.8 13.8 ± 1.9 14.0 ± 1.8

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
		On either side of waist	Non-wear (≥60 min <1.0 METs, with gap (2min ≥1.0 METs))		Total SB	Hours (h)	
	Groups:					All subjects	7.72 ± 2.1
	- disability in IADL					Disability in IADL YES	8.73 ± 2.34
	- no disability in IADL					Disability in IADL NO	7.63 ± 2.04
					Breaks	Number (n)	
						All subjects	59.0 ± 13.2
						Disability in IADL YES	54.5 ± 13.2
						Disability in IADL NO	59.4 ± 13.1
(Claridge e.a., 2015) [77]	N = 42	ActiGraph GT3X	≥5h/d (waking hours)	<100 cpm	Wear-time	Hours (h)	
	Age = 33.5 ± 12	Epoch: 3 sec	≥4d			All subjects	10.50 ± 2.1
			Non-wear (diary)			CP-GMFCS level I	12.08 ± 2.2
	Adults with Cerebral Palsy (CP)					CP-GMFCS level II	12.38 ± 2.1
						CP-GMFCS level III	10.14 ± 1.8
						CP-GMFCS level IV	11.16 ± 2.1
	Groups:					CP-GMFCS level V	11.67 ± 2.1
	- CP-GMFCS level I				Total SB	Hours (h)	
	- CP-GMFCS level II					All subjects	10.50 ± 2.0
	- CP-GMFCS level III					CP-GMFCS level I	9.82 ± 1.09
	- CP-GMFCS level IV					CP-GMFCS level II	10.97 ± 0.45
	- CP-GMFCS level V					CP-GMFCS level III	9.49 ± 0.33
						CP-GMFCS level IV	10.90 ± 0.19
						CP-GMFCS level V	11.51 ± 0.09
					Breaks	Number (n)	
						All subjects	n.a.
						CP-GMFCS level I	24.4
						CP-GMFCS level II	16.0
						CP-GMFCS level III	7.6
						CP-GMFCS level IV	3.3
						CP-GMFCS level V	2.4
						Break-rate (n/SH)	
						All subjects	n.a.
						CP-GMFCS level I	2.63 ± 1.99
						CP-GMFCS level II	1.46 ± 0.62
						CP-GMFCS level III	0.82 ± 0.43
						CP-GMFCS level IV	0.31 ± 0.18
						CP-GMFCS level V	0.20 ± 0.095

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
(Cooper e.a., 2012) [72]	N = 528 Age: 59.8 ± 10.0 Type 2 diabetes	Actigraph GT1M Epoch: 1 min	≥ 3d; Waking hours > 10h/d Non wear (≥20 min zeros)	< 100 cpm	Total SB	(hours) All subjects Men Women	 8.1 ± 1.3 8.0 ± 1.2 8.1 ± 1.3
					Breaks	Number (n) All subjects Men Women	 82.9 ± 13.3 87.3 ± 15.7 85.2 ± 14.5
						Number (n/SH) All subjects	 10.7 ± 2.3
(Davis e.a., 2014) [78]	N = 217 Age = 78.1 ± 5.8 Older adults	ActiGraph GT1M Epoch: 10 sec→1min	≥10h/d; waking hours ≥5d Non-wear (>100 min zeros)	<100 cpm	Wear-time	Hours (h) All subjects Men Women	 14.1 ± 1.4 14.7 ± 1.5 14.2 ± 1.2
					Total SB	% of wear-time (%) All subjects Men Women	 71.3 ± 0.10 72.0 ± 0.10 70.7 ± 0.10
					Breaks	Number (n) All subjects Men Women Break-rate (n/wear-time(h)) All subjects Men Women	 72.8 ± 16.2 n.a. n.a. 5.0 ± 1.0 4.8 ± 1.0 5.2 ± 1.1
(Diaz e.a., 2016) [97]	N = 8096 Age ≥ 45y	Actical Secured to a nylon belt; on right hip Epoch = 1 min	≥10h/d ≥4d Non-wear (≥150 min zeros)	<50 cpm	Wear-time	Hours (h)	14.4 ± 2.0
					Total SB	Hours (h)	11.2 ± 2.1
					Bouts	BL (min) (mean) BL (min) (median)	11.4 ± 8.1 9.7 ± 2.3
						Number (n) All subjects BL: >1 min BL: ≥5 min BL: ≥10 min	 68.3 ± 20.0 28.0 ± 5.9 16.9 ± 3.4

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						BL: ≥20 min	8.8 ± 2.3
						BL: ≥30 min	5.5 ± 1.9
						BL: ≥40 min	3.8 ± 1.6
						BL: ≥50 min	2.6 ± 1.3
						BL: ≥60 min	1.9 ± 1.1
						BL: ≥90 min	0.8 ± 0.7
						Age: 45-54 yr	
						BL: >1 min	77.5 ± 17.3
						BL: ≥5 min	28.7 ± 5.8
						BL: ≥10 min	16.2 ± 3.9
						BL: ≥20 min	7.7 ± 2.6
						BL: ≥30 min	4.4 ± 1.9
						BL: ≥40 min	2.8 ± 1.5
						BL: ≥50 min	1.9 ± 1.1
						BL: ≥60 min	1.3 ± 0.9
						BL: ≥90 min	0.5 ± 0.5
						Age: 55-64 yr	
						BL: >1 min	74.0 ± 18.7
						BL: ≥5 min	28.8 ± 5.5
						BL: ≥10 min	16.7 ± 3.4
						BL: ≥20 min	8.3 ± 2.4
						BL: ≥30 min	5.0 ± 1.8
						BL: ≥40 min	3.3 ± 1.4
						BL: ≥50 min	2.2 ± 1.2
						BL: ≥60 min	1.6 ± 1.0
						BL: ≥90 min	0.6 ± 0.6
						Age: 65-74 yr	
						BL: >1 min	69.5 ± 18.7
						BL: ≥5 min	28.3 ± 5.5
						BL: ≥10 min	16.9 ± 3.3
						BL: ≥20 min	8.8 ± 2.2
						BL: ≥30 min	5.4 ± 1.8
						BL: ≥40 min	3.7 1.5
						BL: ≥50 min	2.6 ± 1.3
						BL: ≥60 min	1.8 ± 1.1
						BL: ≥90 min	0.7 ± 0.6
						Age: ≥75yr	
						BL: >1 min	59.9 ± 20.5
						BL: ≥5 min	26.9 6.6

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						BL: ≥10 min	17.0 ± 3.5
						BL: ≥20 min	9.5 ± 2.1
						BL: ≥30 min	6.3 ± 1.7
						BL: ≥40 min	4.5 ± 1.5
						BL: ≥50 min	3.3 ± 1.4
						BL: ≥60 min	2.4 ± 1.2
						BL: ≥90 min	1.1 ± 0.8
						% of Total SB	
						All subjects	
						BL: >1 min	100
						BL: ≥5 min	88.2 ± 5.7
						BL: ≥10 min	76.7 ± 9.7
						BL: ≥20 min	60.0 ± 13.9
						BL: ≥30 min	48.0 ± 15.5
						BL: ≥40 min	39.1 ± 16.0
						BL: ≥50 min	31.8 ± 15.9
						BL: ≥60 min	26.0 ± 15.4
						BL: ≥90 min	14.2 ± 12.9
						Age: 45-54 yr	
						BL: >1 min	100
						BL: ≥5 min	84.6 ± 6.2
						BL: ≥10 min	70.6 ± 10.2
						BL: ≥20 min	51.5 ± 13.0
						BL: ≥30 min	38.9 ± 13.8
						BL: ≥40 min	30.2 ± 13.3
						BL: ≥50 min	24.0 ± 12.5
						BL: ≥60 min	18.9 ± 11.4
						BL: ≥90 min	9.9 ± 8.4
						Age: 55-64 yr	
						BL: >1 min	100
						BL: ≥5 min	86.4 ± 5.8
						BL: ≥10 min	73.6 ± 9.6
						BL: ≥20 min	55.6 ± 13.0
						BL: ≥30 min	43.2 ± 14.0
						BL: ≥40 min	34.2 ± 13.8
						BL: ≥50 min	27.2 ± 13.3
						BL: ≥60 min	21.8 ± 12.5
						BL: ≥90 min	11.4 ± 10.0

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Age: 65-74 yr	
						BL: >1 min	100
						BL: ≥5 min	87.8 ± 5.4
						BL: ≥10 min	76.2 ± 9.2
						BL: ≥20 min	59.1 ± 13.0
						BL: ≥30 min	46.9 ± 14.4
						BL: ≥40 min	37.8 ± 14.7
						BL: ≥50 min	30.5 ± 14.5
						BL: ≥60 min	24.6 ± 13.9
						BL: ≥90 min	12.9 ± 11.4
						Age: ≥75yr	
						BL: >1 min	100
						BL: ≥5 min	90.8 ± 4.8
						BL: ≥10 min	81.2 ± 8.7
						BL: ≥20 min	66.6 ± 13.3
						BL: ≥30 min	55.5 ± 15.8
						BL: ≥40 min	46.7 ± 17.1
						BL: ≥50 min	39.2 ± 17.6
						BL: ≥60 min	32.8 ± 17.6
						BL: ≥90 min	19.2 ± 16.1
						Female	
						BL: ≥30 min	46.7 ± 15.6
						BL: ≥60 min	25.1 ± 15.2
						BL: ≥90 min	13.9 ± 12.8
						Male	
						BL: ≥30 min	49.7 ± 15.3
						BL: ≥60 min	27.0 ± 15.4
						BL: ≥90 min	14.5 ± 13.0
						BMI: underweight	
						BL: ≥30 min	43.9 ± 15.7
						BL: ≥60 min	22.7 ± 13.6
						BL: ≥90 min	12.5 ± 11.8
						BMI: normal weight	
						BL: ≥30 min	45.1 ± 15.8
						BL: ≥60 min	23.7 ± 15.1
						BL: ≥90 min	12.6 ± 12.6
						BMI: overweight	
						BL: ≥30 min	47.7 ± 14.9
						BL: ≥60 min	25.5 ± 14.6

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						BL: ≥90 min	13.8 ± 12.3
						BMI: obese	
						BL: ≥30 min	50.7 ± 15.6
						BL: ≥60 min	28.2 ± 16.0
						BL: ≥90 min	15.8 ± 13.6
					Breaks	Number (n)	
						All subjects	68.8 ± 20.0
						Age: 45-54	78.0 ± 17.3
						Age: 55-64	74.6 ± 18.7
						Age: 65-74	70.1 ± 18.7
						Age: ≥75	60.4 ± 20.6
						Female	70.6 ± 20.5
						Male	66.7 ± 19.3
						BMI: underweight	76.5 ± 22.0
						BMI: normal weight	73.5 ± 20.6
						BMI: overweight	69.4 ± 18.9
						BMI: obese	64.5 ± 19.9
						Breakrate (n/SH)	
						All subjects	6.4 ± 2.4
						Age: 45-54	8.0 ± 2.5
						Age: 55-64	7.2 ± 2.3
						Age: 65-74	6.6 ± 2.2
						Age: ≥75	5.3 ± 2.1
						Female	6.6 ± 2.4
						Male	6.2 ± 2.3
						BMI: underweight	6.9 ± 2.6
						BMI: normal weight	6.9 ± 2.5
						BMI: overweight	6.5 ± 2.3
						BMI: obese	6.0 ± 2.3
						Duration (min)	
						All subjects	2.8 ± 0.8
						Age: 45-54	3.4 ± 0.9
						Age: 55-64	3.0 ± 0.8
						Age: 65-74	2.8 ± 0.8
						Age: ≥75	2.3 ± 0.6
						Female	2.6 ± 0.7
						Male	2.9 ± 0.9
						BMI: underweight	2.6 ± 0.8

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						BMI: normal weight BMI: overweight BMI: obese	2.8 ± 0.8 2.8 ± 0.8 2.7 ± 0.8
(Ezeugwu, Klaren, A Hubbard, Manns, & Motl, 2015) [98]	N = 439 Age = 47.3 ± 10.0 yrs Adults with MS: - mobility disability absent (PDDS≤2) - mobility disability present (PDDS≥3)	ActiGraph 7164 Epoch = 1 minute On belt around the waist, on the non-dominant hip	≥3d during waking hours ≥10h/d wear-time Non-wear (≥60 min zeros)	<100 cpm	Wear-time	Hours (h) MS, mobility disability absent MS, mobility disability present	 14.01 ± 0.11 13.79 ± 0.14
					Total SB	Hours (h) MS, mobility disability absent MS, mobility disability present	 8.41 ± 0.08 8.89 ± 0.09
					Bouts (≥2min)	BL (min) MS, mobility disability absent MS, mobility disability present	 23.8 ± 1.1 24.2 ± 1.3
						Number(n); BL >30 min MS, mobility disability absent MS, mobility disability present	 4.3 ± 0.1 5.1 ± 0.1
					Breaks (≥2min)	Number (n) MS, mobility disability absent MS, mobility disability present	 13.7 ± 0.2 14.7 ± 0.2
						Duration (min) MS, mobility disability absent MS, mobility disability present	 12.8 ± 0.1 11.6 ± 0.1
(Falconer, Page, Andrews, & Cooper, 2015) [88]	N = 519 Age = 59.9 ± 9.9 Adults with type 2 Diabetes	ActiGraph GT1M Epoch = 1 min Waist-worn belt	≥3d during waking hours ≥10h/d wear-time Non-wear (≥60 min zeros)	<100 cpm	Wear-time	Hours(h)	14.02 ± 1.22
					Total SB	Hours(h)	9.06 ± 1.39
					Bouts	% of Total SB BL: ≥30 min BL: <30 min	 54 46
(Fanning e.a., 2016) [79]	N = 221 Age = 70.7 ± 4.7 Low active older adults - Intervention - Controls	ActiGraph GT1M or GT3X Epoch = 1 min On non-dominant hip	≥3d during waking hours ≥10h/d wear-time	<100 cpm	Total SB	Hours(h) Intervention; month 0 Intervention; month 6 Intervention; month 12 Control; month 0 Control; month 6 Control; month 12	 9.94 ± 1.61 9.89 ± 1.21 9.97 ± 1.41 9.77 ± 1.38 9.69 ± 1.27 9.76 ± 1.23
					Breaks	Number(n) Intervention; month 0	 78.31 ± 16.11

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Intervention; month 6	79.48 ± 15.12
						Intervention; month 12	77.99 ± 16.43
						Control; month 0	80.10 ± 15.95
						Control; month 6	78.61 ± 15.51
						Control; month 12	75.42 ± 17.07
(García-Hermoso, Notario-Pacheco, e.a., 2015) [61]	N = 1365 Age = 20-80 yrs	ActiGraph GT3X Vector magnitude Elastic belt; right side of waist	≥4d (≥ 1 weekend-day) ≥10h/d wear-time Non-wear (≥60 min zeros, with gap (2min <100 cpm))	<100 cpm	Wear-time	Hours(h)	
						All subjects	15,52 ± 3.65
						Men	15,69 ± 3.85
						Women	15,41 ± 3.51
					Total SB	Hours(h)	
						All subjects	9,67 ± 2.93
						Men	10,03 ± 3.11
						Women	9,45 ± 2.79
					Bouts	% of Total SB (%)	
						All subjects	77,0
						Men	75,5
						Women	77,9
					Breaks	Number (n)	
						All subjects	74.4 ± 14.3
						Men	77.3 ± 13.3
						Women	72.9 ± 15.7
						Breakrate (n/SH)	
						All subjects	3.4 ± 1.5
						Men	4.4 ± 1.1
						Women	2.9 ± 1.2
(García-Hermoso, Martínez-Vizcaíno, e.a., 2015) [89]	N = 263 Age = 55.8 ± 12.2	ActiGraph GT3X Vector magnitude Elastic band; right side of waist Epoch = 1 min	≥4d (≥ 1 weekend-day) ≥10h/d wear-time Non-wear (≥10 min zeros)	<100 cpm	Total SB	Hours(h)	
						All subjects	8.46 ± 2.01
						Men	9.15 ± 1.98
						Women	8.03 ± 1.92
					Bouts	Number (n)	
						BL ≥10min; All subjects	14.4 ± 4.8
						BL ≥10min; Men	14.2 ± 3.9
						BL ≥10min; Women	14.5 ± 5.3
						% of Total SB (%)	
						BL ≥10min; All subjects	76.8 ± 29.9

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						BL ≥10min; Men BL ≥10min; Women	70.6 ± 26.5 81.3 ± 32.4
(Gardiner, Eakin, Healy, & Owen, 2011) [99]	N = 59 Age: 74.3 ± 9.3 Older adults Intervention on breaking up SB time	Actigraph GT1M	6+6d ≥10h/d	< 100 cpm	Total SB	% of wear time (%) PRE POST (mean (95% CI))	 71.1 ± 8.9 67.9 (66.9, 69.0)
					Breaks	Number (n) PRE POST (mean (95% CI))	 87.8 ± 14.0 91.8 (89.3, 94.4)
(Gennuso, Gangnon, Thraen-Borowski, & Colbert, 2014) [80]	N = 5076 Age = 43.8 ± 19.5 Groups: - Subjects <8h/d SB - Subjects ≥8h/d SB	ActiGraph AM-7164 Elastic belt, over right hip Epoch = 1 min	≥1d Waking hours ≥10h/d wear-time Non-wear (≥60 min zeros, with gap (2min <100 cpm))	≥100 cpm	Total SB	Hours(h) All subjects (mean ± SD) <8 h/d SB (median, 25% - 75%) ≥8 h/d SB (median, 25% - 75%)	 8.2 ± 2.3 6.6 (5.6 – 7.3) 9.4 (8.7 – 10.6)
					Breaks	Number (n) All subjects (mean ± SD) <8 h/d SB (median, 25% - 75%) ≥8 h/d SB (median, 25% - 75%)	 90 ± 19 89 (78 – 100) 91 (77 – 104)
(Gupta e.a., 2016) [100]	N = 692 Age = 45.1 ± 9.9 Blue-collar workers Time split: - Whole day - Work - Non-work	ActiGraph GT3X+ Placed on the right thigh (like the ActivPAL)	4d; 24h/d ≥10h/d wear-time during waking hours.	If inclination of the thigh is above 45° (Custom classification program)	Wear-time	Hours(h) Whole day Work Non-work	 15.93 ± 1.45 7.60 ± 1.29 8.79 ± 1.60
					Total SB	Hours(h) Whole day Work Non-work	 7.83 ± 2.13 2.45 ± 1.75 5.49 ± 1.46
					Bouts	Hours(h) Whole day BL >30min BL 6-30min BL ≤5min Work BL >30min BL 6-30min BL ≤5min Non-work BL >30min BL 6-30min	 3.17 ± 1.67 3.60 ± 1.28 1.06 ± 0.58 2.45 ± 1.75 0.50 ± 0.94 1.40 ± 1.09 5.49 ± 1.46 2.65 ± 1.40

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						BL ≤5min	2.30 ± 0.80
(Hallman, Mathiassen, Gupta, Korshoj, & Holtermann, 2015) [85]	N = 191 Age = 45 ± 9.5 Blue collar workers	2x Actigraph GT3X Placed on the thigh and trunk (like the ActivPAL)	4d; 24h/d Waking hours ≥4h/day of working time and >75% of average reported working time ≥4h/day of leisure time and >75% of average reported leisure time Non-wear (≥90 min zeros + diary) Excessive values	Acti4 software classification of sitting	Wear-time	Work (h) Leisure (h)	8.4 ± 2.5 8.9 ± 2.7
					Total SB	Work (h) Leisure (h)	3.12 ± 1.5 5.93 ± 1.9
					Bouts	% of wear-time during either Work or Leisure (%) Work Males; BL >30min Females; BL >30min Non-work Males; BL >30min Females; BL >30min	 8.2 ± 10.2 5.6 ± 7.7 34.8 ± 15.1 28.2 ± 14.9
(G. N. Healy e.a., 2008) [70]	N = 168 Age = 53.4 ± 11.8 Adults	Actigraph 7164 Epoch: 1 min	≥ 5d (incl. 1 weekend day) ≥ 10h/d Waking hours Non-wear (≥20 min zeros + dairy)	< 100 cpm	Total SB	(hours) = sum over ≥5 days	56.7 ± 12.1 *
						% of wear-time (%)	57
					Breaks	Number (n) = sum over ≥5 days Intensity (cpm) = sum over ≥5 days Duration (min) = sum over ≥5 days	601 ± 155* 514 ± 94 * 4.50 ± 1.05 *
(G. N. . b Healy, Matthews, Dunstan, Winkler, & Owen, 2011) [4]	N = 4757 Age = 46.5 ± 14.2 Adults	Actigraph 7164 Epoch: 1 min	≥ 10h/d Non-wear (≥60 min zeros, with gap (2min <50 cpm)) Excessive values	< 100 cpm	Wear-time	Hours (h)	14.6 ± 1.45
					Total SB	(hours)	8.44 ± 1.45
					Breaks	Number (n) Duration (min)	92.5 ± 15.6 4.12 ± 1.26
(Helgadóttir, Forsell, & Ekblom, 2015) [57]	N = 165 Age = 43.42 ± 11.42 Groups: - Depressive disorders - Concurrent disorders - Anxiety disorders	ActiGraph GT3X+ On the right hip Epoch = 1 min	≥4d; waking hours ≥10h/d Non-wear (≥60 min zeros, with gap (2min)) If excessive values, whole day excluded from analysis.	<100cpm	Wear-time	Hours(h)	14.14
					Total SB	Hours(h) All subjects Depressive disorders Concurrent disorders Anxiety disorder Men Women	 9.11 ± 1.62 9.66 ± 1.62 9.02 ± 1.59 9.20 ± 1.77 9.43 ± 1.70 8.95 ± 1.56
					Bouts	Total time of BL ≥ 20min (h) All subjects Depressive disorders Concurrent disorders	 3.84 ± 1.8 4.19 ± 1.8 3.77 ± 1.7

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Anxiety disorder	4.00 ± 2.2
						Men	4.37 ± 1.8
						Women	3.59 ± 1.8
						Number of bouts of BL ≥ 20min (n)	
						All subjects	6.41 ± 2.53
						Depressive disorders	7.03 ± 2.73
						Concurrent disorders	6.26 ± 2.34
						Anxiety disorder	6.76 ± 3.29
						Men	7.13 ± 2.39
						Women	6.06 ± 2.53
(Jefferis e.a., 2015) [59]	N = 1403 Age = 78.4 ± 4.6 Older men.	ActiGraph GT3X Only vertical axis Over the hip Epoch = 1 min	≥3d; waking hours ≥10h/d Non-wear (≥90 min zeros; with gap (2min if ≥30 min before and after))	<100cpm	Total SB	Hours (h (95% CI))	
						All subjects	10.3 (10.2-10.4)
						Age: 70 – 74	10.0 (9.9-10.2)
						Age: 75 – 79	10.2 (10.1-10.3)
						Age: ≥80	10.7 (10.6-10.8)
						BMI: <25	10.2 (10.1-10.4)
						BMI: 25 – 29	10.2 (10.1-10.3)
						BMI: ≥30	10.6 (10.5-10.7)
						Smoking: yes	10.3 (10.2-10.3)
						Smoking: no	10.8 (10.5-11.2)
						Depression: no	10.2 (10.2-10.3)
						Depression: yes	10.6 (10.4-10.7)
						Chronic conditions: non	10.4 (10.3-10.5)
						Chronic conditions: 1 – 2	10.5 (10.3-10.7)
						Chronic conditions: ≥3	10.9 (10.6-11.1)
						% of wear time (% (95% CI))	
						All subjects	72.4 (72.0-72.8)
						Age: 70 – 74	69.7 (68.9-70.5)
						Age: 75 – 79	71.2 (70.5-72.0)
						Age: ≥80	76.0 (75.3-76.7)
						BMI: <25	74.5 (70.6-72.3)
						BMI: 25 – 29	74.7 (71.1-72.3)
						BMI: ≥30	75.7 (74.8-76.5)
						Smoking: yes	72.3 (71.9-72.7)
						Smoking: no	74.9 (72.4-77.4)
						Depression: no	71.3 (70.8-71.8)
						Depression: yes	76.4 (75.4-77.3)
						Chronic conditions: non	73.0 (72.3-73.7)

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Chronic conditions: 1 – 2	74.4 (73.1-75.6)
						Chronic conditions: ≥3	78.3 (76.5-80.1)
					Bouts	Number (n (95% CI))	
						All subjects	71.9 (71.2-72.6)
						Age: 70 – 74	73.4 (72.2-74.6)
						Age: 75 – 79	72.7 (71.6-73.8)
						Age: ≥80	69.6 (68.3-70.9)
						BMI: <25	74.5 (73.2-75.8)
						BMI: 25 – 29	72.7 (71.7-73.7)
						BMI: ≥30	65.7 (64.1-67.3)
						Smoking: yes	71.7 (71.0-72.4)
						Smoking: no	77.6 (73.3-82.0)
						Depression: no	73.1 (72.3-73.9)
						Depression: yes	67.4 (65.8-68.9)
						Chronic conditions: non	71.3 (70.1-72.5)
						Chronic conditions: 1 – 2	69.4 (67.4-71.4)
						Chronic conditions: ≥3	66.6 (63.3-70.0)
						Number (n)	
						All subjects	
						BL: >1 min	71.6 ± 15.7
						BL: ≥5 min	27.5 ± 4.6
						BL: ≥10 min	16.5 ± 2.7
						BL: ≥20 min	8.5 ± 1.9
						BL: ≥30 min	5.1 ± 1.6
						BL: ≥40 min	3.3 ± 1.3
						BL: ≥50 min	2.1 ± 1.1
						BL: ≥60 min	1.4 ± 0.9
						BL: ≥70 min	0.9 ± 0.7
						BL: ≥80 min	0.6 ± 0.6
						BL: ≥90 min	0.4 ± 0.4
						BL: ≥100 min	0.3 ± 0.4
						BL: ≥110 min	0.2 ± 0.3
						BL: ≥120 min	0.1 ± 0.2
						% of Total SB (%)	
						All subjects	
						BL: >1 min	100
						BL: ≥5 min	86.5 ± 5.0
						BL: ≥10 min	74.5 ± 8.4

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						BL: ≥20 min	56.5 ± 11.8
						BL: ≥30 min	43.2 ± 13.2
						BL: ≥40 min	33.1 13.2
						BL: ≥50 min	25.1 12.7
						BL: ≥60 min	18.8 ± 11.7
						BL: ≥70 min	14.1 ± 10.7
						BL: ≥80 min	10.5 ± 9.6
						BL: ≥90 min	7.7 ± 8.5
						BL: ≥100 min	5.8 7.5
						BL: ≥110 min	4.4 ± 6.6
						BL: ≥120 min	3.3 ± 6.1
						BL (min; median (IQR)	3.2 (1.1-9.9)
					Breaks	Number/sedentary hour (n/SH (95% CI)	
						All subjects	7.2 (7.1-7.3)
						Age: 70 – 74	7.6 (7.4-7.8)
						Age: 75 – 79	7.4 (7.2-7.6)
						Age: ≥80	6.7 (6.5-6.9)
						BMI: <25	7.5 (7.3-7.7)
						BMI: 25 – 29	7.4 (7.2-7.5)
						BMI: ≥30	6.4 (6.2-6.6)
						Smoking: yes	7.2 (7.1-7.3)
						Smoking: no	7.5 (6.9-8.2)
						Depression: no	7.4 (7.3-7.5)
						Depression: yes	6.6 (6.4-6.8)
						Chronic conditions: non	7.1 (6.9-7.3)
						Chronic conditions: 1 – 2	6.9 (6.6-7.2)
						Chronic conditions: ≥3	6.3 (5.9-6.8)
(Jefferis e.a., 2016) [90]	N = 1078 Age = 78.5 ± 4.7 Older men.	ActiGraph GT3X Only vertical axis On a belt, over right hip Epoch = 1 min	≥3d; waking hours ≥10h/d Non-wear (≥90 min zeros; with gap (2min if ≥30 min before and after))	<100cpm	Wear-time	Hours(h)	14.27 ± 1.12
					Total SB	Hours (h)	10.20 ± 1.38
					Bouts	% of Total SB (%)	
						BL: 01-15min	37
						BL: 16-30min	21
						BL: 31-60min	24
						BL: ≥61min	18
	N = 351 Age = 74.6 ± 7.0	ActiGraph GT1M	≥3d (incl. 1 weekend day) waking hours	<100 cpm	Wear-time	Hours (h)	
						All subjects	13.3

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
(Judice, Silva, & Sardinha, 2015) [47]		Right hip, near the iliac crest Epoch = 1 min	≥10h/d Non-wear (≥60 min zeros + water activities)			Male Female	13.46 13.23
					Total SB	Hours (h) All subjects Male Female	 9.60 ± 1.95 9.87 ± 1.80 9.46 ± 2.02
					Bouts	Number(n) All subjects BL: 5-10min BL: 11-20min BL: 21-30min BL: 31-60min BL: >60min Male BL: 5-10min BL: 11-20min BL: 21-30min BL: 31-60min BL: >60min Female BL: 5-10min BL: 11-20min BL: 21-30min BL: 31-60min BL: >60min	 156.0 ± 27.0 40.0 ± 14.0 16.0 ± 7.5 6.0 ± 3.9 1.3 ± 1.2 156.5 ± 23.8 44.0 ± 13.7 18.1 ± 7.0 7.0 ± 3.8 1.6 ± 1.2 156.2 ± 28.7 38.2 ± 14.6 14.8 ± 7.5 5.4 ± 3.8 1.2 ± 1.2
(Júdice, Santos, Hamilton, Sardinha, & Silva, 2015) [37]	N = 7 Age = 49.7 ± 12.6 Overweight/Obese adult with computer based work. Crossover-RCT: - Control - Intervention	ActivPAL On right thigh. Epoch = 1min ActiGraph GT3X On the right hip, near iliac crest. Only vertical axis Filter: AG-norm Epoch = 1min Actiheart (HR+Acc.)	1w+1w; waking hours ≥10h/day wear-time	ActivPAL: S+R Actigraph: <100 cpm Actiheart: <1.5METs	Total SB	Hours(h) Control ActivPAL ActiGraph GT3x Actiheart Intervention ActivPAL ActiGraph GT3x Actiheart	 8.58 ± 2.4 10.7 ± 1.6 5.93 ± 2.1 5.27 ± 2.9 10.6 ± 2.3 5.7 ± 2.6
					Breaks	Number (n) Control ActivPAL	 46.6 ± 16.7

