From Department of Neurobiology, Care Sciences and Society
Karolinska Institutet, Stockholm, Sweden

ADVANCING THE MEASUREMENT OF SEDENTARY BEHAVIOUR

CLASSIFYING POSTURE AND PHYSICAL (IN-)ACTIVITY

Roman Peter Kuster

Stockholm 2021

All previously published papers were reproduced with permission from the publisher.
Published by Karolinska Institutet.
Printed by Universitetsservice US-AB

ISBN 978-91-8016-107-7
Cover illustration: Sedentary student writing his kappa about sedentary behaviour

ADVANCING THE MEASUREMENT OF SEDENTARY BEHAVIOUR – CLASSIFYING POSTURE AND PHYSICAL (IN-)ACTIVITY

THESIS FOR DOCTORAL DEGREE (Ph.D.)

By

Roman Peter Kuster

Principal Supervisor:
Associate Professor Wilhelmus J.A. Grooten
Karolinska Institutet
Department of Neurobiology, Care Sciences, and Society
Division of Physiotherapy

Co-supervisors:
Professor Maria Hagströmer
Karolinska Institutet
Department of Neurobiology, Care Sciences, and Society
Division of Physiotherapy

Professor Daniel Baumgartner
Zurich University of Applied Sciences
School of Engineering
IMES Institute of Mechanical Systems
Biomechanical Engineering

Opponent:
Professor Andreas Holtermann
National Research Centre for the Working Environment
Department of Musculoskeletal Disorders and Physical Workload

Examination Board:
Professor Elena Gutierrez Farewik
Royal Institute of Technology (KTH)
Department of Engineering Mechanics
KTH MoveAbility Lab
KTH BioMEx Center

Associate Professor David Hallman
University of Gävle
Department of Occupational Health Sciences and Psychology
Centre for Musculoskeletal Research

Associate Professor Jan Christian Brønd
University of Southern Denmark
Department of Sport Science and Clinical Biomechanics
Research Unit for Exercise Epidemiology

AKADEMISK AVHANDLING

som för avläggande av medicine doktorsexamen vid Karolinska Institutet offentligen försvaras i hörsal 4V, Alfred Nobels allé 8, Huddinge, fredagen den 12 mars kl. 09:30.

It never gets easier; you just get faster.

Greg LeMond

POPULAR SCIENCE SUMMARY

«Excessive sitting is a lethal activity» claimed The New York Times (USA). Dagens Nyheter (SWE) headlined *«Being sedentary is as deadly as smoking»*, and the Tagesanzeiger (SUI) postulated *«Sitting all day is life-threatening»*. These are three examples of thousands of newspaper articles published in the last decade about the detrimental health effects of sedentary behaviour – the scientific term for inactive sitting. Inactive means that the energy expenditure is a maximum of 50% higher than when lying, while active would mean the energy expenditure is more than 50% higher. The World Health Organization recently updated its physical activity guidelines and included sedentary behaviour for the first time. The guidelines recommend that *«all adults limit the amount of time spent being sedentary»*, because *«high amounts of sedentary behaviour are associated with diabetes, cardiovascular disease, and mortality»*. However, the evidence relied on by the World Health Organization is not based on measuring sedentary behaviour. Only a handful of scientific studies to date measured the inactivity and the sitting component of sedentary behaviour. These studies have shown that measuring only one of its components gives incorrect results.

For this reason, this thesis developed new methods to simultaneously measure both components of sedentary behaviour – inactivity and sitting. It validated the most promising method to verify whether it actually measures the two components, and finally used it to measure the true amount of sedentary behaviour in daily life.

The results demonstrate that it is possible to measure inactivity and sitting with only one single body-worn sensor, ideally worn on the thigh. Consequently, there is no need to approximate sedentary behaviour with inactivity or sitting. The results also show that physical activity sensors, with which all the evidence for the detrimental health effects was collected, measure inactivity and not sedentary behaviour.

So far, it has been estimated that we spend about 55% – 65% of our wake-time sedentary. However, this thesis shows that office workers, prone to be among the most sedentary people, spend about 60% of the wake-time sitting and 55% of the wake-time inactive, but only 45% of the wake-time sedentary. The reason for the difference is that they accumulate 2 hours a day of active sitting and almost 2 hours a day of inactive standing, both with considerable variability. Some office workers spend one third of their sitting time active, while others spend most of their standing time inactive. This difference plays a vital role in the prevention of chronic diseases related to sedentary behaviour. It determines how we can combat the adverse health effects: by promoting active sitting or promoting standing.

Hence, research should be careful with the term sedentary behaviour and specify whether it examines inactivity, sitting, or sedentary behaviour. At present, the recommendation to reduce sedentary behaviour should be interpreted as a recommendation to reduce inactivity, and the detrimental health effects should be combat with activity rather than standing. For office workers, this questions the use of standing desks, but analysing their impact on human health requires another thesis, ideally using a method developed in here.

ZUSAMMENFASSUNG

«Übermässiges Sitzen ist eine tödliche Aktivität» behauptete die New York Times (USA). Dagens Nyheter (SWE) titelte *«Still sitzen ist so tödlich wie Rauchen»*, und der Tagesanzeiger (SUI) meinte *«Den ganzen Tag sitzen ist lebensgefährlich»*. Tausende Zeitungsartikel haben in den letzten Jahren über die gesundheitsschädlichen Auswirkungen von Sedentary Behaviour berichtet, dem wissenschaftlichen Fachbegriff für inaktives Sitzen. Inaktiv bedeutet, dass der Energieverbrauch maximal 50% höher ist, als beim Liegen, während er bei aktivem Sitzen mehr als 50% höher ist. Die Weltgesundheitsorganisation hat kürzlich ihre Empfehlungen für körperliche Aktivität aktualisiert und zum ersten Mal inaktives Sitzen einbezogen. Sie empfiehlt, dass *«Erwachsene die Zeit, in der sie inaktiv sitzen, begrenzen»*, denn *«Personen die häufig inaktiv sitzen, haben häufiger Diabetes, Herzkreislauferkrankungen, und sterben früher»*. Ein Blick auf die von der Weltgesundheitsorganisation angeführten Beweise zeigt jedoch, dass die zugrundeliegenden Studien nicht inaktives Sitzen gemessen haben, sondern Inaktivität oder Sitzen. In Tat und Wahrheit haben bisher nur eine Handvoll Studien Inaktivität und Sitzen gleichzeitig gemessen, und diese haben gezeigt, dass die Messung nur einer der beiden Komponenten zu falschen Ergebnissen führt.

Deshalb wurden in dieser Arbeit neue Methoden entwickelt, um beide Komponenten gleichzeitig zu messen: Inaktivität und Sitzen. Zudem wurde die vielversprechendste Methode validiert um zu überprüfen, ob sie effektiv beide Komponenten misst. Schlussendlich wurde die Methode verwendet, um das tatsächliche Ausmass von inaktivem Sitzen zu messen.

Die Ergebnisse zeigen, dass es grundsätzlich möglich ist, Inaktivität und Sitzen mit nur einem einzigen am Oberschenkel getragenen Sensor zu messen. Folglich gibt es keinen Grund, nur Inaktivität oder nur Sitzen zu messen. Die Ergebnisse bestätigen zudem, dass bisherige Studien tatsächlich nur Inaktivität und nicht inaktives Sitzen gemessen haben.

Bisher wurde vermutet, dass wir 55% bis 65% unseres Tages (ohne Schlaf) inaktiv sitzen. Diese Arbeit zeigt jedoch auf, dass Büroangestellte etwa 60% des Tages sitzen und 55% des Tages inaktiv sind, aber nur 45% des Tages inaktiv sitzen. Der Grund für diesen Unterschied ist, dass sie 2 Stunden pro Tag aktiv sitzen, und fast 2 Stunden pro Tag inaktiv stehen. Einige verbrachten sogar einen Drittel ihrer Zeit im Sitzen aktiv, während andere den grössten Teil ihrer Zeit im Stehen inaktiv waren. Diese Beobachtung spielt eine entscheidende Rolle bei der Prävention chronischer Krankheiten: Sollen die gesundheitsschädlichen Auswirkungen von inaktivem Sitzen mit aktivem Sitzen oder Stehen bekämpft werden?

Die Wissenschaft sollte mit dem Begriff Sedentary Behaviour vorsichtiger umgehen und klar spezifizieren, ob Inaktivität, Sitzen oder inaktives Sitzen gemessen wird. Die Empfehlung inaktives Sitzen zu reduzieren muss gegenwärtig als Empfehlung zur Reduktion der Inaktivität verstanden werden. Die gesundheitsschädlichen Auswirkungen müssen deshalb mit Aktivität bekämpft werden. Für Büroangestellte stellt dies natürlich die Verwendung von Stehpulten in Frage. Die Analyse derer Auswirkungen auf die Gesundheit erfordert jedoch weitere Forschung, idealerweise unter Verwendung einer hier entwickelten Methode.

ABSTRACT

Sedentary behaviour, defined by a sitting body posture with minimal-intensity physical activity, is an emergent public health topic. The time spent sedentary is associated with the incidence of non-communicable chronic diseases such as type 2 diabetes and cardiovascular disease and significantly shortens life-expectancy in a dose-response relationship. Office workers are at particular risk of developing diseases related to sedentary behaviour due to their excessive sedentary work. Even though thigh-worn posture sensors are recommended to measure sedentary behaviour, the vast majority of the evidence was collected with waist-worn physical activity sensors, and we still lack a method to measure the posture and the physical activity component of sedentary behaviour simultaneously.

This thesis aims to advance the measurement of sedentary behaviour in an office context by developing new device-based methods to measure both components simultaneously, and by validating and subsequently applying the most promising method to measure the actual amount of sedentary behaviour in the daily life of office workers.

The method development showed that it is possible to measure both components of sedentary behaviour with only one sensor, preferably worn on the thigh or waist. While an accelerometer is sufficient for the thigh, an inertial-measurement-unit is preferable for the waist due to a significantly improved posture classification. The method validation subsequently confirmed that waist-worn physical activity sensors, the prevailing choice to measure sedentary behaviour, measure minimal-intensity physical activity. Furthermore, the study uncovered a serious postural dependency causing a systematic overestimation of minimal-intensity physical activity while sitting compared to standing. The subsequent method application considered the posture dependency and combined a thigh-worn posture sensor with a waist-worn physical activity sensor to POPAI, the Posture and Physical Activity Index. POPAI has a sensitivity of 92.5% and a specificity of 91.9% to measure sedentary behaviour and classified 45.0% of the office workers wake-time sedentary. The posture sensor alone overestimated sedentary time by 30.3%, and the physical activity sensor alone overestimated sedentary time by 22.5%. The difference can be explained by active sitting (2.0 hours per day) and inactive standing (1.8 hours per day), both of which are much more common than previously thought.

This thesis confirms the recommendation to use a thigh-worn accelerometer to measure sedentary behaviour and adds the information that such a sensor is also able to measure physical (in-)activity in sitting. Thus, there is no need to approximate sedentary behaviour with sitting, nor is there a need to approximate it with inactivity. In fact, these approximations lead to inaccurate and imprecise results substantially overestimating sedentary behaviour. Due to the predominant use of physical activity sensors to measure sedentary behaviour, recommendations to limit sedentary behaviour should address a limitation of the time spent inactive rather than the time spent sitting. If it turns out that sitting matters, one could expect a much stronger relationship between sedentary behaviour measured with a combined method such as POPAI and detrimental health effects.

LIST OF SCIENTIFIC PAPERS

I. Kuster RP, Huber M, Hirschi S, Siegl W, Baumgartner D, Hagströmer M, and Grooten WJA. *Measuring Sedentary Behavior by Means of Muscular Activity and Accelerometry*. Sensors (Basel). 2018;18(11):4010.

II. Kuster RP, Baumgartner D, Hagströmer M, and Grooten WJA. *Where to Place Which Sensor to Measure Sedentary Behavior? A Method Development and Comparison among Various Sensor Placements and Signal Types.* J Meas Phys Behav. 2020;3(4):274-84.

III. Kuster RP, Grooten WJA, Baumgartner D, Blom V, Hagströmer M, and Ekblom Ö. *Detecting Prolonged Sitting Bouts with the ActiGraph GT3X.* Scand J Med Sci Sports. 2020;30(3):572-82.

IV. Kuster RP, Hagströmer M, Baumgartner D, and Grooten WJA. *Concurrent and Discriminant Validity of ActiGraph Waist and Wrist Cut-Points to Measure Sedentary Behaviour, Activity Level, and Posture in Office Work*. BMC Public Health. 2021; in press.

V. Kuster RP, Grooten WJA, Blom V, Baumgartner D, Hagströmer M, and Ekblom Ö. *Is Sitting Always Inactive and Standing Always Active? A Simultaneous Free-Living activPal and ActiGraph Analysis*. Int J Environ Res Public Health. 2020;17(23):8864.

CONTENTS

LIST OF ABBREVIATIONS

Accel	Accelerometer, used when referring to a specific accelerometer method developed in this thesis
cpm	counts-per-minute, a proprietary unit of physical activity sensors
EMG	Electromyography
EMG+	Electromyography plus Accelerometer, refers to a new method developed in this thesis
IMU	Inertial-Measurement-Unit, consisting of a 3D accelerometer, a 3D gyroscope, and a 3D magnetometer
LIPA	Light-Intensity Physical Activity (1.5 – 3.0 MET)
MET	Metabolic Equivalent
minPA	minimal-intensity Physical Activity (≤1.5 MET)
MVPA	Moderate- to Vigorous-Intensity Physical Activity (≥3.0 MET)
POPAI	Posture and Physical Activity Index
SB	Sedentary Behaviour (minPA while sitting)
WHO	World Health Organization

PREFACE

A bicycle ride around the world begins with a single pedal stroke [Scott Stoll, bike adventurer]. I did my first pedal stroke in the world of sedentary behaviour back in 2012 when I discussed a potential master thesis with two engineers, Daniel and Lukas. Daniel's vision was to make seated office work active, and Lukas was the one who transferred Daniel's vision into prototype office chairs. From that discussion on, the three of us developed a new office chair with a unique type of seat motion. As movement scientist, I started studying seated body movements in the movement laboratory – at this early stage of the project of course without a chair – and we spent hours discussing how to transfer the free-sitting movements to a chair [1, 2]. All the discussions, revisions, nightshifts, and prototypes seem to have been somehow successful. By the end of 2014, we sat on our first hand-built office chair, and more than six years later, I still enjoy sitting on this chair every day.

After launching a new product, an engineer's mind starts to optimise it, aiming to make it better, simpler, more durable, and transfer the technology into other areas [3]. In contrast, a movement scientist's mind starts to think about its daily use. How do office workers control the moveable seat? Find the answer in [4]. Does the moveable seat make a difference in terms of physical activity? Do they use it while daily office work? At that time, I did not even know that my sedentary research had already started. As scientists, we set-up a randomised controlled trial with office workers from a local insurance company to investigate whether and how the new chair affects their sitting behaviour. However, an almost endless, frustrating literature search told me that there is apparently no way to measure active sitting, although I came across a large number of studies examining inactive sitting (the layman's term for sedentary behaviour). Therefore, I took a couple of sensors, a video camera, three chairs and all my workmates, did a spontaneous calibration study, and we could start our randomised controlled trial as planned. At the same time, I swore myself to come back to this method issue when the opportunity arises to **solve the myth of why we are able to measure inactive sitting but not active sitting**.

Now that you are reading the preface of my doctoral thesis about the measurement of sedentary behaviour, it is evident that this opportunity arose. It makes me even more proud that I could include our office chair in one of the studies that comprise this thesis. Before I let you dive into the topic, I want to clarify the use of an imprecise expression in this thesis for the sake of readability. According to the Merriam-Webster dictionary, behaviour is *the way in which someone conducts oneself or behaves*, and it has a plethora of components and facets. However, with the focus on sedentary behaviour, behaviour is here always seen as physical behaviour with only two components, body posture and physical activity.

Och nu önskar jag alla en god läsning.

Roman Kuster

Flemingsberg, February 2021

1 BACKGROUND

1.1 SEDENTARY BEHAVIOUR AND HEALTH

Sedentary Behaviour (SB) is a substantial part of our modern lifestyle, accounting for the vast majority of the wake-time. The average adult citizen in high-income countries spends around 8 – 10 hours or 55% – 65% of the wake-time sedentary [5-8], and the further a country is digitally developed, the more its citizens report to be sedentary [9].

High levels of SB are associated with the incidence of non-communicable chronic diseases such as type 2 diabetes, cardiovascular disease, and cancer [10, 11], and significantly reduce life expectancy in a dose-response relationship [12-15]. An estimated 4% – 6% of all deaths in high-income countries can be traced back to SB [16, 17]. Only people who collect very high amounts (≥30 minutes per day) of moderate- to vigorous-intensity physical activity (MVPA) might be able to counterbalance the detrimental health effects of SB [12, 18].

Preliminary evidence furthermore indicates that regularly interrupting SB with active breaks in light-intensity physical activity (LIPA) might have acute positive effects on disease-relevant biomarkers [19-22]. However, evidence lacks that these effects lead to improved long-term outcomes, and inconsistent results were reported whether the sedentary accumulation pattern (i.e. the time spent in long sedentary bouts) is associated with mortality [23-26].

In summary, the time has not yet come to formulate evidence-based quantitative health guidelines [23, 27]. The recently updated (November 2020) physical activity guidelines of the World Health Organization (WHO) include for the first time SB, but without quantifying a health-relevant threshold [28]. One reason for this lack is the considerable variation in the measurement of SB [12]. Thus, there is an urgent need to develop device-based methods to quantify SB compliant with its definition [10].

1.2 OCCUPATIONAL SEDENTARY BEHAVIOUR AND WORKPLACE INTERVENTIONS

Up to 72% and 81% of the European Union and the United States population, respectively, works in the tertiary service sector, with primarily computer-based sedentary work activities [29]. In Sweden, 85% of all employees use a computer at work, >50% use a computer for >50% of the working time, and almost 25% for almost 100% of the working time [30]. The trend towards more sedentary computer time is not limited to working hours and is expected to continue in the future [30, 31].

Office workers spend around 65% – 75% of their working time sedentary [32-34], and accumulate a large part of it in long bouts ≥30 minutes [35-37]. At the same time, office work is characterised by only a marginal amount of non-stationary activities like walking (around 7% of the work time) [37, 38]. Thus, office workers are at an increased risk of developing SB-related chronic diseases, even though they typically accumulate slightly more recreational MVPA than non-office workers [34, 39].

Due to the large proportion of the population exposed to high levels of sedentary office work, its health effects must be seen as a serious public health issue. Slogans like *sitting is the new smoking* have been introduced to highlight the detrimental health effects [40, 41], and the use of workplace equipment to break up SB is recommended, either by breaking it up with standing or physical activity [42].

Workplace interventions to break up sedentary time with standing show low- to moderate quality evidence to reduce sedentary working time by around 30 – 100 minutes per day [43-45], without compromising performance and productivity [46, 47]. However, there is conflicting evidence whether standing increases physical activity compared to sitting [48-52], questioning whether standing is a sufficiently large stimulus to counteract the detrimental health effects of SB. Furthermore, there is conflicting evidence regarding a compensation effect outside working hours. Using a sit-stand desk at work has the potential to reduce sedentary office time, but it also has the potential to increase the sedentary time outside working hours [53, 54].

Workplace interventions to break up sedentary time with physical activity are less well studied and show inconsistent findings [43-45, 55]. From controlled experiments, it is known that workplace equipment such as cycling desks and some activity-promoting office chairs can increase the energy expenditure [56-59], with conflicting results about their effects on work performance and productivity [46, 47, 59, 60].

In general, several reviews concluded that the original studies examining the effects of workplace interventions use inconsistent, non-standardised, and non-objective SB measurements [61-63]. Thus, there is an urgent need to develop device-based methods to quantify the effects of workplace interventions on SB.

1.3 SEDENTARY BEHAVIOUR – AN EVOLVING DEFINITION

An essential prerequisite for studying a behaviour and its health effects is a clear definition of the behaviour itself, and a serious limitation of the sedentary research field is the definition's evolution with its resulting ambiguity [64].

The term sedentary has initially been used to describe those individuals not engaging in a certain amount of physical activity (e.g. <10% of the daily energy expenditure spent in MVPA, less than the public health recommendations), to describe a reference group showing the lowest amount of physical activity, or to describe activities performed while sitting [65-68]. Historically, the term *sedentary* originates from the Middle French word *sédentaire*, which derives from the Latin *sedentarius*, a synonym for *sitting* and *not in the habit of exercise* [69, 70]. However, there are three alternative SB definitions in use:

- Owen and colleagues proposed in 2000 that ***sedentary behaviour may be defined as having a MET*** **(Metabolic Equivalent)** ***value between 1.0 and 1.5*** [71, p. 156]. According to the Owen-Definition, SB is defined by a particular physical activity intensity only (1.0 – 1.5 MET) and represents the lower end of the physical activity spectrum. The most serious limitation of the Owen-Definition is that it does not include the sitting component from which the term sedentary originates [70].

- Marshall and Ramirez proposed in 2011 that ***sedentary behaviour is best operationalised as sitting*** [72, p. 520], arguing that there are so few behaviours that involve sitting with a MET >1.5. According to the Marshall-Definition, SB is defined by a particular body posture only (sitting) and independent of physical activity. The most serious limitation of the Marshall-Definition is that we lack evidence whether there are actually so few behaviours that involve sitting with a MET >1.5.

- The Sedentary Behavior Research Network proposed in 2012 that one should define ***sedentary behaviour as any waking behaviour characterised by an energy expenditure ≤1.5 MET while in a sitting or reclining posture*** [73, p. 540]. The combination of a posture and a physical activity component was later confirmed in a terminology consensus project among experts in the field and is widely used [74]. The definition simply fuses the two earlier ones by combining the posture component of the Marshall-Definition (sitting) with the physical activity component of the Owen-Definition (1.0 – 1.5 MET). The most serious limitation of this definition is that we lack valid methods to measure both components simultaneously [10].

In summary, caution must be paid when comparing different studies regarding their SB definition. Henceforward, SB refers to the combined posture and physical activity classification as defined by the Sedentary Behavior Research Network [73]. The two components of SB are referred to as sitting (equal to the Marshall-Definition of SB) and, following the terminology in Holtermann et al. (2017), minimal-intensity physical activity (minPA, equal to the Owen-Definition of SB) [64]. Note that, in here, reclining is considered a sitting posture.

METABOLIC EQUIVALENT – A LIKEWISE EVOLVING DEFINITION

The MET used to define the physical activity component of SB is a dimensionless quantity to allow comparisons among different individuals performing different tasks. The value is calculated by dividing the metabolic rate while a particular task by the resting metabolic rate (reference value). Conceptually, a MET value of 1.5 indicates that a person uses 1.5 times the energy expenditure at rest. However, there are three alternative reference values in use, leading to three alternative MET definitions [75]:

- **$MET_{Standard}$**: From a historical perspective, 1 MET was standardised to a fix oxygen uptake of 3.5 $ml \times kg^{-1} \times min^{-1}$, approximately equal to 1 $kilocalorie \times kg^{-1} \times hour^{-1}$ [76]. This value was measured for a 70 kg, 40-year-old man under resting conditions and represents an absolute intensity measure (1.5 MET equals 5.25 $ml \times min^{-1} \times kg^{-1}$) [77, 78].

- **$\text{MET}_{\text{Adapted}}$**: To account for anthropometric effects on the resting metabolic rate, the Harris-Benedict equation can be used to adapt the $\text{MET}_{\text{Standard}}$ to gender, age, and height [79]. The resulting $\text{MET}_{\text{Adapted}}$ represents an estimated relative intensity measure [75]. For the author of this thesis, 1.5 $\text{MET}_{\text{Adapted}}$ equals 5.20 ml×min^{-1}×kg^{-1}.

- **$\text{MET}_{\text{Measured}}$**: To account for other individual factors such as genetics and environmental factors such as temperature, the individual resting metabolic rate must be measured. This makes the $\text{MET}_{\text{Measured}}$ a true relative intensity measure, which can be interpreted as work-to-rest-ratio [80]. For the author of this thesis, 1.5 $\text{MET}_{\text{Measured}}$ equals 5.79 ml×min^{-1}×kg^{-1} at 26.8° Celsius.

The distinction between the three MET definitions might be subtle, but it matters which MET definition is used to classify physical activity [75, 80-82]. The absolute scale ($\text{MET}_{\text{Standard}}$) has a long tradition in physical activity research [78, 83]. In contrast, the relative scale ($\text{MET}_{\text{Measured}}$) got popular to interpret the MET as a multiple of the resting metabolic rate [74, 84]. The $\text{MET}_{\text{Adapted}}$ represents a simplified version of the $\text{MET}_{\text{Measured}}$ without the need to measure the resting metabolic rate [75, 82]. However, it is debatable which MET definition is best to take [75, 85, 86].

In summary, caution must also be paid when comparing studies with the same SB definition regarding their MET definition. Analogous to the physical activity and SB guidelines published by the WHO (defining one MET as *the energy equivalent expended by an individual while seated at rest* [28, p. 1452]), the $\text{MET}_{\text{Measured}}$ as the true work-to-rest-ratio that can be interpreted as a multiple of the resting metabolic rate is used here.

1.4 THE 24-HOUR BEHAVIOUR FRAMEWORK

With the gaining popularity of time-use epidemiology and compositional data analyses [87, 88], it is important to embed the measurement of SB in a 24-hour behaviour framework, which takes both its posture and physical activity component into account (Figure 1, p. 7).

Posture is typically divided into sitting, standing, and locomotion. According to the Merriam-Webster dictionary, sitting is defined as *resting on the buttocks or haunches* [89], standing is defined as *supporting oneself on the feet in an erect position* [90], and locomotion is defined as *an act or the power of moving from place to place* and as such, strictly spoken, not a posture [91]. Here, locomotion is taken as a summary term for all non-stationary (i.e. non-sitting and non-standing), predominantly active behaviours. Further details about locomotion can thus be found in the corresponding physical activity research [92].

Physical activity is typically divided into LIPA (1.5 – 3.0 MET), moderate-intensity physical activity (3.0 – 6.0 MET), and vigorous-intensity physical activity (≥6.0 MET), whereas the latter two are here combined to MVPA (≥3.0 MET) [28, 78]. To summarise all activities below the lower threshold of LIPA, minPA (≤1.5 MET) is used here [64].

Bedtime is included in the 24-hour behaviour framework as it takes up a substantial part of the day. Bedtime consists mainly of sleep, which is defined neither by a particular body posture nor by a particular physical activity intensity. The Merriam-Webster dictionary defines sleep by *the absence of wakefulness and by the loss of consciousness of one's surroundings* [93]. Regarding the combined posture and physical activity classification here, no further separation of bedtime into sleep and non-sleep is made. Details about bedtime and sleep can be found in the corresponding sleep research [94].

The present thesis focuses on stationary activities at the lower end of the physical activity spectrum (Figure 1) and separates the activity level of sitting and standing into inactive (minPA with MET ≤1.5) and active (LIPA and MVPA with MET >1.5). Thus, the behaviours studied are SB (a synonym for inactive sitting), active sitting, inactive standing, active standing, and locomotion (without activity classification). The sum of these five behaviours is, consistent with the literature, called wake-time, even though this is an imprecise expression considering that bedtime is not equal to sleep. An alternative would be to call it sensor wear-time. However, this term assumes that the sensor is not worn for part of the day and is therefore incompatible with the gaining popularity of 24-hour recording protocols.