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
		On an adapted polarband placed on the chest. Epoch = 1min				ActiGraph GT3x Actiheart Intervention ActivPAL ActiGraph GT3x Actiheart	128.0 ± 43.6 258 ± 79.8 53.7 ± 15.2 136 ± 34.5 305 ± 79.2
(Kim, Barry, & Kang, 2015) [33]	N = 11 Age = 30.67 ± 7.24	ActivPAL Mid-anterior position on right thigh ActiGraph GT3X On waist over right hip Epoch = 1s – 1 min	Non-wear based on images (lifelogging)	ActivPAL: S+R Actigraph: <50 cpm <100 cpm <150 cpm Sojourn (vertical axis) Sojourn (three axis) Inclinometer on 1s, 10s, 60s.	Wear-time	Hours(h)	6.11 ± 0.36
					Total SB	Hours(h (95% CI))) ActivPAL GT3X-Soj1x GT3X-Soj3x GT3X-Incli-1s GT3X-<8cnts/10s GT3X-Incli-10s GT3X-<50cpm GT3X-<100cpm GT3X-<150cpm GT3X-Incli-60s	 3.95 (2.90, 4.99) 3.75 (2.81, 4.69) 3.94 (2.88, 4.99) 3.19 (2.31, 4.07) 4.38 (3.63, 5.13) 3.17 (2.30, 4.05) 3.89 (3.04, 4.74) 4.24 (3.46, 5.03) 4.42 (3.65, 5.18) 3.16 (2.26, 4.05)
					Bouts	Number(n (95% CI))) ActivPAL GT3X-Soj1x GT3X-Soj3x GT3X-Incli-1s GT3X-<8cnts/10s GT3X-Incli-10s GT3X-<50cpm GT3X-<100cpm GT3X-<150cpm GT3X-Incli-60s	 18.2 (12.7, 23.6) 23.8 (18.9, 28.8) 13.7 (10.2, 17.2) 55.1 (35.6, 74.6) 137.0 (109.1, 164.9) 53.0 (34.5, 71.7) 32.0 (24.8, 39.2) 27.8 (22.1, 33.5) 24.9 (19.0, 30.8) 22.5 (14.9, 30.0)
						BL (min (95% CI)) ActivPAL GT3X-Soj1x GT3X-Soj3x GT3X-Incli-1s GT3X-<8cnts/10s GT3X-Incli-10s GT3X-<50cpm	 16.7 (8.9, 22.4) 10.1 (6.6, 13.5) 18.7 (12.7, 24.6) 4.3 (2.8, 5.8) 2.2 (1.4, 2.9) 4.4 (2.9, 5.9) 8.5 (5.0, 12.1)

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						GT3X-<100cpm GT3X-<150cpm GT3X-Incli-60s	10.4 (6.5, 14.4) 12.5 (7.4, 17.6) 9.8 (7.0, 12.5)
(Kim, Welk, Braun, & Kang, 2015) [62]	N = 5917	ActiGraph 7164 Right hip Epoch = 1 min	≥4d; Waking hours ≥10h/d wear time Non-wear (≥60 min zeros, with gap (2min <100cpm))	<100 cpm *All estimates were adjusted for accelerometer wear time.*	Total SB	Hours(h (SE)) Total BL: 1 min BL: 2-4 min BL: 5-9 min BL: 10-14 min BL: 15-19 min BL: 20-24 min BL: 25-29 min BL: ≥30 min	 8.05 (0.03) 0.57 (0.00) 1.42 (0.01) 1.57 (0.01) 1.04 (0.01) 0.74 (0.00) 0.56 (0.00) 0.43 (0.00) 1.73 (0.02)
					Bouts	Number(n (SE)) All BL: 1 min BL: 2-4 min BL: 5-9 min BL: 10-14 min BL: 15-19 min BL: 20-24 min BL: 25-29 min BL: ≥30 min	 93.02 (0.31) 34.25 (0.17) 31.53 (0.16) 14.41 (0.05) 5.34 (0.03) 2.65 (0.02) 1.53 (0.01) 0.96 (0.01) 2.35 (0.03)
(Leask, Harvey, Skelton, & Chastin, 2015) [60]	N = 33 Age = 65-82 (median = 73.3) Community dwelling older adults	ActivPAL	≥1d; waking hours	S+R	Total SB	% of wear-time (% (range))	59.2 (28.3 – 94)
					Bouts	Number (n(range)) BL≥2min	 30 (11 – 35)
(Lord e.a., 2011) [74]	N=56 Age: 78.9 ± 4.9 Older adults	ActivPAL sf = 10 Hz;	7d 24h/d	S+L	Total SB	(hours)	12.46 ± 1.94
					Bouts	Gini index (G)	0.836 ± 0.04
						Temporal diversity (D_{1sed})	15.2 ± 5.3
				S→S	Breaks	Number per day	39.0 ± 10.7
(Lyden, Keadle, Staudenmayer,	N = 13 Age: 24.8 ± 5.2	Actigraph GT3X (1D and 3D)	3d 10h/d	Soj-1x model	Total SB	(hours) (mean (95% CI))	6.27 (5.70, 6.85)
					Breaks	Number (n) (mean (95% CI))	39.3 (35.3, 43.3)

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
& Freedson, 2014) [39]		Epoch: 1 second				Breakrate (n/SH) (mean (95% CI))	6.6 (5.5, 7.7)
				Soj-3x model	Total SB	(hours) (mean (95% CI))	5.80 (5.28, 6.33)
					Breaks	Number (n) (mean (95% CI)) Breakrate (n/SH) (mean (95% CI))	29.4 (23.3, 35.5) -1.3 (-12.7, 10.1)
				≤ 100 cpm	Total SB	(hours) (mean (95% CI))	6.52 (6.06, 6.98)
					Breaks	Number (n) (mean (95% CI)) Breakrate (n/SH) (mean (95% CI))	54.4 (51.5, 72.9) 11.2 (8.7, 13.8)
				≤ 50 cpm	Total SB	(hours) (mean (95% CI))	5.95 (5.43, 6.46)
					Breaks	Number (n) (mean (95% CI)) Breakrate (n/SH) (mean (95% CI))	62.2 (51.5, 72.9) 11.2 (8.7, 13.8)
				8 counts per 10 sec	Total SB	(hours) (mean (95% CI))	6.40 (5.91, 6.89)
					Breaks	Number (n) (mean (95% CI)) Breakrate (n/SH) (mean (95% CI))	56.9 (45.3, 68.4) 9.5 (7.2, 11.8)
(Lynch e.a., 2016) [63]	N = 185 Age = 64.2 ± 10.3 Colon cancer survivors	ActiGraph GT3X+ Elastic belt over right hip. Epoch: 1 min	Waking hours ≥10h/d Non-wear (≥60 min zeros, with gap (2min <50 cpm)) Excessive values	<100 cpm	Wear-time	Hours(h)	14.41
					Total SB	Hours(h)	8.77 ± 1.55
					Bouts	Number (n) BL: ≥ 20 min BL: ≥ 30 min	 6.1 3.2
						% of Total SB (%) BL: ≥ 20 min BL: ≥ 30 min	 42.6 ± 1.92 29.3 ± 1.74
(Maddocks & Wilcock, 2012) [75]	N = 85 Age: 66 ± 9 Patients with Thoracic cancer Physical status 0-2	ActivPAL	4d (incl. Sat. and Sun.) 24h/d	S+L	Total SB	Hours (h) of 24h All subjects Physical status 0 Physical status 1 Physical status 2	 17.9 ± 2.1 17.7 ± 2.2 19.7 ± 1.7 21.0 ± 1.7
				S→S	Breaks	Number (n) All subjects Physical status 0 Physical status 1 Physical status 2	 45 ± 17 49 ± 8 47 ± 18 39 ± 19
(Manns, Ezeugwu,	N = 2017 Age = 70.7 ± 7.6	ActiGraph 7164 Over right hip	Waking hours ≥10h/d	<100 cpm	Wear time	Hours (h (95% CI)) - m-disability present	 14.37 (14.06, 14.68)

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
Armijo-Olivo, Vallance, & Healy, 2015) [51]	Community dwelling older adults - mobility disability present - mobility disability absent	Epoch = 1 min	Non-wear (≥60 min zeros, with gap (2min <50 cpm)) Excessive values			- m-disability absent	14.48 (14.21, 14.76)
					Total SB	Hours (h (95% CI)) - m-disability present - m-disability absent	 9.92 (9.60, 10.24) 9.18 (8.8, 9.47)
					Bouts	BL (min) - m-disability present (mean (95% CI)) (median (IQR)) - m-disability absent (mean (95% CI)) (median (IQR))	 7.3 (7.0, 7.7) 6.6 (5.2 – 8.7) 6.4 (6.1, 6.8) 6.1 (5.0 – 7.6)
					Breaks	Duration (min (95% CI)) - m-disability present (mean (95% CI)) (median (IQR)) - m-disability absent (mean (95% CI)) (median (IQR))	 3.0 (2.8, 3.2) 3.2(2.6 – 3.8) 3.7 (3.5, 3.8) 3.7 (3.1 – 4.5)
						Number (n (95% CI)) - m-disability present - m-disability absent	 87.6 (85.1, 90.1) 89.6 (87.3, 91.9)
(Ortlieb e.a., 2014) [101]	N = 168 Age: 65 – 89 Groups - total PA/day: 1) 'rare' (<25%) 2) 'average' (≥25- <75%) 3) 'frequent' (≥75%)	Actigraph GT3X; Epoch: 1 min 1D: vertical axis only	≥4d ≥10h/d Non-wear (≥20 min zeros, with gap (2min))	≤ 100 cpm	Total SB	(hours) All subjects	 8.4 ± 1.48
						% of wear time (median (5%, 95%)) All Rare Average Frequent	 65 (50, 82) 74 (66, 85) 65 (54, 74) 59 (41, 67)
					Bouts	BL (min) (mean (5%, 95%)) All Rare Average Frequent	 7.08 (4.78, 11.81) 8.64 (6.13, 12.58) 6.91 (4.80, 9.97) 6.31 (4.18, 8.58)
						BL (min) (median (5%, 95%)) All Rare	 3.00 (2.00, 4.50) 3.00 (2.00, 5.00)

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Average Frequent	3.00 (2.00, 4.00) 2.00 (2.00, 3.00)
						% of total SB (%) All BL: >3 min Rare BL: >3 min Average BL: >3 min Frequent BL: >2 min	 89 (84, 92) 90 (86, 92) 88 (84, 92) 88 (81, 91)
						Gini index (G (5%, 95%)) All Rare Average Frequent	 0.63 (0.57, 0.68) 0.65 (0.60, 0.68) 0.63 (0.58, 0.68) 0.62 (0.57, 0.67)
(Paraschiv-Ionescu, Buchser, Rutschmann, & Aminian, 2008) [102]	N=30 Groups: 1) Healthy subjects 2) Chronic Pain patients (CP)	*Three inertial sensors (each with two accelerometers and one gyroscope) fixed on the chest, the thigh and the shank.* 40 Hz	5d 8h/d No epoch length reported.	S+L	Sequence of activity-rest periods	Detrended Fluctuation Analysis (DFA) scaling component (α) Healthy subjects Chronic Pain patients	 0.856±0.09 0.756±0.09
						Fano factor scaling component (α_F) Healthy subjects Chronic Pain patients	 0.350±0.085 0.178±0.100
						Probability of words representing: long activity - short rest P_{111} (word: "111") Healthy subjects Chronic Pain patients P_{110} (word: "110") Healthy subjects Chronic Pain patients P_{011} (word: "011") Healthy subjects Chronic Pain patients P_{111111} (word: "111", "111") Healthy subjects Chronic Pain patients	 0.060±0.02 0.043±0.01 0.063±0.01 0.052±0.01 0.065±0.01 0.053±0.01 0.540±0.08 0.400±0.06
(Paraschiv-Ionescu, Perruchoud,	N = 32 Age: 67 ± 13	ASUR (Autonomous Sensing Unit Recorder)	5d 8h/d	S+L	Total SB	% of wear time Healthy subjects Chronic Pain patients	 49±11 63±13

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
Buchser, & Aminian, 2009) [69]	Groups: 1) Healthy subjects 2) Chronic Pain patients (CP)	2D, 40 Hz			Bouts	Burstiness parameter (B) Healthy subjects Chronic Pain patients	 0.40±0.10 0.33±0.12
						Memory parameter (M) Healthy subjects Chronic Pain patients	 0.08±0.07 0.11±0.10
					Breaks	Burstiness parameter (B) Healthy subjects Chronic Pain patients	 0.37±0.05 0.32±0.12
						Memory parameter (M) Healthy subjects Chronic Pain patients	 0.20±0.13 0.09±0.07
					Sequence of activity-rest periods	Complementary cumulative probability distribution (CCPD) 1. Scaling factor ($\tau_{\Delta}^{pos}, \tau_{\Delta}^{neg}$) Healthy subjects Chronic Pain patients	 296±133, 413±208 614±340, 297±158
						2. Characteristic shape parameter ($\beta_{\Delta}^{pos}, \beta_{\Delta}^{neg}$) Healthy subjects Chronic Pain patients	 0.66±0.15, 0.63±0.15 0.71±0.16, 0.77±0.19
						Fano factor scaling component (α_F) Healthy subjects Chronic Pain patients	 0.34±0.08 0.19±0.11
					Structural complexity	Permutation entropy (PE) Healthy subjects Chronic Pain patients	 0.28±0.09 0.16±0.07
(Parry & Straker, 2013) [43]	N = 50 Age: 36.4 ± 8.6 Office workers	Actical Attached to an elastic belt, worn over the right hip. Epoch: 1 min	≥4d (≥3 work, ≥1 non-work) ≥ 8,34 h/d Non-wear (>120 min zeros)	< 91 cpm	Wear-time	Hours (h) Workdays – all day Workdays – work hours Non-workdays	 14.9 ± 1.09 8.9 ± 0.77 13.7 ± 1.43
					Total SB	Hours(h) Workdays – all day Non-Workdays	 11.3 ± 0.98 9.30 ± 1.47
						% of wear time (%)	

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Workdays – all day Non-Workdays	75.9 69.7
					Bouts	% of wear time; BL: >30 min Workdays – all day Workdays – work hours Workdays – non-work hours Non-workdays	 34.1 ± 11.6 40.8 ± 16.6 22.8 ± 10.9 26.9 ± 11.1
					Breaks	Number (n/SH) Workdays – all day Workdays – work hours Workdays – non-work hours Non-workdays	 6.0 ± 1.4 5.1 ± 1.7 7.9 ± 2.1 9.2 ± 9.8
(Parry, Straker, Gilson, & Smith, 2013) [40]	N = 62 Age: 41.4 ± 10.9 Office workers Intervention	Actigraph GT3X Epoch: 1 min 7 days. 60sec epoch. Elastic belt to be worn over the right hip.	≥4+4d (≥3 work, ≥1 non-work) ≥ 8,34 h/d Waking hours Non-wear (≥120 min zeros)	< 100 cpm	Wear-time	Hours (h) Workdays – all day Workdays – work hours	 15.37 ± 1.40 8.36 ± 1.09
					Total SB	% of wear time PRE Workdays – all day Workdays – work hours POST Workdays – all day Workdays – work hours	 72.85 ± 7.06 78.29 ± 8.41 71.25 ± 7.27 76.6 ± 8.6
					Bouts	% of wear time; BL: >30 PRE Workdays – all day Workdays – work hours POST Workdays – all day Workdays – work hours	 24.37 ± 12.73 28.98 ± 19.34 22.29 ± 13.16 25.74 ± 18.66
					Breaks	Break rate (n/SH) PRE Workdays – all day Workdays – work hours POST Workdays – all day Workdays – work hours	 7.81 ± 2.45 6.95 ± 3.20 8.45 ± 2.86 7.67 ± 3.41

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
(Pettapiece-Phillips e.a., 2016) [38]	N = 50 Age = 37.2 (18 – 62) Women: 1) Control; 2) BRCA1 mutation	ActiGraph GT3X Elasticized belt Epoch = 1 sec	7d; waking hours ≥10h/d Non-wear (≥10 min zeros)	ActiLife ver. 6.8.2	Total SB	Hours(h) All subjects	 8.6 ± 1.5
					Bouts	BL – longest bout (in 7days) (min) All subjects	 119.3 ± 64.2
(Prince, Blanchard, Grace, & Reid, 2015) [64]	N = 263 Age = 63.6 9.3 Cardiac rehabilitation graduates	ActiGraph GT3X Right hip Vector Magnitude Epoch = 1 min	≥4d; waking hours ≥10h/d Non-wear (≥60 min zeros, with gap (2min <150 cpm)	≤150 cpm	Wear-time	Hours(h) All subjects Men Women	 14.14 ± 1.30 14.21 ± 1.28 13.93 ± 1.32
					Total SB	Hours(h) All subjects Men Women	 8.0 ± 1.6 8.2 ± 1.5 7.2 ± 1.5
					Bouts	Number (n); BL: ≥10 min All subjects Men Women	 14.1 ± 3.8 14.7 ± 3.6 12.3 ± 3.7
(Prioreschi, Makda, Tikly, & McVeigh, 2015) [65]	N = 29 Age = 52.7 ± 11 Rheumatoid Arthritis, women. - normal bone mass - low bone mass	Actical Velcro belt on hip of dominant leg. Epoch = 1 min	≥4d; waking hours ≥10h/d Non-wear (≥60 min zeros)	≤100cpm	Wear-time	Hours(h) normal bone mass low bone mass	 17 ± 3 16 ± 3
					Total SB	% of wear-time (%) normal bone mass low bone mass	 65 ± 11 74 ± 10
					Bouts	Number (n); BL: ≥60 min normal bone mass low bone mass	 7 ± 3 8 ± 3
					Breaks	Number (n) normal bone mass low bone mass	 72 ± 21 53 ± 18
(N. Reid e.a., 2013) [81]	N = 31 Age: 84.2 (range 61.4-95.8) Older adults In residential care	ActivPAL3™ Epoch: 15 seconds	7d 24h/d Waking hours ≥80% or ≥10h of waking time Non-wear (diary)	S+L	Waking hours	Hours(h)	14.6 ± 2.0
					Total SB	(hours) (mean (CI 95%))	12.4 (11.3, 13.3)
						% of waking hours	85
					Bouts	% of Total SB (%) Duration: ≥30 min Duration: ≥60 min	 73 44

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Bout duration at 10% total SB (min) Bout duration at 50% total SB (min) Bout duration at 90% total SB (min)	11 53 142
(R. E. R. . Reid, Carver, Andersen, Court, & Andersen, 2015) [86]	N = 71 Age = 50.27 ± 9.38 Adults, post bariatric surgery	ActivPAL™3 Adhesive patch on mid-thigh Epoch = 15sec	≥4d ≥22h/d; Sleep time was not analysed	S Break = Transition from sitting to standing	Total SB	Hours (h)	9.74 ± 2.29
					Breaks	Number(n)	48.20 ± 15.40
(L. B. . c Sardinha, Santos, Silva, Baptista, & Owen, 2015) [83]	N = 215 Age =73.3 ± 5.9 Non-institutionalized older adults	ActiGraph GT1M Right hip, near iliac crest Epoch: 15sec → 1 min	≥3d, incl. 1 weekend day ≥10h/d Non-wear (≥60 min zeros)	<100 cpm	Wear-time	Hours(h)	13.38 ± 1.58
					Total SB	Hours(h)	8.55 ± 1.89
					Breaks	Number(n)	78.9 ± 16.0
(L. B. Sardinha e.a., 2015) [103]	N = 371 Age = 74.7 ± 6.9 Non-institutionalized older adults - Low risk for physical dependence - High risk for physical dependence	ActiGraph GT1M Right hip, near iliac crest Epoch: 15sec → 1 min	≥3d, incl. 1 weekend day ≥10h/d Non-wear (≥60 min zeros)	<100 cpm	Wear-time	Hours(h) All subjects Low risk for physical dependence High risk for physical dependence	 13.72 ± 1.54 13.87 ± 1.57 13.30 ± 1.34
					Total SB	Hours(h) All subjects Low risk for physical dependence High risk for physical dependence	 9.00 ± 2.16 8.76 ± 2.09 9.70 ± 2.21
					Breaks	Number(n) All subjects Low risk for physical dependence High risk for physical dependence	 74.9 ± 20.0 78.0 ± 17.6 65.9 ± 23.6
						Number per SB hour (n/SH) All subjects Low risk for physical dependence High risk for physical dependence	 9.0 ± 3.6 9.5 ± 3.3 7.5 ± 3.9
(Sartini e.a., 2015) [67]	N = 1455 Age = 78.5 ± 4.6 Older men	ActiGraph GT3X Only vertical axis On elasticated belt over right hip Epoch = 1 min	≥3d; waking hours ≥10h/d Non-wear (≥90 min zeros, with gap (2min if ≥30 min before and after))	<100cpm	Wear-time	Hours(h, range)	14.22 (14.17,14.28)
					Total SB	% of wear-time (%)	72.6 (72.1, 73.0)
					Bouts ≥60 min	% of bouts at period of the day (%) Evenings (7 p, - 10.59 pm) 8-9 pm	 49 13.6

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
			Only hours with ≥45 valid wear minutes were included. Means were adjusted for various factors			9-10 pm	14.0
(Scheers, Philippaerts, & Lefevre, 2012) [34]	N = 442 Age: 41.4 ± 9.8	SenseWear Pro3 Armband (SWA) Epoch: 1 min Worn over the triceps muscle of the right arm.	≥ 6d (incl. Sat. and Sun.) ≥ 95% of 24h/d (Except during water-based activities)	MET ≤ 1.8 (incl. sleep)	Total SB	(hours) Men – normal weight Women – normal weight Men – Overweight Women – Overweight Men – Obese Women – Obese	 16.82 ± 1.87 16.48 ± 1.59 17.37 ± 1.84 17.52 ± 1.56 17.91 ± 1.60 18.36 ± 2.00
					Bouts	BL (min) Men – normal weight Women – normal weight Men – Overweight Women – Overweight Men – Obese Women – Obese	 13.63 ± 4.49 13.09 ± 3.03 14.52 ± 3.56 15.41 ± 3.68 15.52 ± 3.66 18.44 ± 7.68
					Breaks	Number (n) Men – normal weight Women – normal weight Men – Overweight Women – Overweight Men – Obese Women – Obese	 77.79 ± 15.17 77.13 ± 12.21 73.65 ± 12.61 69.98 ± 13.26 70.84 ± 10.90 64.70 ± 16.61
(Shiroma, Freedson, Trost, & Lee, 2013a) [87]	N = 7247 Women Age = 71.4 ± 5.8	Actigraph GT3X+	≥ 4d ≥ 10h/d Waking hours	< 100 cpm	Wear-time	Hours (h)	14.8 ± 1.2
					Total SB	Hours (h)	9.7 ± 1.5
						% of wear time (95% CI)	65.5 (65.5, 64.7)
					Breaks	Number (n/SH) (95% CI)	9.0 (9.0, 9.1)
					Bouts	Number (n) (95% CI)	85.9 (85.5, 86.3)
						Number (n) Duration: >1 min Duration: ≥5 min Duration: ≥10 min	 85.9 ± 16.1 29.8 ± 4.7 15.9 ± 3.2

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Duration: ≥20 min	7.0 ± 2.2
						Duration: ≥30 min	3.8 ± 1.6
						Duration: ≥40 min	2.2 ± 1.2
						Duration: ≥50 min	1.4 ± 0.9
						Duration: ≥60 min	0.9 ± 0.7
						% of Bouts	
						Duration: >1 min	100
						Duration: ≥5 min	35.5 ± 6.7
						Duration: ≥10 min	19.4 ± 5.9
						Duration: ≥20 min	8.7 ± 4.1
						Duration: ≥30 min	4.8 ± 2.9
						Duration: ≥40 min	2.9 ± 2.1
						Duration: ≥50 min	1.8 ± 1.6
						Duration: ≥60 min	1.2 ± 1.2
						% of Total SB (%)	
						Duration: >1 min	100
						Duration: ≥5 min	81.6 ± 6.4
						Duration: ≥10 min	65.5 ± 10.1
						Duration: ≥20 min	44.5 ± 12.5
						Duration: ≥30 min	31.5 ± 12.4
						Duration: ≥40 min	22.7 ± 11.3
						Duration: ≥50 min	16.5 ± 10.0
						Duration: ≥60 min	11.9 ± 8.6
(Shiroma, Freedson, Trost, & Lee, 2013b) [54]	N = 5032 Mean Age = 70.1 Older women	Actigraph GT3X+	≥ 4d ≥ 10h/d Waking hours	< 100 cpm	Wear-time	Hours (h (SE))	14.3 (+0.02)
					Total SB	Hours (h)	9.6
						% of wear time (median)	67.5
					Bouts	Number (n) (median (95% CI)	
						Duration: 1 min	79.3 (78.7, 79.8)
						Duration: 5 min	27.9 (27.7, 28.0)
						Duration: 10 min	15.2 (15.1, 15.3)
						Duration: 20 min	6.7 (6.7, 6.8)
						Duration: 30 min	3.6 (3.6, 3.7)
						% of Total SB (%) (median (95% CI)	
						Duration: 1 min	100
						Duration: 5 min	35.6 (33.4, 35.9)
						Duration: 10 min	19.4 (19.2, 19.6)

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
						Duration: 20 min Duration: 30 min	8.5 (8.4, 8.6) 4.6 (4.5, 4.7)
(Spinney e.a., 2015) [92]	N = 33 Office workers	ActivPAL	Analysis only during office hours	Sitting	Total SB	% of wear-time (%)	77,0 ± 17.8
				S → S	Breaks	Number per SB hour (n/SH)	4.0 ± 2.8
(Straker e.a., 2014) [31]	N = 24 (3*8) Age: 38.2 ± 8.3 Occupational groups: 1) Seated office workers; 2) Standing office workers 3) Teachers	Actical (omnidirectional) On belt over right anterior iliac spine Epoch: 1min	4d	< 91 cpm	Bouts	% of Wear-time (%); BL: >30 min Seated office workers Standing office workers Teachers	 37.3 25.7 15.7
					Breaks + Bouts	% of Wear-time (%); BL: 0-5 min Seated office workers Standing office workers Teachers	 21.8 26.8 34.6
(Tieges e.a., 2015) [52]	N = 96 Age = 72.2 (64-80) Patients with acute stroke	ActivPAL On unaffected leg	7d Including sleep ≥24h/d	S+L Sleep time was included in the analysis	Total SB	% of day (24h)	81
						Hours of day (24h) (median (IQR) Overall 1mo after stroke 6mo after stroke 12mo after stroke	 19.5 (18.1 – 21.2) 19.9 (18.4 – 22.1) 19.1 (17.8 – 20.8) 19.3 (17.3 – 20.9)
					Bouts	% of Total SB (%) (BL is median IQR) Overall - BL: 102 min 1mo after stroke - BL: 99 min 6mo after stroke - BL: 102.6 min 12mo after stroke - BL: 102 min	 50 (W_{50}) 50 (W_{50}) 50 (W_{50}) 50 (W_{50})
						Number per SB hour (n/SH) Overall 1mo after stroke 6mo after stroke 12mo after stroke	 2.30 (1.80 – 2.90) 2.21 (1.70 – 2.88) 2.41 (1.87 – 2.96) 2.48 (1.91 – 2.94)
(Van Cauwenberg, Van Holle, De Bourdeaudhuij, Owen, & Deforche, 2015) [93]	N = 442 Age = 74.2 ± 6.2 Older adults	ActiGraph GT3X+ Epoch = 1 min	≥5d; waking hours ≥10h/d Non-wear (≥90 min zeros)	<100 cpm	Total SB	Hours(h) Overall	 9.67 ± 1.63
						% of wear-time (%) Morning (7h-12h) Afternoon (12h-17h) Evening (17h-23h)	 50.33 66.40 68.47

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
(van der Berg e.a., 2016) [49]	N = 2497 Age = 60.0 ± 8.1 Adults: - Normal glucose metabolism (NGM) - Impaired glucose metabolism (IGM) - Type 2 Diabetes Mellitus (T2DM) And stratification to number of metabolic syndrome criteria: - 0 criteria - 1-2 criteria - 3-5 criteria	ActivPAL3 On right thigh	8d (24h/d) ≥14h/d of waking time Automated algorithm to identify waking time versus sleep.	S+L	Waking-time	Hours (h) All subjects NGM IGM T2DM	 15.7 ± 0.9 15.7 ± 0.9 15.8 ± 0.8 15.7 ± 1.0
					Total SB	Hours (h (95%CI)) NGM IGM T2DM 0 criteria 1-2 criteria 3-5 criteria	 9.06 (9.0, 9.1) 9.46 (9.3,9.6) 10.10 (10.0, 10.2) 8.69 (8.5, 8.9) 9.19 (9.1, 9.3) 9.96 (9.9, 10.1)
					Bouts	Number (n (95%CI)); BL: ≥30min NGM IGM T2DM 0 criteria 1-2 criteria 3-5 criteria	 4.55 (4.5, 4.6) 4.88 (4.7, 5.0) 5.42 (5.3, 5.5) 4.24 (4.1, 4.4) 4.64 (4.6, 4.7) 5.32 (5.2, 5.4)
						BL (min) NGM IGM T2DM 0 criteria 1-2 criteria 3-5 criteria	 10.54 (10.4, 10.7) 11.15 (10.8, 11.5) 12.62 (21.3, 12.9) 9.8 (9.5, 10.1) 10.6 (10.5, 10.9) 12.42 (12.2, 12.7)
					Breaks	Number (n (95%CI)) NGM IGM T2DM 0 criteria 1-2 criteria 3-5 criteria	 55.69 (55.0, 56.4) 55.00 (53.5, 56.5) 52.78 (51.7, 53.9) 57.11 (55.7, 58.5) 55.73 (54.9, 56.5) 52.71 (51.8, 53.6)
(Van Dommelen e.a., 2016) [91]	N = 205 Age = 45.8 ± 9.6	ActiGraph On right hip	≥4d, waking hours ≥2 work days (≥3h work) ≥10h/d wear-time	<100 cpm	Wear-time	Hours(h) Total time white collar, financial, men white collar, financial, women	 14.9 ± 1.1 14.7 ± 1.0

Study	Population	Sensor & settings	Data cleaning	Classification	Pattern measure	Unit	Per subject / day (mean ± SD)
	Adults; stratification based on occupation: - financial service provider – white collar - research institute white collar - construction company – blue collar		Non-wear (≥60 min zeros, with gap (2min <100 cpm)) Analysis of: 1) total wear-time 2) occupational time			white collar, research, men	15.0 ± 0.8
						white collar, research, women	14.8 ± 0.8
						blue collar, construction, men	15.4 ± 1.2
						Occupational time	
						white collar, financial, men	8.5 ± 1.0
						white collar, financial, women	8.3 ± 1.0
						white collar, research, men	8.2 ± 1.1
						white collar, research, women	7.8 ± 1.5
						blue collar, construction, men	7.7 ± 0.7
					Total SB	% of Wear-time (%)	
						Total time	
						white collar, financial, men	70.0 ± 5.2
						white collar, financial, women	67.4 ± 6.9
						white collar, research, men	65.7 ± 5.3
						white collar, research, women	63.5 ± 6.9
						blue collar, construction, men	55.5 ± 9.3
						Occupational time	
						white collar, financial, men	78.5 ± 5.6
						white collar, financial, women	79.5 ± 5.9
						white collar, research, men	77.0 ± 7.4
						white collar, research, women	76.3 ± 7.6
						blue collar, construction, men	43.6 ± 16.9
					Bouts	% of Total SB (%) BL: ≥30 min	
						Total time	
						white collar, financial, men	22.3 ± 8.9
						white collar, financial, women	21.9 11.2
						white collar, research, men	22.2 ± 6.9
						white collar, research, women	19.2 ± 7.6
						blue collar, construction, men	12.2 ± 7.1
						Occupational time	
						white collar, financial, men	27.4 ± 16.3
						white collar, financial, women	29.8 ± 17.9
						white collar, research, men	30.0 ± 14.9
						white collar, research, women	28.3 ± 15.1
						blue collar, construction, men	7.2 ± 10.7

CHAPTER 3

OPTIMAL SENSOR PLACEMENT FOR MEASURING PHYSICAL ACTIVITY WITH A 3D ACCELEROMETER.

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ABSTRACT

Accelerometer-based activity monitors are popular for monitoring physical activity. In this study, we investigated optimal sensor placement for increasing the quality of studies that utilize accelerometer data to assess physical activity. We performed a two-staged study, focused on sensor location and type of mounting. Ten subjects walked at various walking speeds on a treadmill, performed a deskwork protocol, and walked on level ground, while simultaneously wearing five ProMove2 sensors with a snug fit on an elastic waist belt. We found that sensor location, type of activity, and their interaction-effect affected sensor output. The most lateral positions on the waist belt were the least sensitive for interference. The effect of mounting was explored, by making two subjects repeat the experimental protocol with sensors more loosely fitted to the elastic belt. The loose fit resulted in lower sensor output, except for the deskwork protocol, where output was higher. In order to increase the reliability and to reduce the variability of sensor output, researchers should place activity sensors on the most lateral position of a participant‘s waist belt. If the sensor hampers free movement, it may be positioned slightly more forward on the belt. Finally, sensors should be fitted tightly to the body.

INTRODUCTION

Accelerometer-based activity monitors are currently the most widely used sensors for monitoring physical activity in clinical and free-living settings [104–106]. They can be used for monitoring physical activity to acquire more fundamental knowledge of patterns of physical activity or to generate input for health interventions. For the latter application, activity sensor data is used to determine performance and, subsequently, to provide real-time personalized feedback (e.g., for patients with Chronic Fatigue Syndrome [107] or COPD [108] to increase self-awareness and support behavior change. Studies on the implementation of 3D (tri-axial) accelerometer-based activity monitoring in healthcare have focused predominantly on overall behavior change or on clinical parameters on a group level [107, 109]. One could assume that averaging sensor data over large populations or over time reduces the effects of usage and other non-controllable factors during free living. However, the shift towards individual programs on physical activity patterns makes this assumption no longer valid [110, 111]. To increase the reliability and the validity of monitoring studies the influence of sensor placement and attachment has to be determined. However, the influence of the placement of the activity sensor itself on sensor output has not been studied in-depth before [111, 112].

Most studies in which activity counts or Energy Expenditure (EE) are used as a primary outcome measure, place a single sensor at the lower back (sacrum) or at the waist—close to the center of mass of the human body. These sensors can be directly attached to the skin or indirectly attached by using belts, clips or other accessories [112–114]. As the movement of clothes can cause interference in the accelerometer output, Bouten *et al*. [113] validated the tri-axial Tracmor monitor for predicting EE with the sensor attached directly to the skin. This placement hampered usability and increased subject burden, especially over prolonged periods of time, and in later validation-studies we can see that the sensor was no longer attached directly to the skin, but worn using an elastic belt [114]. Researchers have to choose between minimizing the relative motion between the sensors and the human body on the one hand (by providing a snug fit of the sensor against the body), and maintaining a high level of usability and comfort on the other [112]. But in order to be able to make this decision, they should know the effect of sensor placement on sensor output.

With this study, we aim to improve the quality of accelerometer sensor output for laboratory-based and free-living studies. We have conducted a two-staged study that resulted in concrete guidelines for wearing an activity sensor that increases reliability and reduces the variability of output data without compromising usability and comfort.

BACKGROUND

3D accelerometer-based activity monitors are small, lightweight, portable, non-invasive, and non-intrusive devices that record motion in three planes and provide an indication of the intensity level of physical activity [115]. In the last few years, research with activity monitors is becoming more uniform with the growing availability of assessment guidelines and best practices.

Current Guidelines for Research with Wearable Monitors

Current guidelines for assessing physical activity using wearable monitors focus on both sensor calibration and practical use [106, 116–119]. These guidelines are based on the latest research evidence and on the consensus of researchers in the field of objective monitoring of physical activity. They recommend that researchers provide the rationale for the selection of a particular monitor, like its reliability and validity for the target population. This rationale should also include a description of how the monitor was positioned on the participant during the calibration and validation studies [116].

Most guidelines recommend a systematic calibration to all users to establish the range, sensitivity, accuracy, precision, and inter-unit variability. There are two different distinguishable levels of calibration: (1) Unit calibration: The internal reliability of the accelerometer sensors across multiple units; and (2) Value calibration: The conversion of accelerometer output into more meaningful information, such as EE or time spent in moderate intensity physical activities which would give more clarity to patients or healthcare professionals [120].

Unit calibration is done to reduce inter-instrument variability and to ensure that individual activity monitors are correctly measuring the acceleration to which they are exposed. Such calibrations can be done for both static and dynamic conditions. The latter can be done with a mechanical shaker across a range of standardized accelerations and frequencies [110, 121–124]. Unit calibration is still advised before deployment in actual physical activity measurement to check for any malfunctions, even though contemporary devices with micro-electromechanical accelerometers have initial unit calibration performed at the factory that should remain calibrated for the lifespan of the device [117]. However, as these mechanical shaker studies are not generalizable to free-living conditions, sensor output is often calibrated during standardized activities such as walking on a treadmill or by positioning monitors on the right and left side of the body [124–126].

Effect of Sensor Position

The effect of sensor position on sensor output has been studied with the first generation accelerometers. Positional influences of the accelerometer around the hip were assessed by Jones *et al*. [125]. They positioned accelerometers at three different locations at the right hip, and made subjects walk at 3 mph (4.8 km/h) on a treadmill. They found significant differences in placement for the 1D accelerometer, but no differences for the multidimensional (3D and bidirectional) accelerometers. Welk [120] commented on these results that the multidimensional sensors tested by Jones *et al*. were probably less vulnerable to position differences.

In a more recent study on inter-instrument reliability, Powell *et al*. [127] placed eight 3D activity monitors of the same brand on their subjects: four on the left hip and four on the right hip. During rest and low intensity trials no significant between-unit differences for activity counts were identified. Significant differences were detected, however, during vigorous-intensity trials and relatively high variations were evident during the sit-to-stand task. The findings concerning low intensity activities of Powell *et al*. and Jones *et al*. suggest that there may be an interaction effect between sensor position and activity intensity. This position-intensity effect was also observed by Nichols *et al*. [124] who placed a 3D accelerometer inside a pouch securely fastened to the body with an elastic waist strap on the right and left hip of their participants while they walked on a treadmill. Intra-class correlation coefficients (ICC) of the vector magnitude of the right *vs*. the left sensor declined from 0.87 to 0.73 for respectively walking (3.2 km/h) and running (9.7 km/h). Nichols *et al*. discussed that the lower correlation during running might be caused by the skewed vector magnitude values. These findings on sensor position lead to the hypotheses:

H1. The position of the sensor around the waist affects sensor output.
H2. The effect of sensor positions around the waist on sensor output is mediated by the activity intensity.

Effect of Sensor Mounting

The effect of sensor mounting was observed by Bosch *et al*. [128], who reported that the differences of sensor output from the activity sensor in their study was caused by the two different types of sensor pouches used in several free living conditions. They attributed this finding to the different sensor orientations (wearing the sensor horizontally or vertically). However, the activity sensor used in this study is a 3D accelerometer with equal axes sensitivity. Therefore, it is unlikely that orientation caused the effect in sensor output. Rather, the use of two different types of pouches is more likely to have affected the accelerations measured by the sensors, possibly due to tightness of fit.

A somewhat similar situation can be found in Paul *et al*. [129]. Here, the authors compared two different brands of activity monitors while worn together on an elasticized belt in free living conditions. The authors found a significant lower number of counts per day by the sensor attached to the belt with Velcro compared to the one directly looped through the belt. They concluded that a conversion factor was needed to compare the two brands, due to the proprietary nature of the algorithms on the sensors, while neglecting mounting as factor. While we do not claim we have found the cause for the findings in the aforementioned studies, we do believe that mounting needs to be considered as a factor that affects sensor output. This leads us to our final hypothesis:

H3. Mounting of a sensor with a tighter fit to the body will produce higher sensor output.

STUDY OVERVIEW

In order to test our hypotheses, we have conducted a two-staged study. First, we performed a calibration study to study the quality of our sensor. Second, we studied the effects of usage on sensor output by focusing on: (1) sensor location and (2) type of mounting, in a laboratory study with healthy subjects.

CALIBRATION EXPERIMENT

Sensor

Recently, a new 3D accelerometer physical activity sensor has been introduced: the ProMove3D (63 × 96 × 16 mm, 67 g, Inertia Technology, Enschede, The Netherlands, Figure 5). This monitor has a 3D MEMS inertial sensor (LIS3LV02DL, ST Microsystems, Geneva, Switzerland) which can provide real-time output of raw 3D accelerometer up to 200 Hz with amplitude range of −6 to +6 g, and can run embedded software protocols for example to output activity counts per minute. The ProMove2 (65 × 50 × 30 mm, 70 g) which is used in this study, is the developer model of the ProMove3D containing the same 3D MEMS inertial sensor, see Figure 5. The ProMove 2 and its successive model the ProMove3D have already been implemented in a number of telemonitoring studies [120, 122–124].

Activity monitoring sensors have to be sensitive to accelerations that occur during normal human movement. According to Bouten *et al*. [125], body-fixed accelerometers placed at the waist level should be able to measure an amplitude range of about −6 to +6 g and should measure frequencies up to 20 Hz. These conditions are met by the ProMove2 specifications. The embedded software on the ProMove2 calculates aggregated accelerometer values similar to Bouten *et al*. [125]. These Integral of the Modulus of the Accelerometer output (IMA) values are calculated per minute in metric units (10−3 m/s2), according to Equation (1), with sample frequency *fs* = 100 Hz and time interval T = 60 s. Because of the embedded implementation of the IMA algorithm, the ProMove2 uses a high-pass filter by subtracting a moving average filter based on the last second (100 samples, 100 Hz) from the signal, whereas Bouten *et al*. applied a band-pass filter with cut-off frequencies at 0.11 and 20 Hz:

$$IMA = \frac{1}{f_s T} \sum_{n=n_0}^{n_0+f_s T} |a_x[n]| + |a_y[n]| + |a_z[n]| \quad (1)$$

Figure 5. Images of the ProMove2 (left) and ProMove3D (right).

Method

Four ProMove2 sensors were securely fastened to a mechanical oscillator (Vibration Exciter, type 4809, Brüel & Kjær, Nærum, Denmark) using non-damping materials, see Figure 6. The platform was oscillated at three different frequencies (6.67 Hz; 13.45 Hz; 19.88 Hz) within the range of human physical activity for which an activity sensor should be sensitive, according to Bouten *et al*. [125]. Sensors were oscillated for 5 min per frequency, and for each of the three sensor axes, resulting in nine conditions.

The applied acceleration of each condition was measured by the calibrated mechanical oscillator and expressed by an RMS value ($\mathrm{RMS} = \sqrt{(1/n)\sum_n \left({a_x}^2 + {a_y}^2 + {a_z}^2\right)}$ in 10^{-3} m/s^2). The ProMove2 measured 3D accelerometer data at 200 Hz. This was converted to RMS values, after removing start/stop effects, by only including the steady state of each condition, and removing gravity. The accuracy of the ProMove2 was evaluated by comparing its RMS values to the RMS of the calibrated mechanical oscillator.

Figure 6. Setup of the sensors on the mechanical oscillator. Four ProMove2 sensors were securely fastened to a mechanical oscillator (Vibration Exciter, type 4809, Brüel & Kjær).

Results

The accelerations measured by the ProMove2 showed that the factory calibration was accurate for all three sensor axes on all three tested sensors. The calculated RMS of the ProMove2 sensors was 4%–7% higher than the RMS of the calibrated oscillating platform and had a low variability between individual axes, indicating high accuracy of the sensors, see Table 7.

Table 7. Results from dynamic calibration of four sensors on a mechanical oscillator. Calibrated and measured RMS are the mean RMS and its standard deviation.

Condition	Calibrated RMS	Mean Measured RMS (n = 4)					Mean Difference
		Sensor 1	Sensor 2	Sensor 3	Sensor 4	Average	
6.67 Hz	322	341	337	333	333	336	+4%
13.45 Hz	1237	1309	1313	1313	1281	1304	+5%
19.88 Hz	2377	2474	2646	2532	2551	2551	+7%

Conclusions

The ProMove2 sensor is reliable for measuring accelerations within the frequency range of human movement. No manual calibration is needed, as the factory calibration is sufficiently accurate. Therefore, we could use the sensor in the next stage of the study.

LABORATORY STUDY

Our hypotheses on the effect of sensor position and method of mounting were tested in a laboratory setting.

Subjects

A convenience sample of ten healthy subjects (five male and five female) participated in the study. The physical characteristics of the subjects are presented in Table 8.

Table 8. Subject characteristics (n = 10).

	Mean	SD	Minimum	Maximum
Age (yr)	31	8.5	24	51
Height (m)	1.81	0.08	1.69	1.92
Body mass (kg)	78	12.5	60	96
Body mass index (kg/m^2)	23.7	3.5	18.0	29.4

Method

To study the effect of position of the sensor around the waist on sensor output (H1) and a mediating effect of activity intensity (H2), the subjects performed a number of activities for 5.5 min per activity with a 30 s rest period between each in the following order: walking on a calibrated motorized treadmill at four different walking speeds (3, 4, 5, and 6 km/h); slow jogging at the treadmill at 8 km/h; performing a series of predefined deskwork tasks, for example typing, taking a book from a shelf, reading a book, and making a phone call; and walking through a corridor at a comfortable walking speed (CWS). The activities are common daily activities and can be well controlled. Before the experiment, subjects walked for several minutes on the treadmill to get acquainted with treadmill walking.

Each subject wore five ProMove2 activity sensors simultaneously, at specific locations around the waist, as shown in Figure 7. These locations correspond to positions often reported in literature. The sensors were worn by the subjects in specially made tight fitting pouches which were securely mounted on an elastic waist belt. This resulted in minimal movement between the sensor and the elastic waist belt. The belt was not removed in between the different types of activities and each device was worn on the same location for all subjects. Subjects were not instructed in their choice of clothing and shoes.

To evaluate the effect of method of mounting on the accelerations measured by the sensors (H3), two of the subjects repeated the test protocol with the same sensors in the same sensor locations, but in commercially available pouches (Exilim leather pouch, Casio, Tokyo, Japan), in which the ProMove2 itself had a tight fit. However, the commercially made pouches were more loosely fitted to the elastic waist belt than was the case for the specially made pouches.

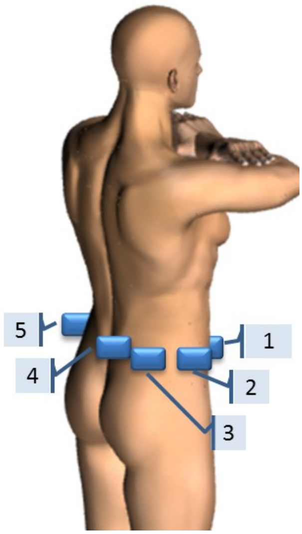

Figure 7. The five sensor locations around the waist. Sensor location 1 = Right hip anterior position; 2 = Right hip most lateral position; 3 = Right hip posterior to position 2; 4 = Sacrum position; and 5 = Left hip most lateral position.

Analyses

Raw accelerometer data were checked for abnormalities. The first and last 20 s of each 5.5 min activity interval were deleted to exclude start and stop effects. The raw acceleration data was then converted to IMA values per minute (Equation (1)). The statistical analyses were done using SPSS (SPSS Statistics, Version 19, IBM, Armonk, NY, USA).

First, position effects on the homogeneity of variances of minute-by-minute IMA values were tested by Levene's test. Equal variances indicate that the reliability of IMA values are not dependent on sensor location. Variances between the different sensor locations are assumed unequal when $p < 0.05$. Degrees of freedom are given by the F statistic. Second, a two-way repeated measures analysis of variance (ANOVA) with Bonferroni corrected pairwise comparisons was used to determine differences in mean IMA values per activity, due to the type of activity, the sensor location and its interaction-effects. The alpha level was set at $p < 0.05$ for all tests. Contrasts were performed with all sensor locations compared to sensor location 2 (see Figure 7), as that is the preferred location from a usability perspective in free-living studies. And all activity types were compared to the CWS as this type of physical activity resembles free-living walking conditions the best. Descriptive statistics of the mean IMA value per activity show the effect of the tightness of fit of the sensors at the different sensor locations and at all types of activities.

RESULTS

Reliability of Raw Accelerations

When checking the data for abnormalities, we found that sensor clipping occurred during the jogging activity (8 km/h at the treadmill), as shown in Figure 8. Clipping means that the true accelerations exceeded the sensibility range of the sensor, which was set at 6 g. Clipping was always present at sensor location 3 (right hip posterior position) and often at sensor location 4 (sacrum), at the vertical axis. Due to this clipping, IMA values of jogging are an underestimation of the true accelerations to which the sensors were exposed. Although this phenomenon was present, no correction for the clipping was done in the analysis that followed, as this would also not be done in uncontrolled free living settings.

Minute-to-minute variability of IMA values was analyzed by comparing the percentage of variation within subjects during each steady state with the mean IMA per condition, which varied from 0.8% to 61%, see Table 9. Relative high variances are evident in the deskwork task as this consisted of multiple small tasks making it more prone to minute-to-minute variations. Low minute-to-minute variability can be seen in the treadmill walking and during LGW. Levene's test for homogeneity showed that minute-to-minute variances did not significantly differ between sensor positions of individual activities.

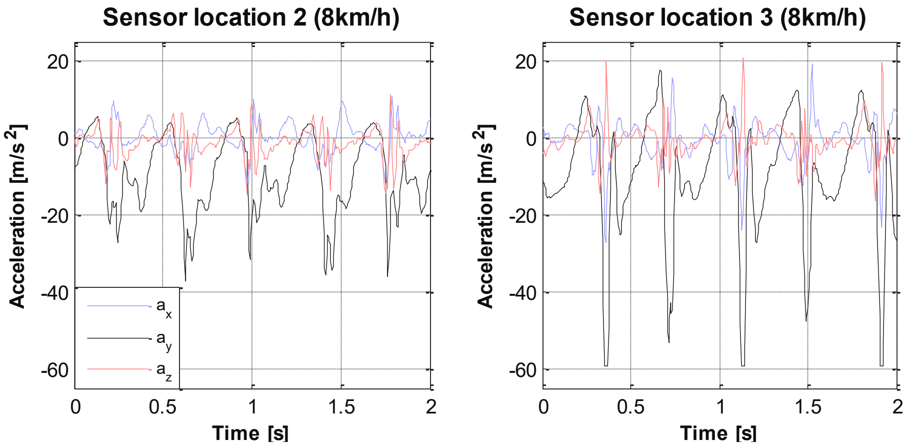

Figure 8. Example of clipping. Example of raw accelerometer data, while jogging 8 km/h. (Left), sensor location 2—no clipping. (Right), sensor location 3—clipping on one axis at 6 g.

Table 9. Minute-to-minute variability in IMA values during activities in absolute percentual deviation from the mean IMA for a specific activity, at a specific sensor location and for each subject. n = number of samples. CWS = Comfortable walking speed. SD = Standard Deviation.

Type of Activity	n	Mean IMA Variability [% (SD)]					Levene's Test	
		Location 1	Location 2	Location 3	Location 4	Location 5	F	p
Deskwork	52	58 (34)	59 (34)	61 (35)	59 (35)	60 (34)	F(4,255) = 0.09	0.986
CWS	43	1.2 (1.1)	1.4 (1.4)	1.4 (1.4)	1.4 (1.4)	1.2 (1.3)	F(4,210) = 0.27	0.897
TMW 3km/h	38	1.1 (0.9)*	1.3 (1.1)	1.8 (1.4)	2.1 (1.3)*	1.8 (1.1)	F(4,185) = 4.10	0.003
TMW 4km/h	39	1.1 (0.9)	1.2 (0.8)	1.2 (0.9)	1.3 (1.1)	1.4 (1.0)	F(4,190) = 0.57	0.683
TMW 5km/h	40	0.9 (0.8)	0.9 (0.8)	1.1 (0.8)	1.0 (0.9)	0.8 (0.7)	F(4,195) = 0.77	0.544
TMW 6km/h	37	1.0 (0.7)	1.0 (0.7)	1.1 (0.7)	1.0 (0.7)	0.9 (0.7)	F(4,180) = 0.43	0.787
TMW 8km/h	34	2.3 (2.1)	1.7 (1.6)	1.6 (1.6)	2.3 (2.1)	2.0 (1.5)	F(4,165) = 1.12	0.348

* *Post-hoc* analysis using Bonferroni correction, shows significant difference p = 0.004.

Usage Effects on Sensor Output

Both main effects (sensor location and type of activity) and their interaction effects were tested with a two-way repeated measures analysis of variance test. Mauchly's test indicated that the assumption of sphericity had only been violated for the main effects of type of activity, $\chi2$ (20) = 98.6. Therefore the degrees of freedom were corrected using the Greenhouse-Geisser estimates of sphericity (ε = 0.32) for the main effect of type of activity. Figure 9 shows the mean IMA values from the group with the sensor locations on the X-axis and a line per activity type.

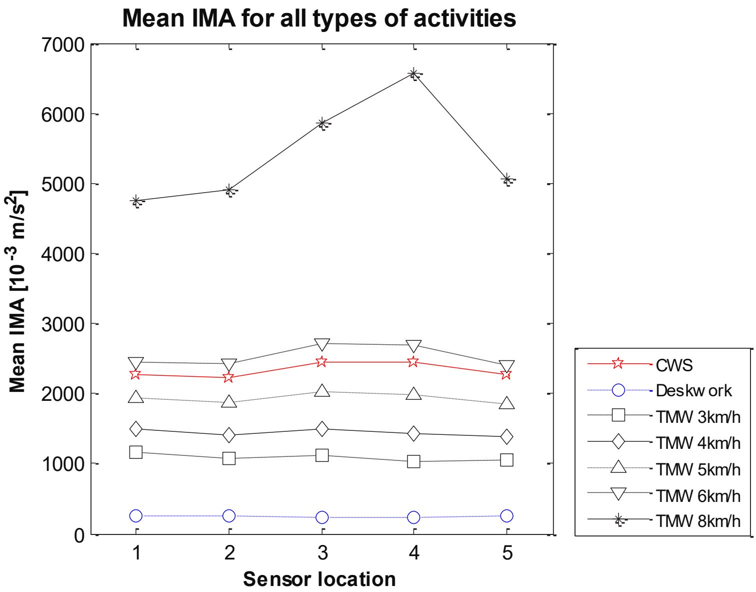

Figure 9. Mean IMA values for sensor locations 1–5, showing different lines for each type of activity (n = 10). TMW = treadmill walking; CWS = comfortable walking speed.

Effect of Type of Activity

There was a significant main effect of the type of activity ($F(1.93, 17.3) = 252.3$, $p < 0.001$): higher walking intensities result in larger accelerations resulting in higher IMA values. This can also be seen in Table 10 and Figure 10 that show the mean IMA values with confidence intervals for each type of activity measured at sensor location 2. Contrasts revealed that IMA values of all activities except treadmill walking at 6 km/h were significantly different from walking at CWS. IMA values of deskwork, 3 km/h, 4 km/h and 5 km/h were lower than CWS, respectively $F(1, 9) = 152.4$, $r = 0.97$, $p < 0.001$; $F(1, 9) = 64.2$, $r = 0.94$, $p < 0.001$; $F(1, 9) = 34.4$, $r = 0.89$, $p < 0.001$; and $F(1, 9) = 7.9$, $r = 0.68$, $p = 0.02$. IMA values of treadmill walking at 8 km/h were higher than CWS, $F(1, 9) = 141.8$, $r = 0.97$, $p < 0.001$.

Table 10. Descriptive statistics of mean IMA values per activity at sensor location 2 in 10^{-3} m/s^2. TMW = treadmill walking.

Activity	N	Minimum	Maximum	Mean	Std. Deviation
Deskwork	10	180	338	248	51
Comfortable walking speed	10	1,426	3,089	2,227	469
TMW 3 km/h	10	935	1,244	1,070	89
TMW 4 km/h	10	1,286	1,575	1,413	93
TMW 5 km/h	10	1,638	2,162	1,867	158
TMW 6 km/h	10	2,037	2,956	2,418	275
TMW 8 km/h	10	4,123	6,003	4,903	491

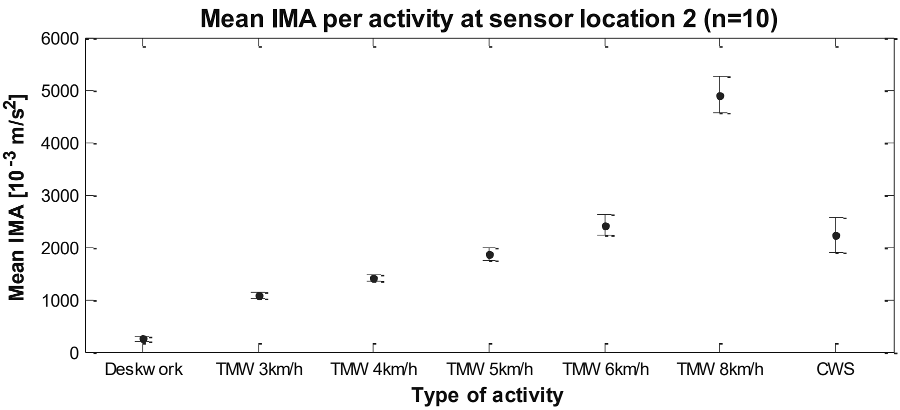

Figure 10. Error bars with 95% confidence intervals for mean IMA values per activity, at sensor location 2 (n = 10); TMW = treadmill walking; CWS = comfortable walking speed.

Effect of Sensor Location

All subjects wore five sensors simultaneously on an elastic waist belt, which makes it possible to study the effect of the sensor positions on the IMA values. Figure 11 gives the mean IMA value and the confidence intervals for each sensor location during CWS. There was a significant main effect of the sensor location on the mean IMA value, $F(4, 36) = 49.2$, $p < 0.001$. Contrasts revealed that only the IMA values of sensor locations 3 and 4 were significantly higher than sensor location 2, respectively $F(1, 9) = 165.7$, $r = 0.97$, $p < 0.001$; and $F(1, 9) = 87.5$, $r = 0.95$, $p < 0.001$. Mean IMA values for sensor locations 2, 3 and 4 and the minimum and maximum values were: 2227 (1426–3089), 2439 (1405–3277), and 2442 (1381–3730). These results support H1: The position of the sensor around the waist affects sensor output.

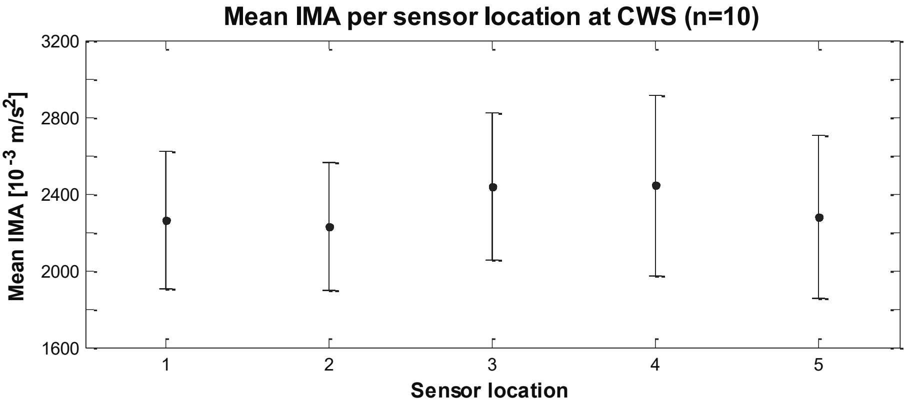

Figure 11. Error bars with 95% confidence Intervals for IMA values from all 5 sensor locations, at comfortable walking speed (CWS).

Interaction Effect of Type of Activity and Sensor Location

The interaction effect between the type of sensor location and the type of activity was significant, $F(24, 216) = 35.9$. This indicates that the sensor location had different effects on the IMA values, depending on the type of activity. To break down this interaction, contrasts were performed comparing all sensor locations to their baseline (location 2) and all types of activities to their baseline (CWS). An overview of the significant interaction effects is given in Table 11, which shows that sensor location 1 *vs*. 2 had only one interaction-effect for treadmill walking at 4 km/h *vs*. CWS, in which the difference between location 1 and location 2 is smaller at CWS than at TMW 4 km/h. Sensor locations 3 and 4 showed interaction effects for almost every activity, indicating that the effect of sensor location is strongly affected by the type of activity one performs, both with low intensity activities (deskwork) and with high walking intensities. Finally, no interaction effects were found for sensor location 5 *vs.* 2, which is in line with the non-significant contrast for the main effect of sensor location 5 *vs.* 2. In both graphs of Figure 12 it can be seen that the IMA values at sensor location 3 and 4 increase more at higher intensities than the self-selected walking speed, compared to sensor location 2. These results support H2: The effect of sensor positions around the waist on sensor output is mediated by the type of activity.

Table 11. Overview of all significant interaction effects. Contrasts for sensor locations to their baseline sensor location 2 and types of activities to their baseline CWS. CWS = comfortable walking speed; TMW = treadmill walking; r = effect size.

Sensor Location	Type of Activity		p	F*	r
1 *vs.* 2	TMW 4 km/h	*vs.* CWS	0.040	5.7	0.62
3 *vs.* 2	Deskwork	*vs.* CWS	< 0.001	36.5	0.90
3 *vs.* 2	TMW 3 km/h	*vs.* CWS	0.004	14.9	0.79
3 *vs.* 2	TMW 4 km/h	*vs.* CWS	0.011	10.0	0.73
3 *vs.* 2	TMW 6 km/h	*vs.* CWS	0.036	6.1	0.64
3 *vs.* 2	TMW 8 km/h	*vs.* CWS	< 0.001	72.0	0.94
4 *vs.* 2	Deskwork	*vs.* CWS	0.012	9.8	0.72
4 *vs.* 2	TMW 3 km/h	*vs.* CWS	0.006	12.8	0.77
4 *vs.* 2	TMW 4 km/h	*vs.* CWS	0.007	12.2	0.76
4 *vs.* 2	TMW 8 km/h	*vs.* CWS	< 0.001	47.8	0.92

* Degrees of freedom for all interaction effects = (1, 9).