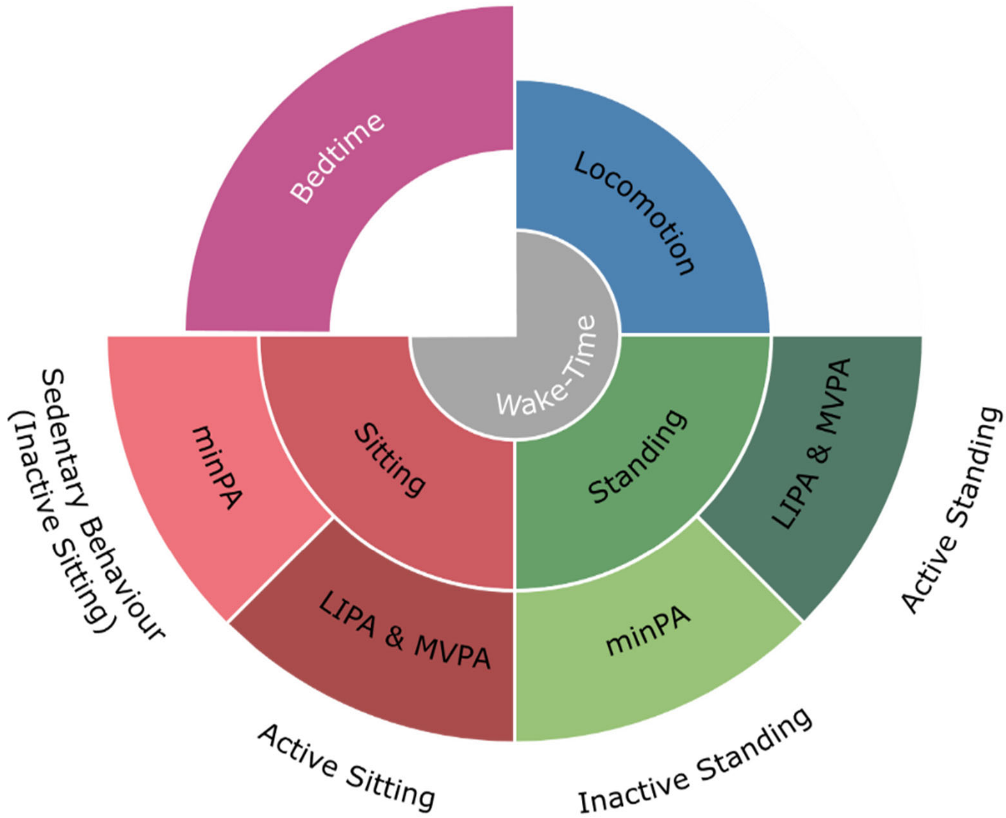

Figure 1. 24-hour behaviour framework to classify human behaviour into posture (1st level, inner ring) and physical activity (2nd level, outer ring). The outermost text expresses the combined posture and physical activity classification, with 1.5 MET separating inactive (minPA, ≤1.5 MET) from active behaviours (LIPA and MVPA, >1.5 MET). Framework inspired by the work of Tremblay et al. (2017) [74]. Abbreviations: minimal-intensity physical activity (minPA), light-intensity physical activity (LIPA), moderate- to vigorous-intensity physical activity (MVPA).

1.5 STATE-OF-THE-ART MEASUREMENT OF SEDENTARY BEHAVIOUR

The choice of the measurement instrument is of utmost importance as it defines how the definition of SB is operationalised, and thus which behaviours are considered sedentary. Studies measuring SB either use self-reporting or device-based methods [95, 96].

1.5.1 Self-Reporting Methods

For a long time, self-reporting with questionnaires was the only way to measure free-living behaviours. For SB, the majorities of questionnaires captured TV viewing or total daily sitting time as a proxy [96]. More recently developed questionnaires and diaries examine detailed context information of SB such as the domain (e.g. occupation, transportation, or leisure) [6, 97]. These methods are still quite often in use, and a substantial part of the evidence for the detrimental health effects of SB is based on self-reports [98-101]. In general, self-reporting is easy to use, cost-effective, readily accessible, provides context information, and has a low participant burden. However, it lacks accuracy and precision due to social/cultural desirability and recall bias, as well as information about the accumulation pattern [96, 102, 103]. Nevertheless, under certain conditions (e.g. national surveillance, focus on domain-specific SB), it is still a reasonable choice to measure SB, preferably alongside device-based methods [97, 102]. Depending on the method used, self-reporting underestimates SB by up to 100 – 400 minutes per day compared to device-based methods [102, 103].

1.5.2 Device-Based Methods

With the rapid technological development in the last decades, device-based methods became more accessible, affordable, and thus popular. Although there is an incredible number of wearable sensor technology available, body-worn accelerometers are the method of choice to measure SB [104, 105]. Accelerometers are small and lightweight, easy to use, allow independent recordings for several days, and put only a minimal burden on the participants. However, compared to self-reporting, they are expensive, time-consuming, and do not collect context information. Due to different placements and data processing techniques, device-based methods can be divided into two groups: sensors to measure posture (sometimes referred to as inclinometers), and sensors to measure physical activity (sometimes referred to as motion sensors) [106].

Posture sensors determine the sensor’s orientation versus gravity. Attached to the thigh, they are well known to provide an accurate estimate of the time spent sitting, standing, and in locomotion [107-112]. The most commonly used posture sensor to measure SB is the activPAL (PAL Technologies Ltd, Glasgow, SCO). The activPAL classifies each instance with a thigh orientation closer than approximately 20° to horizontal as sitting [107], and the time spent sitting is taken as a direct estimate of SB [108]. Thus, the sedentary estimate is based on the posture information only, complying with the Marshall-Definition of SB. However, it remains unknown whether there are actually so few behaviours that involve sitting with MET >1.5 (active sitting, Figure 1, p. 7) as claimed [72], and thus whether the measurement of sitting is an accurate approximation of SB.

Physical activity sensors convert the raw acceleration signal into a proprietary count unit to describe the sensor's movement intensity within a predefined epoch [113-115]. Attached to the waist or wrist, the counts represent a measure of physical activity, and corresponding cut-points provide an estimate of the time spent at different intensity levels [113, 115-117]. The cut-points to classify physical activity differ between sensors, placements, and study populations. The most commonly used physical activity sensor is a waist-worn ActiGraph GT3X (ActiGraph LCC, Pensacola (FL), USA), for which the time spent below 100 counts-per-minute (cpm) on the vertical axis is taken as a direct estimate of SB [118]. Thus, the sedentary estimate is based on the physical activity information only, complying with the Owen-Definition of SB (called minPA here). However, it remains unknown how many behaviours involve a low physical activity level (minPA) without a sitting posture (inactive standing, Figure 1, p. 7), and thus whether the measurement of minPA is an accurate approximation of SB. Even more confusing, the ActiGraph cpm cut-points were calibrated and validated to measure SB, to measure minPA, and to measure sitting, and all studies recommend vertical axis cut-points in between 22 and 200 cpm for the waist placement [108, 109, 119-123].

In summary, the activPAL is the recommended sensor to measure SB, but most evidence for the detrimental health effects of SB was collected with the waist-worn ActiGraph 100 cpm cut-point [124], with conflicting evidence what the cpm actually measures.

1.6 DEVICE-BASED METHOD DEVELOPMENT

Due to the limitations of posture and physical activity sensors to measure both components of SB, numerous studies aimed to advance the device-based measurement of SB and calibrated body-worn sensors against established reference criteria [125-127]. The calibration is required because body-worn sensors do not provide a direct behaviour measurement. The fundamental principle of a calibration is to predict 1) the behaviour of interest 2) with a body-worn sensor suitable for field recordings and 3) a specific data processing (Figure 2). The calibration's key output is an algorithm specifying how the recorded signal needs to be processed to predict the behaviour of interest. Depending on the scope of the calibration, additional aspects of a method can be examined, such as the sensor placement [128], the number of sensors [129], or the classification technique [130]. This is done by developing several algorithms and comparing their cross-validities to predict the behaviour of interest.

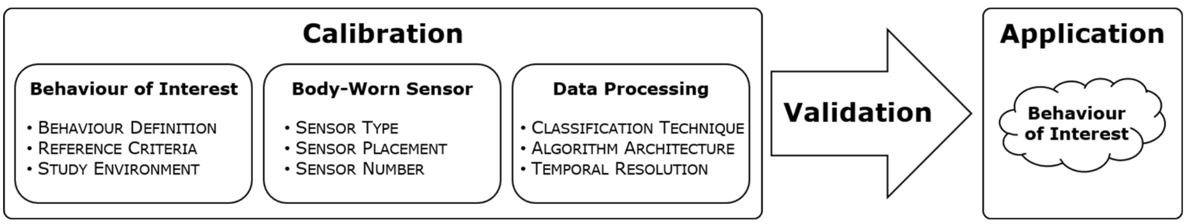

Figure 2. Method development framework. The calibration defines the new method, while the validation replicates the calibration in a new setting and study population without modifying it. The application represents the new method's field use and is strictly spoken not part of the development, but its ultimate goal. Framework inspired by the work of Keadle et al. (2019) [131].

As part of the method development, a validation should follow the calibration to assess the validity of the calibrated method in an independent setting and study population [131]. While the calibration modifies the algorithm to optimise its cross-validity in the training data, the validation assesses the method's validity to estimate its generalisability to new data, without modifying the method. Both, the calibration and the validation thereby compare the method to established reference criteria, while the final application uses the new method without reference criteria to measure the behaviour of interest in the target population. Due to the similarity of the calibration and validation, the validation study might be used to recalibrate the algorithm if the validity is deemed insufficient for future applications. In such a case, it is recommended to proceed with another validation study to assess the validity of the recalibrated algorithm before applying the new method in the target population.

Experts in the field repeatedly asked to work with raw sensor data and machine learning to advance the device-based measurement of SB [132-134]. This is why the present thesis focuses on methods using machine learning applied to raw sensor data. However, this should not be interpreted as the superiority of machine learning over traditional methods, nor as machine learning to be the only method to work with raw sensor data [126]. The method development framework in Figure 2 (p. 9) also applies to traditional method developments.

1.6.1 Behaviour of Interest

BEHAVIOUR DEFINITION

The definition of SB, the behaviour of interest, consists of two components: a particular body posture (sitting), and a particular physical activity intensity (minPA, ≤1.5 MET) [73]. However, it is common practice to simplify the classification and use either sitting or minPA as a proxy for SB [135-140]. Sometimes even sitting activities with MET >2.0 or standing activities are considered sedentary [141-143], which means that these behaviours are classified as SB in later field use. In fact, studies considering posture and physical activity, such as the one by Pavey et al. (2017), are rare [136].

REFERENCE CRITERIA AND STUDY ENVIRONMENT

The choice of valid reference criteria and the study environment are mutually dependent and directly related to the behaviour definition. Roughly, calibration studies can be divided into two groups: a minority is conducted in free-living, and the vast majority is conducted in controlled environments [127].

Studies conducted in free-living typically include a convenient sample of around 20 participants [127]. They use the same natural environment in which the method is later applied. This means that a representative part of the daily life in a representative population is recorded [144]. As reference criteria, the studies use a posture sensor [136, 137] or direct observation [145, 146]. Studies using a posture sensor are limited to the posture classification, while direct observation is used for the posture and the physical activity classification [128, 147, 148]. Trained researchers thereby observe the participants either physically or with pictures recorded by a wearable camera to categorise the daily activities in a predefined taxonomy (e.g. "sitting at a desk", "sitting quietly and watching TV") [145, 147]. Each category is subsequently assigned to a certain body posture and MET value. The MET value is usually taken from the Compendium of Physical Activity, a large database that assigns a $MET_{Standard}$ value to various kinds of daily activities [149]. The MET value is then used to classify physical activity.

Direct observation is very suitable for field recordings, but it has a limited validity to classify physical activity. It typically classifies seated activities as minPA and non-seated activities as LIPA or MVPA, thus turning the physical activity classification into a posture classification [128, 147, 148]. Furthermore, using the Compendium of Physical Activity means that SB is classified on group level, ignoring individual variations (e.g. "sitting at a desk" is always assigned to a MET of 1.3 and classified as SB regardless of the actual individual behaviour) [149].

Studies conducted in controlled environments typically include a convenient sample of around 25 participants [127]. These studies separate the posture and physical activity classification, whereas posture is most commonly prescribed and verified with direct observation [107, 138, 142], and physical activity is classified with an indirect calorimeter [150]. Indirect calorimeters measure the volume as well as the oxygen and carbon dioxide concentration in the inhaled and exhaled air, and their output is used to calculate the MET value of a given task ($MET_{Standard}$, $MET_{Adapted}$, or $MET_{Measured}$). The MET value is then used to classify physical activity.

Indirect calorimeters are known to have a high validity to measure physical activity [151], but they are very expensive, uncomfortable to wear, record only for a few hours, and require a steady state to conclude on the actual physical activity level of a given task [152]. Accordingly, their use in free-living is severely limited and very rare [120], which is why the studies are conducted in controlled environments [135, 140, 153].

The controlled environment requires that a representative part of the daily life is translated into a representative task selection in a representative MET level [144, 154]. From field studies, it is well known that the vast majority of the time is spent <2 MET [155]. Nevertheless, most studies record activities with an average MET of 3 – 4 that would be classified as MVPA [135, 140, 141, 150]. Consequently, the methods typically have a higher validity for higher MET values [115, 116, 141]. Furthermore, it is essential to include tasks just at the border of the categories to strengthen the methods ability to discriminate the behaviours in later field use [147]. For SB, this means just around 1.5 MET. However, most studies use task clusters with an artificial large MET gap between sedentary and non-sedentary tasks, e.g. driving and office work for SB with MET ≤1.5 versus dusting and laundry for LIPA with MET ≥2.4 [135]. This large gap oversimplifies the SB classification by ignoring MET levels just above 1.5, and it ignores seated activities with >1.5 MET (active sitting) and non-seated activities with ≤1.5 MET (inactive standing). In fact, even though studies conducted in controlled environments use an indirect calorimeter, they often use predefined task clusters to define SB, thereby ignoring the measured MET values [135, 141].

In summary, the choice of the reference criteria and study environment is a decision between a limited validity for the physical activity classification in a natural setting (direct observation in free-living) and a high validity for the physical activity classification in an artificial setting (indirect calorimetry in a controlled environment). The vast majority of calibration studies are conducted in controlled environments [127].

1.6.2 Body-Worn Sensor

Sensor Type

The selection of the body-worn sensor type is of utmost importance as the entire behaviour classification is based on the available input signal. Most methods use accelerometers due to their ease of use and excellent field suitability [104, 105]. Accelerometers measure the velocity change and represent a direct measure of motion variability. When attached to the waist or wrist, they can be used to classify physical activity [113, 115-117]. The acceleration signal can also be used to determine the sensor's orientation versus gravity. When attached to the thigh, they can be used to classify posture [109, 110]. However, the inactive nature of SB might make accelerometers not the optimal choice.

Little movements and a limited motion variability characterise SB, and other sensor types might be more suitable to measure physical activity in quasi-static conditions, such as electromyography (EMG). Furthermore, today’s sensors include a 3D accelerometer, a 3D gyroscope, and a 3D magnetometer, forming so-called inertial-measurement-units (IMUs), like the ActiGraph GT9X. However, it is unknown whether the additional sensor signals are of any value for the measurement of SB.

Sensor Placement

Posture sensors are worn on the thigh [110], and physical activity sensors on the waist, with newer protocols recommending the wrist to increase wear-time compliance [113, 156-158]. Only little is known about other sensor placements [125]. New methods are most often developed for the waist or the wrist placement, and the thigh is ranked fourth after the ankle [125-127]. However, direct comparisons between sensor placements are rare, with conflicting evidence which placement is most valid for measuring SB [125, 127].

Number of Sensors

Only little is known about the optimal number of sensors, with limited evidence that a two-sensor-system might increase the validity of the behaviour classification [127, 129, 159, 160]. However, field-studies rarely use two-sensor-systems to measure SB [8, 161, 162], and most new methods employ a single sensor [125-127].

1.6.3 Data Processing

Classification Technique

Calibration studies match signals from body-worn sensors with valid reference criteria, and there is an indefinite number of classification techniques [126]. The measurement of physical activity and SB started with single cut-points [113, 163], and advanced to linear regression [164, 165] and supervised machine learning techniques [125, 127]. These typically use support vector machines, k-nearest neighbours, artificial neural networks, or decision tree ensembles, with no technique appearing to be superior to the other [125-127]. Machine learning is typically used with time and frequency domain features from the pre-processed or raw acceleration signal as input [125, 127, 145]. Although the selection of relevant features plays a crucial part [127, 166], most studies use an arbitrary feature set informed by author experience or extensive feature lists [134, 136, 137, 150]. Accordingly, only limited knowledge is available about relevant signal features to classify SB [130, 134, 157, 167, 168]. While Liu et al. (2012) recommended to include only the most relevant features, Kate et al. (2016) concluded that algorithms perform better the more features they include [130, 134].

Algorithm Architecture

Due to the combined posture and physical activity classification required to measure SB, the classification can be split into its single components using a hierarchical algorithm architecture. This enables combining a priori knowledge of human behaviour with different classification techniques, signal sources, or existing algorithms [145, 153, 169-172]. Regarding the 24-hour behaviour framework (Figure 1, p. 7), a hierarchical classification architecture might first classify the posture (algorithm 1) and then the activity level of sitting (algorithm 2) and standing (algorithm 3). Thus, the final algorithm of such a combined classification consists of several sequential but independent algorithms.

Temporal Resolution

Posture sensors classify the behaviour in an event-based manner by detecting posture transitions [110], and physical activity sensors classify the behaviour in predefined 60-second epochs [113]. Studies calibrating new methods often use epoch lengths of 30 or 60 seconds [125, 127]. Some studies investigated shorter epochs of e.g. 12.8 [173], 10 [136], 5 [137], or even 1 second [139], with a tendency that the cross-validity drops the smaller the epoch gets [125]. Generally spoken, the temporal resolution is a balance between physiological relevance and methodological feasibility [106]. In terms of SB, there is some preliminary evidence that the physiological relevance might be somewhere in between 5 – 10 minutes where sedentary bouts start to have detrimental health effects [174]. On the other hand, the methodological feasibility is a trade-off between a detailed behaviour classification and a sufficiently stable acceleration signal to reach a certain classification accuracy. A completely different approach is to first segment the data in an event-based manner like posture sensors, and second classify the activity level of each event [145, 171, 175].

1.7 RATIONALE

The sedentary research field is an emerging public health topic. The numbers of original articles and reviews about SB covered by Web of Science (Clarivate, Philadelphia (PA), USA) has grown exponentially over the past three decades (Figure 3). On average, the annual number increased by 17% (35%) (median with interquartile range). In the same period, the annual total number of original articles and reviews covered by Web of Science increased by only 4% (3%). Thus, in the 1990s, one in 122’422 studies listed in Web of Science was about SB, while in the 2010s, it was one in 2’147 studies. However, the sedentary research field is still claimed to be in its infancy: in studies calibrating new methods [146, 176]; in studies analysing the relationship with chronic diseases [101, 177-179]; in studies investigating SB interventions [98, 180]; and in studies examining SB guidelines [181, 182].

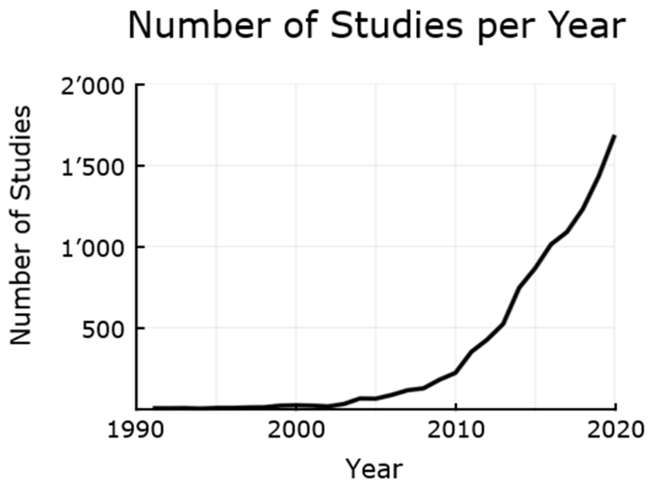

Figure 3. Crude estimate of the annual number of original articles and reviews about sedentary behaviour in the last three decades. Numbers taken from a Web of Science Core Collection search with query: TOPIC: (“sedentary behavio*”), refined by document types (article or review). Last updated on 8 February 2021.

The lowest common denominator in all of these studies is the need for a valid method to measure the two components of SB compliant with its definition. Since we still lack such a method, there is a need 1) to calibrate new methods to measure the two components of SB; 2) to validate the most promising method; and 3) to apply it in a field study to measure the actual amount of SB in real life. This also enables to specify the bias introduced when measuring only the posture or the physical activity component of SB. Due to their extensive amounts, office workers are a population at highest risk of developing SB-related chronic diseases, and there is a particular need to measure SB in the office context.

CALIBRATION

- A seated posture with low energy expenditure characterises SB, and the activity-related energy expenditure is most likely spent to a large degree on keeping body posture. Thus, the measurement of thigh orientation would be a very direct measurement of the seated body posture, and the activity measurement of the muscles as primary energy-consuming tissue would be a very direct measurement of the energy expenditure. Accordingly, there is a need to develop a method to measure SB with accelerometry and EMG.

- The use of thigh-worn posture sensors is justified by their almost perfect validity to classify posture, and the use of waist-worn physical activity sensors is justified by their respectable validity to classify physical activity. Furthermore, the lightweight and small sensor housings of accelerometers (e.g. ActiGraph GT3X) and IMUs (e.g. ActiGraph GT9X) make the sensors very suitable for field recordings. This makes them also a convenient candidate for the measurement of SB, but only very little is known about the optimal sensor placement and whether the additional signal types of IMUs are of any value for the combined posture and physical activity classification. Accordingly, there is a need to investigate where to place which sensor type to measure SB with only one sensor.

- Much data has already been recorded, in particular with the waist-worn ActiGraph GT3X. Thus, a new algorithm to measure SB with the same input signal as for the physical activity classification could be applied retrospectively, without the need to collect new data. Accordingly, there is a need to develop a posture classification for the waist-worn ActiGraph GT3X.

VALIDATION

- Before a new method is used in a field study, it is important to know its validity to measure the behaviour of interest. Accordingly, there is a need to assess the validity of the most promising new method to measure SB.

APPLICATION

- Due to the lack of valid methods to measure SB, the actual amount of SB in daily life is still unknown. Accordingly, there is a need to measure the actual amount of SB in daily life, as well as to measure the amount of active sitting and inactive standing to figure out whether there are actually so few behaviours that involve sitting with MET >1.5 (active sitting) and behaviours that involve standing with MET ≤1.5 (inactive standing). At the same time, this analysis shows whether the time spent sitting (as measured by posture sensors) and the time spent in minPA (as measured by physical activity sensors) are valid approximations of the time spent sedentary.

2 RESEARCH AIMS

This thesis aims to advance the measurement of SB in office work by calibrating new methods to measure the posture and the physical activity component of SB compliant with its definition, and by validating and applying the most promising method to measure the actual amount of SB in the daily life of office workers. Broken down to the three parts of the method development framework (Figure 2, p. 9), this translates into the following specific aims.

THE CALIBRATION AIMS TO

I) develop a new method to measure SB with accelerometry (posture component) and EMG (physical activity component).

II) develop new methods to measure both components of SB with single IMUs to figure out where to place which sensor type.

III) develop a new algorithm to measure the posture component of SB with a waist-worn ActiGraph GT3X.

THE VALIDATION AIMS TO

IV) specify the validity of the most promising method to measure SB.

THE APPLICATION AIMS TO

V) measure the actual amount of SB in the daily life of office workers, and investigate how much time they spend active sitting and inactive standing to figure out whether the time spent sitting and the time spent in minPA are valid approximations of the time spent sedentary.

3 MATERIALS AND METHODS

3.1 OVERVIEW OF DATA COLLECTIONS AND STUDIES

This thesis follows the method development framework (Figure 2, p. 9) and covers the calibration (Study I – III), the validation (Study IV), and the final application (Study V).

In Study I (data collection A, Figure 4), a thigh-worn accelerometer (posture) and an upper-body-worn EMG system (physical activity) were calibrated to measure the two components of SB. **In Study II** (data collection B), a large number of IMUs placed on various body segments were calibrated to figure out where to place which sensor type to measure both components of SB with only one sensor. **In Study III** (data collection C), a waist-worn ActiGraph GT3X, the most commonly used physical activity sensor, was calibrated to measure posture. Study I and II were conducted in a controlled environment and Study III in free-living. **In here**, the results of the three studies were compared to identify the most promising new method, i.e. the one with the highest cross-validity to measure SB deemed most suitable for field recordings.

The measures to limit the spread of COVID-19 stopped the ongoing free-living validation study with the calibrated methods, and no new data could be recorded. The selection of the most promising method for the validation and application was therefore restricted to methods with data captured before March 2020. Accordingly, the Posture and Physical Activity Index (POPAI), a new combination of the most commonly used posture sensor (thigh-worn activPAL) and the most commonly used physical activity sensor (waist-worn ActiGraph GT3X), was identified as the most promising method with available data. The high validity of the activPAL to classify posture is well-established [107-112], which is why the validation **Study IV** assessed only the validity of the ActiGraph cpm cut-points to classify the activity component of SB (minPA). Due to the conflicting evidence of what the cpm cut-points measure (minPA, SB, or sitting [120-122]), the study also analysed the sensor's validity to measure SB and sitting. For this purpose, the data collected for Study II (data collection B) were reused. Subsequently, POPAI measured the actual amount of SB in the daily life of office workers in a final cross-sectional field **Study V**. This last study used the same data as Study III (data collection C) but included a larger sample.

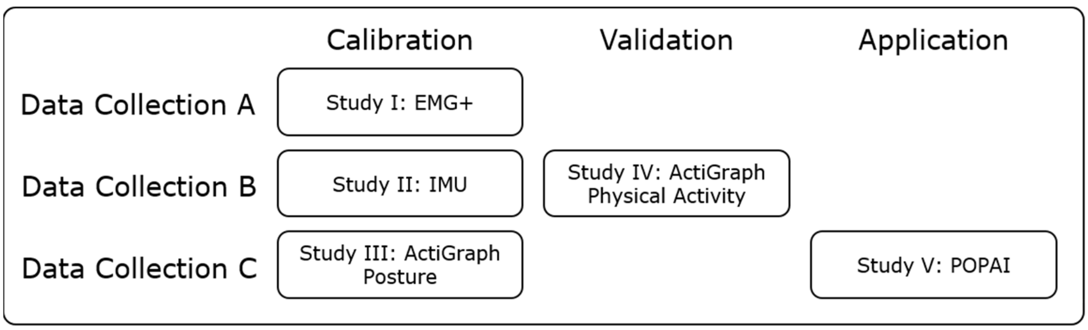

Figure 4. Overview of the three data collections (A – C) and the five studies (I – V) with respect to the method development framework. Abbreviations: Electromyography plus Accelerometer (EMG+), Inertial-Measurement-Unit (IMU), Posture and Physical Activity Index (POPAI).

3.2 ETHICS

This project followed the ethical principles outlined in the latest version of the Declaration of Helsinki [183]. All participants were adult office workers and free to decide whether to participate, and they could withdraw their consent at any time without reasoning. The ethics committee of Stockholm County approved all studies (DNR 2018/554-31 for Study I, II, and IV; DNR 2016/796-31 for Study III and V). The participants shown in Figure 5 (p. 23) gave their written consent to include their images.

Study I, II, and IV collected data in Switzerland and obtained a declaration of non-objection from the ethics committee of the Canton of Zurich. All participants gave their written consent after receiving detailed information about the study. Conducting the studies was a public task, which is why participants were insured under state liability. Participation in the studies was judged no riskier than regular office work, and no adverse events occurred. Participants received a detailed analysis of their energy expenditure, and a homemade elderberry jam and syrup.

Study III and V reanalysed data previously collected for another purpose [184]. Therefore, an addendum was sent in and approved by the ethics committee of Stockholm County (DNR 2018/2315-32) to reanalyse the data without the participants' consent. Only the raw sensor data, the wear-time diary, and the participants' age and body weight were used to conduct the studies, all in encrypted form.

3.3 PARTICIPANTS

Due to the large and still growing proportion of office workers in the general population [29-31] with excessive amounts of SB [32-38], office work is the single largest contributor to SB in the population. Thus, only office workers between 18 and 65 years were included (Table 1). The office workers in data collection A and B had to confirm that they have no silicone allergy due to the use of a silicone facemask for indirect calorimetry. Data collection B further limited study participation to office workers with ≥70% employment rate spending ≥50% of their working hours at an office desk. These additional inclusion criteria ensured that only office workers with an excessive amount of occupational SB and thus at increased risk of developing SB-related chronic diseases were included.

The recruiting in data collection A and B used flyers, emails, and word of mouth. A convenient sample of 25 and 30 office workers from Winterthur and Zurich (Switzerland) was included. Data collection C used the internal communication channels of the involved companies to recruit 330 office workers from two worksites close by Stockholm (Sweden). Study III included a convenient sample of 38 office workers, and Study V followed Martin Bland's recommendation for method comparison studies and included a sample of 100 office workers [185].

Note that Study II and Study IV used the same sample, and Study III was conducted on a sub-sample of Study V (Table 1), resulting in a total of 155 office workers enrolled in the studies.

Table 1. Participant characteristics.

Data Collection	**A**	**B**	**C**	
Study	**I**	**II & IV**	**III**	**V**
Sample Size	25	30	38	100
Gender (male/female)	13 / 12	14 / 16	25 / 13	61 / 39
Age (years)	30.8 ± 8.4 [20.0 – 61.0]	38.8 ± 9.0 [23.8 – 57.0]	42.3 ± 8.4 [27.0 – 59.0]	40.8 ± 9.2 [21.0 – 64.0]
Height (m)	1.75 ± 0.09 [1.55 – 1.90]	1.74 ± 0.08 [1.55 – 1.91]	N/A	N/A
Weight (kg)	69.8 ± 9.6 [57.0 – 93.0]	71.2 ± 11.0 [55.0 – 100.0]	71.2 ± 10.2 [55.1 – 93.0]	71.6 ± 12.6 [49.2 – 104.0]
BMI (kg/m^2)	22.9 ± 2.5 [18.5 – 28.7]	23.6 ± 3.3 [19.5 – 33.0]	N/A	N/A
Place of Data Recording	Winterthur	Winterthur	Stockholm	Stockholm
Responsible University	ZHAW & KI	ZHAW & KI	GIH	GIH

Numbers given in counts or mean ± standard deviation and [minimum – maximum]. Abbreviations: Not Applicable (N/A, height was not measured in data collection C), Body Mass Index (BMI), Zurich University of Applied Sciences (Zürcher Hochschule für Angewandte Wissenschaften, ZHAW), Karolinska Institutet (KI), Swedish School of Sport and Health Sciences (Gymnastik- och idrottshögskolan, GIH).

3.4 DATA COLLECTION AND PROCESSING

An overview of the three data collections (A – C) for the three calibration studies (I – III) in relation to the method development framework is given in Table 2 (p. 22). All three calibration studies used the same SB definition, including the posture (sitting) and the physical activity component (minPA with MET ≤1.5). However, as the cpm cut-points are an established method to measure physical activity with the ActiGraph GT3X [113, 118, 122], Study III calibrated only a posture algorithm. Accordingly, the choice of a valid reference criterion (a posture sensor) allowed using data collected in free-living. In contrast, data collection A and B used direct observation (posture) and indirect calorimetry (physical activity) as reference criteria and therefore took place in a controlled environment. Illustrative pictures for each data collection are given in Figure 5 (p. 23).

Table 2. Overview of the three data collections (A – C) for the three calibration studies (I – III) in relation to the method development framework.

	Data Collection A for Study I	**Data Collection B for Study II**	**Data Collection C for Study III**
Behaviour of Interest			
Behaviour Definition	Sitting with ≤1.5 MET	Sitting with ≤1.5 MET	Sitting
Reference Criteria			
- Posture	Direct Observation	Direct Observation	Posture Sensor (activPAL3)
- Physical Activity	Indirect Calorimetry (COSMED K5)	Indirect Calorimetry (COSMED K5)	N/A
Study Environment			
- Setting	Controlled	Controlled	Free-Living
- Activities	Office Tasks	Office Tasks	N/A
- MET, Median (iqr)	1.50 (0.18)	1.58 (0.20)	N/A
Body-Worn Sensor			
Sensor Type	EMG (ZHAW) plus Accelerometer (ADXL345)	IMU[(a)] (Xsens Biomech Awinda)	Accelerometer (ActiGraph wGT3X-BT)
Sensor Placement	EMG: Forearm, Upper Arm, Shoulder, Back Accelerometer: Thigh	Head, Sternum, Waist, Wrist, Arm, Shoulder, Thigh, Shank, Foot	Waist
Sensor Number	EMG: 8 Accelerometer: 1	15[(b)]	1
Data Processing			
Classification Technique	Decision Tree	Decision Tree Ensemble	Decision Tree Ensemble
Algorithm Architecture	1st level: Posture 2nd level: Physical Activity	1st level: Posture 2nd level: Physical Activity	1st level: Posture
Temporal Resolution	60 seconds	60 seconds	60 seconds

a) two ActiGraph accelerometers (waist- and wrist-worn) not used in the calibration (Study II) but in the validation (Study IV) were additionally used; b) each of the 15 IMUs was calibrated individually. Abbreviations: Metabolic Equivalent (MET), Not Applicable (N/A), interquartile range (iqr), Electromyography (EMG), Zurich University of Applied Sciences (Zürcher Hochschule für Angewandte Wissenschaften, ZHAW), Inertial-Measurement-Unit (IMU).

Figure 5. Illustrative pictures for each data collection. a) the EMG+; b) Participant performing the Deskwork task on Conventional Chair; c) Mouse task on Conventional Chair; d) Typing task on Saddle Chair; e) Deskwork task on Active Chair; f) Sorting task at Standing Desk; g) sensor placement in data collection C. Task and workplace explanations are given in Table 3 (p. 24). Picture a, b and g previously published under CC BY license in MDPI journals. Abbreviation: Electromyography plus Accelerometer (EMG+).

3.4.1 Controlled Environment (Data Collection A and B)

In data collection A and B for Study I, II, and IV, participants were equipped with the measurement instruments and completed various everyday office tasks at the workstation of the author of this thesis at the Zurich University of Applied Sciences. The task selection was inspired by previous studies investigating physical activity in office work [48, 129, 186-188] and included computer-based, hybrid, and non-computer based office tasks (Table 3, p. 24). They were performed at four workplaces (Figure 5): A Conventional Chair representing conventional office work, a Saddle Chair with elevated seat height representing a seated workplace intervention to reduce the hip flexion angle, an Active Chair representing an active workplace intervention to reduce minPA, and a Standing Desk representing a standing workplace intervention to reduce sitting. The Saddle Chair was used to challenge the posture classification and not to investigate the seated posture from a biomechanical perspective. The Active Chair is described in detail in Kuster et al. (2016 and 2018) [1, 2]. In short, the chair has a moveable seat in the frontal plane, allowing the chair user to move the pelvis to the left and right while keeping a stable upright position of thorax and head to not interfere with office work demands. To ensure the seat motion was used, an oral prompting reminded the participant every minute to move the seat if they did not. The Saddle Chair was only analysed in Study II, and the Active Chair was only analysed in Study IV.

Task and workplace order was randomised using the random permutation function of MATLAB (Version 2018a, MathWorks Inc., Natick (MA), USA), but two identical tasks and workplaces were never recorded in succession. Each task was performed for 5 minutes as steady state was reached latest after 4 minutes in the pilot study (n=3). In data collection A, participants completed as many tasks as possible in 45 minutes. All participants completed Watching a video on the Conventional Chair, Typing on the Conventional Chair and at the Standing Desk, and Walking. In data collection B, all participants completed all tasks. To account for different workstation designs, half of the participants in data collection A and a third in data collection B used a Laptop (Figure 5c and 5d, p. 23). The remainder used a desktop computer (Figure 5b, 5e, and 5f, p. 23). The execution of the tasks was neither demonstrated nor standardised in any form. Participants placed the working material in their own way and performed the tasks at their own speed. After completing all office tasks, a 10-minute resting metabolic rate measurement was conducted following best practice recommendations to define the $MET_{Measured}$ of each participant [189-192]. Data collection A took place between 22 May and 18 June 2018, and data collection B between 12 September and 12 November 2018.

Table 3. Office tasks and workplace designs in data collection A and B for Study I, II, and IV.

		Data Collection:	**A**	**B**	
	Representative for…	**Study:**	**I**	**II**	**IV**
Computer-Based Tasks					
Watching (a video)	office activities without own intervention		x		
Mouse (navigating in a game)	office activities with predominant mouse use		x	x	x
Typing (typing a text)	office activities with predominant keyboard use		x	x	x
Hybrid Tasks					
Deskwork (successive short non-/computer based tasks)	office activities with intermittent computer use		x	x	x
Non-Computer Based Tasks					
Sorting (successive short non-computer based tasks)	office activities without computer use			x	x
Walking	non-stationary office activities		x	x	
Workplaces					
Conventional Chair	conventional office work		x	x	x
Saddle Chair	a seated workplace intervention			x	
Active Chair	an active workplace intervention				x
Standing Desk	a standing workplace intervention		x	x	x

Illustrative pictures for tasks and workplaces are given in Figure 5 (p. 23). Note that the Saddle Chair was only used for the Typing task. **Chair Manufacturers**: Conventional Chair: Vitra, Birsfelden, SUI; Saddle Chair: HAG Capisco, Flokk, Oslo, NOR; Active Chair: rotavis, Winterthur, SUI.

The reference criteria were in both data collections direct observation for the posture classification (classifying each task as sitting, standing, or locomotion) and an indirect calorimeter (K5, COSMED Srl, Rome, ITA) for the physical activity classification (classifying sitting and standing tasks into inactive or active). The calorimeter was chosen as it is the only established reference criterion to classify physical activity individually, and the K5 is considered valid even at low physical activity intensities [193, 194]. The device was calibrated in the morning of each recording as recommended by the manufacturer and recorded with 0.1 Hz in the mixing chamber mode. Data were downloaded with Omnia Version 1.6.2 (data collection A) and 1.6.7 (data collection B) (COSMED Srl, Rome, ITA) and converted into kilocalories using the Weir equation [195]. To obtain the MET value for each task, data collection A used the median MET of the final two minutes, and data collection B used the median MET during steady state. Steady state was defined as the time from the first minute with less than 10% deviation from the median of all subsequent minutes until the end of the task. The MET value was then used to classify the activity level of the task into inactive (minPA, ≤1.5 MET) or active (>1.5 MET). Reanalysing Study I data with the steady-state detection used in Study II resulted in the same physical activity classification.

Data collection A for Study I used an EMG plus accelerometer system (EMG+) developed within a Bachelor thesis at the Zurich University of Applied Sciences (Figure 5a, p. 23) [196]. The device was self-developed because existing EMG systems were not considered suitable for long-term field recordings. The EMG electrodes (Ambu BlueSensor N, Ambu A/S, Ballerup, DNK) were placed by the researcher bilateral on the most prominent muscle bellies of M. extensor digitorum (forearm), M. biceps brachii (upper arm), M. deltoideus pars anterior (shoulder), and M. erector spinae (back). The accelerometer (ADXL345, Analog Devices, Norwood (MA), USA) was placed after verbal instruction by the participants lateral on the left thigh with two elastic straps. The analogue EMG signal was processed with a differential amplifier, a high-pass filter (cut-off frequency 1.8 Hz), a rectifier, a low pass filter (cut-off frequency 110 Hz), and together with the accelerometer signal converted to a raw digital signal at 30 Hz. The raw signal was cut into 60-second epochs and directly used to develop the classification algorithms.

Data collection B for Study II used a full-body inertial motion capture system (Biomech Awinda, Xsens Technologies B.V., Enschede, NLD) consisting of 15 IMUs. The IMUs, each featuring a 3D accelerometer, a 3D gyroscope, and a 3D magnetometer, were placed according to the manufacturer's recommendation on the head, sternum, and waist (all unilateral), the wrist, upper arm, shoulder, thigh, shank, and foot (all bilateral). The IMUs recorded at 60 Hz, and the raw signal was cut into 60-second epochs and directly used to develop the classification algorithms.

Data collection B for Study IV used a waist-worn ActiGraph wGT3X-BT and a wrist-worn ActiGraph GT9X-Link, both worn on the left body side. The ActiGraphs recorded at 30 Hz, and the raw signal was converted to cpm using ActiLife Version 6.13.4 (ActiGraph LCC, Pensacola (FL), USA). Following the recommendation for low-intensity activities [197], only the low-frequency-extension filtered data are presented here.

3.4.2 Free-Living Environment (Data Collection C)

Data collection C for Study III and V was conducted by the Swedish School of Sport and Health Sciences within the Brain-Health-Study. The Brain-Health-Study investigated the association between physical activity patterns and cognition, mental health, and sleep in office workers [184]. It is a 3-arm cluster randomised controlled trial targeting physical activity and SB with two multi-component interventions. Study III and V used the baseline data before any intervention took place. Participants wore an activPAL3 on the thigh (attached with waterproof adhesive film) and an ActiGraph wGT3X-BT on a belt around the waist during waking hours, both on the right side (Figure 5g, p. 23). Each participant kept a diary to note sensor wear-time. The activPAL recorded at 20 Hz, and the ActiGraph at 30 Hz. The studies used the raw sensor data and the proprietary data processing output of the corresponding software: event file for the activPAL generated with activPAL3 version 7.2.38, and low-frequency-extension filtered counts-per-second file for the ActiGraph generated with ActiLife version 6.13.4 (only Study V). Participants included in Study III were recorded between 22 February and 14 April 2017, and participants included in Study V were recorded between 24 October 2016 and 14 April 2017.

Data preparation for Study III and V started with the activPAL wear-time detection to ensure only days with ≥500 steps, ≥12 recorded hours (without bedtime), and ≤95% of the time spent in the most dominant activPAL posture were included [198]. Bedtime was identified with an algorithm developed by Winkler et al. (2016) [198]. This algorithm classifies the longest activPAL sitting bout between subsequent noons (12:00 – 12:00) as bedtime and expands bedtime in case it is directly preceded/followed by another long sitting bout. As the algorithm slightly underestimates bedtime [198], both studies used a modified version. Study III expanded bedtime if a second algorithm, developed by Lyden et al. (2016) [199], detected a lying event preceding/following bedtime. The Lyden algorithm classifies each activPAL sitting event as lying when the thigh rotation angle around the longitudinal axis exceeds 65° to the horizontal (0° corresponds to sitting upright). Study V combined the Winkler algorithm with a visual inspection, and adjusted bedtime start and stop if required using the diary information.

The two sensor clocks were thereafter synchronised since there was an obvious delay between the sensors, evident in the raw signal comparison. Major signal changes (e.g. from a smooth line to a fidgeting curve) typically occurred a couple of seconds delayed on the ActiGraph compared to the activPAL. The delay was neither constant among the different sensor pairs nor among the time of the same sensor pairs. The delay was linearly approximated for each sensor pair by searching the highest cross-correlation between the two normalised sensor x-axes (both pointing anteriorly while sitting) over consecutive, non-overlapping 3-hour episodes. The approximated delay was applied to the ActiGraph clock. Further details about the sensor synchronisation can be found in the supplementary online material of Paper V.

ActiGraph non-wear-time was then excluded by inspecting all activPAL events overlapping an ActiGraph epoch with constant raw signal, and removing those in which the activPAL recorded a posture change or locomotion (sensor contradiction), and those in which the ActiGraph signal remained constant for ≥90 minutes (prolonged non-wear). Last, short episodes in between longer excluded episodes were excluded to prevent excessive fragmentation of the data.

In Study III, the event file of the activPAL (with the posture classification sitting, standing, and locomotion) served as reference criterion, and the raw ActiGraph data were directly used to develop the posture classification algorithm. The minute-by-minute raw data were extracted in two different ways: one for the algorithm development (training minutes), and one for the final algorithm selection (testing minutes). The training minutes included only minutes with constant activPAL classification. The testing minutes included all available minutes on days with ≥10 valid hours, just as a typical field study would extract the data [200, 201].

In Study V, the event file of the activPAL was combined with the ActiGraph counts-per-second file to the combined posture and physical activity classification of POPAI. POPAI started with the activPAL posture events and classified each sitting and standing event with the ActiGraph cpm cut-points into inactive and active. Thus, POPAI detected inactive sitting (equal to SB), active sitting, inactive standing, active standing, and locomotion (Figure 6). The activity classification used a minute-by-minute resolution, and the cut-points with the highest validity observed in Study IV (75 cpm for sitting, 150 cpm for standing). The remaining fraction of each event and events <1 minute were classified with the corresponding fraction of the cpm cut-point (e.g. 37.5 counts for a 30-second sitting event) as no major differences exist when applying cut-points to shorter events [109]. In case the activity classification changed during an activPAL event, the event was split accordingly.

To compare with POPAI, the single sensor data were processed in a state-of-the-art manner. For the activPAL, the event file was directly used, whereas sitting was considered sedentary [108]. For the ActiGraph, vertical axis cut-points of 100 and 1’952 cpm were used to classify the behaviour into minPA, LIPA, and MVPA [113, 118, 122], whereas minPA was considered sedentary. Only the sedentary estimates were used here.

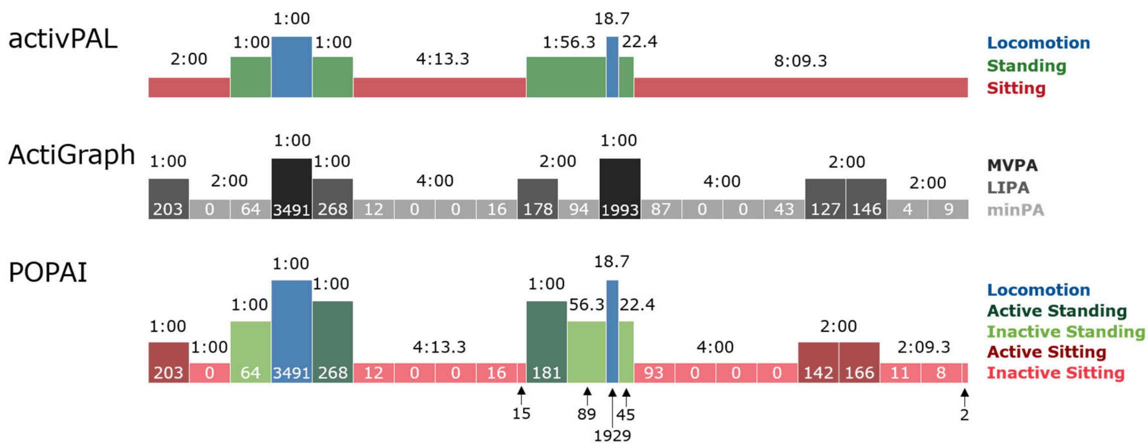

Figure 6. Exemplary classification of a 20-minute recording with the activPAL, ActiGraph, and POPAI. Indicated are the behaviour duration (minutes:seconds) and the ActiGraph counts. Modified version of a figure in Paper V, published under CC BY license in an MDPI journal. Abbreviations: minimal-intensity physical activity (minPA), light-intensity physical activity (LIPA), moderate- to vigorous-intensity physical activity (MVPA), Posture and Physical Activity Index (POPAI).

3.5 DATA ANALYSIS AND STATISTICS

The entire analysis and statistics, summarised in Table 4, was conducted in MATLAB (Version 2018a, 2019a, and 2020a), except the Generalised Estimation Equations (SPSS Version 27, IBM, Armonk (NY), USA). To compare the studies, the validity is given as balanced sensitivity and specificity (mean of sensitivity and specificity) to equally account for the true positive and the true negative behaviour detection [157]. Note that the cross-validity always refers to the calibration (whereas the cross indicates that data of every participant was used for training and testing/validating the algorithm), while the validity always refers to the validation. Both cross-validity and validity represent a measure of concurrent validity against established reference criteria [202]. Whenever inferential statistics were used, data were checked for normal distribution and the corresponding parametric or non-parametric alternatives are given (e.g. mean with 95% confidence interval or median with non-parametric 95% confidence interval). The level of significance was set to 0.05.

Table 4. Overview of statistical analyses.

	Study I	Study II	Study III	Study IV	Study V	Thesis
Descriptive Statistics						
Counts and Percentage	✓	✓	✓	✓	✓	✓
Mean (sd) and Median (iqr)	✓	✓	✓	✓	✓	✓
Minimum and Maximum	✓		✓	✓	✓	✓
5^{th} and 95^{th} Percentile					✓	
Sensitivity and Specificity	✓	✓	✓	✓		✓
ROC Curve / AUC	✓			✓		
Cohen's Kappa				✓		
Inferential Statistics						
Lilliefors Test for Normality	✓	✓	✓	✓	✓	✓
95% Confidence Interval	✓	✓	✓	✓	✓	✓
Standard Error			✓			
Friedman Test		✓		✓		
Wilcoxon Test		✓				✓
Kruskal-Wallis Test						✓
Mann-Whitney U Test						✓
Bland-Altman Statistics			✓		✓	
Generalised Estimation Equations				✓		✓
Matthews Correlation Coefficient	✓					
Pearson Correlation Coefficient	✓				✓	

The column Thesis contains only the additional analyses performed here. The signal features (e.g. mean, 5^{th} percentile) for the algorithm development in Study I – III are not included. Abbreviations: standard deviation (sd), interquartile range (iqr), Receiver Operating Characteristic (ROC), Area Under the ROC Curve (AUC).

3.5.1 Calibration (Study I – III)

The algorithm development in Study I – III followed the 24-hour behaviour framework (Figure 1, p. 7). Each study developed a posture algorithm (1^{st} level), and Study I and II additionally two activity algorithms (2^{nd} level), one for sitting and one for standing. Study I and II finally combined the three algorithms to classify the behaviour compliant with the 24-hour behaviour framework. Study III was limited to the posture classification.

Each algorithm was developed with a similar supervised machine-learning technique. The fundamental principle of supervised machine learning is to train an algorithm to map an input signal (here: the sensor data) to a known output signal (here: the posture or physical activity classification of the reference criteria). Starting with the raw sensor data, the algorithm development included a feature generation, a feature filtering, a feature inclusion, an algorithm optimisation, and a final algorithm selection.

The feature generation transferred the raw sensor data into a limited number of characteristic signal features describing the sensor signal within a given epoch. All studies used time-based features (e.g. mean, 5^{th} percentile) and frequency-based features (e.g. mean frequency, total signal power) calculated for non-overlapping 60-second epochs. The full feature list of each study can be found in the Papers and their supplementary online material. The features were calculated for the raw data, and in Study II and III additionally for the low-pass filtered data (Butterworth 2^{nd} order, 0.5 Hz cut-off), and the 3D angle of the low-pass filtered data [157].

The feature filtering then removed non-relevant features so that the subsequent computational demanding steps did not need to examine the full feature list. Study I used a manual feature filtering with histograms and Pearson correlation coefficients. Study II and III used an automated feature filtering with a random forest classifier to identify the top 100 ranked features (program available at https://github.com/RomanKuster/featureranking).

The feature inclusion subsequently included the features iteratively into the algorithm, with each iteration adding the most relevant remaining feature (known as forward feature selection). Relevance was assessed by calculating the cross-validity with the leave-one-subject-out approach [125, 127]. This approach trains an algorithm on all but one subject (the holdout) and cross-validates the prediction on the holdout subject. The training and cross-validation are repeated until every subject served once as holdout, and the cross-validity is calculated over all holdout subjects. Study I used a simple decision tree with the area under the receiver operating characteristic curve and the Matthews correlation coefficient to measure the cross-validity. Study II and III used a bagged decision tree ensemble with five trees and the balanced sensitivity and specificity to measure the cross-validity. The feature inclusion stopped when the cross-validity reached a maximum value (no further increase for all remaining (Study I) or the next ten (Study II and III) features). This iterative procedure finally resulted in as many algorithms as features included (i.e. the first algorithm with one feature, the second algorithm with two features, etc.).

The algorithm optimisation then identified in Study II and III for each algorithm the optimal training properties (e.g. which ensemble learner method and split criterion, the number of trees and splits in each tree), and retrained each algorithm accordingly. Since Study I trained only simple decision trees, the algorithm optimisation analysed whether combining the decision tree with the largest area under the receiver operating characteristic curve and the tree with the highest Matthews correlation coefficient further increased the cross-validity and combined them accordingly.

Study I trained the posture algorithm with the accelerometer features only, and the two activity algorithms (for sitting and standing) with all available features (EMG and acceleration). For consistency with Study II and III, the algorithms with the highest balanced sensitivity and specificity were selected and combined to generate the combined posture and physical activity classification. The remaining algorithms can be found in Table 4 of Paper I.

Study II trained the posture and the two activity algorithms separately for each sensor placement and signal type (accelerometer only, accelerometer plus gyroscope, accelerometer plus magnetometer, accelerometer plus gyroscope and magnetometer). To identify the signal type with highest cross-validity for each placement, Friedman-tests followed by post hoc Wilcoxon tests with Bonferroni-adjusted p-values were used. Unless there was a significant effect of signal type, only the accelerometer results were selected to account for the fact that the additional sensor signals make the sensor more expensive and the processing more complex. Due to their almost exclusive use in field studies, only the results of the thigh (right side), waist, and wrist placement (left side) are shown here. The results of the remaining placements can be found in Table 3 and 4 of Paper II. To simplify readability, the developed methods are capitalized and given with abbreviated sensor type (e.g. "Thigh Accel" for the thigh accelerometer method, "Waist IMU" for the waist IMU method, etc.).

Study III trained a posture algorithm for a waist-worn ActiGraph wGT3X-BT on data collected in free-living and focused on detecting long sitting bouts. This is why the algorithm with the lowest Bland-Altman bias for the daily time spent in sitting bouts ≥5 and ≥10 minutes was finally selected.

The comparison between the methods developed in Study I – III was done separately for 1) the classification of SB; 2) the classification of sitting; 3) the classification of the activity level while sitting; and 4) the overall behaviour classification compliant with the 24-hour behaviour framework. The comparison included paired (methods developed in the same study) and unpaired data (methods developed in different studies), which is why the Kruskal-Wallis Test for unpaired data was used as omnibus test. In case of a significant effect, a pairwise post hoc comparison with Bonferroni-adjusted p-values identified the methods causing the effect. The Wilcoxon test was used for paired data and the Mann-Whitney U test for unpaired data.