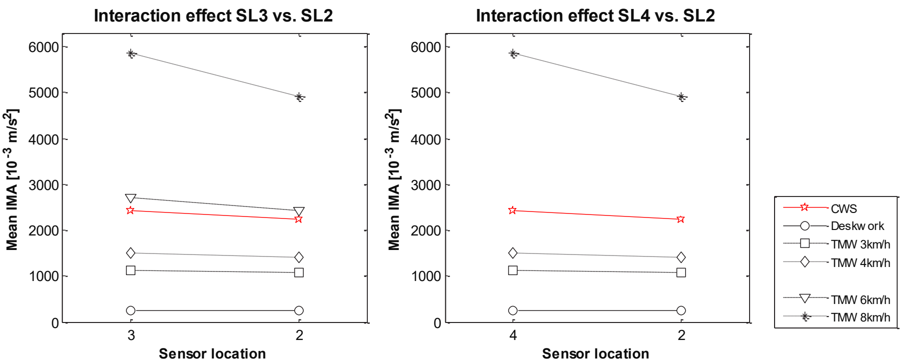

Figure 12. Interaction effects of sensor location and type of setting. Mean IMA values of all 10 subjects for the significant interactions. (Left), Location 3 *vs.* 2; (Right), Location 4 *vs.* 2.

Effect of Mounting

The study for the effect of mounting was explorative with only two subjects (A and B). For both subjects the pouches which were loosely fitted to the waist belt had lower IMA values than those of the more securely fitted pouches. The only exception is the deskwork of subject A. With increased walking speeds on the treadmill the effect of the different mounting methods was found to be stronger at all sensor locations. However at sensor location 2 the effect was minimal.

At this position the IMA values due to the loosely fitted pouch were 2% lower at 3 km/h and 15% lower at 8 km/h compared to the more securely fitted pouch. Finally, at the comfortable walking speed the effect due to mounting at sensor location 2 was 7% and 3% respectively, see Figure 13. These results provide tentative support for H3: Mounting of a sensor with a tighter fit to the body will produce higher sensor output.

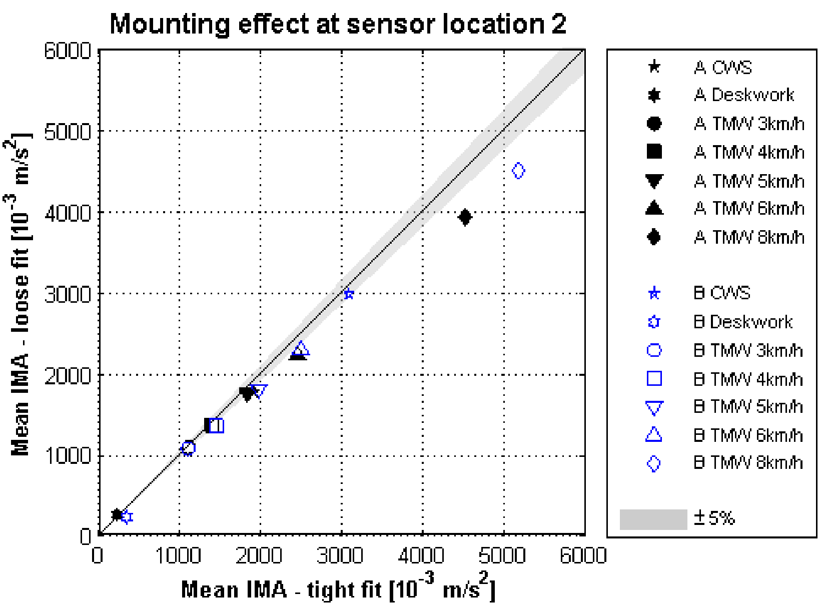

Figure 13. Effect of mounting on IMA values for various activities measured at sensor location 2, for two subjects (A and B, n = 2). IMA values measured with the Exilim pouch (loose fit) *vs*. the more securely fitted pouch.

Estimated Effect of Position on Free Living Data

By taking a few assumptions, the accumulated effect of position on data of a normal day of free living can be estimated. If we assume that an average monitoring day consists of 14 h (=840 min) of wear time [134], during which adults accumulate 7,473 steps per day [135], if we assume an average of 113 steps per minute [136] this takes about 66 min at an intensity level corresponding to the CWS condition in this study. Finally, we assume that the remainder of the day (non-stepping time) is not affected by sensor position. In Table 12 below we can see the effect of sensor positions 3 and 4 with respect to position 2 on the mean daily activity. When applying the assumptions to the mean daily activity in IMA of a healthy control group in the study of Tabak *et al*. [137]. If we replace 66 min (8%) by the average IMA value for CWS at sensor position 2 and calculate the average IMA for the remaining non-stepping time in order to keep the mean daily activity the same with the reference group, we can see that sensor positions 3 and 4 increase the mean IMA value per minute from 1,162 to 1,179, resulting in an increase of the mean daily activity score with 1.4% and 1.5% respectively.

Table 12. Effect of position on mean daily activity in IMA [10^{-3} m/s^2]. Duration is given in minutes per day. Cumm. = cumulative IMA value for the given duration per day.

Scenario	Steps			Non-Stepping Time **			Mean Daily Activity	
	Duration	IMA	Cumm.	Duration	IMA	Cumm.	IMA	%
Reference group	-	-		840	1162	976,080	1162 *	100%
Sensor location 2	66	2227	146,982	744	1071	829,098	1162 *	100%
Sensor location 3	66	2439	160,974	744	1071	829,098	1178.7	101.4%
Sensor location 4	66	2442	161,172	744	1071	829,098	1178.9	101.5%

* Reference IMA values are from 21 healthy controls in the study of Tabak *et al*. [137] that used sensor position 2; ** No sensor position effect assumed.

DISCUSSION

This study has shown that sensor position affects sensor output. Moreover, we have shown that there is an interaction effect between sensor position and type of activity. This makes it impossible to compare free-living studies that applied different sensor positions, due to the inherent nature of free-living behavior, from which it is unknown which types of activities were performed. Finally, we have estimated the position effect on free-living activity monitoring.

In order to increase the reliability, and to reduce the variability of sensor output, instructions for fastening activity sensors should consequently promote the same position on the body. The results from our study indicate that the most lateral position on a waist belt favors all other positions. First, it is a user-friendly position. If the sensor hampers free movement (a person may touch it with a moving arm), the best alternative is to position the sensor slightly more forward on the belt (to a more central position). This has a minimal effect on sensor output, but still creates a large range where the sensor can be worn with high data-reliability. Second, the lateral position on a waist belt showed no clipping during jogging at 8 km/h, while the sensor positions on the back (sensor locations 3 and 4) did. Finally, our exploration of how tightly a sensor should be fitted to the body suggested that for the best results they should be fitted as tightly to the body as possible. Such a tight fit can be facilitated by providing mounting material that ensures this tight fit, such as an elastic waist belt or clips that create a firm connection to a waistband. This will not hamper the participants' freedom to move as they normally would.

The results of this study enable researchers that are interested in studying activity behavior by means of activity sensors to create a more reliable data set. If they make their participants adhere to the instructions on how to wear an activity sensor, they will be provided with a data set that more closely resembles reality than with a data set that is generated by activity sensors placed at other parts of a waist belt. This means that researchers should also instruct all of their participants to wear their activity sensor on the most lateral position of a waist belt, or should position the sensors there themselves. Finally, when reporting studies that are based on activity monitor data, authors should report both the position where the activity monitor is placed, as well as the method of mounting (tightness of fit e.g., by a belt clip, Velcro, or attached to an elastic belt).

Besides the scientific gains of this study, our conclusions are also relevant for the developers of (electronic) health interventions that utilize activity sensor data. As we already mentioned in our introduction, such interventions are increasingly geared towards personalized feedback and based upon personal activity data. As a result, flaws in these data have a direct impact on the quality of the intervention, and indirectly on a patient's health. Therefore, positioning an activity sensor at the most optimal place on a patient's clothing is of great importance and these interventions should come with clear and explicit instructions that specify how to place the activity monitor to the side of the hip.

One could state that the evolution of activity monitors into more lightweight devices would also result in a reduction of position and mounting effects on accelerometer data due to the reduction of inertia. Such a shift has also been expected when transitioning from 1D to 3D sensors. However, our study has shown that in the latter case, this transition has not solved the problem. We are therefore cautious in accepting the thesis that a similar effect will occur when evolving into lightweight activity monitors, and urge the community to first study the effects of position and mounting on lightweight activity monitors carefully.

Limitations

The subjects that participated in this study were a convenience sample. They were young, healthy and had no problems walking on a treadmill at the different walking speeds. As a result, the findings of this study can only be generalized with 100% certainty towards the group of healthy young adults. In order to assess the effect of position and mounting on sensor data for other groups (e.g., children, the elderly, and people with walking difficulties), this study should be repeated with a subject sample, representative for this group. That being said, we think that the results of this study show that position and mounting do affect sensor data and we think that this will also be the case for other populations. However, the size of the effects may differ somewhat per population.

We had a subject sample of only two persons for studying the effect of mounting on sensor data. This has limited our possibilities for statistical analysis and hampers generalization. We think the results for mounting should be interpreted as explorative and highlighting the need for further research. We think we have shown that mounting may have an effect during studies which utilize activity monitors, and should be factored in when determining the quality of data.

We have not included a free living condition in our study as it excludes steady state conditions, limiting comparability of the type of activity among subjects and data variability. We have given a very rough estimate of the combined accumulated effect of position and mounting on free living data. The assumptions for this estimate only include an estimate of time spent in the measured activities and disregards the rich diversity of movements during free living, e.g., during household activities. Future research should delve into this issue.

The estimated effect of position on free living data resulted in only 1.4%–1.5% increase in IMA values on a daily basis if the sensor is worn at a more dorsal position than the most lateral position of a waist belt. This effect can be neglected by researchers, but this increase is based on just the position effect during 66 min of steady-state walking, and it is very likely that the remaining 13 h of monitoring time also consists of sensor position effects, which can increase the main daily score even further. More research on the effect of sensor position is therefore needed. On the other hand, researchers that are only studying steady state walking activities have to factor in the effect of −4% to +12% depending on walking speed and sensor position.

The position and mounting effects in this study are not brand specific. The specifications of the hardware and signal processing will determine how this study results will appear with other devices. Different sensitivity ranges and sample frequencies will probably affect sensor output and thereby also mediate the position and mounting factors. However, if the hardware specifications are sufficient, and the raw accelerometer data is processed in with a similar method as the IMA calculation, our findings are valid.

CONCLUDING REMARKS

In many validation studies, commercially available activity monitors have been validated for their ability to predict energy expenditure, physical activity intensity level, or type of physical activity [114]. Each sensor brand has its own preferred, validated sensor position and method of mounting. We have shown that small position changes or a more tight fit of the sensor have strong effects on sensor output. It is thus to be expected that in past validation studies these factors were not well controlled and various factors might have interfered, resulting in a somewhat ‘blurred‘ state of the art. With the recommendations from this study, more reliable and reproducible datasets can be gathered, by reducing variability, which can be used for better predictors of energy expenditure and types of physical activity. Our recommendations are also of great importance for developing health interventions that draw on activity monitor output. As stated by Esliger *et al*. [138], —the quality of information from accelerometers is only as good as the devices themselves.|| We strongly agree, but propose the following addition: the quality of information from accelerometers is only as good as the devices themselves and how they are worn.

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CHAPTER 4

SEDENTARY BEHAVIOUR PROFILING OF OFFICE WORKERS: A SENSITIVITY ANALYSIS OF SEDENTARY CUT-POINTS.

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Boerema ST, Essink GB, Tönis TM, van Velsen L, Hermens HJ. Sedentary Behaviour Profiling of Office Workers: A Sensitivity Analysis of Sedentary Cut-Points. Sensors. 2016;16:22

ABSTRACT

Measuring sedentary behaviour and physical activity with wearable sensors provides detailed information on activity patterns and can serve health interventions. At the basis of activity analysis stands the ability to distinguish sedentary from active time. As there is no consensus regarding the optimal cut-point for classifying sedentary behaviour, we studied the consequences of using different cut-points for this type of analysis. We conducted a battery of sitting and walking activities with 14 office workers, wearing the Promove 3D activity sensor to determine the optimal cut-point (in counts per minute ($m \cdot s^{-2}$)) for classifying sedentary behaviour. Then, 27 office workers wore the sensor for five days. We evaluated the sensitivity of five sedentary pattern measures for various sedentary cut-points and found an optimal cut-point for sedentary behavior of 1660×10^{-3} $m \cdot s^{-2}$. Total sedentary time was not sensitive to cut-point changes within ±10% of this optimal cut-point; other sedentary pattern measures were not sensitive to changes within the ±20% interval. The results from studies analyzing sedentary patterns, using different cut-points, can be compared within these boundaries. Furthermore, commercial, hip-worn activity trackers can implement feedback and interventions on sedentary behaviour patterns, using these cut-points.

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INTRODUCTION

High amounts of sedentary behaviour—sitting or reclining—are associated with increased risk of morbidity and mortality, independently of the level of moderate- to vigorous-intensity physical activity [3, 23, 24]. Moreover, there is little association between the time spent sitting and the time spent physically active in the course of a day [26], meaning that an individual can be simultaneously very sedentary and sufficiently physically active at a moderate- to vigorous intensity level.

A growing body of evidence indicates that not only the total sitting time, but also the pattern of accumulation of sitting time seems to mitigate health risks (such as a direct effect on metabolism, bone mineral content, and vascular health), independent of the total sitting time [4, 26, 70]. However, the more recent focus on sedentary behaviour has not yet resulted in general guidelines regarding which aspects of sedentary behaviour are most relevant to study.

We can measure the pattern of accumulation of sedentary time with wearable accelerometers on a minute to minute base, over longer periods of time. These sensors are primarily designed to measure intensity of physical activity, and not to distinguish postures such as sitting and reclining from standing and walking. This means that they cannot capture the full definition of sedentary behaviour being "any waking behaviour characterized by an energy expenditure of ≤1.5 metabolic equivalents, while in a sitting or reclining posture" [2]. However, these acceleration intensity based sensors, such as the Actigraph, are often used in sedentary research in which a cut-point is applied to classify a minute as being sedentary or active, based on the average acceleration intensity of that minute.

With the shift of focus from total sedentary time towards the pattern of accumulation of sedentary time, the number of measures capturing aspects of these patterns have also increased. These measures often focus on the duration of sitting periods (bout lengths) during the day. Examples of these bout measures, are the mean and median bout lengths, and more complex bout length distributions, such as the $W_{50\%}$ [36], the bout duration above and below which half of all sedentary time is accrued, and the Gini index [42], describing the inequality of bout lengths.

In literature reported sedentary behaviour measures are often based on different methods of classifying sedentary vs active behaviours and only a few studies have researched the effect of these various methods to the outcome parameters of sedentary behaviour [32, 139, 140]. Lyden *et al.* [32] found different total sedentary time and number of sedentary bouts for the 2 cut-points they studied (100 and 150 counts per minute), with increasing accuracy and precision as the cut-point increased. They conclude that the accuracy in estimating sedentary time and the number of bouts depended, among others, on the cut-point used to distinguish sedentary time, and the behavior of the sample population. However, by only comparing the effect of two different cut-points, it is unclear how strong the effect of the cut-point is, and in what range this effect is apparent. A sensitivity analysis with various cut-points will tell us whether or not it is possible to compare pattern measures of sedentary behaviour of various studies, while reducing the chance of building upon incorrect assumptions regarding sedentary behaviour, when used in interventions towards healthier lifestyles.

In this paper, we study how sensitive sedentary pattern measures are to various cut-points for sedentary behaviour. For this, we first determine the optimal cut-point for sedentary behaviour by means of direct observation of various activities in a laboratory setting (part A). Then, we vary around this optimal cut-point to perform a cut-point sensitivity analysis on a number of sedentary pattern measures of free living office workers (part B). This sensitivity analysis will show how sensitive sedentary pattern measures are to changes in the cut-point applied in accelerometer based sensors. We will conclude this article with the implications resulting from this sensitivity analysis for determining cut-points and the comparability of literature.

METHOD

A—Determining The Optimal Cut-Point for Sedentary Behaviour

Protocol

Fourteen healthy office workers (average age 31.0 ± 8.7; 6 men/8 women) without physical complaints were asked to perform a battery of tasks related to office work in a laboratory setting via a snow ball sample. The task battery consisted of the following active and sedentary tasks:

a) Sitting for 2 minutes on a wheeled office chair;
b) Doing deskwork for 4 minutes (including reading, taking a book from the shelf and typing);
c) Sitting 'restless' on a chair for 2 minutes (*i.e.,* to be active, while being seated);
d) Rising from a chair (one sit-stand transition) followed by 2 minutes of walking;
e) Walking through a corridor;
f) Standing still for 2 minutes.

During these tasks, participants wore the Promove 3D activity sensor (Inertia Technology, Enschede, The Netherlands) on the most lateral position, clipped to their waist belt [141]. Alongside this, a trained researcher annotated the start and stop time of each task on a dedicated smartphone application by direct observation. This application was synchronized with the data from the activity sensor. At the start of each session, participants were provided with an information letter and informed consent form.

Data Analysis

The activity sensor samples the accelerations in three dimensions at 40 Hz and calculates per minute an average sum of the Integral of the Modulus of Accelerations (IMA) according to Equation (1) as described in Boerema *et al.* [141]. This value per minute is in metric units ($m \cdot s^{-2}$). However, for readability and to adhere to jargon in this research field, the values will be referred to as counts per minute (cpm) without its unit.

$$IMA = \frac{1}{f_s T} \sum_{n=n_0}^{n_0+f_s T} |a_x[n]| + |a_y[n]| + |a_z[n]| \qquad (1)$$

The optimal cut-point was defined as the point where sensitivity and specificity of sedentary tasks were equal. With tasks a, b, c and f being sedentary and tasks (based on their intensity level) d and e as active tasks. Sensitivity and specificity were calculated for various cut-points on a minute-by-minute base, see Equations (2) and (3), resulting in an ROC curve (Receiver Operating Characteristic) with sensitivity against the 1-specificity for various cut-points.

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives} \qquad (2)$$

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \qquad (3)$$

B—Analyzing the Sensitivity of Sedentary Behaviour Patterns

Protocol

Twenty-seven healthy office workers (average age 37.9 ± 13.5; 12 men/15 women) without physical complaints were asked to wear the activity sensor during waking hours of five working days. This population includes the 14 office workers who also participated in the first trial. The sensor produced the same IMA values per minute as in the laboratory trial. Again, participants were provided with an information letter and informed consent form at the start of the evaluation.

Data Analysis

Each IMA value was classified as either sedentary or active using a cut-point value. For the sensitivity analysis this cut-point varied up to ±50% of the optimal sedentary cut-point as determined in the laboratory study. For each cut-point the following sedentary behaviour measures were calculated per person over the 5 day period:

Total sedentary time: as percentage of total wear time;

Sedentary bout length: as mean, median and $W_{50\%}$, in minutes. With the $W_{50\%}$ being the bout length above and below which half of all sedentary time is accrued, calculated according to Chastin et al. [36];

Sedentary bout length distribution: Gini index, between 0 and 1. With the Gini index describing the inequality of bout lengths, calculated according to Chastin *et al.* [42].

Statistical significant differences were tested with analysis of variances (ANOVA), with significance level of 0.05, when Levene's test for homogeneity of variances was non-significant. Post-hoc tests were conducted if the ANOVA yielded a significant result, with a Bonferroni post-hoc test. Here, we applied a significance level of 0.01 because of the high number of post-hoc tests conducted. When Levene's test was significant, we used a corrected version of the F-ratio: Welch's F, after which we conducted the same post-hoc test.

RESULTS AND DISCUSSION

A—The Optimal Cut-Point For Sedentary Behaviour

The average counts per minute for the sedentary tasks (a, b, c) was 531 (± 468) × 10^{-3} $m \cdot s^{-2}$, and for the active tasks (d, e) 2770 (± 568) × 10^{-3} $m \cdot s^{-2}$. The average counts per minute while standing still (task f) was 219 (± 182) × 10^{-3} $m \cdot s^{-2}$, as shown in Figure 14.

Task f—standing still—was within the same range of counts per minute as the sitting tasks, and could therefore not be classified as an active task based on a single cut-point. If task f was included in the ROC curve, this resulted in an area under the curve of 0.7548, indicating a rather poor performance. As it is known that standing still cannot be classified, based on counts per minute, we excluded task f from the ROC analysis as commonly done in accelerometer intensity based studies (e.g., by Kozey *et al.* [139] and Aguila-Farías *et al.* [140]). Excluding task f "standing still" from the

ROC analysis resulted in a sensitivity and a specificity curve crossing at 96.43%, corresponding to the optimal cut-point of 1660×10^{-3} $m \cdot s^{-2}$, see Figure 15b. The area under the curve of the ROC was 0.9982, indicating an excellent performance, see Figure 15a.

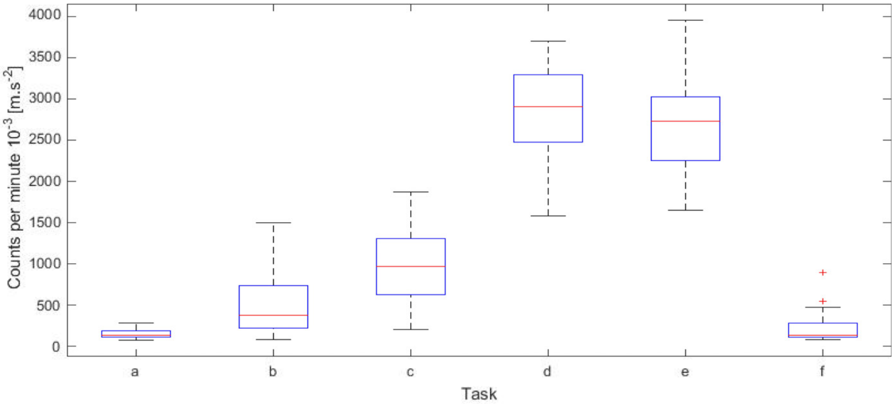

Figure 14 Boxplots of count per minute for the active and sedentary tasks (n=14). (a) sitting; (b) doing deskwork; (c) sitting 'restless'; (d) rising from a chair and walking; (e) walking; and (f) standing still.

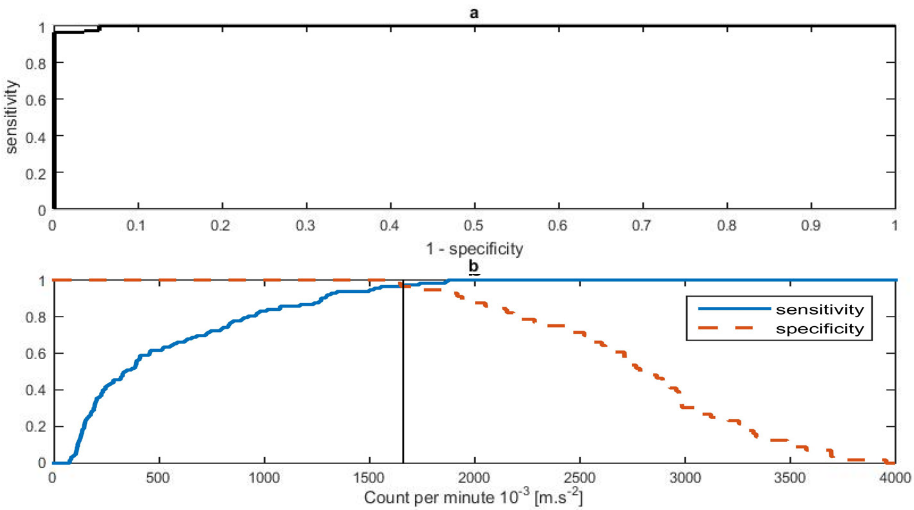

Figure 15 (a) ROC curve in counts per minute (sensitivity vs. 1-specificity), based on tasks a–e. Area under the curve is 0.9982. (b) Sensitivity and specificity vs. cut-point values. The curves intersect at: 1660 × 10−3 m·s−2.

B—Sensitivity of Sedentary Behaviour Patterns

In total, 137 days were measured; on average 5.07 days per subject, of which two subjects wore the sensor for only 4 days. The mean wear time per day was 13 h 18 min ± 2 h 33 min. Sedentary time, bout lengths and the Gini index were calculated for various cut-points as shown in Table 13.

Table 13 Overview of sedentary pattern measures for various cut-points.

Cut-Point		Total Sedentary Time [%]	Sedentary Bout Length [min]			GINI Index [0–1]
[%[a]]	[cpm]		Mean	Median	$W_{50\%}$	
50%	830	76.05[b]	13.51[b]	4.52[b]	39.67[b]	0.66
80%	1328	82.58[b]	15.64	4.56	48.11	0.67
90%	1494	84.16	16.41	4.81	52.04	0.67
95%	1577	84.92	16.83	4.94	53.41	0.67
100%	1660	85.66	17.34	5.09	54.78	0.67
105%	1743	86.40	17.92	5.35	56.07	0.67
110%	1826	87.09	18.39	5.61	58.15	0.67
120%	1992	88.42[b]	19.82	6.02	60.93	0.67
150%	2490	91.90[b]	26.84[b]	8.96[b]	76.96[b]	0.66

[a] Percentage of the optimal cut-point of 1660 counts per minute [cpm] in 10^{-3} [$m \cdot s^{-2}$].

[b] Significant different from the value at cut-point 1660 × 10^{-3} $m \cdot s^{-2}$, with $\alpha = 0.05$.

Total Sedentary Time

Total sedentary time was, on average, 85.66 ± 4.22% for the optimal cut-point, see Figure 16 for a visual representation. Levene's test for homogeneity of variances was non-significant. There was a significant effect of cut-point on total sedentary time, $F(8, 234) = 27.30$, $p < 0.001$. Post-hoc tests showed that the total sedentary time did not change significantly within the −10% and +10% threshold intervals. We did find significant differences outside this range (where −50% differed significantly from all other cut-points; −20% from +10%, +20%, +50%; and +50% from all but +20%).

Sedentary Bout Lengths

The sedentary bout length distribution has a skewed distribution, with a mean duration of 17.3 ± 3.9 min and median duration of 5.1 ± 2.0 min when applying the optimal cut-point. With an increasing cut-point, the mean and median bout length, as well as their standard deviations increase. Since Levene's test was significant for the mean and median sedentary bout length, we calculated Welch's adjusted F ratio for both ANOVA tests.

There was a significant effect of cut-point on the mean sedentary bout length, Welch's $F(8, 97.33) = 8.85$, $p < 0.001$. Post-hoc tests showed that the mean bout length did not change significantly within the −20% and +20% threshold intervals. We did find significant differences outside this range (where −50% differed significantly from +10% and above; and +50% differed significantly from all other cut-points).

There was also a significant effect of cut-point on the median sedentary bout length, Welch's $F(8, 97.14) = 3.50$, $p = 0.001$). Post-hoc tests showed that the median bout length did not change significantly within the −20% and +20% threshold intervals. We did find significant differences outside this range (where +50% differed significantly from all other cut-points).

The $W_{50\%}$ measure (the bout duration above and below which half of all sedentary time is accrued), shows a larger standard deviation for the group than the mean and median bout lengths. Levene's test for homogeneity of variances was non-significant. There was a significant effect of cut-point on $W_{50\%}$, $F(8, 234) = 2.86$, $p = 0.005$. Post-hoc tests showed that the $W_{50\%}$ did not change significantly within the −20% and +20% threshold intervals. We did find significant differences outside this range (where −50% differed significantly from +50%). This indicates that the mean, median and $W_{50\%}$ bout length measures are not sensitive to changes within the ±20% interval of the optimal cut-point, as shown in Figure 17.

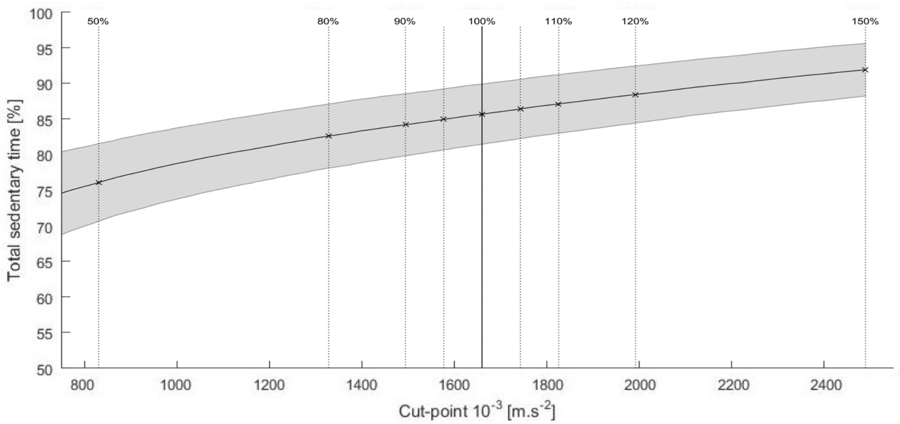

Figure 16 Mean total sedentary time as percentage of wear time for various cut-points. The shaded area is the standard deviation. Vertical lines indicate the various thresholds, with the solid line being the optimal cut-point.

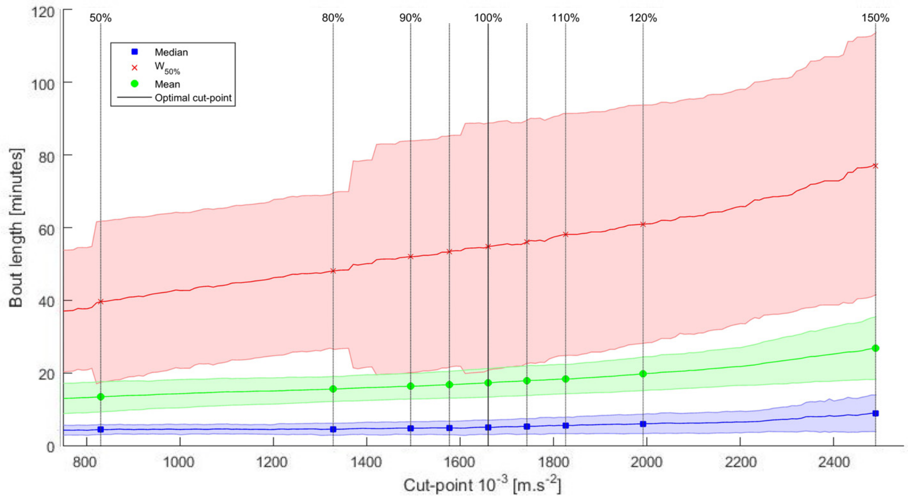

Figure 17 Bout length variables for various cut-points. Blue: Median bout length; green: Mean bout length; red: W50% bout length. Shaded areas are the standard deviations.