3.5.2 Validation (Study IV)

Study IV analysed the validity of waist- and wrist-worn ActiGraph cpm cut-points to measure minPA, SB, and sitting using the Conventional Chair, the Active Chair (active workplace intervention), and the Standing Desk (standing workplace intervention, Figure 5, p. 23).

To test whether there was a workplace effect on the MET values, the minPA classification, and the cpm values, Generalised Estimation Equations followed by pairwise post hoc comparisons with Bonferroni-adjusted p-values were used.

The ActiGraph cut-point validity was assessed with Cohen's kappa including 95% confidence intervals [203] and the receiver operating characteristic curve with balanced sensitivity and specificity, both for 0 – 250 cpm for the waist vertical axis and 0 – 8'000 cpm for the wrist vector magnitude. The agreement with the reference criteria was considered *poor* (kappa <0.00), *slight* (0.00 – 0.20), *fair* (0.21 – 0.40), *moderate* (0.41 – 0.60), *substantial* (0.61 – 0.80), or *almost perfect* (≥0.81) [204]. The validity for minPA, SB, and sitting was analysed across all workplaces and the validity for minPA additionally for each workplace separately.

To calculate the validity of POPAI, the validity of the ActiGraph cut-points with the highest kappa were combined with the average validity of the activPAL reported in the literature: sensitivity and specificity of 97.3% and 98.4% to classify sitting, 88.8% and 97.5% to classify standing, and 94.1% and 96.4% to classify locomotion [107, 109, 110].

3.5.3 Application (Study V)

Study IV measured the actual amount of SB in daily life with the combined posture and physical activity classification of POPAI. The analysis included active sitting and inactive standing to analyse whether these two behaviours are actually so few as thought, as well as active standing and locomotion to comply with the 24-hour behaviour framework (Figure 1, p. 7). The results are described in a pie chart with mean, standard deviation, and 5th and 95th percentile, all in percentage of the daily wake-time. The pie chart also includes bedtime and sensor non-wear time, both in absolute numbers (hours per day). To visualise the behaviours in relation to daytime, profile plots show the proportion of each behaviour in non-overlapping 15-minutes epochs, separately for men and women on weekdays and weekend days.

To specify the bias of posture and physical activity sensors to measure SB, the sedentary estimates of the single sensors were compared to POPAI using Bland-Altman statistics. The bias was considered a measure of accuracy, and the 95% limit of agreement a measure of precision [205]. Bias and 95% limit of agreement were expressed relative to POPAI. The bias of the activPAL was expected to depend on the amount of active sitting, and the bias of the ActiGraph was expected to depend on the amount of inactive standing. Thus, the Pearson correlation coefficient was used to identify the variance of the bias that can be explained with active sitting (activPAL) and inactive standing (ActiGraph). Due to the emerging evidence that the sedentary accumulation pattern might matter [19-22], the Bland-Altman comparison was repeated for the time spent in long sedentary bouts of ≥10 and ≥30 minutes.

4 RESULTS

4.1 CALIBRATION

4.1.1 Recorded Behaviour

All three calibration studies recorded the majority of data while sitting, followed by standing and locomotion (Table 5). In Study I and II, participants spent most of their sitting and standing time inactive (synonymous with sedentary for sitting). No activity classification was done in Study III.

Table 5. Recorded behaviour in the three calibration studies (reference criteria).

Study	Sitting		Standing		Locomotion
	inactive	active	inactive	active	
I	39.7%	5.9%	34.2%	5.7%	14.6%
II	38.0%	12.0%	28.3%	11.7%	10%
III (training minutes)	70.5%		21.9%		7.6%
III (testing minutes)	55.4%		30.6%		14.0%

Amount of time spent in each behaviour in % of the total recording time. The training minutes in Study III contained only minutes with constant posture classification, and the testing minutes all minutes on days with ≥10 recording hours.

In Study I, the resting metabolic rate was 2'011 (802) kilocalories×day^{-1}, and the $MET_{Measured}$ was 4.1 (1.3) ml×kg^{-1}×min^{-1} at 27.2° (1.4°) Celsius (median with interquartile range). In Study II, the resting metabolic rate and the $MET_{Measured}$ were significantly lower (1'696 (607) kilocalories×day^{-1} and 3.5 (0.9) ml×kg^{-1}×min^{-1}, $p \leq 0.047$) at a significantly lower temperature (25.0° (1.6°) Celsius, $p<0.001$, Mann-Whitney U test). The General Estimating Equation detected no MET difference between the same tasks and workplaces in Study I and II ($p=0.650$), which is why descriptive data were merged (Table 6).

Table 6. MET and activity classification for each task and workplace in Study I and II.

Task	Conventional Chair	Saddle Chair	Standing
Watching	1.09 (0.22), 100.0% $^{n=25}$		1.13 (0.20), 100% $^{n=13}$
Mouse	1.20 (0.20), 90.7% $^{n=43}$		1.20 (0.24), 100% $^{n=44}$
Typing	1.26 (0.28), 94.5% $^{n=55}$	1.20 (0.27), 96.7% $^{n=30}$	1.27 (0.18), 89.1% $^{n=55}$
Deskwork	1.36 (0.33), 71.7% $^{n=46}$		1.34 (0.30), 68.5% $^{n=45}$
Sorting	1.72 (0.42), 16.7% $^{n=30}$		1.75 (0.33), 16.7% $^{n=30}$

Median MET with interquartile range, % of participants classified as minPA (MET ≤1.5), and sample size (n). Walking had a MET of 3.16 (0.89), with 0% of participants classified as minPA (n=55). Abbreviations: Metabolic equivalent (MET), minimal-intensity physical activity (minPA).

4.1.2 Sedentary Behaviour Classification

In Study II, the additional sensor signals of the IMU outperformed the accelerometer data to classify SB only for the waist (p=0.006, Wilcoxon Test). However, since the waist accelerometer is so commonly used in field studies, both methods were kept in the analysis.

Across all calibrated methods to classify SB (Table 7), there was a significant overall effect (Kruskal-Wallis, $\chi^2(4) = 53.9$, $p<0.001$). The post hoc comparison showed that the EMG+, the Thigh Accel, and the Waist IMU outperformed the Waist Accel and the Wrist Accel, and the Waist Accel outperformed the Wrist Accel (Figure 7). The EMG+ used the thigh-worn accelerometer and six of the eight EMG channels to classify SB.

Table 7. Cross-validity to classify sedentary behaviour.

Study	Method	Balanced	Sensitivity	Specificity
I	EMG+	96.7 [90.0 – 100.0]	93.3 [80.0 – 100.0]	100.0 [100.0 – 100.0]
II	Thigh Accel	93.4 [91.1 – 96.3]	95.0 [86.9 – 100.0]	96.7 [92.4 – 100.0]
II	Waist IMU	91.9 [88.0 – 93.2]	91.0 [85.0 – 100.0]	96.7 [88.0 – 100.0]
II	Waist Accel	84.9 [80.0 – 88.9]	80.0 [69.3 – 92.9]	92.7 [87.9 – 96.7]
II	Wrist Accel	75.1 [70.0 – 78.3]	80.0 [65.0 – 90.0]	76.7 [66.3 – 83.5]

Numbers are given in % with median and 95% confidence interval, sorted by balanced sensitivity and specificity (Balanced). Abbreviations: Electromyography plus Accelerometer (EMG+), Accelerometer (Accel), Inertial-Measurement-Unit (IMU).

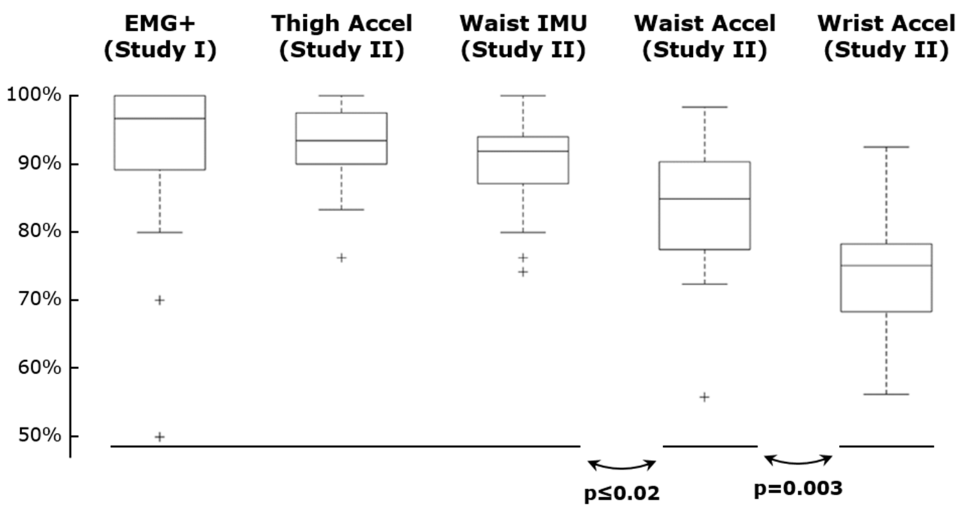

Figure 7. Boxplot of the cross-validity (balanced sensitivity and specificity) to classify sedentary behaviour. Significances of the post hoc comparison indicated with p-values at the bottom. Abbreviations: Electromyography plus Accelerometer (EMG+), Accelerometer (Accel), Inertial-Measurement-Unit (IMU).

4.1.3 Sitting Classification

Across all calibrated methods to classify sitting (Table 8), there was a significant overall effect (Kruskal-Wallis, $\chi^2(5) = 219.6$, $p<0.001$). The post hoc comparison showed numerous statistical differences between the methods, except between the EMG+ and the Thigh Accel, and between the Waist Accel developed in Study II and III (Figure 8). The EMG+ used only the thigh-worn accelerometer to classify sitting.

Table 8. Cross-validity to classify sitting.

Study	Method	Balanced	Sensitivity	Specificity
I	EMG+	100.0 [100.0 – 100.0]	100.0 [100.0 – 100.0]	100.0 [100.0 – 100.0]
II	Thigh Accel	100.0 [99.3 – 100.0]	100.0 [100.0 – 100.0]	100.0 [100.0 – 100.0]
II	Waist IMU	94.0 [91.3 – 98.0]	100.0 [92.0 – 100.0]	100.0 [92.0 – 100.0]
II	Waist Accel	89.6 [86.0 – 94.0]	92.0 [79.4 – 100.0]	92.0 [88.0 – 97.8]
III	Waist Accel	87.8 [84.0 – 90.7]	95.6 [94.7 – 97.2]	79.6 [74.0 – 85.2]
II	Wrist Accel	74.0 [69.6 – 78.0]	79.1 [70.5 – 88.0]	72.0 [57.1 – 84.0]

Numbers are given in % with median and 95% confidence interval, sorted by balanced sensitivity and specificity (Balanced). Abbreviations: Electromyography plus Accelerometer (EMG+), Accelerometer (Accel), Inertial-Measurement-Unit (IMU).

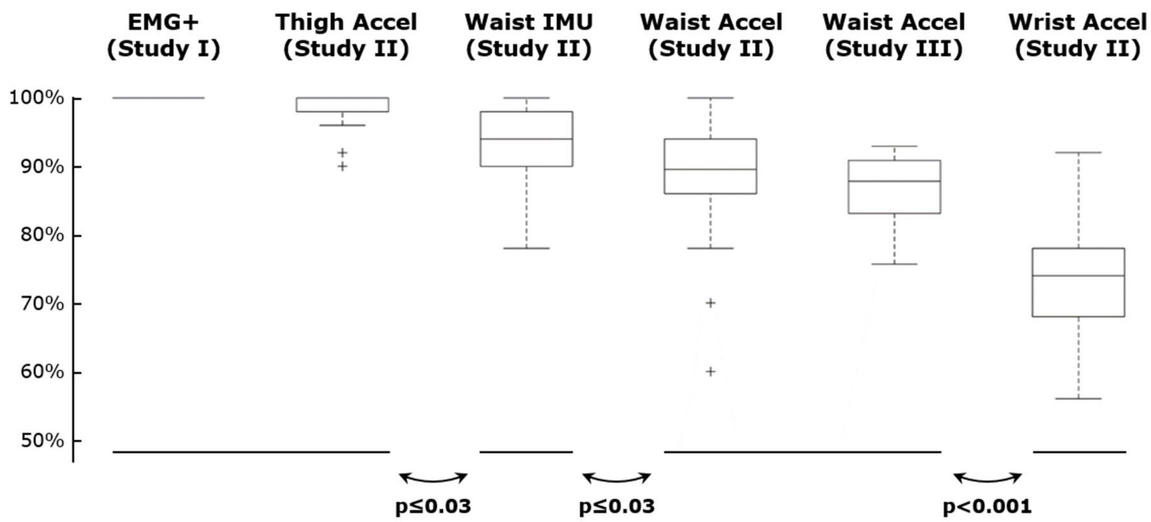

Figure 8. Boxplot of the cross-validity (balanced sensitivity and specificity) to classify sitting. Significances of the post hoc comparison indicated with p-values at the bottom. Abbreviations: Electromyography plus Accelerometer (EMG+), Accelerometer (Accel), Inertial-Measurement-Unit (IMU).

The Waist Accel developed in the free-living Study III overestimated the time spent in sitting bouts ≥5 minutes by 0.2 [-6.4 – 6.8] minutes per day and the time spent in sitting bouts ≥10 minutes by 7.1 [-0.3 – 14.5] minutes per day compared to the activPAL (Bland-Altman bias with 95% confidence interval).

4.1.4 Physical Activity Classification while Sitting

Across all calibrated methods to classify the activity level while sitting (Table 9), there was no significant overall effect (Kruskal-Wallis, $\chi^2(4) = 4.1$, p=0.40, Figure 9). The EMG+ used only six of the eight EMG channels to classify physical activity while sitting.

Table 9. Cross-validity to classify physical activity while sitting.

Study	Method	Balanced	Sensitivity	Specificity
II	Wrist Accel	97.2 [86.6 – 100.0]	96.7 [81.3 – 100.0]	94.4 [86.8 – 98.9]
II	Waist IMU	94.5 [86.6 – 100.0]	90.0 [84.4 – 96.7]	90.6 [86.4 – 95.2]
I	EMG+	93.3 [80.0 – 100.0]	100.0 [88.4 – 100.0]	90.0 [86.0 – 95.7]
II	Thigh Accel	90.0 [85.0 – 95.7]	92.5 [80.0 – 100.0]	87.8 [84.1 – 96.7]
II	Waist Accel	90.0 [83.2 – 95.0]	92.9 [80.0 – 100.0]	90.0 [85.5 – 95.0]

Numbers are given in % with median and 95% confidence interval, sorted by balanced sensitivity and specificity (Balanced). Abbreviations: Electromyography plus Accelerometer (EMG+), Accelerometer (Accel), Inertial-Measurement-Unit (IMU).

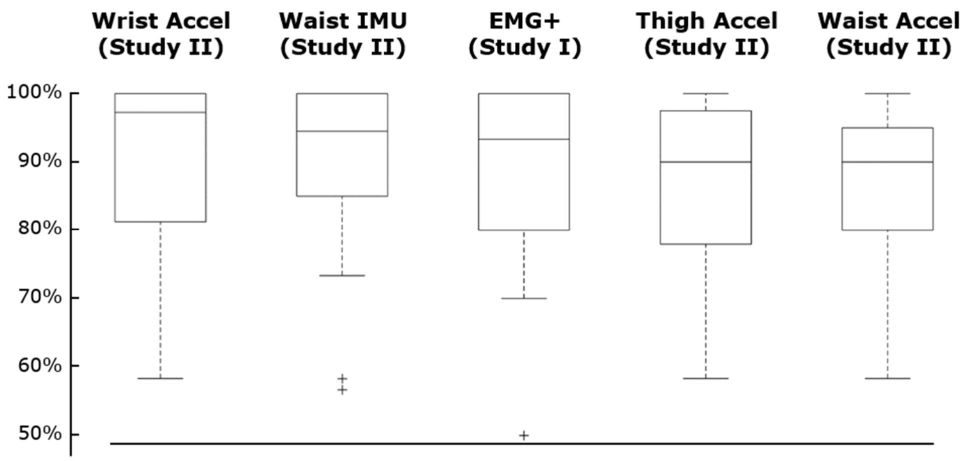

Figure 9. Boxplot of the cross-validity (balanced sensitivity and specificity) to classify physical activity while sitting. Abbreviations: Electromyography plus Accelerometer (EMG+), Accelerometer (Accel), Inertial-Measurement-Unit (IMU).

4.1.5 Overall Behaviour Classification

Across all calibrated methods classifying the behaviour in line with the 24-hour behaviour framework (Table 10), there was a significant overall effect for the overall behaviour classification (Kruskal-Wallis, $\chi^2(4) = 54.6$, p<0.001). The post hoc comparison showed the same significances as for the SB classification. The EMG+, the Thigh Accel, and the Waist IMU outperformed the Waist Accel and the Wrist Accel, and the Waist Accel outperformed the Wrist Accel (Figure 10). The EMG+ used the thigh-worn accelerometer and all eight EMG channels for the overall behaviour classification.

Table 10. Cross-validity to classify posture and physical activity.

Study	Method	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Overall
I	EMG+	96.7 [90.0 – 100.0]	97.1 [90.0 – 100.0]	100.0 [95.0 – 100.0]	100.0 [94.2 – 100.0]	96.3 [94.2 – 98.4]
II	Thigh Accel	93.4 [91.1 – 96.3]	92.9 [89.6 – 97.9]	95.0 [93.3 – 96.8]	96.0 [80.0 – 100.0]	93.2 [92.0 – 97.5]
II	Waist IMU	91.9 [88.0 – 93.2]	93.3 [86.3 – 98.2]	91.9 [89.2 – 94.6]	92.3 [88.5 – 99.3]	93.0 [90.1 – 94.3]
II	Waist Accel	84.9 [80.0 – 88.9]	87.8 [83.0 – 90.7]	85.7 [82.3 – 88.3]	90.0 [86.3 – 98.9]	89.2 [86.9 – 91.3]
II	Wrist Accel	75.1 [70.0 – 78.3]	89.4 [71.6 – 96.2]	68.5 [62.1 – 76.8]	80.0 [75.0 – 94.6]	81.6 [79.1 – 86.5]

Balanced sensitivity and specificity in % with median and 95% confidence interval, sorted by overall column. All methods detected Locomotion with a cross-validity of 100.0% [100.0% – 100.0%] (data not shown). Abbreviations: Electromyography plus Accelerometer (EMG+), Accelerometer (Accel), Inertial-Measurement-Unit (IMU).

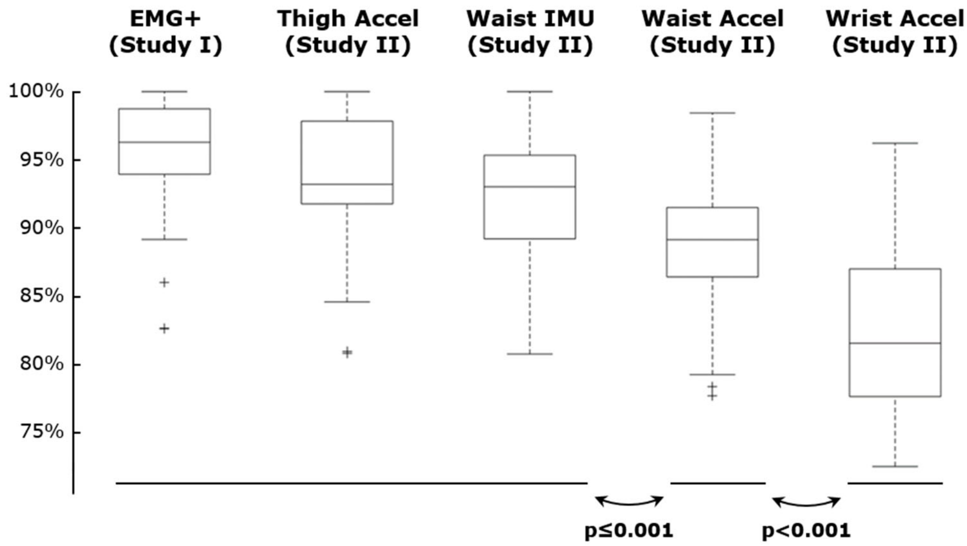

Figure 10. Boxplot of the cross-validity (balanced sensitivity and specificity) for the overall behaviour classification. Significances of the post hoc comparison indicated with p-values at the bottom. Abbreviations: Electromyography plus Accelerometer (EMG+), Accelerometer (Accel), Inertial-Measurement-Unit (IMU).

4.2 VALIDATION

4.2.1 Workplace Effects

There was an overall workplace effect on the MET value and the minPA classification ($p<0.001$, detected with General Estimating Equations). The post hoc comparison showed that the Active Chair caused the highest MET value (1.53 [1.39 – 1.71] versus 1.39 [1.29 – 1.47] for the Conventional Chair and 1.36 [1.34 – 1.48] for the Standing Desk (median [95% confidence interval]), $p<0.001$). The Active Chair also caused the lowest minPA classification (48.3% versus 70.9% for the Conventional Chair and the Standing Desk, $p<0.001$). No differences were found between the Conventional Chair and the Standing Desk ($p=1.000$).

There was an overall workplace effect on the ActiGraph cpm value for the waist ($p<0.001$) but not the wrist ($p=0.742$, detected with General Estimating Equations). For the waist, the post hoc comparison showed that the Active Chair caused the highest cpm value (150 [117 – 243]), followed by the Standing Desk (113 [101 – 176]) and the Conventional Chair (59 [36 – 88]) ($p\leq0.001$).

4.2.2 Validity of ActiGraph Cut-Points

Across all workplaces, the ActiGraph waist and wrist placements reached a *moderate* validity to classify minPA (kappa ≤0.58), a *fair* validity to classify SB (≤0.36), and a *slight* validity to classify sitting (≤0.06, Figure 11). The balanced sensitivity and specificity confirmed kappa, with the minPA classification reaching the highest value (≤78.1%), followed by the SB classification (≤68.8%) and the sitting classification (≤53.5%). For the waist, the highest kappa was reached at around 80 cpm to classify minPA, and for the wrist, the highest kappa was reached at around 3'650 cpm to classify minPA.

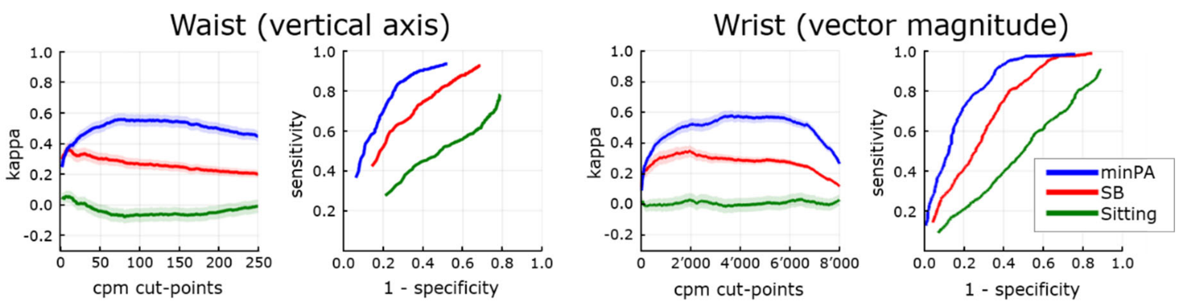

Figure 11. Kappa and receiver operating characteristic curve of cpm cut-points to detect minimal-intensity physical activity (minPA), sedentary behaviour (SB), and sitting. The shaded areas indicate the 95% confidence interval of kappa. Abbreviations: counts-per-minute (cpm).

Separated by workplace, the validity to classify minPA increased for the Conventional Chair and the Standing Desk to *substantial* (kappa ≤0.69, balanced sensitivity and specificity ≤82.4%, Figure 12), and decreased for the Active Chair to *fair* for the waist (≤0.38 and ≤68.9%, respectively) but remained *moderate* for the wrist (≤0.51and ≤75.5%, respectively). However, for the waist, the highest kappa was reached at lower cpm cut-points for the Conventional Chair (around 75 cpm) than for the Standing Desk (around 150 cpm). When using the same cut-point for both workplaces (e.g. 100 cpm with a kappa of 0.65 for both workplaces), there was a higher sensitivity (95.8% vs 89.7%) but lower specificity (63.4% vs 74.9%) for the Conventional Chair compared to the Standing Desk (indicated with arrows in Figure 12). No such posture-dependency was found for the wrist, but the highest kappa was reached at lower cpm cut-points for the Active Chair (around 2'000 cpm) than for the Conventional Chair and the Standing Desk (around 6'000 cpm).

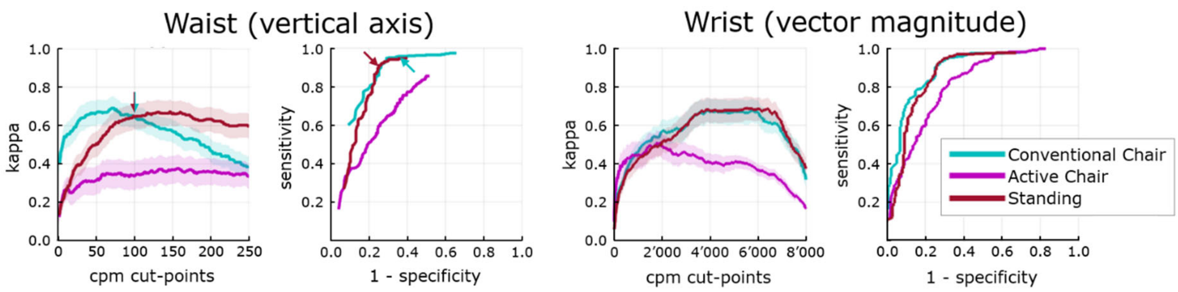

Figure 12. Kappa and receiver operating characteristic curve of cpm cut-points to detect minimal-intensity physical activity, separated by workplace. The arrows indicate the values of the 100 cpm waist cut-point for the Conventional Chair and Standing Desk. Abbreviations: counts-per-minute (cpm).

4.2.3 Validity of the Posture and Physical Activity Index

The validity of the combined posture (activPAL) and physical activity (waist-worn ActiGraph) classification of POPAI is given in Table 11. POPAI uses the 75 cpm cut-point with a sensitivity and specificity of 95.1% and 69.7% to classify minPA while sitting (equal to SB), and the 150 cpm cut-point with a sensitivity and specificity of 93.2% and 70.9% to classify minPA while standing (equal to inactive standing). Combined with the activPAL, POPAI has a validity to classify the five behaviours investigated in this thesis of 87.8%, with locomotion (95.2%) and SB (92.2%) having the highest validity.

Table 11. Validity of the Posture and Physical Activity Index.

	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Locomotion
Balanced	92.2%	82.6%	88.5%	80.4%	95.2%
Sensitivity	92.5%	67.8%	82.8%	63.0%	94.1%
Specificity	91.9%	97.3%	94.3%	97.9%	96.4%

The validity was calculated by combining the validity of the activPAL to classify posture described in the literature [107, 109, 110] with the validity of the 75 cpm (physical activity in sitting) and 150 cpm cut-point (physical activity in standing) observed in here. Abbreviation: Balanced sensitivity and specificity (Balanced), counts-per-minute (cpm).