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Sedentary Bout Distribution

The Gini index is very stable over the full range of cut-points of ±50% of the optimal cut-point, with a mean of 0.67 ± 0.04 at the optimal cut-point. Levene's test for homogeneity of variances was non-significant. Moreover, there was no significant effect of cut-point on the Gini index, $F(8, 234) = 0.30$, $p = 0.967$, indicating that the Gini index is not sensitive to changes within the ±50% interval of the cut-point, as show in Figure 18.

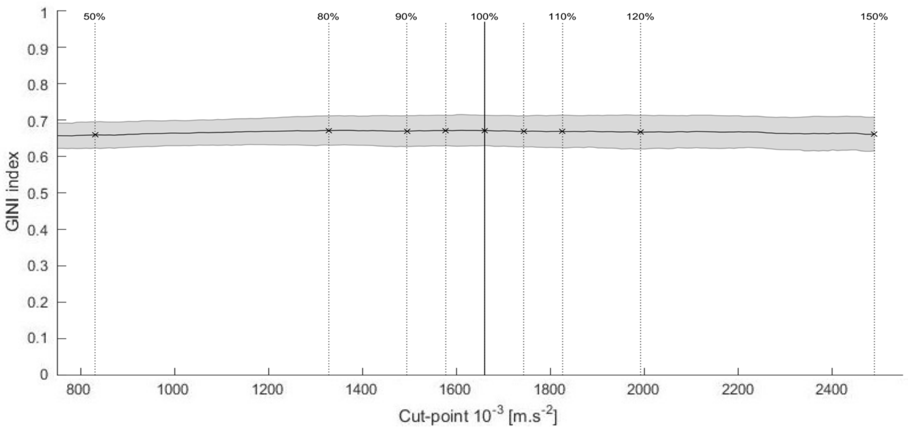

Figure 18 Mean Gini index for various cut-points. The shaded area is the standard deviation. Vertical lines indicate the various thresholds, with the solid line being the optimal cut-point.

DISCUSSION

In this study we have shown that sedentary pattern measures of daily living of office workers showed relatively low sensitivity to changes in the cut-point for sedentary behaviour. This makes 3D accelerometry very suitable for sedentary pattern analysis, without dedicated calibration studies. Some of these measures were more sensitive than others. The percentage of sedentary time was the most sensitive parameter, the mean, median bout length and $W_{50\%}$ were less sensitive and the Gini index was the least sensitive, showing no significant change within the ±50% interval that was studied around the optimal cut-point.

The results of this study indicate that sedentary pattern measures that are applied and reported in literature are comparable if they are measured by an acceleration based activity sensor with a cut-point for sedentary behaviour defined in a likewise manner. This means that the cut-point is defined for sedentary behaviours versus active behaviours, in which "standing still" is considered to be an sedentary behaviour, which is a commonly accepted approach [26, 32, 139, 140]. Based on our findings, these sedentary pattern measures are comparable if they are based on slight deviations from the optimal cut-point to distinguish active and sedentary behaviours, and this allowed deviation depends on the specific pattern measures, ranging from ±10% for total sedentary time, up to at least ±50% for the Gini index.

The calibration study described in this paper has shown that the counts per minute measured during the office related active and sedentary behaviours show almost no overlap, except for the behaviour "standing still". This behaviour has an even lower acceleration intensity than sitting restless on a chair, thereby making it impossible to distinguish these two activities based on only the mean counts per minute. Other studies have shown that it is possible to classify specific behaviours based on a single wearable sensor. However, they need more detailed sensor information than one value per minute, such as high frequency data or additional sensors such as gyroscopes [142]. These more complex sensing and analysis methods often need calibration for groups or even individual subjects, which is hindering the comparability of reported behaviour patterns.

Moreover, it strongly depends on the research questions if 'misclassification' of standing is a problem or not. Chau *et al.* [143] showed that office workers were standing about 45 min ± 28 min per day, while sitting for 5 h 47 min ± 59 min per day. In this study sample, standing would only comprise 11% of the total sedentary time measured by the sensor. The vast number of studies using the ActiGraph and alike sensors, show that standing time classified as sedentary is a generally accepted limitation of the sensing method.

Limitations

The sensitivity of the sedentary pattern measures described in this study, might be dependable on the limited number of type of activities in the free-living dataset. Because we focused on office workers, and predominantly during working hours, there were only a limited number of types of activities measured. These activities were predominantly sitting, walking, standing, and commuting by car or bike. And it is unknown what the contribution is to the sensitivity of the pattern measures with the current amount of the activity ”standing still”.

Changes in behaviour can be reflected differently in various sedentary patterns measures. Lyden *et al.* [32] did an intervention study in which office workers were asked to reduce and break up their sedentary time by replacing “sitting time” to “standing still” time at a sit-to-stand desk. Their definition of sedentary time included “standing still” and the change in behaviour resulted, therefore, in a larger overestimation of number of sedentary bouts, while the accuracy of the number of breaks per sedentary hour improved. These opposite effects on sedentary pattern measures with changes in the behaviour are strongly affected by the applied definition of sedentary behaviour and can also affect estimates of total sitting time and bout lengths described in the present study. However, our findings are valid for office workers when only including sitting time.

CONCLUDING REMARKS

Both our findings on the sensitivity of sedentary patterns to various cut points, and our finding that previous studies with different cut-points can be compared within certain boundaries, opens avenues for more focused research in sedentary behavior patterns and in creating an in-depth understanding of habitual physical activity rhythms of sedentary and active periods. Understanding these rhythms and predicting active and sedentary behaviour clears the way for new innovative physical activity interventions towards healthy behaviour.

Additionally, it is valuable to investigate the quality of the full range of sedentary pattern measures described in literature, such as number of bouts [87], breaks per sedentary hour [72], and sequences of activity-rest periods [68]. In this paper we discussed five pattern measures and their sensitivity to various cut-points, but there are many more sedentary pattern measures described in literature. These are tested with various populations on their ability to capture the specific behaviour patterns of populations and their variability within groups. As in physical activity research has been done on reported intensity levels and bout lengths, sedentary behaviour researchers should work towards an overview of the best measures for specific research questions with indications of their strengths and weaknesses. This should help the field in applying sedentary information in clinical practice and thereby further maturing the research field.

Finally, commercially hip-worn activity trackers, like those developed by Fitbit, Misfit and Jawbone, can also benefit from the findings of this study. Their sensing methods are often accelerometer intensity based, which is the same method as is investigated in this study. Our findings, therefore, can also serve as valuable input for the development of feedback and intervention protocols focused on sedentary behavior for these sensors. This way, these sensors can enter a new domain within activity tracking by means of consumables, and provide their customers with an overview of their daily sedentary behaviour additional to the number of steps and burned calories.

ACKNOWLEDGEMENTS

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CHAPTER 5

AN MHEALTH INTERVENTION TO REDUCE SEDENTARY BEHAVIOUR AND TO BREAK UP PROLONGED SEDENTARY PERIODS AMONG OLDER OFFICE WORKERS IN THE NETHERLANDS.

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Submitted 2018

ABSTRACT

Background: Office workers spend a high percentage of their time sitting, often in long periods of time. Research suggests that it is healthier to break these long bouts into shorter periods by being physically active. In order to promote breaking up long sedentary bouts, we developed an innovative, context-aware activity coach for older office workers. This coach provides activity suggestions, based on a physical activity prediction model, consisting of past and current physical activity and digital agendas.

Methods: Fifteen office workers, aged 55+, participated in an observational study in which they used the intervention, consisting of a 3D accelerometer and intervention App on a smartphone, for one week. This week was preceded by a one week baseline period.

Results: Fourteen participants gathered sufficient data for inclusion of data analyses. In total, 107 days of data collection were analysed. Total sedentary time was not reduced as a result of using the intervention (baseline vs. intervention: 47.8 ± 3.6 vs 46.8 ± 3.0, n.s.). When using the intervention, participants reduced their total time spent in long sitting bouts (≥45 minutes) from 19.3 to 14.4 minutes per hour of wear-time ($p<.05$). The participants indicated that the main added value of the intervention lies in creating awareness on your personal their sedentary behaviour pattern. Finally, the participants were compliant to 53% of the suggestions; a number that could be increased by improving the timing of suggestions.

Conclusions: Using a mobile intervention (using a 3D accelerometer and smartphone application) has the potential to improve the sedentary behaviour of older office workers. The gain can especially be found in breaking up long sedentary periods by being physically active. Older office workers value that it makes them aware of their sedentary behaviour. We also found that focusing on total sedentary time as an outcome of a public health intervention, aimed at reducing sedentary behaviour, is too simplistic. Rather, one should take into account both the duration and the number of bouts when determining effect. We conclude this article by summarizing our design recommendations for eHealth interventions that aim to improve sedentary behaviour.

BACKGROUND

Prolonged sitting is a health risk [3, 23, 24] as prolonged sitting periods are associated with higher waist circumference, BMI, and triglyceride and blood glucose levels[70]. In industrialized countries, most working adults spend a high proportion of their waking hours in sedentary occupations, as many modern work environments include tasks that promote sedentary behaviour, such as computer work while seated at a desk. Clemes et al [144] identified that for older office workers, the percentage of sedentary time is 68%. And Thorp et al. [145] even found that office workers were sedentary for 76% of their working hours, of which almost half of this time is accumulated in prolonged sedentary periods of 20 minutes or more, and approximately one third is accumulated in periods of 30 minutes or more. These are concerning numbers, as spending a lot of time in prolonged sedentary periods leads to substantially elevated cardio metabolic risk [26]. And while much attention has been devoted (in research as well as public health campaigns) to reducing the overall sitting time of office workers, reducing the average time of a sitting bout -a period of uninterrupted continuous sitting time, often characterized by its duration- has only recently been recognized as an important aspect of studies or campaigns. The workplace can therefore be considered an important target for public health interventions, promoting more physical activity, reducing sitting time, and alternating long sitting periods with other postures or activities (e.g., standing or walking).

Multicomponent interventions (using for example prompts, feedback and goalsetting) have been found to effectively improve prolonged sedentary behaviour in the office [15, 16, 146]. Technical, context-aware interventions (also called mHealth, for mobile health) can be an excellent means to support people in breaking through these sedentary rhythms and reducing sedentary bouts. These mHealth interventions have the great advantage that they can take into account the specific work-rhythms and demands of individual professions when providing health advice. For example, advising someone to take a short walk while he or she is in the middle of a meeting will not be very effective. Such tailoring of health advice requires an understanding of the context of the current work and the personal physical activity rhythm. For this purpose a Context Aware Activity Coach, that consists of a smartphone app and physical activity sensor, has been developed. The Context Aware Activity Coach builds a personal activity profile and only suggests a short break from prolonged sitting or becoming physical activity, when this is a suitable time for the user, matching the personal rhythm.

By means of an observational study, we will evaluate the effect of the Context Aware Activity Coach (CAAC) on the physical activity pattern of office workers and their experiences with the intervention. Our main research question is: How does the use of the CAAC affect the physical activity pattern of office workers? We have the following hypotheses for this study: Upon use of the CAAC, office workers will increase their overall activity level (H1); reduce their total sitting time (H2); and change their sitting pattern (H3). Regarding their sitting pattern, we expect that users of the CAAC will sit more time in short bouts (H3a) and less time in medium (H3b) and long sitting bouts (H3c). And in line with that, we expect that subjects will accumulate more bouts of short duration (H3d), and less bouts of medium (H3e) and long duration (H3f).

METHODS

The Context Aware Activity Coach intervention

The CAAC aims to 1) increase physical activity up to 30 minutes during working hours and 2) breaking up long sitting periods of more than 45 minutes, by providing intervention messages and feedback via a smartphone application, see Figure 19.

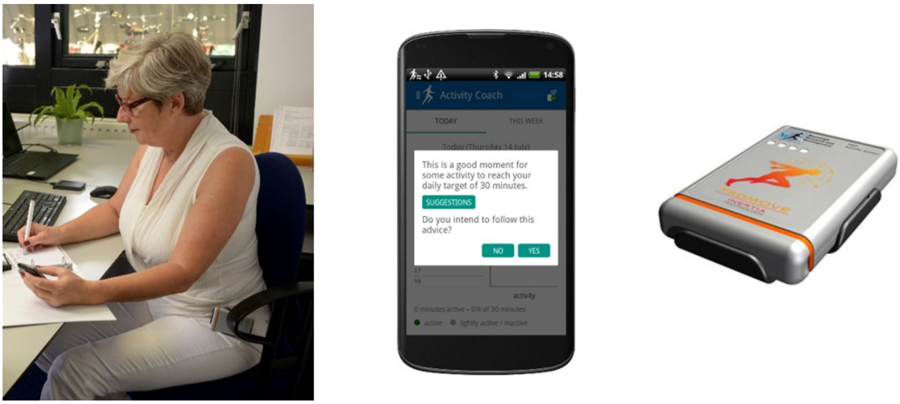

Figure 19 Intervention set-up and materials. Left: example of how a subject wears the activity sensor and checks the smartphone while being at work. Middle: smartphone with intervention application. Right: activity sensor.

To tailor the intervention to the personal physical activity rhythm of the user, the coach uses context information from a wearable activity sensor and calendar items in Outlook™. Physical activity is measured by the ProMove 3D activity sensor (Inertia Technology, Enschede, The Netherlands) and this sensor is worn over the right hip [141]. The sensor converts 3D accelerations to counts per minute (unit: 10^{-3} m/s^2) [141] and the coach uses the number and timing of physical activity minutes (based on the cut-point for comfortable walking speed [141]) for the intervention.

The coach continuously learns from the behaviour of the user and updates the individual activity profile with this information. This profile contains the daily physical activity rhythm and specific activity behaviours around the start- and end-times of calendar items. The physical activity profile and the current behaviour, are input for the real-time evaluation of all decision rules on the intervention goals, resulting in optimized timing of intervention messages prompted by the smartphone application. Thereby, only suggesting a short break from prolonged sitting or becoming physical activity, when this is a suitable time for the user. Figure 20 shows the architecture of the Context Aware Activity Coach.

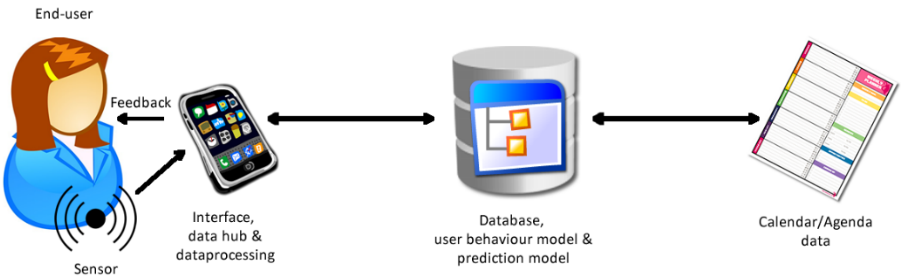

Figure 20 Architecture of the Context Aware activity Coach, consisting of: a body-worn activity sensor, smartphone, online database, and calendar.

The Context Aware Activity Coach has been developed by Roessingh Research and Development, Enschede, the Netherlands and has a Technology Readiness Level (TRL) of 7 being a "system prototype demonstration in operational environment". TRLs are indicators of the maturity level of particular technologies originally defined by NASA [147]. Additionally, TRLs provide guidance on which stage of evaluation and corresponding evaluation methods and outcome measures would be most appropriate. The elaborated staged approach evaluation framework for Telemedicine by Jansen-Kosterink [148], based on Dechant et al. [149], states that a small observational study is appropriate for an advanced prototype, with the following goals: 1) investigate the working mechanism and 2) potential effect of the telemedicine service, Both were assessed using single endpoints regarding 1) *Physical activity behaviour change* and 2) *user experience*.

Study design

We conducted an observational study consisting of a pre- and post-measurement, and an intervention by means of the Context Aware Activity Coach. Participants were asked to use the Context Aware Activity Coach for two weeks, during waking hours of their working days. The first week was a Baseline week. During this week, subjects received no feedback on their physical activity pattern; sensor data was gathered for creating the individual behaviour model. During the second week, the Context Aware Activity Coach provided feedback and intervention messages. Participants were questioned about their experiences with the intervention both during the intervention week and directly after the intervention. The user experience was evaluated by means of the Experience Sampling Method (ESM) [19, 20, 150] during the intervention period by means of questionnaires. During the intervention, each intervention message was followed by a question regarding the intention of the participant to become physically active at that moment (i.e., adherence to the intervention), as shown in Figure 21c and 3d. Then, at 18:00 hours of each intervention day, the participant received a short questionnaire in the App regarding their 1) satisfaction with their day, 2) satisfaction with the amount of physical activity during that day; and 3) if the intervention messages came at suitable moments during the day. See Figure 21 for a flowchart of these questions. After the intervention week, the User Experience was assessed by means of the System Usability Scale (SUS) [151] and the User Version of the Mobile Application Rating Scale (uMARS) [152]. A structured interview was conducted to triangulate results (see the Appendix A for the interview scheme).

Participants

Participants were recruited via the Human Resource department of the University of Twente, Enschede, the Netherlands. A general invitation to participate was send around selected departments of the university, after which interested persons could volunteer. Inclusion criteria were: 1) age ≥ 50 years old and 2) being an office worker and using a PC or laptop for at least 50% of their working time. Exclusion criteria were: physical impairments that hindered effective use of the intervention (e.g. colour blindness or not being able to walk properly). Eligible volunteering employees received an email inviting them to participate by means of the information letter of the study and request to sign the informed consent. The study protocol was reviewed by the Medical Ethical Committee of Medisch Spectrum, Enschede, the Netherlands and declared that the need for approval was waived.

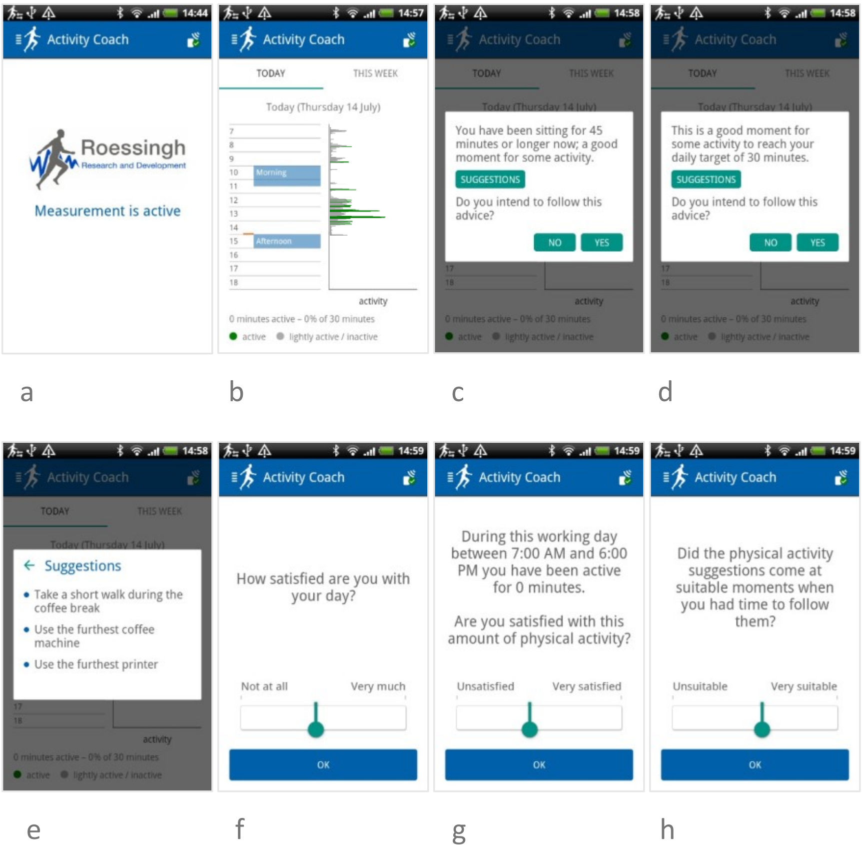

Figure 21 Screenshots during Baseline week (a) and Intervention week (b-h). (a) home screen indicating that the sensor is measuring the physical activity pattern; (b) home screen indicating the physical activity and Outlook™ calendar items of the current day; (c) and (d) two types of intervention message including the Experience Sampling Question (ESM) regarding follow up of the intervention; (e) suggestions for physical activity when selected in (c) or (d). (f-h) three ESM questions regarding satisfaction with the day (f), satisfaction with physical activity (g), and satisfaction with the timing of the intervention messages (h).

Scoring and statistical analysis

Physical activity pattern. Physical activity measures were calculated on a daily level. A valid day consists of at least four hours of wear-time. Only valid days were included in the analyses. The overall physical activity level was assessed via the mean intensity of counts per minute per day and the percentage of sedentary minutes per day. Minutes were classified as being sedentary when ≤ 1660 10^{-3} m/s^2 [30].

The physical activity pattern was measured by the number of sedentary bouts. We distinguish short (<20 minutes), medium (20-44 minutes) and long bouts (≥45 minutes) and analysed both the number and total time in these bout lengths. Total time was normalized to minutes per hour of wear-time. Finally, compliance with the intervention was measured. A subject was considered compliant if physical activity in the 10 minutes directly after answering "yes" or "no" to the question regarding the intention of the participant to become physically active at that moment.

Changes in physical activity were statistically tested for Intervention versus Baseline period using the paired t-test or Wilcoxon signed ranks test, in IBM SPSS Statistics 19. Descriptive statistics were calculated for physical activity, the intervention messages and response to messages, providing the mean and standard deviation, unless stated differently.

User experience and added value. Each ESM question was to be answered on a Visual Analog Scale (VAS), which was analysed as a continuous variable on a scale from 0 to 10. The System Usability Scale (SUS) provides a single number representing a composite measure of the overall usability of the context aware activity coach, ranging from 0 to 100 [151], whereby a score below 50 denotes unacceptable usability, 50 to 70 marginal usability, and higher than 70 acceptable usability. The items in the User Version of the Mobile Application Rating Scale (uMARS) are clustered within six different categories: the engagement, functionality, aesthetics, information quality, subjective quality, and perceived impact and are analysed according to Stoyanov et al. [152].

In order to generate useful conclusions out of the responses of the participants in the interview, the question analysis approach was applied [153]. This approach focuses on the participant's responses to all questions (general and module specific) posed by the researcher during the evaluation. This resulted in: 1) a frequency table for the answers to each closed question 2) a list of recommendations and; 3) a short summary including the first impression of the participants, the added value of the Context Aware Activity Coach and whether they have the intention to use it.

RESULTS

Participants

Fifteen subjects participated. Their mean age was 58.93 ± 5.4 and seven were male. Their professions were categorized as researcher (n=5), administration (n=4), technician (n=3), (project)management (n=2) and care professional (n=1). Participants indicated to work, on average, 69% of their worktime with a PC, varying from 30% for some researchers up to 100% for some technicians.

In sum, the participants wore the activity sensor for 126 days of which 110 were valid (at least 4 hours of wear-time). One subject did not have any valid intervention days, due to forgetting to charge the sensor and work obligations in which he could not use the intervention. This subject was excluded from analyses. Therefore, the physical activity data analysis was done with 14 participants and 107 valid days. Participants had, on average, 3 baseline days (range 1-5) and 4.6 intervention days (range 2-16), with an average wear-time of, respectively, 9.6 and 9.5 hours.

Physical activity pattern

Table 14 displays the different outcome measures and sub measures that the CAAC intervention aimed to affect. Results are split out over the baseline period, and the period in which the participants used the intervention.

Table 14 Overview of the physical activity pattern measures during the baseline and intervention period.

Outcome measure	Unit	Sub measure	Baseline[h]	Intervention[h]	Sign.
Physical Activity Intensity	cpm[a]		958 ± 208	1019 ± 174	n.s.
Total SB time	min/h[b]	Total	47.8 ± 3.6	46.8 ± 3.0	n.s.
		Short bouts[d]	14.8	16.9	p<.05
		Medium bouts[e]	15.1	15.9	n.s.
		Long bouts[f]	19.3	14.4	p<.05
		Medium + Long bouts[g]	35.2	31.2	p<.01
Number of SB bouts	n/h[c]	Total	3.75 ± 0.62	4.11 ± 0.66	p<.05
		Short bouts[d]	2.93	3.34	p<.05
		Medium bouts[e]	0.49	0.54	n.s.
		Long bouts[f]	0.28 ± 0.06	0.22 ± 0.09	p<.05
		Medium + Long bouts[g]	0.79	0.74	n.s.

Sign. = significance. [a] cpm = mean counts per minute [10^{-3} m/s^2] per monitoring day; [b] min/h = sedentary minutes per hour of wear-time; [c] n/h = number of bouts per hour of wear-time; [d] <20 minutes; [e] 20-44 minutes; [f] ≥45 minutes; [g] ≥20 minutes; [h] reported in mean ± standard deviation, unless not normally distributed, then reported in median.

First, we looked at overall changes at the day level. A paired-samples t-test indicated that participants' daily physical activity level (expressed as the average counts per minute) did not differ significantly between the baseline (M = 958, SD = 208) and the intervention period (M = 1019, SD = 174), $t(13) = 1.43$, $p = .176$. And the average overall sedentary time per day (in minutes per hour of wear-time) did not significantly change between the baseline (M = 47.8, SD = 3.6) and the intervention period (M = 46.8, SD = 3.0), $t(13) = -1.24$, $p = .239$.

Then, we analysed the changes in time spent in sedentary bouts of various durations. A Wilcoxon Signed-Ranks test indicated that the median time in long bouts was significantly lower during the intervention (M*dn* = 14.4), Z = -2.54, p = .011, compared to the baseline period (M*dn* = 19.3). The median time in short bouts was significantly higher during the intervention (M*dn* = 16.9), Z = -2.29, p = .022 compared to the baseline period (M*dn* = 14.8). Finally, the median time in medium bouts did not significantly differ between the baseline (M*dn* = 15.1) and intervention (M*dn* = 15.9), Z = -.53, p = .594, while the combined medium and long bouts were significantly lower during the intervention (M*dn* = 35.2), Z = -2.92, p = .004, compared to the baseline period (M*dn* = 31.2).

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Finally, we analysed the changes in the number of sedentary bouts. A paired-samples t-test indicated that the total number of bouts per hour of wear-time increased significantly from baseline (M = 3.75, SD = .62) to intervention (M = 4.11, SD = .66), $t(13) = 2.71$, $p = .018$. We also found that the total number of long bouts per hour of wear-time decreased significantly from baseline (M = .279, SD = .06) to intervention (M = .222, SD = .09), $t(13) = -2.77$, $p = .016$. A Wilcoxon Signed-Ranks test indicated that the median number of short bouts significantly increased from baseline (M*dn* = 2.93) to intervention (M*dn* = 3.34), Z = -.2.48, p = .013. The ranks of the median number of medium bouts did not significantly change from baseline (M*dn* = 0.491) to intervention (M*dn* = 0.537), Z = -.345, p = .73, nor did the sum of the number of medium and long bouts change significantly from baseline (M*dn* = 0.785) to intervention (M*dn* = 0.739), Z = -1.60, p = .109

The statistical analyses we conducted suggested that longer bouts of sedentary behaviour were replaced by shorter bouts. We have plotted these distributions in minutes to an hour of wear time (see Figure 22). Use of the intervention led to a shift in sitting time from longer bouts into shorter bouts, while total sedentary time did not change.

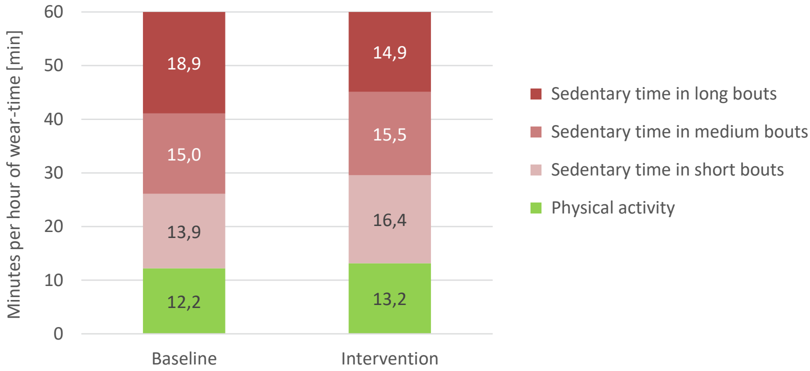

Figure 22 Distribution of the average time per hour of wear-time in sedentary and physically active time.

The physical activity pattern of participants was different during the intervention period and Table 14 summarizes the hypotheses regarding this change. Subjects did not change their overall activity level (H1); nor did they change their total sitting time (H2); however, they did change their sitting pattern by accumulating more sedentary bouts (H3). They sat more time in short bouts (H3a) and less time in long sitting bouts (H3c). And the time in medium bouts did not change (H3b). In analogy to this, subjects accumulated more short bouts (H3d), and less long bouts (H3f). And the number of medium bouts did not change (H3e). However, the time in medium and long bouts combined decreased (H3b + H3c), while this is not reflected by a change in the combined number of medium and long bouts (H3e + H3f).

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Compliance with the intervention

The Context Aware Activity Coach continuously determined whether 'now' is a good moment for an intervention message. Therefore, not every intervention day had intervention messages to promote physical activity. Furthermore, for 6% of the messages, the actual behaviour in the first 10 minutes after the answer was given was not recorded and therefore excluded from analyses. In total there were 57 intervention days with 276 valid messages. Participants received on average 6 messages per day. They intended to follow the advice ("YES") for 3.2 of these messages (52.6%). This is reflected in the self-reported satisfaction with the timing of the intervention messages. Participants (n=12) rated the timing of the intervention messages at the end of each workday on average a 3.2 ± 1.6 on a scale from 0 to 10.

The actual compliance with the intervention was slightly higher. The confusion matrix of the predicted and actual compliance shows that even though subjects answered

“NO”, these subjects did become physically active 0.97 times per day (34% of the instances), see Table 15. The opposite behavior also occurred. This results in an overall actual compliance with the intervention of 53.1% (the prevalence) and an accuracy of the predictor of 68.2%.

Table 15 Confusion matrix of the Compliance to the intervention.

		Actual compliance		
	n=14	PA* in 10 minutes after message	NOT PA* in 10 minutes after message	
Predicted compliance by the user	Answer YES	2.23	0.94	3.17
	Answer NO	0.97	1.89	2.86
		3.21	2.83	6.04

* PA = physical activity.