4.3 APPLICATION

4.3.1 Descriptive Time Use

The 100 office workers provided 725 valid days, with an average wake-time of 15.0 ± 0.8 hours per day. The office workers spent on average 45.0 ± 8.2% of the wake-time sedentary, 13.7 ± 4.1% active sitting, and 12.0 ± 5.4% inactive standing (mean ± standard deviation, Figure 13).

Of the total sitting time, 23.9 ± 7.0% [14.6% – 35.6%] was spent active, and of the total standing time, 41.3 ± 12.6% [22.1% – 63.5%] was spent inactive (mean ± standard deviation [5^{th} – 95^{th} percentile]). The visual inspection of the behaviour profiles in Figure 14 shows a different accumulation pattern for weekdays and weekend days, and indicates that men accumulated slightly more time in SB and active sitting, while women accumulated slightly more time inactive standing.

The single sensors classified 58.6 ± 8.4% (activPAL) and 55.1 ± 7.7% (ActiGraph) of the wake-time sedentary (mean ± standard deviation).

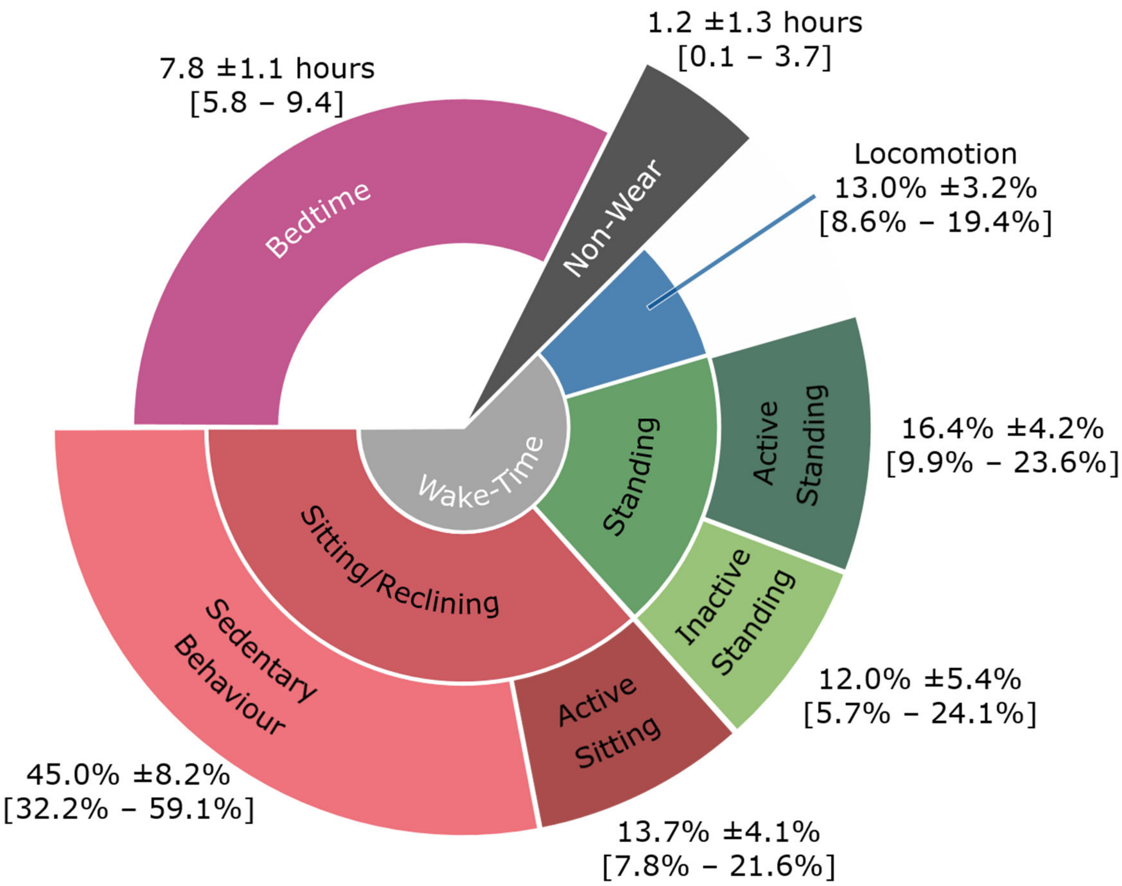

Figure 13. 24-hour behaviour framework measured with POPAI. The numbers indicate the mean ± standard deviation [5^{th} – 95^{th} percentile]. Bedtime and non-wear are given in absolute numbers (hours per day), and the remainder relative to wake-time (100% equals 15.0 hours), n=100. Abbreviations: Posture and Physical Activity Index (POPAI).

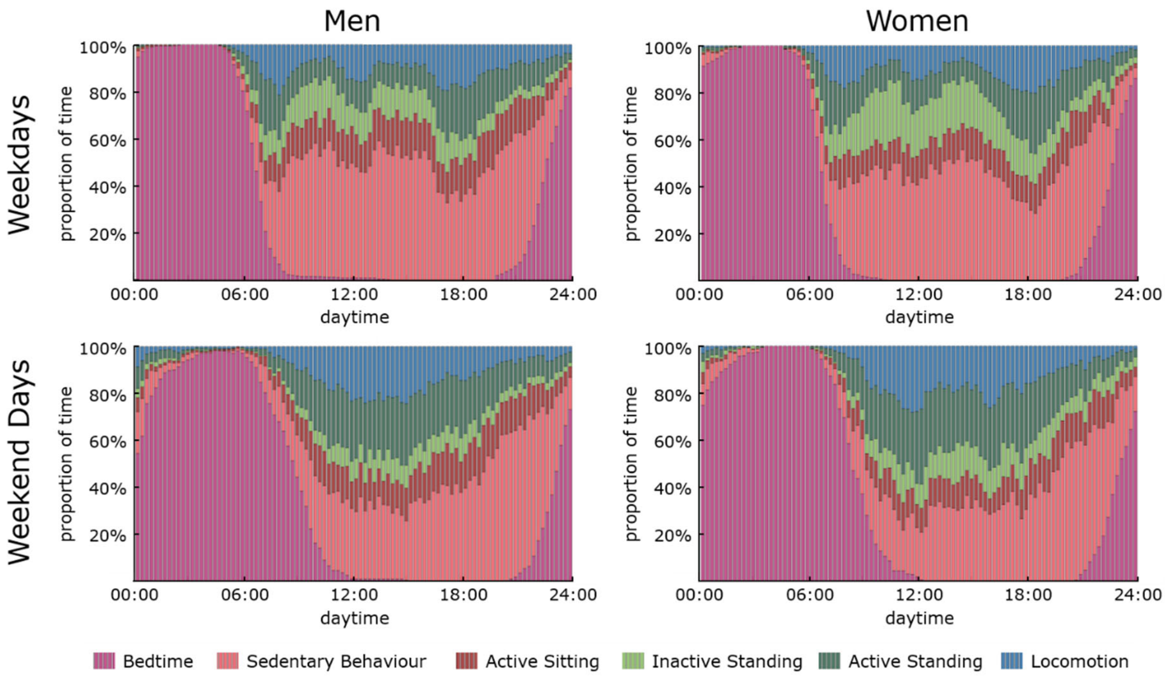

Figure 14. Behaviour profiles showing the occurrence of each behaviour in 15-minute epochs during weekdays and weekend days, separately for men (n=61) and women (n=39).

4.3.2 Bland-Altman Comparison

The activPAL and the ActiGraph substantially overestimated total sedentary time. Relative to POPAI, the activPAL overestimated sedentary time by 30.3% [28.5% – 32.1%], and the ActiGraph by 22.5% [20.6% – 24.5%] (bias with 95% confidence interval), both with wide 95% limit of agreement (Figure 15). The bias depended for both sensors not on sedentary time, but for the activPAL on active sitting (1.0 [1.0 – 1.0]) and for the ActiGraph on inactive standing (0.92 [0.89 – 0.95], r^2 with 95% confidence interval). Prolonged sedentary time was likewise overestimated by both sensors (Figure 15). Relative to POPAI, the activPAL overestimated the time spent in bouts ≥10 minutes by 82.6% [77.3% – 87.8%] and the time spent in bouts ≥30 minutes by 232.9% [218.1% – 247.8%] (bias with 95% confidence interval). The ActiGraph overestimated the time spent in bouts ≥10 minutes by 25.4% [22.8% – 27.9%] and the time spent in bouts ≥30 minutes by 35.8% [31.0% – 40.6%].

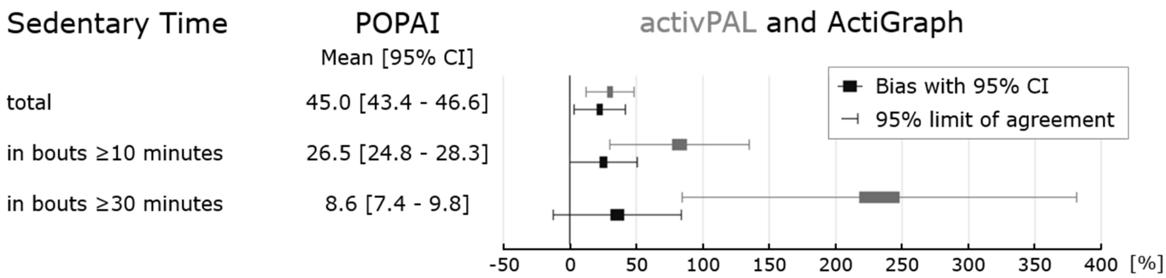

Figure 15. Bias and 95% limit of agreement of the activPAL (grey) and the ActiGraph (black) relative to POPAI. POPAI data given relative to wake-time. Abbreviations: Posture and Physical Activity Index (POPAI), Confidence Interval (CI).

5 DISCUSSION

First, the **calibration** studies developed new methods to advance the measurement of SB in an office context by classifying posture and physical activity compliant with the definition of SB. The new methods reached cross-validities between 75% (Wrist Accel) and 97% (EMG+) to measure SB, demonstrating that it is possible to measure both components of SB in a respectable cross-validity on an individual level. The subsequent **validation** study showed that waist- and wrist-worn ActiGraph cpm cut-points measure physical activity (minPA with MET ≤1.5) and not SB or sitting. However, the optimal waist cut-point to classify minPA depends on body posture. A lower cut-point should be used for sitting (75 cpm) than for standing (150 cpm). The final **application** study considered the posture dependency and used the combined posture and physical activity classification of POPAI with a validity of 92.2% to measure SB. POPAI measured a substantially lower amount of SB in the daily life of office workers (45% of the wake-time) compared to the single sensors (55% – 59%) because active sitting (14%) and inactive standing (12%) are much more common as previously thought. This leads to the conclusion that approximating SB with sitting (posture sensors) or minPA (physical activity sensors) leads to inaccurate and imprecise estimates overestimating sedentary time. Future studies are advised to measure SB by classifying posture and physical activity simultaneously. For the time being, the health recommendations on SB must be viewed critically.

5.1 CALIBRATION

5.1.1 Method Comparison

A thigh accelerometer should be the method of choice to measure the two components of SB when the results of the calibration studies (Figure 7, p. 34) are combined with practical aspects of data recording such as the number of sensors, sensor pricing, and ease of use. This conclusion confirms the recommendation to use a thigh accelerometer to measure SB [6, 108, 109] and adds the information that a thigh accelerometer can be used to classify minPA while sitting, demonstrating that there is no need to use sitting as a proxy for SB. The thigh was also among the methods with the highest cross-validity to classify the overall behaviour, including active sitting, inactive standing, active standing, and locomotion.

The other two methods with similar cross-validity to measure SB were the EMG+ and the Waist IMU. The EMG+ required six EMG channels and a thigh-worn accelerometer limiting its suitability for field use. The waist placement required an IMU, which makes the sensor more expensive and complicates data processing. However, the waist placement has so far been the prevailing choice in large-scale field studies to measure physical activity and SB. This thesis showed that the waist is an equally valid alternative to measure SB only when an IMU is used.

THIGH PLACEMENT

The thigh accelerometer was used by two methods for the posture classification (EMG+ in Study I and Thigh Accel in Study II) and solved the classification both times almost perfectly. The EMG+ used only the accelerometers y-axis (pointing upwards while standing), and classified a minute as sitting when the 5th percentile was ≥-7.59 m/s^2. This translates to a thigh orientation closer to 51° to the horizontal for 57 seconds of a minute to detect sitting. The 51° is substantially larger than the 20° required for the activPAL [107] but comparable to the 45° required for the Acti4 software [138]. However, the activPAL uses an event-based and Acti4 a 2-second-based approach, while here a minute-based approach was used. The Thigh Accel in Study II combined the 90th percentile of the accelerometer y-axis with the band power above 3 Hz of the accelerometer x-axis (pointing anteriorly while standing) due to the inclusion of the Saddle Chair in Study II (Figure 5d, p. 23). The Saddle Chair is a seated workplace intervention to decrease the hip flexion angle and causes a vertically aligned thigh, making it impossible to separate sitting from standing only with the thigh orientation. This is why a second feature to be seen as a measure of the thigh movement pattern was included.

In summary, the one-feature EMG+ algorithm should be the method of choice to detect sitting unless a future study records participants sitting on a Saddle Chair. Applying this algorithm (trained on 30 Hz data, sensor worn on left body side) to Study II data (60 Hz, sensor worn on right body side) shows a perfect sitting classification for the Conventional Chair, but the expected misclassification for the Saddle Chair. This leads to the conclusion that the posture algorithm is independent of the recording frequency, the sensor manufacturer, and the body side. A future validation study might combine the EMG+ posture algorithm with the physical activity algorithm of the Thigh Accel trained in Study II to measure SB.

WAIST PLACEMENT

The waist accelerometer was also used in two studies for the posture classification (Study II and Study III), with likewise no different cross-validity (Figure 8, p. 35). Both studies used a similarly valid reference criterion (direct observation in Study II, posture sensor in Study III), but Study III recorded data in free-living while Study II used a controlled environment. Thus, the Waist Accel trained in Study III should be the posture algorithm of choice due to the natural study setting. Furthermore, this algorithm had a bias of fewer than 8 minutes per day to measure the time spent in long sitting bouts. However, the number must be viewed with caution. The bias was calculated on minutes extracted slightly differently than for the algorithm training (testing versus training minutes) but using the same participants. Just as the cross-validity is not a measure of an algorithm's generalisability, neither is the presented bias.

The Waist IMU outperformed the Waist Accel in Study II with a significantly improved posture classification. The additional sensor signals could, for example, be found in the ActiGraph GT9X-Link, but not in the ActiGraph wGT3X-BT used in Study III. In general, the posture classification is a much more challenging task for waist sensors than thigh sensors. The waist orientation changes from standing to sitting by around 18° [206], while the thigh orientation changes by around 90°. Furthermore, waist sensors are loosely worn with an elastic belt, while thigh sensors are rigidly attached with adhesive film. Interestingly, all presented waist algorithms primarily used features to be seen as a measure of the waist movement pattern rather than the waist orientation. To better account for the waist orientation, future studies are warranted to attach waist sensors with adhesive film, and/or realign the sensor orientation to the waist in instances with known waist orientation [8, 207]. Attaching the sensor with adhesive film might also positively influence wear-time compliance and avoid sensor misplacement (e.g. upside down, wrong body side).

Wrist Placement

The wrist accelerometer got popular as it allows for 24-hour recording protocols with high wear comfort and wear-time compliance [156-158], but the difference to the waist and thigh might be marginal when using a 24-hour protocol for these placements [208, 209]. Here, the wrist placement has shown its strength in the activity classification but dropped significantly in the posture classification compared to the other placements. Accordingly, the wrist placement had the significantly lowest cross-validity to detect SB, and it must be questioned whether a higher wear-time compliance could counterbalance the lower cross-validity.

EMG+

The EMG+ solved the SB classification with the highest cross-validity, but it is not the recommended method due to seven sensors limiting its field suitability. The system should be seen as a first step towards the measurement of SB with EMG. In contrast to accelerometers and IMUs, EMG can measure the activity of quasi-static postures. Whether this advantage is relevant for the measurement of SB must be questioned based on the results presented. However, there is a need to examine whether the number of EMG channels can be reduced and whether a more sophisticated algorithm as for the other methods developed here improves the cross-validity. Furthermore, incorporating the device into a smart textile will likely increase the field suitability, and it might make the number of EMG channels irrelevant (Figure 16). In its current form (Figure 5a, p. 23), the system might be more suitable for ergonomic workplace assessments due to the additional information it provides (muscular activity over an entire working day). For the field measurement of SB, it might be a sledgehammer to crack a nut.

Figure 16. A revised version of the EMG+ (accelerometer not shown) to improve its suitability for field use. The smart shirt uses only the three most relevant EMG channels presented in Paper I, including one reference electrode. Abbreviations: Electromyography plus Accelerometer (EMG+), Electromyography (EMG).

5.1.2 Comparison to Literature

CONTROLLED STUDY ENVIRONMENT

The presented cross-validities to measure SB in Study I and Study II are low compared to the literature. Cross-validities to measure SB with accelerometers range up to 99.7% for the thigh, up to 98.2% for the waist, and up to 98.8% for the wrist [128, 173]. The presented cross-validities are 6.3% (thigh), 13.3% (waist), and 23.7% (wrist) lower. However, unique in comparison to the literature, Study I and II included tasks with an average MET of 1.1 – 1.8 (except walking), recorded the same tasks while sitting and standing, and classified SB on an individual level with consideration of posture and physical activity. Accordingly, the same task could be classified for one individual as SB, but for another as active sitting. This stays clearly in contrast to previous calibration studies having a large MET gap between sedentary and non-sedentary tasks, with all sitting tasks being classified as SB [128, 135, 173]. Thus, the algorithms presented in the literature classify SB through a correctly detected posture OR activity level. In contrast, the algorithms presented here classify SB through a correctly detected posture AND activity level. When comparing the literature data to either the posture OR the physical activity classification (i.e. to the higher of the two), the cross-validities presented here are 0.3% higher for the thigh, 8.2% lower for the waist, and 1.6% lower for the wrist.

A rare exception of equating sitting with SB is a calibration study by Pavey et al. (2017), which included a stationary+ category summing the active sitting, inactive and active standing categories of the present thesis [136]. The study presented a wrist-worn accelerometer method with a cross-validity to measure SB of 89% (13.9% higher as here). However, the study also neglected individual variations by classifying SB on task level, which turns the SB classification into a task detection. For all these reasons, the comparison to the literature on controlled study environments should be made with caution.

FREE-LIVING STUDY

The cross-validity of the Waist Accel in Study III is in a similar range compared to the literature. The posture algorithm has a cross-validity to detect sitting of 87.8% compared to the activPAL, while Ellis et al. (2016) reported a cross-validity of 90.8% compared to direct observation, and Kerr et al. (2018) reported a cross-validity of 66.7% compared to the activPAL [137, 157]. All three studies used the same waist-worn ActiGraph, but the study by Kerr et al. (2018) used a 5-second epoch to classify sitting, while the other two used a 60-second epoch.

5.1.3 Generalisability

The generalisability of the new methods to measure SB cannot be assessed based on the presented cross-validities. The cross-validity, calculated with the leave-one-subject-out approach, is an established measure of the method performance in the calibration data, but it does not generalise to the validity in future method use in other populations and settings [125]. It has been repeatedly observed that the validity drops around 0% – 20% from the calibration (cross-validity) to the validation (independent validity) [125, 127, 146, 147, 210, 211]. Since the measures to limit the spread of COVID-19 stopped the free-living validation study with the new methods, the drop for the new methods can only be estimated.

CONTROLLED STUDY ENVIRONMENT

There are a couple of arguments why the validity drop for the presented methods might be small with respect to potential reasons discussed in the literature [146, 147, 211].

- Limited variability within the study population: Both controlled calibration studies recorded participants in a broad range of age (≤24 to ≥57 years), weight (≤57 to ≥93 kg), height (1.55 to ≥1.90 m), and BMI (≤19.5 to ≥28.7 kg/m^2), with balanced gender.
- Standardised nature of the included tasks: The tasks were not standardised nor demonstrated; participants performed the tasks in their own way and speed. In fact, a considerable variation was observed for Deskwork and Sorting, but not for Watching, Mouse and Typing, which might naturally have less variability.
- Ignoring transitions between tasks: Transitions between tasks were ignored due to the use of an indirect calorimeter requiring a steady state. Given the prolonged nature of SB in office work [35-37], this limitation is likely less critical in office work than in other daily life situations such as household activities.
- Limited amount of tasks not representing the full variability seen in free-living: The studies included a broad range of office tasks, from an inactive Mouse task up to an active Sorting task, recorded the same tasks while sitting and standing, with part of the participants using a laptop and the remainder a desktop computer.

Furthermore, the validity drop is typically larger for locomotion (walking, running, cycling) than for sitting and standing. Montoye et al. (2018) recommended focusing on tasks that lie at the border of the behaviour categories to strengthen the methods' ability to separate the behaviours, just as Study I and II did [147]. This also includes recording tasks that are naturally performed while sitting and standing, such as office tasks, while sitting and standing, as well as to cover a MET range seen in free-living (<2 MET [155]). Furthermore, the forward feature selection and algorithm optimisation resulted in relatively simple algorithms (≤22 features, ≤169 decision trees) compared to the literature (≥40 features, ≥500 decision trees) [137, 153, 157]. All these aspects can be interpreted as arguments why the validity of the presented methods might drop closer to 0% than to 20% when moving from the calibration to the validation.

There are also arguments why the validity drop for the presented methods might be large.

- The combined use of two algorithms to classify SB, one for posture and one for minPA, might mean that the drop is twice as large.
- The studies included only office tasks, which is why it remains unknown how the methods perform outside the office.

- The forward feature selection, with each iteration evaluating the cross-validity on all data, might have led to overfitting since, from the second iteration onwards, the algorithm development was no longer independent of the algorithm evaluation.

Despite the sample size of Study I and II being comparable with the literature [127], it is questionable to extrapolate from 25 and 30 office workers recruited in one geographical area to the entire office worker population. In both studies together, 20% of the participants were overweight (BMI ≥25) and 4% obese (BMI ≥30), but only 8% in Study I and 33% in Study II were older than 40 years. Participants in Study II reported to sit for 78% of the working hours at the office desk, while the average office worker spends 65% – 75% of the work-time sedentary [32-34]. Thus, the included sample might be representative of a relatively young office worker population with a balanced gender.

FREE-LIVING STUDY

The validity drop of the new ActiGraph posture algorithm developed in Study III might be smaller due to the natural, free-living study setting. The ActiGraph sensor was also included in data collection B, and these data can be used to get a first idea of the algorithms generalisability. In fact, the validity drops by 5.8% from the cross-validity (Study III) to the validity in the population and setting of Study II (Table 12). However, data collection B was conducted in a controlled environment recording only office tasks, and the validity will likely drop more when the algorithm is applied to field data. On the other hand, Study II recorded the same tasks while sitting and standing, which might make the posture classification more challenging as in free-living where some tasks are more likely to be performed while sitting and others while standing. Furthermore, the ActiGraph was worn on the left body side in Study II, and the axes had to be rotated to the right body side to use the algorithm. This makes the validity more likely to appear too low rather than too high. Without rotating the axes, the validity dropped by 20.8%, clearly indicating that body side matters. Last, the sample in Study III consisted mostly of men (61%). Even though there was no difference between the validity for men and women when applying the algorithm to Study II data, a future validation study has to prove whether the algorithm is equally valid for both genders.

Table 12. ActiGraph posture algorithm developed in Study III applied to Study II data.

Study		Balanced	Sensitivity	Specificity
III	Cross-Validity	87.8 [84.0 – 90.7]	95.6 [94.7 – 97.2]	79.6 [74.0 – 85.2]
II	Validity	82.0 [74.0 – 86.0]	100.0 [96.0 – 100.0]	70.0 [56.0 – 78.5]

Numbers are given in % with median and 95% confidence interval. Abbreviation: Balanced sensitivity and specificity (Balanced).

In summary, it is imperative that a future validation study analyses the validity independent of the development to specify the methods' generalisability to new data.

5.2 VALIDATION

The ActiGraph cpm cut-points measured minPA most valid, no matter whether the waist or the wrist placement was used. Across all workplaces, the highest validity to measure minPA was reached at around 80 cpm for the waist, and at around 3'650 cpm for the wrist (balanced sensitivity and specificity of 78% with kappa = 0.58 for both placements). Thus, it is strongly recommended that studies using an ActiGraph cpm cut-point talk about minPA. The measurement of SB and sitting with ActiGraph cpm cut-points is far less valid.

5.2.1 ActiGraph Cut-Points to Assess Workplace Interventions

For the Standing Desk, representing a standing workplace intervention, the cpm waist and wrist cut-points reached a *substantial* validity to detect minPA, just like for the Conventional Chair (kappa = 0.69). However, the most valid waist cut-point was substantially higher for standing (around 150 cpm) than for sitting (around 75 cpm), indicating an important limitation of the cpm cut-points. When using the same waist cut-point for sitting and standing (e.g. the popular 100 cpm), the detection of minPA has a higher sensitivity (+6.1%) but lower specificity (-11.4%) for sitting. This means that minPA is more validly detected while sitting (higher sensitivity), but more LIPA minutes are wrongly classified as minPA (lower specificity). Accordingly, minPA is systematically overestimated while sitting compared to standing, and sitting is considered less active than standing. Here, conventional seated office work had an average of 59 cpm and standing office work an average of 113 cpm at the same activity level. Studies investigating the use of sit-stand desks should therefore avoid using ActiGraph cpm cut-points. The reduced occupational minPA time when office workers use a sit-stand desk, as observed by Mansoubi et al. (2016), might simply reflect the systematic overestimation of minPA while sitting compared to standing [53].

The systematic overestimation of minPA while sitting can be remedied with posture specific cut-points, which means the ActiGraph should be combined with a posture sensor and different cut-points for sitting (75 cpm) and standing (150 cpm) should be employed (as for POPAI). An equal valid alternative would be to use a wrist-worn ActiGraph, for which no posture dependency was found. However, the most valid wrist cut-point here (3'650 cpm) is substantially higher as reported by others (1'853 cpm in [123], 2'860 cpm in [212]), and future studies are needed to clarify this issue. Without the unique Active Chair investigated here, the most valid wrist cut-point would have been even higher (Figure 12, p. 39).

For the Active Chair, representing an active workplace intervention, both placements showed a substantial lower validity to detect minPA compared to the Conventional Chair and the Standing Desk. The additional discriminant validity analysis presented in Paper IV indicated a *poor* (wrist) and *fair* (waist) validity to detect changes in minPA caused by the Active Chair. The wrist placement failed to detect any cpm differences between the Active Chair and the Conventional Chair. In contrast, the waist placement detected a cpm difference, but no single cut-point reached a suitable validity to separate inactive from active sitting. Accordingly, neither the waist nor the wrist can be recommended to investigate minPA when using a seated workplace intervention such as the Active Chair, which actually reduced minPA and thus SB.

5.2.2 Misleading Posture Interpretation of ActiGraph Cut-Points

The ActiGraph cpm cut-points do not measure sitting, although several studies calibrated them to do so. For example, Koster et al. (2016) reported a balanced sensitivity and specificity of 75.9% to detect sitting with the waist-worn 100 cpm cut-point (here: 46.7%), and 79.1% to detect sitting with the wrist-worn 1’852 cpm cut-point (here: 51.2%) [123]. Interestingly, the numbers reported by Koster et al. (2016) are very close to those reported here for minPA (77.1% and 76.4% for waist and wrist). The difference is likely caused by the study setting.