User Experience

The user experience with the CAAC was captured via various measures. The usability was rated ‘acceptable’, with a score of 77.9 on the System Usability Scale. The application on the smartphone was rated ‘acceptable’ to ‘good’ with an overall score of 3.59 on a scale from 0 to 5 on the User Version of the Mobile Application Rating Scale (UMARS). This composite score averages the scores for Engagement, Functionality, Aesthetics and Information, respectively 3.08, 3.68, 3.71 and 3.88. Additionally, the average UMARS subjective quality score was ‘good’ (2.98). Participants mainly indicated that they would not pay for the intervention, but expected their employer to pay for this. Finally, the UMARS perceived impact scale was rated 3.18 on average, indicating that participants slightly agreed that the Coach increased their knowledge, attitudes and intentions related to the target health behaviour.

In the structured interview, most participants indicated that they felt that the CAAC could be of added value to them (n=11). They mentioned that it created awareness on the need to become more physically active during the workday and provided insight into their physical activity pattern. Additionally, it motivated them to become active if the Coach indicated that they were not active enough. One participant stated: “The module gave me insight that I am active, so in that way it was nice, but I do not think I would use it on the long term.” Another person said: “[The added value is] mainly [on] interrupting long periods of sitting.” Those participants that indicated that the intervention was not of added value to them, believed that they were sufficiently physically active during the day.

Participants were questioned about what they thought was positive and negative about the intervention. Most participants stated that the intervention created awareness on their physical activity and sitting behaviour (n=9) and provided good insight in their physical activity pattern (n=9). Physical activity suggestions (n=3) were appreciated, as well as the graphical user interface (n=2). Negative aspects mentioned by the participants were mainly about timing of the suggestions (n=10), the size of the sensor (n=6) and losing wireless connections (n=2). Participants suggested to improve the timing of suggestions in such a way that it is not disturbing them (e.g., when being in a creative process, while lecturing, or a while after being physically active). Remarks regarding the sensor were that it hindered them or was difficult to combine with wearing a dress. Finally, participants wondered if the smartphone and activity sensor could be integrated into one device, so that only an application needed to be downloaded and only one device needed to be used.

DISCUSSION

In this study, we evaluated the effect of the Context Aware Activity Coach on the sedentary behaviour of older office workers in the Netherlands and their tendency to remain seated for longer periods of time. Additionally, we questioned their subjective experiences with the mHealth intervention. The office workers in our study were sedentary for a large percentage of their working days, both during the baseline period as well as during the intervention period (about 80% of the time). A percentage that is higher than found among a similar population [144]: 68 %. This could suggest that our population was especially suited for an intervention to improve upon this sedentary behaviour. Therefore, it may be considered surprising that the implementation of the intervention did not lead to an improvement in overall sitting time. However, the older office workers were able to decrease the sitting time in bouts of 20 minutes and over from 56.5% to 50.1% while using the Context Aware Activity Coach. So, although the intervention seems to have no effect on a global outcome measure, our study does show that mobile health technology can have a positive influence on the number of prolonged sedentary bouts of older office workers. And especially these long periods of sedentary behaviour pose the biggest health risk [70].

Studies that focus on break-up sedentary periods commonly use pattern outcome measures based on sitting bouts of 20 minutes or longer. However, this measure should be interpreted with care. Our study shows that the behaviour change (resulting from implementing an mHealth intervention) predominantly occurred in the sitting bouts of 45 minutes and longer. Therefore, using a cut-point of 20 minutes can result in both significant and non-significant changes, depending on whether the focus of analyses lies on the total time in these bouts or the total number of these bouts. We found that the total sedentary time in bouts ≥20 minutes was significantly decreased during the intervention, while the number of bouts ≥20 minutes was not. We suggest that the best measure for describing a sitting pattern is the total time in various bout durations. Although the total number of bouts could provide insight in the overall fragmentation of the sitting time, it is not sufficiently sensitive to changes in behaviour. For example, when a person is breaking up a sedentary period of 60 minutes into one of 50 and two of 5 minutes, this is relevant for both the increase of time in short bouts and the decrease of time in long bouts. However, in this example the number of long bouts remains unchanged, giving no information on 'how' the person has changed his or her behaviour towards more short bouts.

The office workers in our study were asked to predict their compliance with the intervention's advice to become physically active. In 68% of these instances, they were able to predict their own behaviour correctly. One would expect that office workers should well be capable of predicting their behaviour on such a short time interval. Other factors seem to be playing a role here. These can only be found outside the individual (e.g., a colleague unexpectedly asks a person to join him/her for a lunch walk) or work on a subliminal level (i.e. the person is not aware of the effect of an advice to become physically active). This means that an mHealth technology, aimed at reducing sedentary behaviour can only do so much. Things happen outside the influence sphere of the intervention (recall the colleague who wants to go for a lunch walk), both in a positive and a negative way. It seems that we can only accept these 'disturbances' as a fact of life.

Timing of the Context Aware Activity Coach intervention messages to become physically active turned out to be one of the most important aspects of end-user satisfaction. The office workers in our study indicated that the timing needed to be improved, in such that it better followed their work rhythm. This, and other important aspects to achieve high end-user satisfaction were translated into design recommendations for future mHealth technologies that aim to reduce sedentary behaviour in prolonged periods, following the themes: devices, Graphical User interface, context awareness and content (see Table 16).

Table 16 Recommendations for a Context Aware Activity Coach.

Theme	Recommendations
Devices	#1. The smartphone should react promptly to interaction. #2. Use the accelerometer of the smartphone; integrate to one device.
Graphical User Interface	#3. The device should easily present insights into the total sitting time and relevant pattern measures to the older office worker.
Context Awareness	#4. Improve the timing of suggestions in such a way that it is not disturbing. For example, when being in a creative process, while lecturing, or while being 'in the flow'; more context awareness is needed. #5. Make sure the suggestions come at a convenient time and fit the activity pattern of the user (e.g., a while after being physically active). #6. Leave an interval of about 60 to 90 minutes between suggestions, so as not to overload the office worker.
Content	#7. Make the physical activity suggestions more motivating by mentioning some extra health facts, so people become aware of the importance of physical activity. #8. Display how many steps are taken each day.

Limitations

We included a relatively small number of participants (n = 15) in our study. Although this somewhat limits the external validity of our study, focusing on a small number of office workers was the only feasible way to conduct a study that provides the fine-grained results we were aiming for. Studies in which activity data is collected by means of activity sensors and with a very high sampling frequency, like ours, lead to huge amounts of activity data. Therefore, the inclusion of a small number of participants, of which large amounts of data are analysed in detail is a common and sensible approach [154].

The intervention and measurement period was relatively short (two weeks) and the timing was restricted to the month of September. This means that the study did not allow for the assessment of sustained behaviour change, but focused mainly on the initial stage of use of the intervention. Nonetheless, the study showed that an mHealth intervention, such as the Context-Aware Activity Coach, is capable of achieving this change quite rapidly, as the participants of our study changed their sedentary behaviour in a positive way. Next, the consequences of using the intervention may be affected by the time of year in which it is used, as the amount of physical activity is partly determined by the season and the weather conditions [155].

CONCLUSION

In a time where sedentary behaviour is recognized as an important health problem (and is even typed as 'the new smoking'), mobile health technology may prove to be an excellent means to get office workers out of their chairs. Our study has shown that the Context Aware Activity Coach (which utilizes a smartphone application and physical activity sensor) can successfully withhold older office workers from long periods of sitting. We also uncovered, however, that the current technology is far from realizing its full potential. Proper timing of the advice to become physically active turned out to be a crucial aspect. In our case, timing was decided by proper alignment with the office worker's agenda, but this did not turn out to be sufficiently matching the desired rhythm. Future research should establish a model of which factors define 'proper timing' in this sense, so that future technologies can make use of these insights in their recommendation rules.

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APPENDIX CHAPTER 5

APPENDIX A – STRUCTURED INTERVIEW SCHEME

Demographics

Age
Gender
Profession
Colour-blind
Number of contract hours per week
Percentage of worktime working with PC

Intervention as a whole

What is your first (overall) impression of the intervention?
Do you think it could be of added value in your job? (If yes, why?)
Do you have the intention to use this intervention in the future?

Added value & Potential effect

Do you feel this intervention was of added value to you?
If yes, in what way? (Continue by asking each of the following questions. Ask for a really short reply on each suggestion, only the first thing that comes to their mind.)
If no, do you feel it could be of added value to others? If so, why?
By supporting you in your work? If yes, in what way?
By relaxing? If yes, in what way?
Training/increasing your physical health? If yes, in what way?
To stay focused during your workday? If yes, in what way?
Otherwise?

Content questions

Could you name three things you like about the intervention?
Could you name three things you dislike about the intervention?
Is this (messages including physical activity suggestions) how you would like to be motivated to be more physically active during the workday?

CHAPTER 6

VALUE-BASED DESIGN FOR THE ELDERLY: AN APPLICATION IN THE FIELD OF MOBILITY AIDS.

Published:

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ABSTRACT

In the aging society, the need for the elderly to remain mobile and independent is higher than ever. However, many aids supporting mobility often fail to target real needs and lack acceptance. The aim of this study is to demonstrate how value-based design can contribute to the design of mobility aids that address real needs and thus, lead to high acceptance. We elicited values, facilitators, and barriers of mobility of older adults via ten in-depth interviews. Next, we held co-creation sessions, resulting in several designs of innovative mobility aids, which were evaluated for acceptance via nine in-depth interviews. The interviews resulted in a myriad of key values, such as “independence from family” and “doing their own groceries.” Design sessions resulted in three designs for a wheeled walker. Their acceptance was rather low. Current mobility device users were more eager to accept the designs than non-users. The value-based approach offers designers a close look into the lives of the elderly, thereby opening up a wide range of innovation possibilities that better fit their actual needs. Product service systems seem to be a promising focus for targeting human needs in mobility device design.

INTRODUCTION

Society is aging and the need for the elderly to remain independent is higher than ever. In the Netherlands, the population of 65 years and older will increase from 2.5 million in 2010 to 4 million elderly in 2030—This works out to about one in four inhabitants [156]. Of this elderly population in 2030, it is expected that 1 million are frail elderly of which two thirds are living solitary [157]. To keep the costs for society manageable, supporting these elderly in their independence is very important. This can be done by supporting their mobility as described by Satariano et al. [158], who emphasized that optimal mobility is a key component of healthy aging and that mobility relates to all facets of daily life:

> Mobility refers to movement in all of its forms, including basic ambulation, transferring from a bed to a chair, walking for leisure and the completion of daily tasks, engaging in activities associated with work and play, exercising, driving a car, and using various forms of public transport. [158] (Satariano et al. p. 1508)

Reasons for using mobility aids, related to functional impairments, are often a need and desire to continue to be active and to continue performing everyday activities, including the potential to take part in social activities [159]. La Grow et al. [160] showed that mobility was directly related to quality of life and this relation was mediated by the satisfaction with functional capacity. The individual desire to be mobile is therefore expected to vary extensively between individuals, and to depend on personal needs, values, and the environment.

A study among Dutch, community-dwelling 85-year-olds concluded that the presence and use of assistive devices (including mobility aids) could be improved upon [161]: A large group of elderly lacks the device they need, does not use them when they are available, or does not accept assistive aids when they were offered to them. Hirsch et al. [162] stated that assistive technology (including technology for mobility) is often underused or used erroneously, due to amismatch between design and the context of use. They (and others, like Häggblom-Kronlöf and Sonn [163] and McMillen and Söderberg [164]) suggested that designers should “immerse” themselves into the lives of elderly to fully understand their needs on a functional, emotional, and social level. This immersion, and the subsequent translation of findings into product design, is often typed as user- or human-centered design. In this design approach, it is advocated to consult potential end-users as early as possible in the design process, and to involve them continuously [165], as (potential) end-users have been found to supply critical contextual information to the design team, that can consequently

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translate this into product innovations [166]. Recently, the concept of *value-based* design originated in business science [167] and has merged with the human-centered design approach. Value-based design focuses on eliciting the most important values a person has in life, and to cater for these values. As such, value-based design can be considered to be an extension of human-centered design. Where human-centered design is mainly “artefact-centered” and focused on identifying product features that are desired by (potential) end-users, value-based design aims to create *useworthy* design that caters for a person’s values in life [168]. Values have been defined as “ideals or interests a (future) end user aspires to or has” [169] (Van Velsen et al. p. 5). For example, a value for parents can be that their children can grow up safely, and their actions in life will be motivated by this value. Value-based design can be considered a way in which user values and the factors that motivate them to use a specific product are elicited, analyzed, and mapped within a human-centered design process (which also includes activities such as testing the acceptance and usability of a new service or product; [170, 171]). Recently, value-based design has also been applied to the design of health interventions (e.g., Van Velsen et al. [17]) and social services [172].

The premise behind value-centered design is that its strong focus on human values, on top of the fulfillment of their explicit needs as a result of the application of a human-centered design focus, results in a design that is both useful as well as elusive [168]. Value-based design can therefore be considered a means to prevent product from failing when it is not accepted while fulfilling the potential end-users’ needs after applying a human-centered design focus, an occurrence we have seen often among mobility devices [173]. Nonetheless, many factors have been identified to explain this phenomenon, such as financing, as well as more person-based barriers regarding attitudes and beliefs [164, 174, 175], such as a personal unwillingness to display dependence on mobility aids [159]. Therefore, besides identifying and designing for end-user values, a strong focus on determining why a specific (prototypical) mobility device is accepted or not during the design process is crucial [159, 175]. Two of the most critical factors that explain this acceptance include coping style and subjective norm [176]. Coping style determines for an important part how one acts in times of difficult situations (e.g., not being able to walk as well as one used to) and how one goes about solving this situation [177]. This can have a great impact on how an elderly person makes a decision to use a mobility device (or not). Subjective norm is “the perceived social pressure to perform or not to perform the behaviour” in question [176] (Ajzen, p. 188).

In this article, we aim to demonstrate how value-based design can contribute to the design of mobility aids that address real human needs and thus, lead to high acceptance. We will do so by discussing the application of a human-centered, value-based design approach for the creation of innovative products and services that aim to increase the mobility of solitary-living, community-dwelling elderly. This process consists of in-depth interviews with elderly persons to elicit their values in life, followed by the activities we undertook in creating initial designs: a brainstorm and a first selection of ideas. Using in-depth interviews with the elderly with the focus on device acceptance, three prototypes will be presented. We conclude this article with a discussion in which we will set out how future design projects can benefit from our experiences, and how designers should deal with acceptance issues for mobility aids for the elderly.

MAPPING ELDERLY VALUES

The first step in our design process consisted of eliciting individual values of solitary-living, community-dwelling elderly. Therefore, we conducted in-depth interviews, as this method allows for a good exploration of what is important for an individual concerning health-related matters [178].

Methods

Participants

Ten aging individuals who need, or may need to, use mobility aids in the near future to sustain daily activities were recruited via a professional homecare organization in the Netherlands. Inclusion criteria were: solitary-living, community-dwelling older adults with minimum age of 70 who receive a small volume of personal and medical homecare of maximally 9 hours per week, without cognitive or communicative disabilities that could hamper the interview.

Data collection

A semi-structured interview guide with open-ended questions was constructed, focusing on personal values with a focus on current physical activity and mobility aids (Appendix 1). The interviews were conducted at the interviewees' homes. Values were elicited by asking an interviewee about their hobbies and what gives them energy. To identify a value, we asked the interviewees where, how, how often, and with whom they carry out each hobby or activity that gives them energy and that they mentioned. Next, we asked them whether or not this has become more troublesome than it used to be, due to recent functional decline. Additionally, we asked them what (kind of) things they *want* to do, but cannot (anymore) due to health problems (in other words, the values they aspire to). Then, we questioned the interviewee how they travelled about, to what goal, how often, and with who. And we asked the interviewee to list the mobility aids they used, asked about adaptations to their house, and how the decision is made whether or not to start using a mobility device. These last two questions were asked in order to map the interviewees' mobility situation. Finally, we asked whether or not the interviewee used technology (e.g., the Internet, a mobile phone) and for what goal(s). Current physical activity was assessed by the Physical Activity Scale for the Elderly (PASE) questionnaire [179]. The instructions for use given in the PASE Administration and Scoring Manual were followed (http://www.neri.org). The PASE addresses leisure-time, household, and work-related physical activity.

Data analysis

The interviews were transcribed and translated into a mind map per participant. This visualization form was chosen as it provides a good snapshot of what an interviewee experiences as important in life, and allows for easy sharing of results with others [180]. Each item on the mind map was determined by means of inductive thematic analysis [181] performed by two coders. First, the coders familiarized themselves with the data. Next, each interview section that concerned a value, attribute, facilitator, or inhibitor was marked as such and provided with a code. For example, *family* and *doing things with others* were mentioned as things people like to do (and thus, were coded as attributes); the value *social interaction* was linked to these two (and other) attributes. Finally, specific issues that contribute to or hinder attributes such as a *taxi service to visit the family* was coded as facilitator or barrier. Each time a new value or attribute was deduced from the transcriptions, the values, and attributes that were identified until that point in time were reconsidered. As facilitators and inhibitors were very personal, this was not done for these categories. Disagreements on codings were discussed between the coders until agreement was reached. Ultimately, this process led to a mind map that displays a person's values, the attributes that make-up this value (i.e., the activities or wishes that the interviewees mentioned), and the facilitators and inhibitors that play a role for each attribute.

The PASE was scored according to the instructions in the PASE Administration and Scoring Manual (http://www.neri.org). The PASE sub scores were computed by multiplying time spent in each activity (hours per day) or participation in an activity (for household-related activities), with empirically derived weightings, and then summarizing all items to a single PASE score, ranging from 0 to 361, in which a higher score, indicated a higher level of physical activity.

Ethics

The study was evaluated by the institutional review board (IRB) of Twente, and they determined that the study was exempt from further IRB review according to the principles expressed in the Declaration of Helsinki. However, the participants did receive written and oral information about the study, including: aim of the study, voluntary participation, no risks, confidentiality and anonymity. And participants gave their informed consent for the interview including audio-recording. The same ethics procedure was applied during the evaluation (reported in the third section).

Results

The 10 interviewees (average age 80.5 (SD=8.1)) scored low to very low on the physical activity level (average PASE score 40 (SD=13)). Biking and walking were their main means of transport. Public transport was considered too difficult or impossible to use (too far from the home, difficult route, etc.), and technology use was predominantly restricted to TV, (mobile) phone, and radio; see Table 17.

Table 17 Description of the participants based on demographics and the PASE scores (n=10).

Demographics	1	2	3	4	5	6	7	8	9	10
Gender (M/F)	F	F	F	M	F	F	F	F	F	F
Age (years)	93	72	84	76	69	89	83	69	87	83
PASE score (0-361)	38	73	34	23	52	37	36	45	33	31
Where they life[a]	V	V	C	V	V	C	C	V	V	V
Transportation means[b]	T	EB*, Cr*	EB, Cr	EB, Cr, Sc	EB, Cr	B*				
Mobility aids[c]	Ca, WW	Ca*, WW	WW'	WW	WW	WW	Ca, WW			
Technology use [d]		MP, PC		MP						MP, D

[a] C = city; V = village. [b] B = bike, EB = E-bike, Cr = Car, Sc = Scootmobile, PT = Public Transport, T = Taxi. [c] Ca = Cane, WW = Wheeled Walker (Rollator). [d] All users have a Television, phone (land line) and radio. Other communication technologies: MP = Mobile Phone; PC = Personal Computer / Laptop with internet connection, Tb = Tablet, D = domotics (front door camera, automatic sun blinds). *owned but not used

The 10 resulting mind maps display unique overviews of the interviewees' values, how they live toward fulfilling these values, and what helps and hinders them in striving toward their values (Figure 23). For example, subject 8 explained after asking for hobbies, that she makes postcards and creates dolls from clay. After explaining how these activities are done in a social context and if she often spends time on these hobbies she replies: “Yes, what else should I be doing all day?” This was coded as a facilitator for the attribute “getting through the day” and categorized as contributing to the value “killing time.”

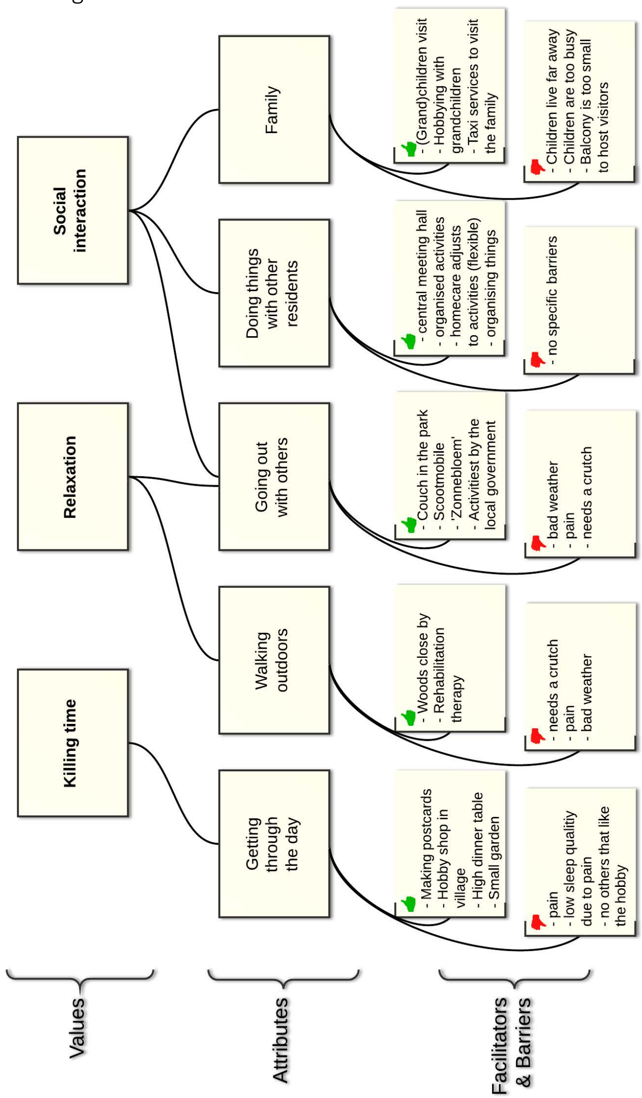

Figure 23 Excerpt of mind map of subject 8. The three levels indicating the values, attributes, and facilitators & barriers connected by lines indicating their relationships.

The mind maps visualize three levels: values, attributes, and facilitators and barriers. Several values were shared by multiple interviewees: (1) *social interaction*, (2) *independence*, (3) *relaxation*, (4) *killing time*, and (5) *good physical health*. An overview of all values shared by the interviewees is given in Table 18.

Table 18 Overview of values described by the participants (n=10).

Values	Count
Social interaction	10
Independence	8
Relaxation	7
Expanding life space / social world	2
Killing time	4
Good physical condition	3
Self-control / being in charge of own life	1
Not being a burden to somebody else, due to the need for informal care	1
Nostalgia / traditions	1
Peace of mind	1

The way in which each value was sought after differed per person. For example *social interaction* consisted for one interviewee of meeting all kinds of people, for another of going on holiday, and for yet another of doing groceries with others. Social interaction was also hampered by a wide range of causes. For example, one participant wanted to mingle with other people, but was afraid for visiting the adult day care facilities around her, as she did not know what to expect. For another subject *social interaction* was facilitated by means of the voluntary work of "De Zonnebloem," that organizes trips for people with disabilities. Several people designated *killing time* as something they strived for. They indicated that activities such as doing jigsaw puzzles or creating greeting cards are not experienced as leisure activities, but as means for having something to do.

The attributes (or, activities or wishes that are linked to a value) that we encountered often include: (1) *Doing groceries*. This was an important aspect of the interviewees' life and served both, remaining independent and social interaction (as groceries were regularly done in a group). (2) *Hobbies*. A wide range of hobbies was named as an enabler for relaxation, including fishing and walking outside. (3) *Riding a bike or driving a car*. For many, being able to ride a bike or a car was very important, as it allowed them to get around and to join social activities or to remain independent.

The inhibitors and facilitators for each attribute were highly personal and often resulted in a complex overview. For example, one subject wanted to be able to do her own groceries, in order to remain independent. This was made possible by a supermarket being close to her house, and the fact that she was still able to ride her bike. However, winter weather makes her afraid of falling and she then opts to stay indoors.

DESIGNING NEW MOBILITY AIDS

New mobility aids were developed by means of two workshops based on the mind maps and a collaboration among researchers, industrial designers, and professional caregivers.

Methods

Brainstorm meeting

A brainstorm meeting was held to co-create new ideas for mobility aids, based on the mind maps. Four researchers in health service design, two industrial designers, one community nurse, and one geriatric care manager participated. The mind maps were presented one by one to enable participants to "immerse" themselves into each of the interviewees. A presentation consisted of discussing the individual mind map and of telling the anecdotes that came with each mind map (as derived from the interview transcriptions). The brainstorm participants asked questions about the particular interviewee for clarification until they had a full grasp of the life of the elderly person. Next, they were asked to write down all ideas (products, services, or important topics) that crossed their minds on sticky notes. This was a creative activity that was not bound to any procedure. Each participant was then asked to share the ideas that they consider most valuable, after which all sticky notes were combined into clusters and prioritized.

Selection of designs

A second session was held among the eight experts of the brainstorm session, complemented by a physical and an occupational therapist, and focused on selection of three designs to be evaluated on acceptance by the elderly. The industrial designers presented ten product ideas for mobility aids based on those ideas that were prioritized highest during the brainstorm. The industrial design company chose to work with (traditional) product designs and to focus on wheeled mobility aids.

Each product idea was discussed openly on various aspects such as safety for the elderly user, relation to the interviewees' values, and level of innovation. Together, the participants choose the three most promising ideas based on (1) the added value to mobility (predominantly judged by the care professionals), (2) the ergonomics of each product, and (3) the expected acceptance by the elderly. After this second session, redesigns of these three ideas were made, which were approved by the participants. needs of the end-users, while the first two requirements have a non-functional, general nature.

Results

Brainstorm meeting

The clustered sticky notes resulted in four main areas for product ideas: (1) products that reduce fear (of falling) or increase self-assurance or safety; (2) product designs that increase acceptance and decrease the negative associations people have with mobility aids; (3) mobility aids that provide means for moving objects indoors, like a cup of tea and meals, with reduced risk of cups falling while taking obstacles such as doorsteps; and (4) mobility aids that support reaching for high or low objects, such something that fell on the floor or is stored in an overhead cupboard. The third and fourth ideas address specific functional needs of the end-users, while the first two requirements have a non-functional, general nature.

Selection of designs

The industrial designers created ten designs that focused on mobility by means of walking and biking, as these were the most important modes of transport reported by the interviewees. The healthcare providers commented on for example stability and safety by explaining about the location of the wheels with respect to the user. Based on the four main areas for product ideas from the brainstorm meeting, it was decided that three variations of the wheeled walker were the most promising designs, (Figure 24):

1. Multifunctional wheeled walker.

This wheeled walker has a tray with cup holders, an anti-slip layer, and a large basket for transporting groceries. The tray can be converted to a seat with back support. This design was made to solve the problem of cups falling of the tray when crossing a doorstep with the wheeled walker.

2. Grow-along grocery bag.

This wheeled walker has three settings. First, it is a grocery bag someone can pull along. Second, wheels can be expanded that provide some support, and third, the wheels can be adjusted in such a way that the grocery bag becomes a wheeled walker with a bag in front. This design was made to ease the acceptance of wheeled walkers. At first, the person walks with a grocery bag and the shift to using a wheeled walker is smaller as the person already owns one.

3. Electric wheeled walker.

This wheeled walker functions as a regular one, but also has a plateau which can be folded out and on which the elderly person can stand when he or she is tired. Then, the wheeled walker can move about electronically. This design was made to cater for an interviewee's fear that she would not have the energy to walk back home when she was outdoors. This prevented her from leaving her house.

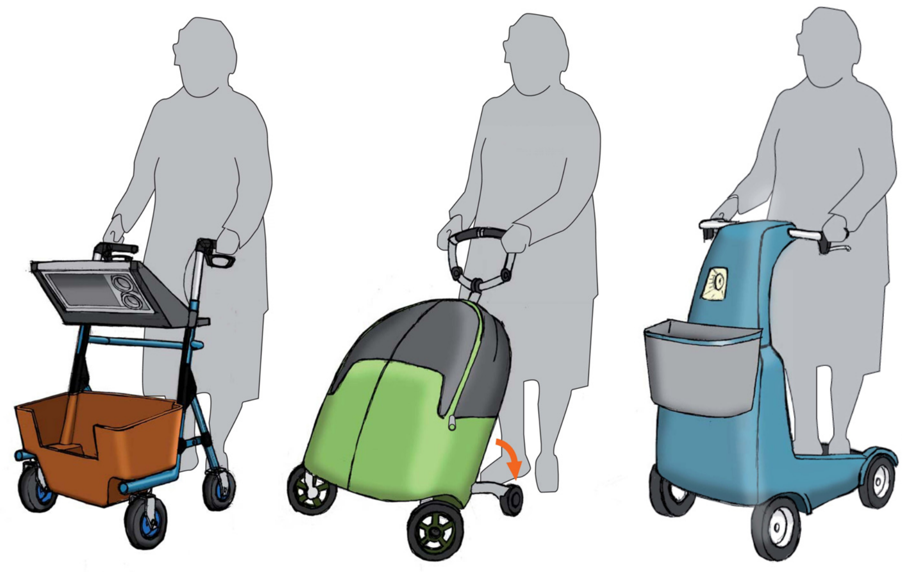

Figure 24 The three selected designs. Left: the multifunctional wheeled walker; Middle: the grow-along grocery bag; and Right: the electric wheeled walker. For more details see Appendix 2.

GAUGING FOR ACCEPTANCE

The acceptance of mobility aids is a major concern (Bright & Coventry, 2013). Therefore, we gauged the acceptance of the three selected designs among a sample of the target population.

Methods

Participants

Nine participants were recruited via a professional homecare organization in the Netherlands. Inclusion criteria were solitary-living, community-dwelling older adults with minimum age of 70, without cognitive or communicational problems, and receiving a small amount of homecare. Six of the interviewees from the value-based interviews joined again.

Data collection

An interview guide with semi-structured open-ended questions was constructed, with a focus on acceptance of each design, subjective norm, coping style, and current physical activity (Appendix 3). The interviews were conducted at the interviewees' homes. The designs were introduced in a random order, to rule out order effects. Each of the three designs was introduced by describing it and showing its drawing (Appendix 2). Then, the interviewees were asked per design what the design reminded them of, whether they thought it would be useful, easy to use, and whether they would want to use it. Finally, we asked them whether they had experience with similar aids and what others would think if the interviewee would use this product. Subjective norm was evaluated by asking about the thoughts of friends, spouse, family, and the general practitioner of him or her using mobility aids, and whether those opinions mattered to the interviewee. Furthermore, we asked the interviewees about their coping style by presenting them with a fictitious scenario about a mobility device and asking them how they would deal with it by giving three options: use problem focused coping, stop unpleasant emotions and thoughts, and getting support from friends and family (classification by Chesney et al. [182]). Finally, current physical activity was assessed by the PASE questionnaire [179].