Study IV used a controlled environment and measured the same tasks while sitting and standing. Hence, the reported validity to detect sitting is independent of minPA. In contrast, the study by Koster et al. (2016) was conducted in free-living, with a well-known agreement between the activPAL-measured sitting and the ActiGraph-measured minPA time [6, 213]. As different ActiGraph cut-points are recommended to detect sitting in different studies [108, 109, 123] and sometimes even within the same study depending on the performed activities [121], the agreement between activPAL-measured sitting and ActiGraph-measured minPA varies substantially. This issue becomes all the more apparent when looking at prolonged sitting. The ActiGraph 100 cpm cut-point significantly underestimates the time spent in prolonged sitting [137, 213], indicating that long sitting bouts contain some LIPA minutes breaking up minPA but not sitting. Strictly spoken, studies calibrating ActiGraph cpm cut-points to measure sitting search for an intensity threshold that results in the most similar amount of time compared to sitting. In other words, the reported cut-points reflect more a description of the activity level while sitting rather than an actual posture detection. However, a detailed description of the activity level while sitting requires a synchronised analysis with both sensors, as for example with POPAI.

5.2.3 Posture and Physical Activity Index

POPAI has a validity of 92.2% to measure SB (balanced sensitivity and specificity). This value is within the 95% confidence interval of the calibrated methods reaching the highest cross-validities to classify SB (Table 7, p. 34). Since the cross-validity is subject to a certain validity drop when moving from the calibration to the validation, POPAI must be seen as at least equal but most likely superior to the calibrated methods. However, the validity for the physical activity classification in POPAI relates only to office work, and the validity outside the office remains unknown. Furthermore, it is important to note that the presented validities were calculated by combining the reported validity of the activPAL to classify posture with the validity of the ActiGraph to classify minPA, and a future validation study might report slightly different values. Apparent from Table 11 (p. 39), POPAI has a substantially higher sensitivity and slightly lower specificity to detect SB and inactive standing compared to active sitting and active standing. Thus, POPAI might slightly overestimate minPA while sitting (equal to SB) and standing.

5.3 APPLICATION

5.3.1 Descriptive Time Use

POPAI classified 45.0% ± 8.2% of the wake-time or 6.8 ± 1.2 hours a day sedentary, while the single sensor estimates were well within the 55% – 65% or 8 – 10 hours per day reported in the literature [5-8]. In contrast to previous studies, POPAI differentiates between SB, active sitting, and inactive standing. Both active sitting and inactive standing account for a significant amount of time: active sitting for 2.0 ± 0.6 hours per day, and inactive standing for 1.8 ± 0.8 hours per day. The behaviour profiles indicate that both behaviours are spread throughout the wake-time, with differences between weekdays and weekend days. Interestingly, the separation by gender indicates that men accumulated more time sedentary and active sitting, while women accumulated more time inactive standing. This observation is in line with Johansson et al. (2020), which observed more sitting in men and more standing in women [37]. POPAI adds the information that men sit more inactive and active, while women just stand more inactive. However, a detailed gender analysis is reserved for future studies.

5.3.2 Bland-Altman Comparison

The single sensors substantially overestimate SB compared to POPAI: the activPAL by 30.3%, and the ActiGraph by 22.5%. Together with the wide 95% limit of agreements (Figure 15, p. 41), this indicates a low accuracy and low precision of the single sensors. When taking into account that POPAI might overestimate SB, the true bias of the single sensors would be even larger. The overestimation aggravated when looking at sedentary time spent in bouts ≥10 and ≥30 minutes, most severely for the activPAL (up to 233%). This indicates that prolonged SB is broken up more often by activity (i.e. active sitting) than by changing posture (i.e. inactive standing).

The reason for the overestimation of SB is active sitting and inactive standing. Active sitting explains the activPAL bias perfectly (r^2=1.00), and inactive standing explains the ActiGraph bias almost perfectly (r^2=0.92). On average, one out of four sitting minutes was active, and two out of five standing minutes were inactive. Apparent from the 95th percentile, some office workers even spent one out of three sitting minutes active, while others collected more than half of the standing minutes inactive. Should a future study confirm the gender differences with more active sitting and less inactive standing in men, it would mean that the activPAL bias might be larger and the ActiGraph bias might be smaller for men and vice-versa for women. Future studies are thus recommended to investigate the bias with respect to gender, but also with respect to time (weekday vs weekend day, worktime vs non-worktime).

The overestimation of SB by the single sensors confirms the results previously reported for other sensor combinations [169, 170]. As here, the sample in Fanchamps et al. (2017) spent more time sitting than in minPA, leading to a larger bias for the posture sensor [169]. In contrast, the sample in Myers et al. (2017) spent more time in minPA than sitting, leading to a larger bias for the physical activity sensor [170]. Other studies using both sensors without a combined analysis reported quite similar amounts of activPAL and ActiGraph measured SB

[6, 213]. Here, the more sitting than minPA and thus the larger bias for the activPAL could be a result of the male dominance in the sample (61% of the participants). However, the office sector is, at least in Sweden, dominated by men (58%) [30].

To check whether the bias was introduced by the posture specific cut-points, the POPAI processing was repeated using the 100 cpm cut-point for sitting and standing. This increased sedentary time from 45.0% to 47.1% of the wake-time, and thus reduced the activPAL and ActiGraph bias from 30.3% to 24.4% and from 22.5% to 17.0%. However, Study IV demonstrated that the posture-dependent cut-points are more valid, and the presented sensitivity and specificity of POPAI (Table 11, p. 39) make an overestimation of SB more likely than an underestimation.

In conclusion, SB makes up the largest part of the wake-time, but it is not as omnipresent as claimed with the single sensors neglecting active sitting (activPAL) or inactive standing (ActiGraph). Approximating SB with sitting or minPA substantially overestimates sedentary time, and neither the activPAL nor the ActiGraph can be recommended to measure SB. Since the time spent active sitting and inactive standing might be different for men and women, future studies should investigate the bias in relation to gender.

5.4 IMPLICATIONS

5.4.1 Device-Based Method Development

The present thesis used a method development framework to embed the various steps and decisions required to develop new device-based methods to measure SB (Figure 2, p. 9). The framework was inspired by the work of Keadle et al. (2019), which separated the development into an initial mechanical signal testing (phase 0), followed by a laboratory development (phase 1), semi-structured evaluation (phase 2), naturalistic validation (phase 3), and adoption (phase 4) [131]. The three parts used in here correspond to phase 1 (calibration), phase 3 (validation), and phase 4 (application), with the most serious difference that the measures to limit the spread of COVID-19 made it impossible to conduct the validation (phase 3) in a naturalistic setting. Phase 0 and 2 were intentionally omitted here.

Phase 0 aims to ensure the reliability and validity of the raw sensor data. This phase was omitted due to the use of established sensors from renowned manufacturers (Study II and III), or since it was already covered in the Bachelor thesis developing the EMG+ (Study I) [196]. Phase 2 aims to refine or recalibrate the algorithm developed in phase 1. This phase would have been included here if the validation (phase 3) would have yielded an insufficient validity. In this case, the validation data would have been used to recalibrate the algorithm [210], and a new data collection would have been used to assess the validity. This procedure is also recommended for a future validation study in case the validity is deemed insufficient for the intended application, or when the algorithms are used with sensors other than those used here. Ideally, such a validation includes an assessment of reliability by recording part of the participants twice (test-retest reliability). As there was a lack of valid methods to measure the two components of SB compliant with its definition, this thesis focused on validity, which should be followed by an examination of reliability [202]. The sedentary research field so far primarily focused on validity, and the reliability of the behaviour classification is somewhat underrepresented.

BEHAVIOUR OF INTEREST

This thesis strictly applied the SB definition of the Sedentary Behavior Research Network, used well-established reference criteria considered valid, and classified the behaviour on an individual level. Interestingly, the studies are among the first to measure SB compliant with its definition in such an exact and individual manner. It should generally be viewed critically that calibration studies simplify the behaviour classification, for example, by using predefined task-clusters instead of calorimetry results [135, 141], or by classifying physical activity with direct observation [128, 147, 148]. With direct observation, all seated office tasks in Study I and II would be classified as "sitting at a desk" with 1.3 MET or as "sitting tasks" with 1.5 MET and thus sedentary in both cases [149]. However, a very serious limitation in here is that all methods classifying SB were developed in controlled environments due to a lack of valid reference criteria for the physical activity classification in free-living. To overcome this limitation, future studies are required to examine the validity of indirect calorimetry in field studies, especially concerning the steady-state criterion. In the stopped free-living validation study, an algorithm to detect steady state in walking seemed most suitable [214, 215]. Another field-ready but less valid solution would be POPAI as a best-available reference method.

BODY-WORN SENSOR

This thesis investigated which sensor type should be placed at which body segment to measure SB, and recommends to use a thigh accelerometer or a waist IMU calibrated to measure sitting and minPA. EMG was also successfully used for the physical activity classification, but the limited field suitability and additional information the EMG+ collects (muscular activity) might make it of greater value for ergonomic workplace assessments than for the field measurement of SB. For the accelerometers, neither the sensor manufacturer (Analog Devices, Xsens, ActiGraph) nor the recording frequency (30 Hz and 60 Hz) influenced the cross-validity. Despite some evidence that two-sensor-systems might detect SB more valid, field studies rarely use two-sensor-systems, which is why no such combination was calibrated. However, POPAI is a two-sensor-system. Until the calibrated methods are validated, the recommendation is to use POPAI to measure SB.

DATA PROCESSING

Experts in the field repeatedly asked to work with raw sensor data and machine learning to develop new methods, which is why this thesis did so. However, this thesis has not investigated the classification technique, the algorithm architecture, nor the temporal resolution (epoch length). Numerous studies already compared different machine-learning methods, with none outperforming the other [125-127]. The thesis followed the recommendation of Liu et al. (2012) to identify the most relevant signal features when building an algorithm [134]. All identified features were published alongside the algorithms in the supplementary online material to inform future method developments. The algorithm architecture was, for physiological reasons, predefined and consistent with the 24-hour behaviour framework. Each method calibrated to measure SB uses a hierarchical architecture and first classifies posture and second physical activity, both in 60-second epochs. This temporal resolution was deemed sufficient concerning the prolonged nature of SB. However, the high validity of posture sensors to detect sitting events might make an event-based posture classification followed by a minute-based physical activity classification as in POPAI the better choice for future method developments. One key advantage of the hierarchical algorithm architecture is that the single classification algorithms can be used in whatever combination, as long as the required input signal is available.

5.4.2 State-of-the-Art Measurement of Sedentary Behaviour

It is well established that posture sensors provide a valid measurement of posture (i.e. sitting, standing, and locomotion) [107-112], but there was conflicting evidence what physical activity sensors measure [120-122]. Study IV, therefore, analysed the cpm cut-point validity of the ActiGraph and observed the far highest validity to measure minPA. Accordingly, studies using a waist- or wrist-worn ActiGraph sensor with cpm cut-points should always interpret their results as minPA and not as SB or sitting. However, it is important to keep in mind that the 100 cpm waist cut-point systematically overestimates minPA while sitting compared to standing. Even though solely based on office work, it seems unlikely that the recommendation to use a lower cut-point to classify minPA in sitting (75 cpm) than in standing (150 cpm) holds not true outside office work, but the most valid cpm cut-point might be different.

The placement and processing define whether a particular sensor is a posture (thigh-worn) or physical activity sensor (waist- or wrist-worn), and not the sensor manufacturer. From studies attaching the ActiGraph to the thigh, it is well known that the sensor provides equal valid posture estimates [111, 138, 216]. However, whether waist-worn physical activity sensors will once provide equal valid posture estimates than posture sensors [e.g. 137, 157, Study III], and thigh-worn posture sensors will once provide equally valid physical activity estimates than physical activity sensors [e.g. 217, 218, Study II] remains subject for further research. As long as this is not the case, the valid measurement of SB requires both sensors, ideally combined with self-reporting to collect context information.

5.4.3 The 24-hour Behaviour Framework

The 24-hour behaviour framework used in here (Figure 1, p. 7, and Figure 13, p. 40) first separates posture and second the physical activity level, which is exactly the other way round as in Tremblay et al. (2017) [74]. The order was chosen because it was expected that a different motion behaviour changes physical activity in sitting compared to standing and locomotion, mainly because the pelvis remains relatively stable while sitting. This decision appears to be justified by the results. The validity of the popular waist-worn ActiGraph cpm cut-points depends on posture, and Study II showed that the upper-body-worn sensors outperform the lower-body- and waist-worn sensors for the physical activity classification in sitting, but not in standing.

Unique in here was the separation of sitting and standing into inactive and active. The relevance of this separation was confirmed by POPAI, which showed that 23.9% of the total sitting time was spent active, and 41.3% of the total standing time was spent inactive. Future studies are therefore recommended to make this separation as well. Inactive and active standing was separated with a threshold of 1.5 MET, just as for sitting. In contrast, the Sedentary Behavior Research Network recommends using a threshold of 2.0 MET, arguing that a couple of standing activities considered inactive have a MET in between 1.5 and 2.0 [74]. However, standing with 1.8 MET would then be classified as inactive standing (≤2.0 MET) and LIPA (1.5 – 3.0 MET) at the same time, which would be confusing. In case there are different health effects of sitting and standing at the same MET value, they should be attributed to posture.

5.4.4 Sedentary Behaviour – A Still Evolving Definition

The present thesis followed the recommendation of the Sedentary Behavior Research Network and defined *sedentary behaviour as any waking behaviour characterised by an energy expenditure ≤1.5 MET while in a sitting or reclining posture* [73, p. 540]. This definition is widely used but not the only one. When defining SB only by its posture component [72], active sitting must also be considered sedentary. When defining SB only by its physical activity component [71], inactive standing must also be considered sedentary. However, even when considering only the physical activity component, as for example outlined in a new expert statement of the Prospective Physical Activity, Sitting and Sleep Consortium [219], a preceding posture classification might be justified to account for different movement patterns affecting physical activity while sitting and standing. Future studies might thus use the information presented in this thesis, no matter how they define SB.

While conducting this thesis, the Sedentary Behavior Research Network revised the SB definition and included lying [74]. On the one hand, this simplifies the measurement of SB since there is no need to separate sitting from lying. On the other hand, however, it pronounces an existing measurement challenge: the detection of sleep. So far, bedtime was excluded from SB due to the lying posture, but with the new definition, only sleep should be excluded, and there is a need to develop methods to detect sleep, posture, and physical activity to comply with the new definition.

There is a lack of evidence for the relevance of the posture component of SB. The largest body of device-based evidence for the detrimental health effects of SB was collected with waist-worn physical activity sensors (i.e. ActiGraph GT3X with 100 cpm cut-point) [124]. Evident from Study IV and V, this sensor measures minPA and not SB, supporting the message that only the physical activity component of SB is of relevance. Accordingly, it is reasonable to argue that the current measurement of SB is just physical inactivity by another name. When assuming a constant MVPA and bedtime, the time spent in SB measured with physical activity sensors is just the inverse of the time spent in LIPA [220]. Thus, there is an urgent need to use device-based methods able to classify posture and physical activity to assess the relevance of the posture component. Some preliminary evidence indicating different effects of sitting and minPA on cardiometabolic biomarkers was already collected [213, 221].

The physical activity threshold of SB (≤1.5 MET) was arbitrarily chosen, and it should be verified whether this threshold was chosen sensibly. The frequently cited guidance paper by Garber et al. (2011), for example, set the lowest physical activity threshold to ≤2.0 MET [78].

The definition of 1.0 MET is ambiguous. Upon introduction, the MET was defined by a fix oxygen consumption of 3.5 $ml \times kg^{-1} \times min^{-1}$ ($MET_{Standard}$), representing an absolute intensity measure [77, 78]. However, it is common practice to interpret the MET as multiple of the resting metabolic rate, which implies the use of a relative measure ($MET_{Measured}$) [74, 84]. The well-established thresholds for, e.g., moderate-intensity physical activity (3.0 – 5.9 MET) were defined as absolute intensities, and should be adapted to the study populations age (e.g. 4.8 – 7.1 MET for 20 – 39 years, and 4.0 – 5.9 MET for 40 – 64 years) [78]. For SB, the MET level is never adapted, and it is debatable which MET definition is best to take [75, 85, 86]. An alternative would be to replace the MET with, for example, the mass-specific net oxygen uptake as outlined in Arvidsson et al. (2019) [222]. This value does not express the oxygen consumption relative to a reference value, but calculates the difference to a reference value, and seems to better account for age and stature.

Here, the $MET_{Measured}$ was used to eliminate individual and environmental factors. As a result, there were no differences between the individual office tasks in Study I and II (Table 6, p. 33), but a significant difference in the average $MET_{Measured}$ (4.1 and 3.5 $ml \times kg^{-1} \times min^{-1}$), most likely as a result of the different ambient temperatures in the two studies (27.2° and 25.0° Celsius). If the $MET_{Standard}$ had been used, participants in Study I would have had 17% higher MET values on average, resulting in different physical activity classifications between the studies. More precisely, the studies did not express the $MET_{Measured}$ as oxygen consumption, as outlined in the physical activity and SB guidelines of the WHO [28], but in kilocalories, which also considers carbon dioxide production and make 1.0 MET equal to the resting metabolic rate [71]. For low-intensity activities as recorded here, the difference is likely small or even inexistent. The inclusion of carbon dioxide only comes into play for the anaerobic energy expenditure, but it is reasonable to have a consistent method across the entire physical activity spectrum. Accordingly, to eliminate individual and environmental factors, it might be wise to change the definition of SB to *any waking behaviour characterised by an energy expenditure ≤1.5 <u>times the resting metabolic rate</u> while in a sitting, reclining, or lying posture*. On the one hand, concluding on a relative intensity (multiple of the resting metabolic rate) with a sensor having an absolute scale (acceleration in m/s^2) will never be perfect. On the other hand, given the large effect the use of the $MET_{Standard}$ would have had here, it might be the better alternative.

In summary, the measurement of SB compliant with its definition is a huge challenge and requires an accurate detection of wake-time, body posture, and physical activity. So far, there is no single device-based method able to measure all three components. This fundamentally questions the relevance of SB for human health. The only studies considering the posture and the physical activity component showed that considering only one component overestimates SB [169, 170, Paper V]. Two ways could resolve this issue: 1) adapting the definition of SB to the possibilities of the device-based methods with which the evidence was collected by equating SB with minPA; 2) developing the device-based methods further to measure SB compliant with its definition and, unless successfully done, not conclude on SB with single body-worn sensors. As it is predominantly measured nowadays, SB is nothing else than minPA, with minPA overestimated while sitting compared to standing.

5.4.5 Occupational Sedentary Behaviour and Workplace Interventions

Office workers are known for their excessive amounts of SB [32-34] that they often accumulate in long bouts [35-37]. However, the single sensors with which all the evidence was collected substantially overestimate SB, most prominent for long bouts. The 100 office workers in Study V spent 49% of the sitting time in bouts ≥30 minutes (measured with the activPAL, the previously recommended sensor to measure SB), but only 18% of the sedentary time in bouts ≥30 minutes (measured with POPAI, the new recommended method to measure SB). As the single sensors overestimation of sedentary time is not limited to office hours (Figure 14, p. 41), there is no reason to question the sedentary nature of office work in general, but the exact figures need to be quantified in future field studies with valid methods. Such studies ideally include self-reporting methods to analyse whether the context in which SB takes place is relevant for its detrimental health effects.

A variety of devices is currently used to study workplace interventions. The Cochrane review by Shrestha et al. (2018) [45], for example, considered the ActiGraph, the activPAL, and the SenseWear armband (BodyMedia Inc., Pittsburgh (PA), USA) valid to measure SB. Only studies using self-reports were judged to have a high risk of bias. This example shows how the various methods to measure SB are considered interchangeable even though they measure different behaviours.

The vast majority of workplace interventions aim to break up SB with standing, most often using a sit-stand desk [45]. The effects of sit-stand desks on posture should be analysed with a posture sensor, such as the activPAL. The use of a physical activity sensor such as the ActiGraph is not valid to detect body posture. Furthermore, the popular waist-worn ActiGraph records more cpm while standing than while sitting, leading to the conclusion that standing is more active than sitting even when there is no real activity difference. Accordingly, the effects of sit-stand desks on physical activity should be analysed with a combined thigh-worn posture and waist-worn physical activity sensor and posture specific cut-points. An alternative to assess physical activity only would be to use a wrist-worn ActiGraph, but this sensor might fail to detect potential compensation effects [53, 54].

A minority of workplace interventions aim to break up SB with physical activity. These interventions typically use cycling desks or activity-promoting office chairs, such as the Active Chair in here. The Active Chair reduced SB by reducing minPA, which, however, was not validly detected by the ActiGraph cpm cut-points. This is all the more remarkable as the chair directly affected the waist motion. One can assume that other active workplace interventions not involving a substantial waist motion, such as cycling desks, might have a similarly low or even lower validity (the activity underestimation of cycling is well described in the literature [117, 223, 224]). Thus, ActiGraph cut-points should not be used to assess the effects of active workplace interventions, and we lack a valid method to do so.

Another minority of workplace interventions aim to break up both components of SB simultaneously (e.g. treadmill desks). No such intervention was analysed here, which is why one can only speculate about the validity of device-based methods. However, since the measurement of SB itself requires both sensors, the use of only one seems useless. There might be a compensation effect, making sitting less active or shifting standing to sitting, and posture or physical activity sensors alone will not detect these effects. The same conclusion might also be true for other, non-environmental based workplace interventions not discussed here, such as activity breaks or standing meetings.

In conclusion, future studies investigating workplace interventions to break up SB should carefully select their measurement method and preferably measure posture and physical activity. Systematic reviews are advised to separate the original studies by the measurement method (self-reporting, posture sensors, physical activity sensors, and combined posture and physical activity methods). The simultaneous analysis of posture and physical activity will likely lead to new evidence regarding occupational SB, minPA, and sitting. For the time being, the recommendation to use workplace interventions must be viewed with caution. In here, standing office work was equally active than seated office work, confirming the findings in [48, 51, 52] and contradicting the findings in [49, 50]. Whether the Active Chair combined with oral prompting increases physical activity in everyday office work needs to be assessed in a future field study. However, there is first a need to develop a valid method to measure the effect of such an active workplace intervention on SB.

5.4.6 Sedentary Behaviour and Health

SB accounts for the vast majority of the wake-time, but it is not as omnipresent as previously claimed. The strict application of the SB definition led to 45% of the wake-time spent sedentary, while the individual sensors measuring either sitting or minPA led to 55% – 59%. The difference can be explained by the fact that sitting is not always inactive, and standing is not always active. The consequences of this observation for human health must be analysed in future studies using a combined posture and physical activity classification such as POPAI. If the combined occurrence of sitting and minPA is relevant, one would in fact expect an even stronger relationship between SB and adverse health outcomes. As the overestimation of the single sensors aggravated for prolonged SB, future studies are required to verify the preliminary evidence that the sedentary accumulation pattern matters for human health.

The WHO's recently updated physical activity guidelines (November 2020) include for the first time SB [28]. This could be seen as a huge milestone in the research field's journey to maturity. However, it is advisable to reflect upon the research field's credibility. Even though the WHO recommends breaking up SB by any kind of physical activity and not by standing, the definition of SB was adopted from the Sedentary Behavior Research Network. Thus, strictly spoken, it supports implicitly the message that SB can be broken up by standing. Based on the available evidence collected with physical activity sensors [124], it is advisable not to recommend a reduction of the sitting time as done, for example, in the American guidelines (*move more and sit less* [225, p. 2025]). However, in doing so, SB could be seen as the lower end of the physical activity spectrum, questioning its posture component [23]. In fact, the inclusion of SB in the physical activity guidelines reflects more an inclusion of minPA than an inclusion of SB. The WHO is thus advised to remove the posture component from the guideline definition or to replace SB with minPA to comply with the available evidence.

6 CONCLUSIONS

- A thigh accelerometer calibrated to classify sitting and minimal-intensity physical activity simultaneously should be the method of choice to measure sedentary behaviour with a single body-worn sensor. The waist is an equally valid alternative only in case an inertial-measurement-unit is used.

- The ActiGraph counts-per-minute cut-points measure minimal-intensity physical activity, and neither sedentary behaviour nor sitting. However, wearing the sensor on the waist systematically underestimates physical activity while sitting compared to standing, which is why posture specific cut-points should be used: 75 counts-per-minute for sitting, and 150 counts-per-minute for standing (vertical axis).

- Standing workplace interventions should be investigated with a combined posture and physical activity classification. Active workplace interventions should not be investigated with the methods examined here.

- POPAI, the Posture and Physical Activity Index, should be the method of choice to measure sedentary behaviour. POPAI combines the proprietary data processing of a thigh-worn activPAL with a waist-worn ActiGraph, and has a sensitivity and specificity of 92.5% and 91.9% to measure sedentary behaviour compliant with its definition.

- Sedentary behaviour accounts for 45% of the wake-time and is not as omnipresent as the measurement of posture or physical activity suggests (≥55%). The overestimation of posture (30.3%) and physical activity sensors (22.5%) can be explained by active sitting and inactive standing, both of which take about 2 hours per day, with large inter-individual variation. The overestimation of the single sensors aggravates when analysing sedentary time spent in long bouts.

- There is a lack of evidence for the relevance of the posture component of SB. The sedentary behaviour guidelines should thus be interpreted as recommendations to reduce minimal-intensity physical activity. The World Health Organization is advised to remove the posture component from the guideline definition or to change the wording from sedentary behaviour to minimal-intensity physical activity to comply with the available evidence. If the posture and the physical activity component are relevant, one could expect a much stronger relationship between sedentary behaviour and detrimental health effects.

- It is recommended to replace the metabolic equivalent in the sedentary behaviour definition with the resting metabolic rate to account for individual and environmental factors.

- Research needs to stop mixing sedentary behaviour, minimal-intensity physical activity, and sitting to clarify the relevance of each behaviour to human health.

7 POINTS OF PERSPECTIVE

- There is a need to use POPAI to measure sedentary behaviour in all kinds of studies all over the research field. Numerous studies already recorded data with the two sensors [6, 137, 162, 184, 213]. These studies are advised to repeat their analyses with POPAI to uncover the true relevance of sedentary behaviour, minimal-intensity physical activity, and sitting. Detailed instructions on how to use POPAI are published in the supplementary online material of Paper V.

- There is nothing more obvious than calibrating an activPAL to measure minimal-intensity physical activity. The thigh is the recommended placement to measure sedentary behaviour, and the activPAL is an established and highly valid thigh sensor to measure sitting in an event-based manner. With POPAI as a reference, the same data as in Study III can be used. The additional participants of Study V could serve as the population for validating both, the new activPAL activity algorithm and the ActiGraph posture algorithm developed in Study III. This study will tell whether one can reduce POPAI and thus the measurement of sedentary behaviour to only one sensor. Expect to see this study published soon.

- There is a need to validate the methods developed here before applying them in future field studies. The validation should ideally take place in free-living, although the use of valid reference criteria for the physical activity classification is not without limitation. Indirect calorimetry requires a steady state to draw valid conclusions about physical activity. However, there are algorithms addressing this issue in other research areas that might be applicable to sedentary behaviour [152, 214]. An alternative to overcome the pragmatic decisions required when creating a controlled environment is to use POPAI as a best-available reference method. The validation should include an assessment of reliability, and both should be investigated with respect to the participant characteristics (e.g. gender, job type). If the validity is deemed insufficient for a future application or if the algorithms are used with sensors other than those used here, the algorithms shall be recalibrated.

- There is a need to compare the data (i.e. signal features) collected in controlled environments and free-living. Such a study might explain the cause for the validity drop when moving from the calibration to the validation. The study might also identify features that remain stable to be recommended for future method developments in controlled settings. Furthermore, detailed misclassification analyses of new methods in free-living (e.g. in Study III with the help of POPAI) might further advance the knowledge to develop more valid classification algorithms in the future.

- There is a need to investigate why the raw data of the activPAL and the ActiGraph have a temporal mismatch, and why no one else reported on it previously.

8 PERSONAL CONCLUSIONS

A bicycle ride around the world ends with a single pedal stroke, but this very last pedal stroke will not be your last. My pedals already started to spin again – well, they never stopped – with the activPAL calibration. As soon as I finish the study, I will enjoy all the pedal strokes between Stockholm and Winterthur. I cannot wait to feel every single of them.

I started my sedentary research to measure active sitting on our self-developed office chair and ended up trying to **solve the myth of why we are able to measure inactive sitting but not active sitting**. The answer was, unfortunately, quite disappointing: We could neither measure inactive sitting nor active sitting, at least before POPAI. Accordingly, I am very proud to contribute with POPAI and this thesis as a whole to the knowledge about measuring physical (in-)activity while sitting. In fact, I was very surprised about the large numbers POPAI displayed for active sitting – an astonishing 2 hours a day! From the randomised controlled trial with the office workers from the local insurance company and the couple-of-sensors-video-camera-three-chairs-workmate-algorithm, the only reason why I even suspected that there is such a thing as active sitting, I expected to see around 5% or 45 minutes per day at maximum. With the knowledge and skills I gathered during this thesis, however, it might be worth to reanalyse the data with a better algorithm from Study II. From Study IV, I now know that the moveable seat can make a difference in terms of physical activity and break up sedentary behaviour if the chair is actively used. However, whether office workers use it actively in everyday office remains a question for my future work.

As a movement scientist, I am trained to question whether I measure what I claim to measure. On a very detailed level, this can quickly turn into a never-ending story, and there are pragmatic decisions to be made and uncertainties to be accepted. I made and accepted a couple of them myself while conducting this thesis. However, I was repeatedly surprised how the sedentary research field handles this issue. One chapter in this thesis is about the evolution of the sedentary behaviour definition, including changes in the definition while I conducted this thesis. Another chapter is about the state-of-the-art measurement of sedentary behaviour, describing methods developed more than a decade ago. Interestingly, revising the definition had absolutely no influence on how the behaviour is measured. From my movement science perspective, I consider the best and most reasonable behaviour definition to be useless as long as we are not able to measure the behaviour. There is even the risk to stipulate recommendations (*move more and sit less*) that might not hold true when we might once be able to measure what we already claim to measure. On the other hand, I also consider the best and most valid method to be useless as long as there is no simple way to use it. Dozens of methods have been developed in the last couple of years with sophisticated algorithms (including here), but hardly any has been validated, let alone used in a field study. With that in mind, I see a lot of work for a movement scientist in the field of sedentary behaviour, and I will continue pedalling once I arrive in Winterthur. Wherever the pedals will take me, *a bicycle ride from Stockholm to Winterthur ends with a single pedal stroke, but this very last pedal stroke will not be my last.*

9 ACKNOWLEDGEMENTS

This thesis would just be a random selection of 27’259 words consisting of 176’474 characters without the amazing support I got. A huge **tack så mycket** and **merci villmal** to all of you:

Wim. First, you are a fantastic friend. I highly appreciate the time we spent together, having so much fun whatever we did. Second, you are a terrible Ping-Pong player, and I still do not know why I wrote this thesis myself. Third, I will never forget that you did not believe I catch a fish. I proved you wrong ☺. Fourth and foremost important for this thesis, you are an amazing supervisor and mentor, teaching me all the stuff you won't learn from a textbook, although they make up the life as a researcher. Just as behaviour has a plethora of components and facets, so did your contribution. Thanks for the great time and for backpacking me with all those skills.

Maria. I never forget when Wim recommended including one of his highly skilled heads. As announced, you were the highly skilled expert I needed to conduct this project. Your input was concise, precise, and regularly a trigger to bring me on the right track. Tusen tack!

Daniel. You started your contribution way too early (the IAAF would have disqualified you for a false-start). Way too early for this thesis, but not for me. I do not know where I would be today if you had not supported and promoted me back in the days. A massive thank for your countless contributions over the last nine (!) years. You gave me the right support at the right time, and became a very good friend. On all the projects that are yet to come…

rotavis with **Daniel and Lukas.** What a crazy idea to develop our own office chair. I still cannot believe what we did. With all those nightshifts, chair-travels, pizzas…

Örjan, Victoria, and the entire team at GIH involved in the Brain Health Study. What an amazing, straightforward collaboration. If I have to explain what a perfect collaboration looks like, I cannot avoid our example. Many thanks to all of you.

Mirco, Silas, and Walter. Another crazy idea. Develop our own device to measure sedentary behaviour. We walked from challenge to challenge, but we mastered all of them!

Björn. Thanks for being my Nordic mentor. The *Svensk Klassiker* is still on my bucket list. **Christoph**. Thanks for being my Southern mentor. You made me believe that a PhD abroad is doable. What a pity we never met up in the north.

All my fellow PhD students joining me on the road to perdition: Andreas, Anna, Axel, Elena, Emelie, Fabian, Hanna, Ingrid, John, Malin, Pernilla, Sebastian, Sheila …

All my mates at the Institute of Mechanical Systems. Adrian, Benny, Bernd, Bruno, Dario, Dominik, Erika, Jonas, Lea alias Benny 2.0, Lukas, Markus, Michaela, Roger, Rolli, Röni, Steffi. You made work so much fun. @ Luki, Benny, und Bruno, Hulftegg dä Dunnschtig?

Annette, Balbir, Catty, Ellinor, Kathrin, Martina. Always there if I had a stupid question (yes, I had plenty of them). Thanks for making my student life so much easier.

Birgitta, Carina, Christina, Elena, Eva, Gabriele, Graciela, Lena, Marie, Wim, Åsa. Thank you for including me in your research group, for letting me contribute to the amazing review of reviews, and for providing me with so much valuable input on my kappa. Tack så mycket och ledsen för min dåliga svenska.

Division of Physiotherapy. I met so many amazing people, had so many inspiring discussions, and learned so much. A huge thank you for letting me be a part of it. **Karolinska Institutet**. I do not know how much work I caused you, but I know I appreciate every bit of it. **School of Engineering** at the Zurich University of Applied Sciences, particularly Jürg, Egon, Martina, and Robert. This thesis would not exist without your commitment. **Swiss National Science Foundation**. The Doc.Mobility made so much possible. I would not be at the place I am without you (right now in home-office at Alfred Nobels Allé 33). Thanks to P1SKP3_187637.

Lucian. Thanks for being my Swedish buddy and Ping-Pong sparring partner, or shall I say, victim? I will always remember that *a comeback is pointless if you don't make it*.

Andreas and Riccardo. Thanks for your critical input on my kappa. **Anton and Pluto**. You are the guys, even though you lived in the wrong countries. Please forgive me. **Cahit**. Thanks for being my software buddy. **Clare**. Thanks for all the inspiring seminars about the sense and non-sense of science. **COVID-19**. I would have preferred to live without you, but you taught me stuff I would never have learned without you, like throwing a research plan on a Wednesday afternoon overboard, almost exactly one year before dissertation, just to come up on Thursday morning with a new one. **Joanna**. Thanks for asking me to apply my processing skills to your data. I learned so much and got the feeling that my skills could help to draw the big picture. **Liyun**. Thanks for connecting me with Örjan, the basis for two-fifths of this work. **Meitschi**. Ich danke dir. **Page 8**. The only page that will never have a bug. We loved you. What a pity you left. **Paul the Beast**. *It takes an hour to learn, but a lifetime to master*. **Rike and Geri**. Thanks for showing me all those remote places in the countryside of Stockholm and Södermanland. **uMove** with **Anna, David, Erika**. Thank you for the activPAL. It was literally the last piece of the puzzle I needed to start the validation study I stopped a couple of days later.

Ingrid, Fabian, Jeanette, Thiago, Kaleo, Martin, Peter, and **Ernst, Judith, Mäge, Geraldine**. Even though I left, I was always there. You are family. Thanks for keeping my focus away from sedentary behaviour even when we were sedentary. Looking forward to you.

Mami. Du häsch mir all die Fähigkeite bihbracht, demit ich hüt da stahn, won ich stahn. Danke villmal, dass du immer zu mier gstande bisch.

The last author of a scientific publication takes a special role, as does the last person to whom my thank belongs. **Mary**. Last in this enumeration, first in my life. Whenever I need you, you are there. No matter where I am, and no matter where you are. Home is where you are, and I would like to grow old with you, but there is no hurry. Even if this work turns out to be useless for research, it is among the reasons we met and thus priceless.

10 REFERENCES

1. Kuster RP, Bauer CM, Oetiker S, and Kool J. *Physiological Motion Axis for the Seat of a Dynamic Office Chair*. Hum Factors. 2016;58(6):886-98.
2. Kuster RP, Bauer CM, Gossweiler L, and Baumgartner D. *Active Sitting with Backrest Support: Is It Feasible?* Ergonomics. 2018;61(12):1685-95.
3. Bauer CM, Rast FM, Bock C, Kuster RP, and Baumgartner D. *Determination of a Sagittal Plane Axis of Rotation for a Dynamic Office Chair*. Appl Ergon. 2018;72:107-12.
4. Kuster RP, Bauer CM, and Baumgartner D. *Is Active Sitting on a Dynamic Office Chair Controlled by the Trunk Muscles?* PLoS One. 2020;15(11):e0242854.
5. Hagströmer M, Troiano RP, Sjostrom M, and Berrigan D. *Levels and Patterns of Objectively Assessed Physical Activity - a Comparison between Sweden and the United States*. Am J Epidemiol. 2010;171(10):1055-64.
6. Matthews CE, Kozey-Keadle S, Moore SC, Schoeller DS, Carroll RJ, Troiano RP, et al. *Measurement of Active and Sedentary Behavior in Context of Large Epidemiologic Studies*. Med Sci Sports Exerc. 2018;50(2):266-76.
7. Santos DA, Judice PB, Magalhaes JP, Correia IR, Silva AM, Baptista F, et al. *Patterns of Accelerometer-Derived Sedentary Time across the Lifespan*. J Sports Sci. 2018;36(24):2809-17.
8. Johansson MS, Korshoj M, Schnohr P, Marott JL, Prescott EIB, Sogaard K, et al. *Time Spent Cycling, Walking, Running, Standing and Sedentary: A Cross-Sectional Analysis of Accelerometer-Data from 1670 Adults in the Copenhagen City Heart Study: Physical Behaviours among 1670 Copenhageners*. BMC Public Health. 2019;19(1):1370.
9. Moreno-Llamas A, García-Mayor J, and De la Cruz-Sánchez E. *The Impact of Digital Technology Development on Sitting Time across Europe*. Technol Soc. 2020;63:101406.
10. Katzmarzyk PT, Powell KE, Jakicic JM, Troiano RP, Piercy K, Tennant B, et al. *Sedentary Behavior and Health: Update from the 2018 Physical Activity Guidelines Advisory Committee*. Med Sci Sports Exerc. 2019;51(6):1227-41.
11. de Rezende LF, Rodrigues Lopes M, Rey-Lopez JP, Matsudo VK, and Luiz Odo C. *Sedentary Behavior and Health Outcomes: An Overview of Systematic Reviews*. PLoS One. 2014;9(8):e105620.
12. Dempsey PC, Biddle SJH, Buman MP, Chastin S, Ekelund U, Friedenreich CM, et al. *New Global Guidelines on Sedentary Behaviour and Health for Adults: Broadening the Behavioural Targets*. Int J Behav Nutr Phys Act. 2020;17(1):151.
13. Patterson R, McNamara E, Tainio M, de Sa TH, Smith AD, Sharp SJ, et al. *Sedentary Behaviour and Risk of All-Cause, Cardiovascular and Cancer Mortality, and Incident Type 2 Diabetes: A Systematic Review and Dose Response Meta-Analysis*. Eur J Epidemiol. 2018;33(9):811-29.
14. Zhao R, Bu W, Chen Y, and Chen X. *The Dose-Response Associations of Sedentary Time with Chronic Diseases and the Risk for All-Cause Mortality Affected by Different Health Status: A Systematic Review and Meta-Analysis*. J Nutr Health Aging. 2020;24(1):63-70.
15. Ekelund U, Tarp J, Steene-Johannessen J, Hansen BH, Jefferis B, Fagerland MW, et al. *Dose-Response Associations between Accelerometry Measured Physical Activity and Sedentary Time and All Cause Mortality: Systematic Review and Harmonised Meta-Analysis*. BMJ. 2019;366:l4570.
16. de Rezende LFM, Sa TH, Mielke GI, Viscondi JYK, Rey-Lopez JP, and Garcia LMT. *All-Cause Mortality Attributable to Sitting Time: Analysis of 54 Countries Worldwide*. Am J Prev Med. 2016;51(2):253-63.
17. Chau JY, Grunseit AC, Chey T, Stamatakis E, Brown WJ, Matthews CE, et al. *Daily Sitting Time and All-Cause Mortality: A Meta-Analysis*. PLoS One. 2013;8(11):e80000.
18. Ekelund U, Tarp J, Fagerland MW, Johannessen JS, Hansen BH, Jefferis BJ, et al. *Joint Associations of Accelerometer Measured Physical Activity and Sedentary Time with All-Cause*

Mortality: A Harmonised Meta-Analysis in More Than 44 000 Middle-Aged and Older Individuals. Br J Sports Med. 2020;54(24):1499-506.

19. Benatti FB, and Ried-Larsen M. *The Effects of Breaking up Prolonged Sitting Time: A Review of Experimental Studies*. Med Sci Sports Exerc. 2015;47(10):2053-61.
20. Chastin SF, Egerton T, Leask C, and Stamatakis E. *Meta-Analysis of the Relationship between Breaks in Sedentary Behavior and Cardiometabolic Health*. Obesity (Silver Spring). 2015;23(9):1800-10.
21. Saunders TJ, Atkinson HF, Burr J, MacEwen B, Skeaff CM, and Peddie MC. *The Acute Metabolic and Vascular Impact of Interrupting Prolonged Sitting: A Systematic Review and Meta-Analysis*. Sports Med. 2018;48(10):2347-66.
22. Loh R, Stamatakis E, Folkerts D, Allgrove JE, and Moir HJ. *Effects of Interrupting Prolonged Sitting with Physical Activity Breaks on Blood Glucose, Insulin and Triacylglycerol Measures: A Systematic Review and Meta-Analysis*. Sports Med. 2020;50(2):295-330.
23. Stamatakis E, Ekelund U, Ding D, Hamer M, Bauman AE, and Lee IM. *Is the Time Right for Quantitative Public Health Guidelines on Sitting? A Narrative Review of Sedentary Behaviour Research Paradigms and Findings*. Br J Sports Med. 2019;53(6):377-82.
24. Diaz KM, Howard VJ, Hutto B, Colabianchi N, Vena JE, Safford MM, et al. *Patterns of Sedentary Behavior and Mortality in U.S. Middle-Aged and Older Adults: A National Cohort Study*. Ann Intern Med. 2017;167(7):465-75.
25. Evenson KR, Herring AH, and Wen F. *Accelerometry-Assessed Latent Class Patterns of Physical Activity and Sedentary Behavior with Mortality*. Am J Prev Med. 2017;52(2):135-43.
26. Dohrn IM, Kwak L, Oja P, Sjostrom M, and Hagströmer M. *Replacing Sedentary Time with Physical Activity: A 15-Year Follow-up of Mortality in a National Cohort*. Clin Epidemiol. 2018;10:179-86.
27. Dempsey PC, Matthews CE, Dashti SG, Doherty AR, Bergouignan A, van Roekel EH, et al. *Sedentary Behavior and Chronic Disease: Mechanisms and Future Directions*. J Phys Act Health. 2020;17(1):52-61.
28. Bull FC, Al-Ansari SS, Biddle S, Borodulin K, Buman MP, Cardon G, et al. *World Health Organization 2020 Guidelines on Physical Activity and Sedentary Behaviour*. Br J Sports Med. 2020;54(24):1451-62.
29. OECD. *OECD Labour Force Statistics 2017*.2018.
30. Arbetsmiljö Verket. *Arbetsmiljön 2017, Rap 2018:2 (the Work Environment 2017)*. Arbetsmiljö Verket; 2018.
31. Yang L, Cao C, Kantor ED, Nguyen LH, Zheng X, Park Y, et al. *Trends in Sedentary Behavior among the US Population, 2001-2016*. JAMA. 2019;321(16):1587-97.
32. Clemes SA, O'Connell SE, and Edwardson CL. *Office Workers' Objectively Measured Sedentary Behavior and Physical Activity During and Outside Working Hours*. J Occup Environ Med. 2014;56(3):298-303.
33. Nooijen C, Kallings L, Blom V, Ekblom O, Forsell Y, and Ekblom M. *Common Perceived Barriers and Facilitators for Reducing Sedentary Behaviour among Office-Workers*. Int J Environ Res Public Health. 2018;15(4):792.
34. Prince SA, Roberts KC, Reed JL, Biswas A, Colley RC, and Thompson W. *Daily Physical Activity and Sedentary Behaviour across Occupational Classifications in Canadian Adults*. Health Rep. 2020;31(9):13-26.
35. Parry S, and Straker L. *The Contribution of Office Work to Sedentary Behaviour Associated Risk*. BMC Public Health. 2013;13:296.
36. Ryan CG, Dall PM, Granat MH, and Grant PM. *Sitting Patterns at Work: Objective Measurement of Adherence to Current Recommendations*. Ergonomics. 2011;54(6):531-8.

37. Johansson E, Mathiassen SE, Lund Rasmusse C, and Hallman DM. *Sitting, Standing and Moving During Work and Leisure among Male and Female Office Workers of Different Age: A Compositional Data Analysis*. BMC Public Health. 2020;20(1):826.

38. Gorman E, Ashe MC, Dunstan DW, Hanson HM, Madden K, Winkler EAH, et al. *Does an 'Activity-Permissive' Workplace Change Office Workers' Sitting and Activity Time?* PLoS One. 2013;8(10):e76723.

39. Prince SA, Elliott CG, Scott K, Visintini S, and Reed JL. *Device-Measured Physical Activity, Sedentary Behaviour and Cardiometabolic Health and Fitness across Occupational Groups: A Systematic Review and Meta-Analysis*. Int J Behav Nutr Phys Act. 2019;16(1):30.

40. Vallance JK, Gardiner PA, Lynch BM, D'Silva A, Boyle T, Taylor LM, et al. *Evaluating the Evidence on Sitting, Smoking, and Health: Is Sitting Really the New Smoking?* Am J Public Health. 2018;108(11):1478-82.

41. Chau JY, Reyes-Marcelino G, Burnett AC, Bauman AE, and Freeman B. *Hyping Health Effects: A News Analysis of the 'New Smoking' and the Role of Sitting*. Br J Sports Med. 2019;53(16):1039-40.

42. Buckley JP, Hedge A, Yates T, Copeland RJ, Loosemore M, Hamer M, et al. *The Sedentary Office: An Expert Statement on the Growing Case for Change Towards Better Health and Productivity*. Br J Sports Med. 2015;49(21):1357-62.

43. Nguyen P, Le LK, Nguyen D, Gao L, Dunstan DW, and Moodie M. *The Effectiveness of Sedentary Behaviour Interventions on Sitting Time and Screen Time in Children and Adults: An Umbrella Review of Systematic Reviews*. Int J Behav Nutr Phys Act. 2020;17(1):117.

44. Peachey MM, Richardson J, A VT, Dal-Bello Haas V, and Gravesande J. *Environmental, Behavioural and Multicomponent Interventions to Reduce Adults' Sitting Time: A Systematic Review and Meta-Analysis*. Br J Sports Med. 2020;54(6):315-25.

45. Shrestha N, Kukkonen-Harjula KT, Verbeek JH, Ijaz S, Hermans V, and Pedisic Z. *Workplace Interventions for Reducing Sitting at Work*. Cochrane Database Syst Rev. 2018;6(6):CD010912.

46. Ojo SO, Bailey DP, Chater AM, and Hewson DJ. *The Impact of Active Workstations on Workplace Productivity and Performance: A Systematic Review*. Int J Environ Res Public Health. 2018;15(3):417.

47. Sui WY, Smith ST, Fagan MJ, Rollo S, and Prapavessis H. *The Effects of Sedentary Behaviour Interventions on Work-Related Productivity and Performance Outcomes in Real and Simulated Office Work: A Systematic Review*. Appl Ergon. 2019;75:27-73.

48. Burns J, Forde C, and Dockrell S. *Energy Expenditure of Standing Compared to Sitting While Conducting Office Tasks*. Hum Factors. 2017;59(7):1078-87.

49. Gao Y, Silvennoinen M, Pesola AJ, Kainulainen H, Cronin NJ, and Finni T. *Acute Metabolic Response, Energy Expenditure, and EMG Activity in Sitting and Standing*. Med Sci Sports Exerc. 2017;49(9):1927-34.

50. Gibbs BB, Kowalsky RJ, Perdomo SJ, Grier M, and Jakicic JM. *Energy Expenditure of Deskwork When Sitting, Standing or Alternating Positions*. Occup Med (Lond). 2017;67(2):121-7.

51. Monnard CR, and Miles-Chan JL. *Energy Cost of Standing in a Multi-Ethnic Cohort: Are Energy-Savers a Minority or the Majority?* PLoS One. 2017;12(1):e0169478.

52. Miles-Chan JL, and Dulloo AG. *Posture Allocation Revisited: Breaking the Sedentary Threshold of Energy Expenditure for Obesity Management*. Front Physiol. 2017;8:420.

53. Mansoubi M, Pearson N, Biddle SJ, and Clemes SA. *Using Sit-to-Stand Workstations in Offices: Is There a Compensation Effect?* Med Sci Sports Exerc. 2016;48(4):720-5.

54. Renaud LR, Huysmans MA, van der Ploeg HP, Spekle EM, and van der Beek AJ. *Natural Patterns of Sitting, Standing and Stepping During and Outside Work-Differences between Habitual Users and Non-Users of Sit-Stand Workstations*. Int J Environ Res Public Health. 2020;17(11):4075.

55. MacEwen BT, MacDonald DJ, and Burr JF. *A Systematic Review of Standing and Treadmill Desks in the Workplace*. Prev Med. 2015;70:50-8.

56. Backe EM, Kreis L, and Latza U. *Interventions at the Workplace That Stimulate Changes in Sitting Behavior. Review and Assessment*. Zentralbl Arbeitsmed Arteitsschutz Ergon. 2019;69(1):1-10.

57. Koepp GA, Moore GK, and Levine JA. *Chair-Based Fidgeting and Energy Expenditure*. BMJ Open Sport Exerc Med. 2016;2(1):e000152.

58. Tudor-Locke C, Schuna JM, Jr., Frensham LJ, and Proenca M. *Changing the Way We Work: Elevating Energy Expenditure with Workstation Alternatives*. Int J Obes. 2014;38(6):755-65.

59. Cao C, Liu Y, Zhu W, and Ma J. *Effect of Active Workstation on Energy Expenditure and Job Performance: A Systematic Review and Meta-Analysis*. J Phys Act Health. 2016;13(5):562-71.

60. Podrekar N, Kozinc Z, and Sarabon N. *The Effects of Cycle and Treadmill Desks on Work Performance and Cognitive Function in Sedentary Workers: A Review and Meta-Analysis*. Work. 2020;65(3):537-45.

61. Hutcheson AK, Piazza AJ, and Knowlden AP. *Work Site-Based Environmental Interventions to Reduce Sedentary Behavior: A Systematic Review*. Am J Health Promot. 2018;32(1):32-47.

62. Howarth A, Quesada J, Silva J, Judycki S, and Mills PR. *The Impact of Digital Health Interventions on Health-Related Outcomes in the Workplace: A Systematic Review*. Digit Health. 2018;4:18.

63. Stephenson A, McDonough SM, Murphy MH, Nugent CD, and Mair JL. *Using Computer, Mobile and Wearable Technology Enhanced Interventions to Reduce Sedentary Behaviour: A Systematic Review and Meta-Analysis*. Int J Behav Nutr Phys Act. 2017;14(1):105.

64. Holtermann A, Schellewald V, Mathiassen SE, Gupta N, Pinder A, Punakallio A, et al. *A Practical Guidance for Assessments of Sedentary Behavior at Work: A PEROSH Initiative*. Appl Ergon. 2017;63:41-52.

65. Weyer C, Linkeschowa R, Heise T, Giesen HT, and Spraul M. *Implications of the Traditional and the New ACSM Physical Activity Recommendations on Weight Reduction in Dietary Treated Obese Subjects*. Int J Obes. 1998;22(11):1071-8.

66. Bernstein MS, Morabia A, and Sloutskis D. *Definition and Prevalence of Sedentarism in an Urban Population*. Am J Public Health. 1999;89(6):862-7.

67. Bennett JA, Winters-Stone K, Nail LM, and Scherer J. *Definitions of Sedentary in Physical-Activity-Intervention Trials: A Summary of the Literature*. J Aging Phys Act. 2006;14(4):456-77.

68. Pate RR, O'Neill JR, and Lobelo F. *The Evolving Definition of "Sedentary"*. Exerc Sport Sci Rev. 2008;36(4):173-8.

69. Online Etymology Dictionary. *Sedentary (Adj.)*. https://www.etymonline.com/word/sedentary: Online Etymology Dictionary, Accessed 31 Oct. 2020.

70. Gibbs BB, Hergenroeder AL, Katzmarzyk PT, Lee IM, and Jakicic JM. *Definition, Measurement, and Health Risks Associated with Sedentary Behavior*. Med Sci Sports Exerc. 2015;47(6):1295-300.

71. Owen N, Leslie E, Salmon J, and Fotheringham MJ. *Environmental Determinants of Physical Activity and Sedentary Behavior*. Exerc Sport Sci Rev. 2000;28(4):153-8.

72. Marshall SJ, and Ramirez E. *Reducing Sedentary Behavior: A New Paradigm in Physical Activity Promotion*. Am J Lifestyle Med. 2011;5(6):518-30.

73. Sedentary Behavior Research Network. *Letter to the Editor: Standardized Use of the Terms "Sedentary" and "Sedentary Behaviours"*. Appl Physiol Nutr Metab. 2012;37(3):540-2.

74. Tremblay MS, Aubert S, Barnes JD, Saunders TJ, Carson V, Latimer-Cheung AE, et al. *Sedentary Behavior Research Network (SBRN) - Terminology Consensus Project Process and Outcome*. Int J Behav Nutr Phys Act. 2017;14(1):75.

75. Kozey S, Lyden K, Staudenmayer J, and Freedson P. *Errors in MET Estimates of Physical Activities Using 3.5 $ml{\cdot}kg^{-1}{\cdot}min^{-1}$ as the Baseline Oxygen Consumption*. J Phys Act Health. 2010;7(4):508-16.

76. Ainsworth BE, Haskell W, Leon AS, Jacobs DR, Montoye HJ, Sallis JF, et al. *Compendium of Physical Activities: Classification of Energy Costs of Human Physical Activities.* Med Sci Sports Exerc. 1993;25(1):71-80.