Data analysis

The interviews were transcribed and two individual coders analyzed for each interviewee the interviewee's coping style and subjective norm, and for each design the user acceptance. Disagreements were discussed until agreement was reached.

The PASE score was calculated as described in the data analysis paragraph of the first section *Mapping elderly values*.

Results

The interviewees (average age 81.1 (SD=8.1)) scored low on the physical activity level (average PASE score 63 (SD=40)). Walking was the main means of transport, although it was frequently reported that they had serious walking difficulties. Two subjects reported to be fully depended on their wheeled walker; the other subjects use it only outdoors or are not current users; see Table 19.

Table 19 Description of the participants based on demographics and the PASE scores (n=9).

Demographics	11	12	13	14	15	16	17	18	19
Gender (M/F)	F	F	F	F	F	F	M	F	F
Age (years)	72	94	84	69	70	87	86	84	84
PASE score (0-361)	25	n.a.	53	123	91	31	9	50	118
Where they life[a]	V	V	C	V	V	V	C	C	C
Transportation means[b]		T	B, Cr	Sc			Sc	EB	PT, T
Mobility aids[c]	WW	Ca, WW	WW*	WW	WW	Ca, WW	WW	WW*	WW*

n.a. Subject was too tired to finish the PASE. [a] C = city; V = village. [b] B = bike, EB = e-bike, Cr = car, Sc = scootmobile, PT = public transport, T = taxi. [c] Ca = cane, WW = wheeled walker (rollator). *owned but not used.

6

Subjective norm and coping styles

Most of the participants' family and friends accept the mobility device they use. Only one subject did not know her family's opinion and two subjects did not know their friend's opinion. The role of the general practitioner (GP) was reported differently. Most GPs recommended a mobility device to the interviewees. In the cases where the GP did not recommend it, the GP was also not informed about the subject using a mobility device. The importance of others (subjective norm) was considered "not important" by most subjects. Half of the subjects indicated that they preferred the coping style of "seeking help from others" and the other half choose "solving it themselves" or a combination of these two. None reported that "ignoring the problem for a while" was a coping style they would apply. When seeking help from others, the interviewees would go to family and/or health professionals (mainly to homecare nurses).

Designs

In general (All designs). Subjects were either satisfied with their current mobility device (mostly the wheeled walker) or were not using one, and not planning to start using one. Nonusers had more difficulty imaging using the product ideas than current users. And currents users were focused more on supportive functions of the walker.

Multifunctional wheeled walker. The interviewees that are current users of a wheeled walker said that this design does not replace or improve their current wheeled walker, except for one subject who felt that the additional functionalities such as the large basket, and cushioned seat would help her in daily life. The two subjects that were not current users remarked that they would only accept a wheeled walker alike the given design, when their walking ability worsens. They predominantly reported barriers being related to the stigma of mobility aids, while the current users of wheeled walkers were mainly focused on functionality of the design.

Grow-along grocery bag. This device was not accepted as a device that the subjects would like to use, and it did not provide any added value over their current wheeled walker. Subjects expected that the shopper cannot provide sufficient balance support. And the most dominant feature of this design, the ability to store more goods (e.g., groceries), is not needed by most subjects, either because they do not need that much groceries or the bulk of their groceries are done by others. However, the participants found that its appearance reduced the stigma of a mobility device.

Electric wheeled walker. The electric walker was also not accepted as a device that would be used by the interviewees. The electric walking support was perceived as being difficult to operate and the platform is not an added value for situations in which one is tired. Standing is tiring as it requires balance and effort, and this worsens when already being tired. Subjects required a seat instead. Only this design triggered questions regarding corresponding services such as driving lessons, maintenance and range of the battery. Finally, most subjects said that it had a nice, appealing look, and that they would like to be seen with it.

DISCUSSION

The value-based approach towards determining what matters most in the lives of solitary-living, community-dwelling elderly resulted in a very wide range of values, how people live by these values, and what hampers and helps them in fulfilling these values. The identified values relate to variables associated with life satisfaction such as *quality of social network* and *internal locus of control* [183]. The level on which these terms describe the things people strive for in life are alike. This suggests that the value-based approach as applied in this study is a suitable means to get an in-depth insight into the lives of a group of people, and to elicit the problems that hinder them in fulfilling their life goals. This information can be valuable for inspiring new product designs that appeal to the target population's needs and wishes, and therefore have a high chance of success. We see no reason why this approach would not yield the same results when applied to other target groups with specific needs. Value-based research can therefore open up new lines of thinking for health product and service design and can be easily integrated into a user- or human-centered design process, as it mainly entails the integration of questions or exercises aimed at eliciting life values into activities that are often used to guide end-user involvement, such as interviews, focus groups, and co-design sessions.

Given the positive experiences we gained by using a value-based approach for mapping what matters most in terms of mobility for the elderly, it was disappointing that the product designs that resulted from the brainstorm were not accepted by potential end-users. We see two probable explanations for this paradox: first the translation from mind maps into designs, and second, the narrow scope that was applied on product design only.

When looking back, we think that the translation from mind map into design has not been done successfully. There is no "set" method for conducting such a brainstorm session. It was difficult to cram all the insights that were generated by the interviews into the limited time of the brainstorm session and this may make it difficult to come up with designs that appeal to important values while taking into account the myriad of barriers and facilitators described in the mind maps.

Second, we think that the focus of the design company on products (wheeled walkers) rather than product–service solutions might have created a mismatch with the original values [172]. The actual needs are often of a nonmaterialistic nature, like the need for being somewhere or the need for information, for which a single product is not always the best answer. A solution here is to shift the design of mobility aids to product service systems. Such systems are a combination of products and services for fulfilling a need (or value) and provide end-users with solutions of higher quality. New designs should provide an added value, substantially greater than the subjects' current mobility aids, or the ones they know. In the design cycle itself, thinking in product service systems tremendously increases the number of new product (combinations) that are imaginable [184]. For example, when looking at the mind maps in this way, the following product–service system could be envisioned. One interviewee told us that she did not make use of the taxi as much as she would like to, due to different taxi services available and the different restrictions each service had. Some services required a transcription, some services waited for you when you visited the hospital, some were reimbursed by the health insurer, and the different services each had a different maximum amount of kilometers they would ride. An information kiosk at a central place in the neighborhood, or a website, with a wizard could help this person by determining which taxi service is most suitable for each trip. Then, it can provide an advice for a service and reserve a taxi for the person at the moment he or she wants to make the trip. Such a “taxi-wizard” would cater for the value independency and increase mobility by providing a service rather than a product.

Finally, from the second set of interviews it became clear that subjects were either satisfied with their current mobility device (mostly the wheeled walker) or were not using one, and not planning to start using one. This is in line with findings from others, such as Hedberg-Kristensson *et al.* [159] (p. 18), describing that “for participants who accepted that they had to use mobility aids, positive feelings such as increased independence, security and confidence had been generated,” while non-acceptance was related to the “experience of realizing the need for mobility assistance causing feelings of depression […]. Participants spoke of thresholds to overcome before starting to use mobility aids.” This is in line with our findings, as we clearly see that the participants that were current users were more focused on functions supporting their independence, security and confidence in using the mobility device, than the non-users that already had difficulty imaging using the product ideas. The results from our interviews did not suggest a relation between subjective norm and coping style on the one hand, and the acceptance of mobility aids, on the other hand.

The introductory section identified that the aim of this study was to demonstrate how value-based design can contribute to the design of mobility aids that address real human needs. Our reflection on the design process suggests that value-based design has great potential for maximizing the fit between end users’ lives and context. We also determined that product service design thinking should supersede device thinking in design mobility aids for the elderly. Future research should determine how insights into the values of older adults’ lives should be translated into design in an empirical manner.

Limitations

The number of persons that were interviewed (10 and 9) is too small for making generalizable statements. This is also true for having the views of only one male subject in each interview session. However, for the case of the exploration of elderly persons' values we do not see this as a problem, given the goal of our research. The interviews were held to gain deep insight into the individual lives and to identify new possibilities for new product or service designs, and by that build upon the knowledge base on mobility device use [185]. Such possibilities are most often not found in large numbers. Instead, a single story can spark the inspiration of a design team and make them design something revolutionary. For the case of gauging the acceptance of the three mobility device designs, our results should be seen as exploratory. Here, the reasons *why* someone accepts a device or not, are more important to us than the absolute percentages of who will or will not use such an device in the future. Related, the interview guides cannot be used as a standard for eliciting human values or for testing acceptance in relation to mobility aids, as their development was too dependent on the specific design context. We do think, however, that they can be used as a source of inspiration for other researchers and designers that work in the same or a similar field.

It may be somewhat difficult for people to comment on their intention to use a product, based on a low-fidelity prototype, such as the stories and pictures we showed to our participants [186]. On the other hand, low-fidelity prototypes are the only affordable option to explore the usefulness of different concepts at the same moment in time [186]. For the latter reason we have decided to use these prototypes. As they were presented to the interviewees in a face-to-face situation and were accompanied by oral presentation and the possibility to pose questions about the design immediately, we think we have minimized the difficulty people may have had with imagining what the mobility aids could do for them. Nonetheless, this limitation leads to the question whether low-fidelity prototypes are only suitable for conveying the idea behind specific features (as a result of human-centered design) or can also convey the experience and emotional aspects of the product that are the result of value-based design. It is possible that other communication means (like animations that show the products and its use within a real-life context) do a better job here. This question can only be answered by future design research.

CONCLUDING REMARKS

In this article, we have discussed our experiences with value-based design for mobility aids for the elderly. Applying a strong focus on values (ideals or interests a [future] end user aspires to or has) when interviewing elderly about their lives resulted in a myriad of valuable insights. Although these values created large potential appealing designs, it appeared not to be a guarantee for successful product design. In order to come to a new generation of mobility aids or product service systems [187] that will allow people to deal with the challenges the aging society poses, value-based design is a promising means to increase the match between user context and device. Nonetheless, researchers need to work on how to translate a value into a new design so that the elderly can benefit from ideas that align with how they want to live their lives.

ACKNOWLEDGMENTS

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APPENDICES CHAPTER 6

APPENDIX 1: INTERVIEW GUIDE—MAPPING ELDERLY VALUES

Introduction

Introduce yourself. * Introduce the research: We would like to gain knowledge on independence, mobility and the things people value in life, by means of interviews with solitary-living, community-dwelling elderly in the Netherlands. * Go through the information letter with the interviewee and ask if he/she has any questions. * Go through the informed consent form * and ask if the interviewee agrees with the statements and ask to sign it. * Start the voicerecorder.

Demographics

Speak out loud the following information / features:

1. Date and interview code no.
2. Sir or Madam
3. Name
4. City name
5. The type of residence (flat, detached house, garden, bedroom upstairs etc.)

Start with the interview:

6. What is your age?
7. Do you have family living close by?
8. How long are you living in this residence by yourself?

Values

We would like to get a general impression of your life

9. What are your hobbies? What do you enjoy to do?
10. What makes you happy? What gives you energy? (which activities)

For each activity (attribute) mentioned:

- Where do you do this?
- How often?
- How do you go there?
- With who do you go there? (family, friends, neighbours)
- How long are you already doing this activity? (recently started, for months, years)
- Have you noticed that doing this has become more difficult due to changes in your health?

Wishes:

11. What would you wish to do? (but is currently out of reach)

PASE questionnaire

Ask all questions of the PASE questionnaire.

Mobility / Current Physical activity

For those things not yet discussed while going through the PASE questionnaire:

12. Do you walk?
13. Do you bicycle?
    a. Do you own an (electric) bike?
14. Do you participate in sports?
15. Do you drive?
    a. Do you own a car?
    b. Do you have a drivers licence?
16. Do you use Public Transport?
    a. Train; bus?
17. Do you make use of taxi services?

In general:

18. Do you go out?
19. How often?
20. Where to? (for what purpose)
    a. Daily living – essentials (groceries, hair dresser)
    b. Social activities / relaxation
    c. Walking a dog?
21. With who do you go?

Mobility aids – indoors & outdoors

22. Do you use mobility aids? And for which purposes?
    a. Rollator?
    b. Cane?
23. Do you have adjustments in your house?
24. Is your social environment encouraging you to use mobility aids? (postponing behaviour / stigma?)
25. When is it for you acceptable to use a rollator (=wheeled walker)?
26. What if it is not a rollator? What could help you when walking?

Technology use

What do you think of new technologies such as the internet and mobile phones?

27. Do you use these technologies?
28. Are these easy to use?
    a. Mobile phone?
    b. Computer / laptop / tablet ?
    c. Digital photo camera / videocamera?

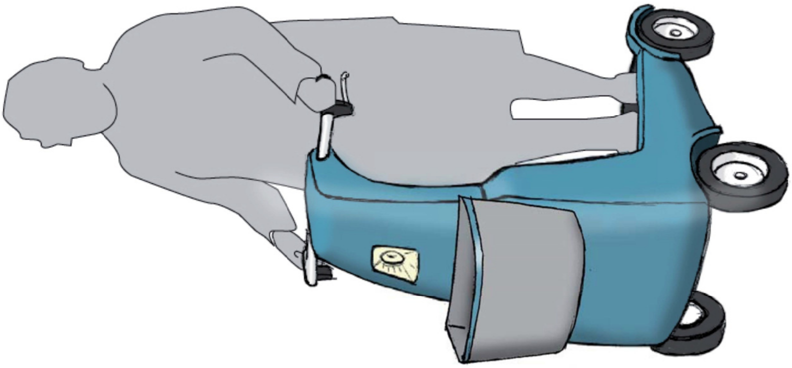
"This is the end of the interview. I have no further questions for you. Do you have any questions you would like to ask me?"

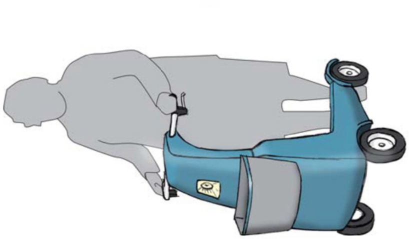
APPENDIX 2: THE THREE PROTOTYPES, INCLUDING DETAIL GRAPHICS OF FEATURES AND WRITTEN DESCRIPTIONS OF EACH DESIGN.

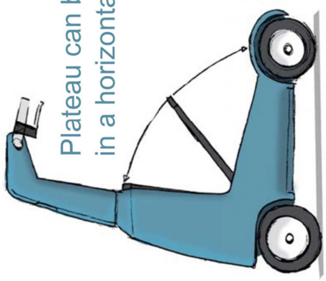
Electric wheeled walker

Features

- Has a plateau which can be folded out when you are tired
- 2 modes: walking with support or standing on the plateau
- Size is the same as a ´regular´ walker
- It has lights for safety when walking after dusk







6

Grow-along grocery bag

Features

- Grocery bag with 3 configurations:
  - one that you can pull along
  - one that you can push, with more stability (three wheels)
  - one that you can push, but with the stability of a regular wheeled walker

- Large storage space for groceries, while still being compact

- Easily adjustable to your desired stability level

Multifunctional wheeled walker

Features

- In height adjustable groceries basket
- Basket provides ample space for groceries
- The (padded) backrest can be folded into a serving tray
- The tray has 2 cup holders that prevent cups from falling
- The anti-slip layer of the tray will hold objects in place

APPENDIX 3: INTERVIEW GUIDE—GAUGING FOR ACCEPTANCE

Introduction

Introduce yourself. * Introduce the research: We would like to gain knowledge on independence, mobility and the things people value in life, by means of interviews with solitary-living, community-dwelling elderly in the Netherlands. * Go through the information letter with the interviewee and ask if he/she has any questions. * Go through the informed consent form * and ask if the interviewee agrees with the statements and ask to sign it. * Start the voicerecorder.

Demographics

1. Male/Female
2. Age
3. Marital status? (Widowed?)
4. City
5. The type of residence (flat, detached house, garden, bedroom upstairs, sheltered living etc.)
6. Do you have (mobility) aids? [e.g. rollator, cane, adjustments in the bathroom, bedroom etc.)
7. <health status> Are there specific changes in your health that reduces your general fitness? [If the interviewee wants to sum up their whole medical history, ask for the 3 most important / most limiting medical complaints]
8. Do you receive (care) services at home? (cleaner (domestic chores), homecare, meals, hairdresser, etc.)

General: Subjective Norm

9. How do your friends respond if you are using aids like a rollator, shower chair or cane?
10. <if applicable> How does your spouse respond if you are using aids like a rollator, shower chair or cane?
11. How does your family respond if you are using aids like a rollator, shower chair or cane?
12. How does your General Practitioner respond if you are using aids like a rollator, shower chair or cane?
13. Do you value the opinions of these people? Do the influence your behaviour on using or not using a (mobility) aid?
14. <Follow up> who’s opinion do you value most?

Questions per design (3x)

Introduction: These are product ideas created by a design company, and ‘you’ are not related to them, so you “won’t mind if the interviewee will give positive feedback or burn them down completely” <to reduce bias of social desirable answers>

- <Introduce the idea / drawings> Show the drawings.
- <Read the description out loud>
- <Ask if the interviewee has any questions>

<u>Personification & Stigma</u>

15. <first impression>

    a. Which 3 words come to your mind when you see this?
    b. Do these words fit you?
16. Is there someone in your environment who could use this?
17. Why? And can you describe this person? (Hobbies, health status ets.)
18. Would you feel ashamed if you would use this? OR would you enjoy being seen with it? Why?

<u>Perceived usefulness – Ease of use – Intention to use</u>

19. Do you think this could help you?
20. Do you think it is easy to use? What makes it easy or difficult?
21. Would you like to have this? Why?
22. In which situations would you use it? And would this occur often?
23. What would be a reasonable price for this?

<u>Experience with devices alike / recognition</u>

24. Is this the first time that you see something like this? (do you recognize it? Have you seen something like this before?)
25. Have you used something like this before?
    a. <If YES> Did this go well? Or not?
    b. <if YES> Were you satisfied with that similar device?

<u>Subjective norm</u>

26. What would others think if you would be using this?
27. Do you value others opinions about you using this?
28. Who would you ask if you would consider getting such a thing?

<continue with the next idea. 3x>

General: order of preference

29. Could you order the 3 ideas, starting with the idea you like most? <rank 1, 2 and 3>

General: Coping Style

Introduce the following scenario to the interviewee:

Imaging that your walking ability is slightly reduced. You have visited the General Practitioner for this, however he cannot help you. So, you just have to make the best of it. And there are mobility aids available to help you with walking outdoors and moving around within the house.

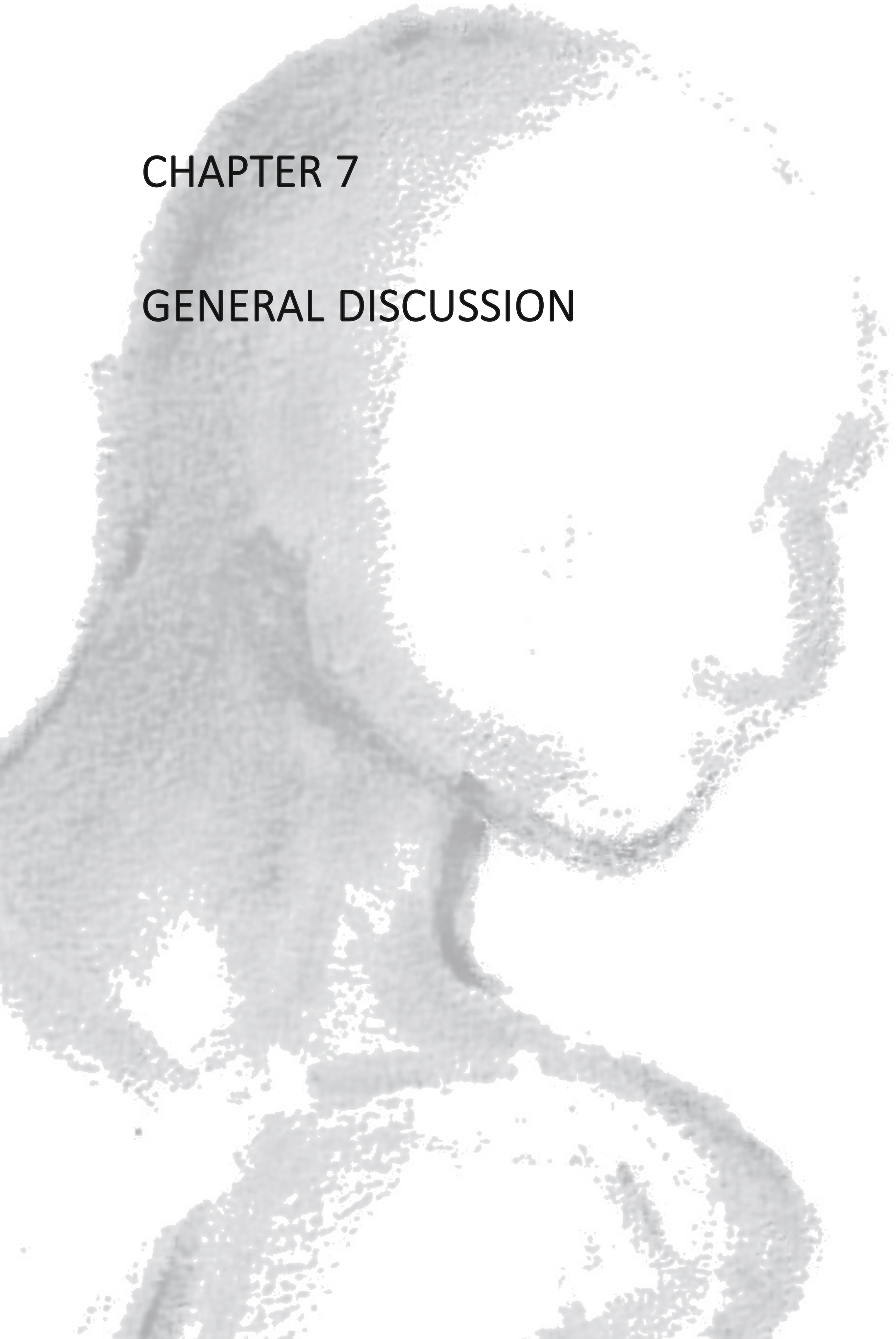
30. What would be your approach to this:
    a. "I would try to find out how these mobility aids work and what they do, by myself."
    b. "I would probably try not to think about it, and try to life as nothing has changed."
    c. "I would seek support with my family and friends and find out a solution for me, together with them"
31. Which approach is most appealing to you? Why?
    a. Or would you combine multiple answers? Which?

PASE questionnaire

Ask all questions of the PASE questionnaire.

CHAPTER 7

GENERAL DISCUSSION



The aim of this thesis was to contribute to knowledge on how **sensing human activity can improve sedentary lifestyle**. This thesis followed an expanding scope: starting from the level of the activity sensor up to the level of public health. The first part of this thesis focused on the *measurement* of sedentary behavior and its patterns by means of wearable activity sensors. The second part focused on the *development and evaluation* of mHealth interventions that utilize these wearable activity sensors.

In this general discussion, the findings of the different studies are integrated and discussed in the context of current knowledge and future developments for improving the technology and approach to support sedentary behavior change.

FROM SENSOR TO DATA TO INFORMATION

The evolution from questionnaire-based sedentary behavior research into sensor-based research, suggests only improvements: eliminating subjective bias, providing data of high granularity and providing the opportunity for interventions to incorporate real-time available behavior information. We have, however, seen that sedentary behavior assessment with sensors has specific limitations that should be handled.

The sensing method and protocol, and more specifically the variability of sensor use during free-living conditions, were studied in a laboratory setting to understand the effect of sensor location and how the sensor is worn on the activity data (Chapter 3). From this study we concluded that the most lateral position around the waist was preferred and that sensors should be fitted tightly to the body. Refining accelerometer design [188] or improving classification of sedentary behavior from other positions on the body can reduce user burden and improve acceptability and wear-compliance.

A literature review on sedentary pattern measures (Chapter 2) described the diversity of difficulties with sedentary behavior assessment, data interpretation and comparability. From this review, two main conclusions were drawn: 1) objective sedentary pattern measures serve different goals, varying from a quick overview to in-depth analysis and prediction of behavior. The answer to which measures are most suitable to report, is therefore strongly dependent on the research question. And 2) the pattern measures identified in the review, such as total sedentary time, bouts, breaks and composite measures of sedentary behaviour, are affected by a) the sensing technology, b) the classification method, c) the experimental and data cleaning protocol, and d) the applied definitions of bouts and breaks.

The effect of the classification method on pattern measures was studied in detail in laboratory and free-living conditions with office workers (Chapter 4). In this study we found that, when cut-points for classifying sedentary behavior are within the boundaries of ±10-20% of the optimal cut-point, the outcome measures are robust – the data does not change. However, Chapter 2 describes that the currently in literature reported cut-points are not within this range, which hinders generalization of the current body of knowledge. Nevertheless, the insights we listed in Chapter 2 will aid researchers and professionals in developing health interventions that benefit from sensor-based sedentary behavior assessment with currently available wearable sensors. These recommendations include to always report total wear-time, total sedentary time, number of bouts and at least one measure describing the diversity of bout lengths in the sedentary behavior, such as the W50. And to report the measurement conditions and data processing steps.

The sensitivity of sedentary behavior measures to the applied cut-point for classifying sedentary behavior, is strongest for the most reported measure of sedentary behavior in literature: the percentage of total sedentary time (chapter 2 and 4). Sedentary pattern measures based on bout length are more robust, and most robust was the Gini index, a distribution measure of bout lengths (Chapter 4). For intervention studies, these differences in sensitivity would suggest to apply the more robust pattern measures.

Activity sensors and data analysis methods will both continue to develop, resulting in (small) deviations of sensor data and outcome measures describing sedentary behavior. We strived for a uniform sensor output in metric units combined with openly available algorithms to enable reproducibility and uniformity (Chapter 3 and 4). However, with the current rapid development of sensors and analysis methods it seems to make more sense to express the measured behavior in terms of the actual behavior than in counts or metric units. Examples of such measures are the number of sitting hours, bouts, transitions from sitting to standing or the number of minutes in moderate intensity physical activity. And this last measure can be further specified into specific activities, such as fast walking, jogging, swimming or bicycling. Additionally, converting counts per minute from one sensor type to another is not feasible due to the various sources of bias on the sensors output such as sensor location and type of activity (Chapter 3) as well as the aforementioned biases due to the sensing technology, the specific algorithm to calculate the counts (Chapter 2). And this challenge seems to only increase with the increase of numerous activity trackers for research and at the consumer market [189].

Currently, most research is still done based on cut-points applied to accelerometry-based data and inclinometry-based classification methods (Chapter 2). It is to be expected that (embedded)software in these sensors will continue to develop and thereby hinder the comparability of sensor data. This we have seen in the development of the Actigraph models developing from 1D to 3D [120, 125], as well as in consumer physical activity monitors in which proprietary algorithms are updated often according to companies' own discretion and time frame [189].

The developments in sensors and data analysis methods will improve classification of sedentary behavior and replace the current gold standards of intensity- and inclination-based approaches. Cut-point-based analyses make only very limited use of the wealth of data that can be measured by activity sensors. Whereas, machine learning techniques can classify human activity into specific behavior with higher accuracy, thereby moving forwards from the intensity-based behavior analysis towards specific types of behavior [9]. This can be done, for example, by incorporating information from the frequency domain of accelerometers or by using additional inertial sensors such as gyroscopes.

Human factors in real-world deployments of wearable sensors challenge proper quantification of physical activity. The findings in this thesis regarding sensor position and looseness of fit (Chapter 3) are acknowledged [190–192] and can be dealt with by either incorporation of strict instructions for use or by applying (machine learning) techniques to handle these uncertainties. Also, specific populations such as older adults can challenge the algorithms used for classification of physical activity and sedentary behavior, for example because of their lower walking speed resulting in lower accelerations [193].

HEALTH INTERVENTION

To bring health interventions further, a match is needed between sensor and context information. A good approach for this is tracking both the measures of behavior as well as the important triggers or context on how to improve outcome measures [194]. In Chapter 5, we combined the knowledge on sensor use, data processing steps and outcome measures with context-aware technology to develop an intervention for older office workers. The intervention had a two-fold focus regarding sedentary behavior. It coaches its user towards 1) a reduction of the total sedentary time and 2) towards breaking-up prolonged sedentary bouts. The users showed a more fragmented sedentary pattern during the intervention and were positive about the increased awareness regarding their sedentary behavior. Still, the intervention was not matched to the users' personal goals regarding sedentary behavior or physical activity. And it had limited implementation of often applied theoretical frameworks such as the Social Cognitive Theory [195], the Transtheoretical Model of Behavior Change [196] or the Theory of Planned Behavior [176]. The most important feedback from the users to improve the intervention was that they were not satisfied with the timing of coaching messages (Chapter 5). This links to Bandura's [196] note that feedback needs to be informative and in-time (i.e., immediate) to the relevant behavior in order to be effective. This could indicate that the integration of real-life context by predicting behavior based on their agenda was not sufficiently implemented in the intervention or that the timing of the intervention was not perceived as immediately actionable.

The developed intervention also incorporated the Experience Sampling Method (ESM) for in-depth understanding of the context of sedentary behavior. Awareness of the where, when, why, with whom and experienced emotions can further tailor the intervention to the individual end-user to overcome specific social barriers to become physically active, or to understand better in which environment one is sedentary in prolonged bouts [19, 60]. Additionally, self-reporting by ESM increases awareness and self-reflection [194]. In this case, the combined activity monitoring and ESM data were analyzed retrospectively regarding contextual and emotional information, motivation and satisfaction [150, 197, 198]. Future interventions should incorporate this type of context-, mood- and emotional-awareness in the real-time tailored coaching strategy [19, 199, 200], for example by referring to previously experienced positive emotions related to specific activities, such as feeling refreshed, after taking a short break from a prolonged sedentary period.

Intention to be compliant to each coaching message was also evaluated by means of ESM questions. We found that the accuracy of the intention to be compliant and the actual compliance to become physically active in the 10 minutes following a message, appeared to be rather marginal (Chapter 5). If subjects have difficulty to predict if they will be sitting or will be active for the upcoming 10 minutes, we can assume that coaching towards a healthier activity pattern should intervene within this short time span, at the right moment, under free-living conditions.

This study also showed that the effect of the intervention on the sedentary pattern could not be properly described by a single sedentary behavior measure such as total sedentary time or the total number of bouts. Evaluation of the effect on the sedentary behavior needs multiple sedentary pattern measures to describe if and how the sedentary behavior was changed (Chapter 5). And we expect that total sedentary time in various bout lengths can better capture the actual behavior change.

PUBLIC HEALTH

To gain a better understanding of how a health intervention could match personal goals, a method from Industrial Design was explored for the field of mobility aids. In Chapter 6, we applied this value-based design approach to understand the real-life context of older adults with mobility difficulties – meaning difficulty with walking, biking, and/or activities of daily living. Their values in life, and the barriers and facilitators to these values were gathered via in-depth interviews. This provided rich information on individuals, being very valuable for designers. In this chapter, the designers focused on mobility aids, but could as well have used this in-depth understanding of the values of life for the development of health interventions focused on sedentary behavior. This should lead to tailoring of goals and coaching strategies for behavior change to individual values.

Optimizing the match between the quantitative sensor information and qualitative real-life context is also required at the level of populations with specific health needs or limitations. A concrete example regarding sedentary behavior patterns are patient groups suffering from fatigue, such as persons with Multiple Sclerosis. These persons might benefit from a more fragmented activity and rest pattern, as longer periods of sedentary behavior may indicate overload or deconditioning [41]. Here, a pattern measure is needed that is sensitive to changes in both the short bouts and breaks, as well as the presence of long sedentary bouts. Context-awareness on current health state and capacity can tailor the individual goals and strategies towards these goals.

FUTURE RESEARCH

To create a strong body of knowledge on sedentary patterns and their health implications, the field has to mature further by adopting standardized reporting methods and converging the diversity of outcome measures. Adaptation of a limited set of outcome measures should be done based on the robustness of measures for biases that will always be present in free-living research, sensitivity for variations in data analysis and sensitivity for changes in behavior. This can be achieved by expert meetings focused on exchange of knowledge, creating consensus about a first set of recommendations, and by publishing this as the standard, as has been done for the current definition of sedentary behavior by the Sedentary Behaviour Research Network [2].

The current wearable sensors should further develop towards activity recognition, thereby overcoming the difficulties of classification based on thresholds. This will be possible with the increasing (embedded) calculation capacity of wearables and improving wireless connectivity [201]. The latter makes it possible to use calculation capacity on other wearable (local) devices such as smartphones or in the cloud. Additionally, recent developments towards open data and open algorithms will speed up this process as researchers and developers can build upon available knowledge. The resulting improvement in activity classification will help to further develop the outcome measures, as they can build upon richer information than the common binary information of active versus sedentary minutes. Behavior patterns will then be expressed as true behavior, which improves comparability of studies. And expressed as behaviors, this input is easier to adopt in interventions, as total sitting time and active breaks are better understandable than for example counts – matching the real-world knowledge of users.

Sedentary pattern measures should be supportive to behavior change. This requires that the measure is easy to interpret – what does a specific number mean [202]; easy to relate to and relevant – I recognize this as a representation of my sedentary behavior of that day and its fits the conception of myself [203]; and sensitive to change – if I change my sedentary behavior, I want that to be reflected by a change in the pattern measure (Chapter 2 and 5). A measure that cannot grasp relevant behavior change is not valuable for intervention studies, neither as input for the intervention, nor as actionable feedback to the end-user. Sensitivity to behavior change should receive more attention in future research on sedentary patterns.

Finally, it is interesting to reflect on the full spectrum of physical activity – from sedentary behavior to vigorous physical activity. We see that light-intensity physical activity is rarely targeted by health interventions. Health guidelines focus on either sedentary behavior or moderate to vigorous intensity physical activity, and neglect the light intensity physical activity that lies between the two. Outcome measures on this low intensity physical activity level could be fine indicators of behavior change in intervention studies, and can be easily understood by users. One could think of promoting goals on both the low and moderate to high physical intensity levels, instead of the more difficult to communicate ‘reduction of sitting time’.

CLOSING REMARKS

Activity sensors can provide valuable information on the pattern of sedentary behavior, which can be useful for health interventions. We have shown the strengths of current practice and opportunities for improvement, by applying a broad scope with a focus on measuring sedentary behavior and developing and evaluating mHealth interventions. The combination of the bottom-up approach: from sensor, data and information levels, with the top-down approach: from user values related to public health to interventions and its specific feedback and coaching strategies, contributed to diverse, strongly connected and interdependent domains of applying wearable activity sensors in health interventions focused on sedentary behavior.

&

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Summary

Samenvatting

Dankwoord

Curriculum Vitae

List of publications

Progress range

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SUMMARY

Recent public health campaigns often communicate the alarming phrase: “Sitting is the new smoking”. Sitting is related to all-cause mortality, cardiovascular disease, type 2 diabetes, and metabolic syndrome. Sedentary behavior is generally understood as “sitting or reclining while expending ≤1.5 metabolic equivalents” and the interesting aspect of sedentary behavior is that it is a modifiable health risk. The health risk can be reduced if a person changes his or her behavior towards a healthier one; to sit less and to become more physically active.

Research focusing on patterns of sedentary behavior has taken off since the rise of both wearable technologies and activity sensors. They provide opportunities for uncovering sedentary patterns within the context of daily life. As a consequence, the sedentary research field moved forward towards fine-grained, objective monitoring of sedentary behavior in free-living conditions for substantial time frames. Current wearable activity sensors are, however, not flawless in measuring sedentary behavior. It is therefore important to understand the effects of possible measurement bias, in order to deal with it in the best way.

People are often unaware of their sedentary behavior, making it difficult to change the behavior. mHealth interventions can improve awareness and trigger behavior change by tailoring the intervention to the user’s needs by providing direct feedback and coaching on physical activity and sedentary behavior together with real-time information on the context. Context information can be gathered by integrating relevant data sources or by posing questions about the here-and-now. Further increase of acceptance of mHealth interventions can be achieved by tailoring to individual values, and barriers and facilitators to these values.

The aim of this thesis is to determine how wearable activity sensors can be applied successfully in health interventions focused on sedentary behavior.

This thesis follows an expanding scope: starting from the level of the activity sensor up to the level of public health. The first part of this thesis focuses on the *measurement* of sedentary behavior and its patterns by means of wearable activity sensors (Chapter 2, 3 and 4). The second part of this thesis focuses on the *development and evaluation* of mHealth interventions that utilize these wearable activity sensors (Chapter 5 and 6).

The pattern of sedentary behavior during the day is an independent health risk. Prolonged sedentary time affects cardio-metabolic and inflammatory biomarkers, independent of the total sedentary time. Since the rise of both wearable technologies and activity sensors, there is however, no consensus among researchers on the best outcome measures for representing the sedentary pattern during the day, based on wearable activity sensors. Chapter 2 provides an overview of current pattern measures of sedentary behavior in adults, by means of a literature review. Simple measures of sedentary behavior were most often reported, like the number of bouts, the medium or median bout length. More complex pattern measures, such as the GINI index or the W50 were reported sparsely. Due to the differences among measurement devices, data analysis protocols and a lack of basic outcome parameters such as total wear-time and total sedentary time, the sedentary patterns, reported in the various studies, were difficult to compare. The simple and complex measures of sedentary time accumulation serve different goals, varying from a quick overview to in-depth analysis and prediction of behavior. The answer to which measures are most suitable to report, is therefore strongly dependent on the research question. From this overview in Chapter 2 we conclude that the reported measures were dependent on 1) the sensing method, 2) the classification method, 3) the experimental and data cleaning protocol, and 4) the applied definitions of bouts and breaks. Based on these findings, we recommend to always report total wear-time, total sedentary time, number of bouts and at least one measure describing the diversity of bout lengths in the sedentary behavior such as the W50. Additionally, we recommend to report the measurement conditions and data processing steps.

One of the factors influencing the output of activity sensors mentioned above is the experimental protocol (Chapter 2). This was studied in more depth in Chapter 3 in which we focused on optimal sensor placement for measuring physical activity. Subjects walked at various speeds on a treadmill, performed a deskwork protocol, and walked on level ground, while simultaneously wearing five activity sensors with a snug fit on an elastic waist belt. We found that sensor location, type of activity, and their interaction-effect affected sensor output. The most lateral positions on the waist belt were the least sensitive for interference. Additionally, the effect of mounting was explored by repeating the experimental protocol with sensors more loosely fitted to the elastic belt. The loose fit resulted in lower sensor output, except for the deskwork protocol, where output was higher. We conclude that, in order to increase the reliability and to reduce the variability of sensor output, researchers should place activity sensors on the most lateral position of a participant‘s waist belt. If the sensor hampers free movement, it may be positioned slightly more forward on the belt. Finally, we recommend to wear sensors tightly fitted to the body.

Another factor influencing the output of activity sensors mentioned above (Chapter 2) is the classification method. Currently, the most applied method to distinguish sedentary from active time is by applying a cut-point to accelerometry-based data. This means that the intensity of the measured behavior is classified as being sedentary when below this cut-point. The effect of the classification method on sedentary pattern measures was studied in detail in laboratory and free-living conditions with office workers (Chapter 4). In this study we found that the outcome measures are robust – meaning that the outcome measures do not change –, when cut-points for classifying sedentary behavior are within the boundaries of ±10-20% of the optimal cut-point. This conclusion implies that results from studies analyzing sedentary patterns based on different cut-points, can only be compared if the cut-points are within these boundaries.

In Chapter 5, we combined the knowledge on sensor use, data processing steps and outcome measures with context-aware technology in an intervention for older office workers towards sitting less and breaking up sitting time. Office workers spend a high percentage of their time sitting, often in long periods of time. Research suggests that it is healthier to break these long bouts into shorter periods by being physically active. In order to promote breaking up long sedentary bouts, we developed an innovative, context-aware activity coach for older office workers. This coach provides activity suggestions, based on a physical activity prediction model, consisting of past and current physical activity (measured by a wearable activity sensor) and digital agendas. The total sedentary time in the intervention week, was not reduced compared to the baseline week. However, the pattern of the sedentary behaviour did change – the office workers reduced their total time spent in long sitting bouts (≥45 minutes). Additionally, the office workers indicated that the main added value of the intervention resided in creating awareness about their personal sedentary behaviour pattern. Finally, the participants were compliant to 53% of the suggestions; a number that could be increased by improving the timing of suggestions. We conclude that the mobile intervention (using an activity sensor, smartphone application and context information) has the potential to improve the sedentary behaviour of older office workers. The gain can especially be found in breaking up long sedentary periods by being physically active. Older office workers value that it makes them aware of their sedentary behaviour. We also found that focusing on total sedentary time as an outcome of a public health intervention, aimed at reducing sedentary behaviour, is too simplistic. Rather, one should take into account both the duration and the number of bouts when determining the effect of the intervention. We conclude this article by summarizing our design recommendations for eHealth interventions that aim to improve sedentary behaviour.

In Chapter 6 we focused on a design approach to further increase acceptance of mHealth interventions – by tailoring to individual values, and barriers and facilitators to these values. In this study, we demonstrated how value-based design can contribute to the design of a product or service that addresses real needs and thus, lead to high acceptance. We described the methods and application of value-based design. We elicited values, facilitators and barriers of their reduced mobility – meaning difficulty with walking, biking, and/or activities of daily living – of older adults via in-depth interviews. These interviews resulted in a myriad of key values, such as 'independence from family' and 'doing their own groceries'. Co-creation design sessions resulted in innovative mobility aids from which three designs for a wheeled walker were selected for evaluation on acceptance, again via in-depth interviews. Their acceptance was rather low. Current mobility device users were more eager to accept the designs than non-users. The value-based approach offered designers a close look into the lives of the elderly, thereby opening up a wide range of innovation possibilities that better fit the actual needs. However, mobility is related to physical capacity and not being sedentary. In-depth understanding of the values of life to be mobile, can therefore directly inspire designers focused on mobility aids. Nevertheless, this understanding can as well tap into the context and personal goals needed to tailor health interventions on sedentary behavior.

In Chapter 7, the general discussion, we discuss the rapid development of sensors and analysis methods, as well as gathering rich context information by means Experience Sampling. Cut-point-based analyses make only very limited use of the wealth of data that can be measured by activity sensors and has various challenges which hinders generalization of the current body of knowledge (Chapter 2, 3 and 4). It seems to make more sense to express the measured behavior in terms of the actual behavior, such as bicycling and climbing stairs, rather than expressing physical activity in counts or metric units representing its intensity. Machine learning techniques are very capable of this with higher accuracy, and their application seems to be a logical step forwards. And when expressed as behavior, machine learning output will be easier to adopt in interventions, as total sitting time and active breaks are better understandable than for example counts – matching the real-world knowledge of users. The Experience Sampling Method (ESM) incorporated in the developed intervention (Chapter 5) provided in-depth understanding of the context of sedentary behavior – the where, when, why, with whom and experienced emotions. Future interventions should incorporate this type of context-awareness in real-time tailored coaching strategies to increase awareness and behavior change.

The studies in this thesis have shown that activity sensors can provide valuable information on the pattern of sedentary behavior, and that these can be useful for health interventions. We have shown the strengths of current practice and opportunities for improvement, by applying a broad scope with a focus on measuring sedentary behavior and developing and evaluating mHealth interventions. Based on the study we conclude that:

The combination of the bottom-up approach (from sensor, to data to information levels) and the top-down approach (from user values related to public health to interventions and its specific feedback and coaching strategies), contribute to diverse, strongly connected and interdependent domains of applying wearable activity sensors in health interventions focused on sedentary behavior.

SAMENVATTING

Recente volksgezondheidscampagnes communiceren vaak de alarmerende zin: "Zitten is het nieuwe roken". Zitten is gerelateerd aan verhoogde kans op sterfte, cardiovasculaire aandoeningen, diabetes type 2 en het metabool syndroom. Sedentair gedrag wordt over het algemeen gedefinieerd als "zitten of liggen met een laag inspanningsniveau, kleiner of gelijk aan 1,5 metabole equivalenten". Het interessante aspect van sedentair gedrag is dat het een aanpasbaar gezondheidsrisico is. Het gezondheidsrisico kan worden verminderd als een persoon zijn of haar gedrag verandert: minder zitten en fysiek actiever worden.

Sinds de opkomst van draagbare technologieën en activiteitensensoren heeft onderzoek gericht op patronen van sedentair gedrag een vlucht genomen. Deze technologieën bieden namelijk nieuwe mogelijkheden tot het meten van sedentaire patronen binnen de context van het dagelijks leven. De nieuwe technologieën maken bovendien mogelijk om sedentair gedrag tijdens het dagelijks leven niet alleen gedetailleerder en objectiever te meten maar ook gedurende langere meetperioden. De huidige draagbare activiteitensensoren zijn echter niet feilloos in het meten van sedentair gedrag. Het is dan ook belangrijk om de effecten van mogelijke meetfouten te begrijpen, om daar vervolgens op de beste manier om te gaan.

Omdat mensen zich vaak niet bewust zijn van hun sedentair gedrag, is het moeilijk om het gedrag te veranderen. Door interventies af te stemmen op de behoeften van de gebruiker door middel van zogenaamde mHealth-interventies, kan het persoonlijk bewustzijn worden vergroot en is de kans groter dan een interventie ook daadwerkelijk een gedragsverandering teweeg brengt. Afstemmen op de individuele behoefte kan door directe feedback en coaching te bieden over fysieke activiteit en sedentair gedrag samen met real-time informatie over de context. Deze context informatie kan worden verzameld door relevante gegevensbronnen te integreren of door vragen te stellen aan de gebruiker over het hier en nu. Verdere toename van acceptatie van mHealth-interventies kan worden bereikt door personaliseren op individuele waarden en de belemmeringen en facilitators voor deze waarden.

Het doel van dit proefschrift is bepalen hoe draagbare activiteiten sensoren succesvol kunnen worden toegepast in gezondheidsinterventies gericht op sedentair gedrag.

Dit proefschrift volgt een steeds groter wordende scope: van het niveau van de activiteitensensor tot het niveau van de volksgezondheid. Het eerste deel van dit proefschrift richt zich op het *meten* van sedentair gedrag en de patronen ervan door middel van draagbare activiteiten sensoren (Hoofdstuk 2, 3 en 4). Het tweede deel van dit proefschrift richt zich op de *ontwikkeling en evaluatie* van mHealth-interventies die gebruik maken van deze draagbare activiteiten sensoren (hoofdstuk 5 en 6).

Het patroon van sedentair gedrag gedurende de dag is een onafhankelijk gezondheidsrisico. Langere perioden van zitten beïnvloedt cardio-metabole en inflammatoire biomarkers, onafhankelijk van de totale sedentaire tijd. Sinds de opkomst van draagbare technologieën en activiteiten sensoren, hebben onderzoekers nog geen consensus bereikt over de beste uitkomstmaten voor het weergeven van het sedentaire patroon gedurende de dag. Hoofdstuk 2 geeft een overzicht van de huidige patroonmaten van sedentair gedrag bij volwassenen, aan de hand van een literatuuronderzoek. Eenvoudige maten van sedentair gedrag werden het meest gerapporteerd, zoals het aantal zitperioden, de gemiddelde of mediane duur van de zitperiode. Complexere patroonmaten, zoals de GINI-index of de W50, werden weinig gerapporteerd. Door het gebruik van verschillende meetinstrumenten, data-analyseprotocollen en een gebrek aan basis uitkomstmaten zoals totale draagtijd en totale sedentaire tijd, zijn sedentaire patronen uit de verschillende onderzoeken, moeilijk met elkaar te vergelijken. De eenvoudige en complexe maten van sedentaire tijd dienen verschillende doelen variërend van een snel overzicht tot diepgaande patroon analyse en voorspelling van gedrag. Welke patroonmaten het meest geschikt zijn om te rapporteren, is daarom sterk afhankelijk van de onderzoeksvraag. Op basis van de samenvattende studie beschreven in hoofdstuk 2 concluderen we dat de gerapporteerde metingen afhankelijk waren van 1) de meetmethode, 2) de classificatiemethode, 3) het experimentele en data-opschoningsprotocol, en 4) de toegepaste definities van sedentaire perioden en onderbrekingen hiervan. Op basis van deze bevindingen raden we aan om altijd de totale sensor-draag-tijd, de totale sedentaire tijd, het aantal zitperioden en ten minste één patroonmaat te vermelden die de diversiteit van de lengte van perioden van het sedentaire gedrag zoals de W50 beschrijft. Daarnaast adviseren wij om de meetcondities en gegevensverwerkingsstappen goed te beschrijven.

Een van de factoren die de output van de hierboven genoemde activiteitensensoren beïnvloeden, is het experimentele protocol (Hoofdstuk 2). Dit werd in hoofdstuk 3 dieper behandeld, waarbij we ons concentreerden op de optimale sensorplaatsing voor het meten van fysieke activiteit. De proefpersonen liepen met verschillende snelheden op een loopband, voerden een bureauwerk-protocol uit en liepen op een vlakke ondergrond, terwijl ze tegelijkertijd vijf activiteitensensoren droegen op een elastische heupband. Uit dit onderzoek bleek dat de sensorlocatie, het type activiteit en hun interactie-effect de sensordata beïnvloedden. De meest laterale posities op de heupband waren het minst gevoelig voor interferentie. Daarnaast hebben we het effect van de bevestiging van de sensor onderzocht door het experimentele protocol te herhalen met sensoren die losser op de elastische riem waren geplaatst. De losse pasvorm resulteerde in een lagere sensoroutput, behalve het bureauwerk-protocol, waar de output hoger was. Om de betrouwbaarheid te vergroten en de variabiliteit van sensoruitvoer te verminderen, zouden onderzoekers daarom activiteiten-sensoren op de meest laterale positie van de riem van een deelnemer moeten plaatsen. Als de sensor op deze locatie de vrije beweging hindert, kan de sensor het beste iets verder naar voren op de riem worden geplaatst. En daarnaast is het aan te bevelen sensoren stevig, nauwsluitend op het lichaam te dragen.

Een andere factor die van invloed is op de output van activiteitensensoren is de classificatiemethode(hoofdstuk 2). Momenteel is de meest toegepaste methode om sedentaire en actieve tijd te onderscheiden, het toepassen van een drempelwaarde bij accelerometrie gebaseerde data. Dit betekent dat het gemeten gedrag wordt geclassificeerd als sedentair wanneer de intensiteit hiervan onder de drempelwaarde ligt. We hebben het effect van de classificatiemethode op sedentaire patroonmaten met kantoormedewerkers bestudeerd in laboratorium- en free-living-omstandig-heden (hoofdstuk 4). In deze studie vonden we dat de uitkomstmaten robuust zijn, wanneer drempelwaarden voor het classificeren van sedentair gedrag binnen de grenzen van ± 10-20% van de optimale drempelwaarde liggen. Met drempelwaarden van ± 10-20% veranderen de sedentaire patronen niet ten gevolge van de classificatiemethode. Deze conclusie impliceert dat resultaten van studies die sedentaire patronen analyseren op basis van verschillende drempelwaarden, alleen kunnen worden vergeleken als de drempelwaarden binnen deze grenzen liggen.

In hoofdstuk 5 hebben we de kennis over sensorgebruik, gegevensverwerkings-stappen en uitkomstmaten gecombineerd met technologie die zich van de context bewust is, in een interventie voor oudere kantoormedewerkers. Deze interventie was gericht op het stimuleren van zowel minder zitten als ook de zittijd op te breken in kortere perioden. Kantoormedewerkers brengen een hoog percentage van hun tijd zittend door en vaak in lange zitperioden. Het is gezonder om deze lange perioden in kortere perioden op te breken door korte tijd fysiek actief te zijn. Om dit opbreken van lange sedentaire periodes te bevorderen bij kantoormedewerkers, hebben we een innovatieve, contextbewuste activiteitencoach ontwikkeld. Deze coach geeft suggesties voor activiteiten, gebaseerd op een voorspellingsmodel voor fysieke activiteit. Het model bestaat uit de huidige fysieke activiteit en die in het verleden (gemeten aan de hand van een draagbare activiteitensensor) en digitale agenda's. De totale sedentaire tijd in de interventieweek was niet lager dan in de week voor de interventie. Het patroon van het sedentaire gedrag veranderde echter wel: de kantoormedewerkers verminderden hun totale tijd doorgebracht in lange zitperioden (≥45 minuten). Bovendien gaven de kantoormedewerkers aan dat de interventie bij droeg aan hun bewustzijn en inzicht in hun persoonlijk sedentair gedragspatroon. De activiteiten suggesties van de interventie werden in 53% van de momenten opgevolgd door de deelnemers. Deelnemers gaven aan dat dit percentage verhoogd zou kunnen worden door de timing te verbeteren. We concluderen dat de mobiele interventie (met behulp van een activiteitensensor, smartphone-applicatie en contextinformatie) het sedentaire gedrag van oudere kantoormedewerkers kan verbeteren. De gezondheidswinst komt dan vooral voort uit het opsplitsen van lange sedentaire perioden door fysiek actief te zijn. Oudere kantoormedewerkers waardeerden dat de interventie hen bewust maakte van hun sedentaire gedrag. Op basis van deze uitkomsten, lijken interventies voor de volksgezondheid die enkel gericht zijn op het verminderen van de totale sedentair tijd, te simplistisch. In plaats daarvan is het bij het bepalen van het effect van een interventie belangrijk om rekening te houden met zowel de duur als het aantal perioden waarin iemand sedentair is. Tenslotte benoemen we onze ontwerpaanbevelingen voor eHealth-interventies gericht op het verbeteren van sedentair gedrag.

In Hoofdstuk 6 hebben we ons gericht op een ontwerpbenadering om de acceptatie van mHealth-interventies verder te vergroten - door af te stemmen op individuele waarden en barrières en facilitators van deze waarden. In deze studie hebben we aangetoond hoe waarde gericht ontwerpen kan bijdragen aan het ontwerp van een product of dienst die de echte behoeften aanpakt en zo tot een hoge acceptatie leidt. We hebben de methoden en toepassing van waarde gericht ontwerpen beschreven. We hebben waarden, facilitators en belemmeringen van oudere volwassenen uitgevraagd via diepte-interviews met een focus op hun beperkte mobiliteit - wat betekent dat ze moeilijk kunnen wandelen, fietsen en/of activiteiten van het dagelijks leven kunnen uitvoeren. Deze interviews resulteerden in een groot aantal kernwaarden, zoals 'onafhankelijkheid zijn van familie' en 'zelf boodschappen doen'. Vervolgens resulteerden co-creatie ontwerpsessies in innovatieve mobiliteitshulpmiddelen. Uit deze innovatieve mobiliteitshulpmiddelen werden drie ontwerpen geselecteerd voor evaluatie van de acceptatie, opnieuw via diepte-interviews. De oudere volwassenen hun acceptatie van de drie rollator-achtige ontwerpen was nogal laag. De huidige gebruikers van mobiliteitshulpmiddelen waren positiever over de ontwerpen dan de ouderen die nog geen hulpmiddelen gebruikte. Deze op waarden gebaseerde ontwerpbenadering bood ontwerpers een kijkje in de levens van ouderen, waardoor een breed scala aan innovatiemogelijkheden werd gecreëerd die beter aansluiten op de werkelijke behoeften. Mobiliteit is echter gerelateerd aan fysieke capaciteit en niet aan het zitten. Toch kan een grondig begrip van de waarden van het leven om mobiel te zijn, zowel ontwerpers die zich richten op mobiliteitshulpmiddelen direct inspireren als ook ontwerpers van gezondheids-interventies om sedentair gedrag aan te passen, waarin persoonlijke doelen en context even waardevol zijn.

In hoofdstuk 7, de algemene discussie, bespreken we de snelle ontwikkeling van sensoren en analysemethoden, evenals het verzamelen van waardevolle contextinformatie door middel van Experience Sampling (het uitvragen van iemands beleving). Activiteiten sensoren zouden veel rijkere informatie over het gedrag kunnen opleveren. De drempelwaarde-gebaseerde analyses maken daar echter slechts zeer beperkt gebruik van. Daarnaast kent deze analyse methode diverse beperkingen (hoofdstuk 2, 3 en 4) waardoor generalisatie van de huidige literatuur maar beperkt mogelijk is. Het lijkt daarom zinvoller om het gemeten gedrag uit te drukken in termen van het werkelijke gedrag zoals fietsen, traplopen en dergelijke, in plaats van deze uit te drukken in (metrische) eenheden van intensiteit. Machine Learning technieken zijn in staat om met een hogere nauwkeurigheid direct het werkelijke (beweeg)gedrag te bepalen en de toepassing hiervan lijkt een logische stap voorwaarts. Daarnaast zal de output van Machine Learning gemakkelijker te gebruiken zijn in interventies wanneer deze wordt uitgedrukt in gedrag, omdat dit past bij de kennis van gebruikers; meer dan uitkomstmaten als totale intensiteit, zittijd en aantal actieve perioden. De Experience Sampling Method (ESM) die was ingebouwd in de ontwikkelde interventie (Hoofdstuk 5), gaf inzicht in de context van sedentair gedrag: waar, wanneer, waarom en met wie is het subject wanneer hij of zij zit en welke emoties worden dan ervaren. Toekomstige interventies zouden dit type context moeten integreren in real-time, gepersonaliseerde coaching strategieën om bewustwording en gedragsverandering te realiseren.

De studies in dit proefschrift hebben aangetoond dat activiteitensensoren waardevolle informatie kunnen verschaffen over het patroon van sedentair gedrag en dat deze nuttig kunnen zijn voor gezondheidsinterventies. We hebben de sterke punten van de huidige praktijk en de mogelijkheden voor verbetering getoond door een brede scope toe te passen met een focus op het meten van sedentair gedrag en het ontwikkelen en evalueren van mHealth-interventies. Op basis van de studie kunnen we concluderen dat:

De combinatie van de bottom-up benadering (van sensor-, naar data- en informatieniveaus) met de top-down benadering (van gebruikerswaarden gerelateerd aan volksgezondheid tot interventies en haar specifieke feedback- en coaching strategieëen) bijdraagt aan diverse, sterk verbonden en onderling afhankelijke domeinen van het toepassen van draagbare activiteiten sensoren voor gezondheidsinterventies gericht op sedentair gedrag.

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Mijn ouders, Theo en Sieneke, jullie leerden mij van kinds af aan om mijn best te doen, door te zetten en niet op te geven om mijn doelen te bereiken. Jullie stimuleerden mijn nieuwsgierigheid en hebben daarmee de basis gelegd voor mijn onderzoek. Mams, zeker in tijden dat mijn gezondheid mij behoorlijk beperkte, verzette jij bergen om mij te helpen en door te gaan – ik waardeer dat enorm. Het heeft mij gebracht waar ik nu ben.

Lieve Thijs, jouw liefde, steun en ruimte om hier aan te werken zijn erg belangrijk geweest. Lieve Minke, jouw komst was een geschenk en voor mij een uitdaging om door te werken aan dit proefschrift. Veel liefde en aandacht als je wakker was en typen als je sliep. Lieve Lise, jouw komst was een cadeautje en voor mij de drijfveer om vol gas te geven richting eindstreep. Gelukt. Nu heel veel genieten!

The finish line is an end of a hard fought journey of many steps.

It’s the passion, dedication and determination that make it so sweet.

– Fb/runlikeagirlbc

CURRICULUM VITAE

Simone Boerema (1983) werd geboren in Uithuizermeeden en ging naar de middelbare school Het Hogeland College in Warffum. Op haar middelbare school was ze al erg geïnteresseerd in techniek, maar dan vooral in techniek rondom de mens. De keuze voor Biomedische Technologie aan de Universiteit Twente was dan ook de ideale combinatie van een technische opleiding gericht op de mens. Tijdens deze opleiding interesseerde Simone zich steeds meer in het meten en beïnvloeden van gedrag. Simone deed onder andere onderzoek naar het effect van openbare feedback op persoons- en groepsniveau in een kantooromgeving. Na het behalen van haar Master-titel startte ze in 2009 als Junior Onderzoeker bij Roessingh Research and Development. Hier heeft zij gewerkt aan diverse telemedicine projecten waaronder, Alwen, CareBOX, Senior, SmaCS, CRISP en PEARL. Hierin heeft zij onderzoek gedaan naar technologie voor het meten van beweeggedrag van diverse doelgroepen, zoals mensen met beginnende dementie, mensen die thuis revalideren na een totale heup operatie, thuis wonende ouderen die moeite hebben met lopen en/of fietsen en kantoorwerkers. Ieder met eigen behoeften, belanghebbenden en randvoorwaarden. Een aantal onderzoeken rondom sensoren en zitgedrag hebben bijgedragen in de totstandkoming van dit proefschrift.

Simone zich ook geschoold tot de Green Belt van de Lean methode voor kwaliteitsverbetering. Lean heeft overeenkomsten met beïnvloedingstheorieën voor gezondheidsgedrag: voordat je kunt veranderen heb je inzicht nodig in de processen en inzicht in hoe mensen mee willen en kunnen gaan in verandering.

Sinds mei 2017 werkt Simone bij GGD Twente als Epidemioloog / Onderzoeker Publieke Gezondheid gericht op het monitoren en inzichtelijk maken van de publieke gezondheid. Daarnaast is Simone werkzaam bij Vitaal Twente als netwerk coördinator, waarbij ze organisaties helpt verbinden zodat deze tot duurzame implementatie van technologische innovaties komen. Hierin hebben het identificeren van behoeften, monitoring en evaluatie een centrale rol – net als in dit proefschrift.

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