77. Jette M, Sidney K, and Blumchen G. *Metabolic Equivalents (METS) in Exercise Testing, Exercise Prescription, and Evaluation of Functional Capacity*. Clin Cardiol. 1990;13(8):555-65.

78. Garber CE, Blissmer B, Deschenes MR, Franklin Ba, Lamonte MJ, Lee IM, et al. *Quantity and Quality of Exercise for Developing and Maintaining Cardiorespiratory, Musculoskeletal, and Neuromotor Fitness in Apparently Healthy Adults: Guidance for Prescribing Exercise*. Med Sci Sports Exerc. 2011;43(7):1334-59.

79. Harris JA, and Benedict FG. *A Biometric Study of Human Basal Metabolism*. Proc Natl Acad Sci U S A. 1918;4(12):370-3.

80. McMurray RG, Soares J, Caspersen CJ, and McCurdy T. *Examining Variations of Resting Metabolic Rate of Adults: A Public Health Perspective*. Med Sci Sports Exerc. 2014;46(7):1352-8.

81. Kim D, Lee J, Park HK, Jang DP, Song S, Cho BH, et al. *Comparing the Standards of One Metabolic Equivalent of Task in Accurately Estimating Physical Activity Energy Expenditure Based on Acceleration*. J Sports Sci. 2017;35(13):1279-86.

82. Melzer K, Heydenreich J, Schutz Y, Renaud A, Kayser B, and Mader U. *Metabolic Equivalent in Adolescents, Active Adults and Pregnant Women*. Nutrients. 2016;8(7):438.

83. Warburton DER, Katzmarzyk PT, Rhodes RE, and Shephard RJ. *Evidence-Informed Physical Activity Guidelines for Canadian Adults*. Appl Physiol Nutr Metab. 2007;32(Suppl. 2E):S16-S68.

84. Troiano RP, Stamatakis E, and Bull FC. *How Can Global Physical Activity Surveillance Adapt to Evolving Physical Activity Guidelines? Needs, Challenges and Future Directions*. Br J Sports Med. 2020;54(24):1468-73.

85. Howley E. *Letter to the Editor (Comment): Errors in MET Estimates of Physical Activities Using 3.5 ml·kg⁻¹·min⁻¹ as the Baseline Oxygen Consumption*. J Phys Act Health. 2011;8(1):141-2.

86. Kozey-Keadle S, Lyden K, Staudenmayer J, and Freedson P. *Letter to the Editor (Author Reply): Errors in MET Estimates of Physical Activities Using 3.5 ml·kg⁻¹·min⁻¹ as the Baseline Oxygen Consumption*. J Phys Act Health. 2011;8(1):143-4.

87. Dumuid D, Pedisic Z, Palarea-Albaladejo J, Martin-Fernandez JA, Hron K, and Olds T. *Compositional Data Analysis in Time-Use Epidemiology: What, Why, How*. Int J Environ Res Public Health. 2020;17(7):2220.

88. Pedišić Ž, Dumuid D, and Olds T. *Integrating Sleep, Sedentary Behaviour, and Physical Activity Research in the Emerging Field of Time-Use Epidemiology: Definitions, Concepts, Statistical Methods, Theoretical Framework, and Future Directions*. Kinesiology. 2017;49(2):252-69.

89. Merriam-Webster Online Dictionary. *Sit*. https://www.merriam-webster.com/dictionary/sit: Merriam-Webster, Accessed 31 Oct. 2020.

90. Merriam-Webster Online Dictionary. *Stand*. https://www.merriam-webster.com/dictionary/stand: Merriam-Webster, Accessed 31 Oct. 2020.

91. Merriam-Webster Online Dictionary. *Locomotion*. https://www.merriam-webster.com/dictionary/locomotion: Merriam-Webster, Accessed 31 Oct. 2020.

92. Ndahimana D, and Kim EK. *Measurement Methods for Physical Activity and Energy Expenditure: A Review*. Clin Nutr Res. 2017;6(2):68-80.

93. Merriam-Webster Online Dictionary. *Sleep*. https://www.merriam-webster.com/dictionary/sleep: Merriam-Webster, Accessed 31 Oct. 2020.

94. Fekedulegn D, Andrew ME, Shi M, Violanti JM, Knox S, and Innes KE. *Actigraphy-Based Assessment of Sleep Parameters*. Ann Work Expo Health. 2020;64(4):350-67.

95. Troiano R, Pettee Gabriel K, Welk GJ, Owen N, and Sternfeld B. *Reported Physical Activity and Sedentary Behavior: Why Do You Ask?* J Phys Act Health. 2012;9(Suppl 1):S68-75.

96. Atkin AJ, Gorely T, Clemes SA, Yates T, Edwardson C, Brage S, et al. *Methods of Measurement in Epidemiology: Sedentary Behaviour*. Int J Epidemiol. 2012;41(5):1460-71.

97. Bakker EA, Hartman YAW, Hopman MTE, Hopkins ND, Graves LEF, Dunstan DW, et al. *Validity and Reliability of Subjective Methods to Assess Sedentary Behaviour in Adults: A Systematic Review and Meta-Analysis*. Int J Behav Nutr Phys Act. 2020;17(1):75.

98. Chau JY, van der Ploeg HP, van Uffelen JGZ, Wong J, Riphagen I, Healy GN, et al. *Are Workplace Interventions to Reduce Sitting Effective? A Systematic Review*. Prev Med. 2010;51(5):352-6.

99. van Uffelen JGZ, Wong J, Chau JY, van der Ploeg HP, Riphagen I, Gilson ND, et al. *Occupational Sitting and Health Risks: A Systematic Review*. Am J Prev Med. 2010;39(4):379-88.

100. Biswas A, Oh PI, Faulkner GE, Bajaj RR, Silver MA, Mitchell MS, et al. *Sedentary Time and Its Association with Risk for Disease Incidence, Mortality, and Hospitalization in Adults*. Ann Intern Med. 2015;162(2):123-32.

101. van der Ploeg HP, Chey T, Korda RJ, Banks E, and Bauman A. *Sitting Time and All-Cause Mortality Risk in 222 497 Australian Adults*. Arch Intern Med. 2012;172(6):494-500.

102. Chastin SFM, Dontje ML, Skelton DA, Cukic I, Shaw RJ, Gill JMR, et al. *Systematic Comparative Validation of Self-Report Measures of Sedentary Time against an Objective Measure of Postural Sitting (activPAL)*. Int J Behav Nutr Phys Act. 2018;15(1):21.

103. Prince SA, Cardilli L, Reed JL, Saunders TJ, Kite C, Douillette K, et al. *A Comparison of Self-Reported and Device Measured Sedentary Behaviour in Adults: A Systematic Review and Meta-Analysis*. Int J Behav Nutr Phys Act. 2020;17(1):31.

104. Boudet G, Chausse P, Thivel D, Rousset S, Mermillod M, Baker JS, et al. *How to Measure Sedentary Behavior at Work?* Front Public Health. 2019;7:167.

105. Sanders JP, Loveday A, Pearson N, Edwardson C, Yates T, Biddle SJH, et al. *Devices for Self-Monitoring Sedentary Time or Physical Activity: A Scoping Review*. J Med Internet Res. 2016;18(5):e90.

106. Kang M, and Rowe DA. *Issues and Challenges in Sedentary Behavior Measurement*. Meas Phys Educ Exerc Sci. 2015;19(3):105-15.

107. Bassett DR, Jr., John D, Conger SA, Rider BC, Passmore RM, and Clark JM. *Detection of Lying Down, Sitting, Standing, and Stepping Using Two activPAL Monitors*. Med Sci Sports Exerc. 2014;46(10):2025-9.

108. Kozey-Keadle S, Libertine A, Lyden K, Staudenmayer J, and Freedson PS. *Validation of Wearable Monitors for Assessing Sedentary Behavior*. Med Sci Sports Exerc. 2011;43(8):1561-7.

109. Kim Y, Barry VW, and Kang M. *Validation of the ActiGraph GT3X and activPAL Accelerometers for the Assessment of Sedentary Behavior*. Meas Phys Educ Exerc Sci. 2015;19(3):125-37.

110. Grant PM, Ryan CG, Tigbe WW, and Granat MH. *The Validation of a Novel Activity Monitor in the Measurement of Posture and Motion During Everyday Activities*. Br J Sports Med. 2006;40(12):992-7.

111. Stemland I, Ingebrigtsen J, Christiansen CS, Jensen BR, Hanisch C, Skotte J, et al. *Validity of the Acti4 Method for Detection of Physical Activity Types in Free-Living Settings: Comparison with Video Analysis*. Ergonomics. 2015;58(6):953-65.

112. Lyden K, Kozey Keadle SL, Staudenmayer JW, and Freedson PS. *Validity of Two Wearable Monitors to Estimate Breaks from Sedentary Time*. Med Sci Sports Exerc. 2012;44(11):2243-52.

113. Freedson PS, Melanson E, and Sirard J. *Calibration of the Computer Science and Applications, Inc. Accelerometer*. Med Sci Sports Exerc. 1998;30(5):777-81.

114. Brønd JC, Andersen LB, and Arvidsson D. *Generating ActiGraph Counts from Raw Acceleration Recorded by an Alternative Monitor*. Med Sci Sports Exerc. 2017;49(11):2351-60.

115. Rothney MP, Schaefer EV, Neumann MM, Choi L, and Chen KY. *Validity of Physical Activity Intensity Predictions by ActiGraph, Actical, and RT3 Accelerometers*. Obesity (Silver Spring). 2008;16(8):1946-52.

116. Kim Y, and Welk GJ. *Criterion Validity of Competing Accelerometry-Based Activity Monitoring Devices*. Med Sci Sports Exerc. 2015;47(11):2456-63.

117. Wetten AA, Batterham M, Tan SY, and Tapsell L. *Relative Validity of 3 Accelerometer Models for Estimating Energy Expenditure During Light Activity*. J Phys Act Health. 2014;11(3):638-47.

118. Migueles JH, Cadenas-Sanchez C, Ekelund U, Delisle Nystrom C, Mora-Gonzalez J, Lof M, et al. *Accelerometer Data Collection and Processing Criteria to Assess Physical Activity and Other Outcomes: A Systematic Review and Practical Considerations*. Sports Med. 2017;47(9):1821-45.

119. Lopes VP, Magalhães P, Bragada J, and C V. *Actigraph Calibration in Obese/Overweight and Type 2 Diabetes Mellitus Middle-Aged to Old Adult Patients*. J Phys Act Health. 2009;6(1):133-40.

120. Crouter SE, DellaValle DM, Haas JD, Frongillo EA, and Bassett DR. *Validity of ActiGraph 2-Regression Model and Matthews and NHANES and Cut-Points for Assessing Free-Living Physical Activity*. J Phys Act Health. 2013;10(4):504-14.

121. Clarke-Cornwell AM, Farragher TM, Cook PA, and Granat MH. *Empirically Derived Cut-Points for Sedentary Behaviour: Are We Sitting Differently?* Physiol Meas. 2016;37(10):1669-85.

122. Matthews CE, Chen KY, Freedson PS, Buchowski MS, Beech BM, Pate RR, et al. *Amount of Time Spent in Sedentary Behaviors in the United States, 2003-2004*. Am J Epidemiol. 2008;167(7):875-81.

123. Koster A, Shiroma EJ, Caserotti P, Matthews CE, Chen KY, Glynn NW, et al. *Comparison of Sedentary Estimates between activPAL and Hip- and Wrist-Worn ActiGraph*. Med Sci Sports Exerc. 2016;48(8):1514-22.

124. WHO. *WHO Guidelines on Physical Activity and Sedentary Behaviour: Web Annex Evidence Profiles*. 2020 (25 November).

125. Farrahi V, Niemela M, Kangas M, Korpelainen R, and Jamsa T. *Calibration and Validation of Accelerometer-Based Activity Monitors: A Systematic Review of Machine-Learning Approaches*. Gait Posture. 2019;68:285-99.

126. de Almeida Mendes M, da Silva ICM, Ramires VV, Reichert FF, Martins RC, and Tomasi E. *Calibration of Raw Accelerometer Data to Measure Physical Activity: A Systematic Review*. Gait Posture. 2018;61:98-110.

127. Narayanan A, Desai F, Stewart T, Duncan S, and Mackay L. *Application of Raw Accelerometer Data and Machine-Learning Techniques to Characterize Human Movement Behavior: A Systematic Scoping Review*. J Phys Act Health. 2020;17(3):360-83.

128. Montoye AHK, Pivarnik JM, Mudd LM, Biswas S, and Pfeiffer KA. *Validation and Comparison of Accelerometers Worn on the Hip, Thigh, and Wrists for Measuring Physical Activity and Sedentary Behavior*. AIMS Public Health. 2016;3(2):298-312.

129. Altini M, Penders J, Vullers R, and Amft O. *Estimating Energy Expenditure Using Body-Worn Accelerometers: A Comparison of Methods, Sensors Number and Positioning*. IEEE Journal of Biomedical and Health Informatics. 2015;19(1):219-26.

130. Kate RJ, Swartz AM, Welch WA, and Strath SJ. *Comparative Evaluation of Features and Techniques for Identifying Activity Type and Estimating Energy Cost from Accelerometer Data*. Physiol Meas. 2016;37(3):360-79.

131. Keadle SK, Lyden KA, Strath SJ, Staudenmayer JW, and Freedson PS. *A Framework to Evaluate Devices That Assess Physical Behavior*. Exerc Sport Sci Rev. 2019;47(4):206-14.

132. Troiano RP, McClain JJ, Brychta RJ, and Chen KY. *Evolution of Accelerometer Methods for Physical Activity Research*. Br J Sports Med. 2014;48(13):1019-23.

133. Freedson P, Bowles HR, Troiano R, and Haskell W. *Assessment of Physical Activity Using Wearable Monitors: Recommendations for Monitor Calibration and Use in the Field*. Med Sci Sports Exerc. 2012;44(1 Suppl 1):S1-4.

134. Liu S, Gao RX, and Freedson PS. *Computational Methods for Estimating Energy Expenditure in Human Physical Activities*. Med Sci Sports Exerc. 2012;44(11):2138-46.

135. Staudenmayer J, He S, Hickey A, Sasaki J, and Freedson P. *Methods to Estimate Aspects of Physical Activity and Sedentary Behavior from High-Frequency Wrist Accelerometer Measurements*. J Appl Physiol (1985). 2015;119(4):396-403.

136. Pavey TG, Gilson ND, Gomersall SR, Clark B, and Trost SG. *Field Evaluation of a Random Forest Activity Classifier for Wrist-Worn Accelerometer Data*. J Sci Med Sport. 2017;20(1):75-80.

137. Kerr J, Carlson J, Godbole S, Cadmus-Bertram L, Bellettiere J, and Hartman S. *Improving Hip-Worn Accelerometer Estimates of Sitting Using Machine Learning Methods*. Med Sci Sports Exerc. 2018;50(7):1518-24.

138. Skotte J, Korshoj M, Kristiansen J, Hanisch C, and Holtermann A. *Detection of Physical Activity Types Using Triaxial Accelerometers*. J Phys Act Health. 2014;11(1):76-84.

139. Hildebrand M, Hansen BH, van Hees VT, and Ekelund U. *Evaluation of Raw Acceleration Sedentary Thresholds in Children and Adults*. Scand J Med Sci Sports. 2017;27(12):1814-23.

140. Montoye AHK, Pivarnik JM, Mudd LM, Biswas S, and Pfeiffer KA. *Evaluation of the activPAL Accelerometer for Physical Activity and Energy Expenditure Estimation in a Semi-Structured Setting*. J Sci Med Sport. 2017;20(11):1003-7.

141. Montoye AH, Dong B, Biswas S, and Pfeiffer KA. *Validation of a Wireless Accelerometer Network for Energy Expenditure Measurement*. J Sports Sci. 2016;34(21):2130-9.

142. Zhang S, Murray P, Zillmer R, Eston RG, Catt M, and Rowlands AV. *Activity Classification Using the GENEA: Optimum Sampling Frequency and Number of Axes*. Med Sci Sports Exerc. 2012;44(11):2228-34.

143. Altini M, Casale P, Penders J, and Amft O. *Personalized Cardiorespiratory Fitness and Energy Expenditure Estimation Using Hierarchical Bayesian Models*. J Biomed Inform. 2015;56:195-204.

144. Welk GJ. *Principles of Design and Analyses for the Calibration of Accelerometry-Based Activity Monitors*. Med Sci Sports Exerc. 2005;37(11 Suppl):S501-11.

145. Lyden K, Keadle SK, Staudenmayer J, and Freedson PS. *A Method to Estimate Free-Living Active and Sedentary Behavior from an Accelerometer*. Med Sci Sports Exerc. 2014;46(2):386-97.

146. Kerr J, Patterson RE, Ellis K, Godbole S, Johnson E, Lanckriet G, et al. *Objective Assessment of Physical Activity: Classifiers for Public Health*. Med Sci Sports Exerc. 2016;48(5):951-7.

147. Montoye AHK, Westgate BS, Fonley MR, and Pfeiffer KA. *Cross-Validation and out-of-sample Testing of Physical Activity Intensity Predictions with a Wrist-Worn Accelerometer*. J Appl Physiol (1985). 2018;124(5):1284-93.

148. Davies A, Allman-Farinelli M, Owen K, Signal L, Hosking C, Wang L, et al. *Feasibility Study Comparing Physical Activity Classifications from Accelerometers with Wearable Camera Data*. Int J Environ Res Public Health. 2020;17(24):9323.

149. Ainsworth BE, Haskell WL, Herrmann SD, Meckes N, Bassett DR, Jr., Tudor-Locke C, et al. *2011 Compendium of Physical Activities: A Second Update of Codes and MET Values*. Med Sci Sports Exerc. 2011;43(8):1575-81.

150. Staudenmayer J, Pober D, Crouter S, Bassett D, and Freedson P. *An Artificial Neural Network to Estimate Physical Activity Energy Expenditure and Identify Physical Activity Type from an Accelerometer*. J Appl Physiol (1985). 2009;107(4):1300-7.

151. McLaughlin JE, King GA, Howley E, Bassett DR, and Ainsworth BE. *Validation of the Cosmed K4 B2 Portable Metabolic System*. Int J Sports Med. 2001;22(4):280-4.

152. Schwartz MH. *Protocol Changes Can Improve the Reliability of Net Oxygen Cost Data*. Gait Posture. 2007;26(4):494-500.

153. Ellis K, Kerr J, Godbole S, Lanckriet G, Wing D, and Marshall S. *A Random Forest Classifier for the Prediction of Energy Expenditure and Type of Physical Activity from Wrist and Hip Accelerometers*. Physiol Meas. 2014;35(11):2191-203.

154. van Hees VT, Golubic R, Ekelund U, and Brage S. *Impact of Study Design on Development and Evaluation of an Activity-Type Classifier*. J Appl Physiol (1985). 2013;114(8):1042-51.

155. Westerterp KR. *Physical Activity and Physical Activity Induced Energy Expenditure in Humans: Measurement, Determinants, and Effects*. Front Physiol. 2013;4:90.

156. Freedson PS, and John D. *Comment on "Estimating Activity and Sedentary Behavior from an Accelerometer on the Hip and Wrist"*. Med Sci Sports Exerc. 2013;45(5):962-3.

157. Ellis K, Kerr J, Godbole S, Staudenmayer J, and Lanckriet G. *Hip and Wrist Accelerometer Algorithms for Free-Living Behavior Classification*. Med Sci Sports Exerc. 2016;48(5):933-40.

158. Doherty A, Jackson D, Hammerla N, Plotz T, Olivier P, Granat MH, et al. *Large Scale Population Assessment of Physical Activity Using Wrist Worn Accelerometers: The UK Biobank Study*. PLoS One. 2017;12(2):e0169649.

159. Cleland I, Kikhia B, Nugent C, Boytsov A, Hallberg J, Synnes K, et al. *Optimal Placement of Accelerometers for the Detection of Everyday Activities*. Sensors (Basel). 2013;13(7):9183-200.

160. Atallah L, Lo B, King R, and Guang-Zhong Y. *Sensor Positioning for Activity Recognition Using Wearable Accelerometers*. IEEE Trans Biomed Circuits Syst. 2011;5(4):320-9.

161. Leskinen T, Pulakka A, Heinonen O, Pentti J, Kivimäki M, Vahtera J, et al. *Changes in Non-Occupational Sedentary Behaviours across the Retirement Transition: The Finnish Retirement and Aging (Firea) Study.* J Epidemiol Community Health. 2018;72(8):695-701.

162. Wahlstrom V, Bergman F, Ohberg F, Eskilsson T, Olsson T, and Jarvholm LS. *Effects of a Multicomponent Physical Activity Promoting Program on Sedentary Behavior, Physical Activity and Body Measures: A Longitudinal Study in Different Office Types*. Scand J Work Environ Health. 2019;45(5):493-504.

163. Ekelund U, Aman J, Yngve A, Renman C, Westerterp K, and Sjöström M. *Physical Activity but Not Energy Expenditure Is Reduced in Obese Adolescents: A Case-Control Study*. Am J Clin Nutr. 2002;76(5):935-41.

164. Crouter SE, Clowers KG, and Bassett DR, Jr. *A Novel Method for Using Accelerometer Data to Predict Energy Expenditure*. J Appl Physiol (1985). 2006;100(4):1324-31.

165. Hildebrand M, VT VANH, Hansen BH, and Ekelund U. *Age Group Comparability of Raw Accelerometer Output from Wrist- and Hip-Worn Monitors*. Med Sci Sports Exerc. 2014;46(9):1816-24.

166. Guyon I, and Elisseeff A. *An Introduction to Variable and Feature Selection*. J Mach Learn Res. 2003;3:1157-82.

167. Kate RJ. *Using Dynamic Time Warping Distances as Features for Improved Time Series Classification*. Data Min Knowl Discov. 2015;30(2):283-312.

168. Rosati S, Balestra G, and Knaflitz M. *Comparison of Different Sets of Features for Human Activity Recognition by Wearable Sensors*. Sensors (Basel). 2018;18(12):4189.

169. Fanchamps MHJ, van den Berg-Emons HJG, Stam HJ, and Bussmann JBJ. *Sedentary Behavior: Different Types of Operationalization Influence Outcome Measures*. Gait Posture. 2017;54:188-93.

170. Myers A, Gibbons C, Butler E, Dalton M, Buckland N, Blundell J, et al. *A Novel Integrative Procedure for Identifying and Integrating Three-Dimensions of Objectively Measured Free-Living Sedentary Behaviour*. BMC Public Health. 2017;17(1):979.

171. Ellingson LD, Schwabacher IJ, Kim Y, Welk GJ, and Cook DB. *Validity of an Integrative Method for Processing Physical Activity Data*. Med Sci Sports Exerc. 2016;48(8):1629-38.

172. Preece SJ, Goulermas JY, Kenney LP, Howard D, Meijer K, and Crompton R. *Activity Identification Using Body-Mounted Sensors - a Review of Classification Techniques*. Physiol Meas. 2009;30(4):R1-33.

173. Zhang S, Rowlands AV, Murray P, and Hurst TL. *Physical Activity Classification Using the GENEA Wrist-Worn Accelerometer*. Med Sci Sports Exerc. 2012;44(4):742-8.

174. Kim Y, Welk GJ, Braun SI, and Kang M. *Extracting Objective Estimates of Sedentary Behavior from Accelerometer Data: Measurement Considerations for Surveillance and Research Applications*. PLoS One. 2015;10(2):e0118078.

175. Granat MH. *Event-Based Analysis of Free-Living Behaviour*. Physiol Meas. 2012;33(11):1785-800.

176. Ellingson LD, Hibbing PR, Kim Y, Frey-Law LA, Saint-Maurice PF, and Welk GJ. *Lab-Based Validation of Different Data Processing Methods for Wrist-Worn ActiGraph Accelerometers in Young Adults*. Physiol Meas. 2017;38(6):1045-60.

177. Edwardson CL, Gorely T, Davies MJ, Gray LJ, Khunti K, Wilmot EG, et al. *Association of Sedentary Behaviour with Metabolic Syndrome: A Meta-Analysis*. PLoS One. 2012;7(4):e34916.

178. Dempsey PC, Larsen RN, Dunstan DW, Owen N, and Kingwell BA. *Sitting Less and Moving More: Implications for Hypertension*. Hypertension. 2018;72(5):1037-46.

179. Biddle SJH, Bennie JA, De Cocker K, Dunstan D, Gardiner PA, Healy GN, et al. *Controversies in the Science of Sedentary Behaviour and Health: Insights, Perspectives and Future Directions from the 2018 Queensland Sedentary Behaviour Think Tank*. Int J Environ Res Public Health. 2019;16(23):4762.

180. Stephens SK, Eakin EG, Clark BK, Winkler EAH, Owen N, LaMontagne AD, et al. *What Strategies Do Desk-Based Workers Choose to Reduce Sitting Time and How Well Do They Work? Findings from a Cluster Randomised Controlled Trial*. Int J Behav Nutr Phys Act. 2018;15(1):98.

181. Klepac Pogrmilovic B, O'Sullivan G, Milton K, Biddle SJH, Bauman A, Bull F, et al. *A Global Systematic Scoping Review of Studies Analysing Indicators, Development, and Content of National-Level Physical Activity and Sedentary Behaviour Policies*. Int J Behav Nutr Phys Act. 2018;15(1):123.

182. Rollo S, Antsygina O, and Tremblay MS. *The Whole Day Matters: Understanding 24-Hour Movement Guideline Adherence and Relationships with Health Indicators across the Lifespan*. J Sport Health Sci. 2020;9(6):493-510.

183. World Medical Association. *World Medical Association Declaration of Helsinki: Ethical Principles for Medical Research Involving Human Subjects*. JAMA. 2013;310(20):2191-4.

184. Nooijen CFJ, Blom V, Ekblom O, Ekblom MM, and Kallings LV. *Improving Office Workers' Mental Health and Cognition: A 3-Arm Cluster Randomized Controlled Trial Targeting Physical Activity and Sedentary Behavior in Multi-Component Interventions*. BMC Public Health. 2019;19(1):266.

185. Bland JM. *How Can I Decide the Sample Size for a Study of Agreement between Two Methods of Measurement?* 2004. Available from: https://www-users.york.ac.uk/~mb55/meas/sizemeth.htm, Accessed 07 February 2020.

186. Ellegast RP, Kraft K, Groenesteijn L, Krause F, Berger H, and Vink P. *Comparison of Four Specific Dynamic Office Chairs with a Conventional Office Chair: Impact Upon Muscle Activation, Physical Activity and Posture*. Appl Ergon. 2012;43(2):296-307.

187. Grooten WJA, Conradsson D, Ang BO, and Franzen E. *Is Active Sitting as Active as We Think?* Ergonomics. 2013;56(8):1304-14.

188. Grooten WJA, Ang BO, Hagstromer M, Conradsson D, Nero H, and Franzen E. *Does a Dynamic Chair Increase Office Workers' Movements? - Results from a Combined Laboratory and Field Study*. Appl Ergon. 2017;60:1-11.

189. Fullmer S, Benson-Davies S, Earthman CP, Frankenfield DC, Gradwell E, Lee PS, et al. *Evidence Analysis Library Review of Best Practices for Performing Indirect Calorimetry in Healthy and Non-Critically Ill Individuals*. J Acad Nutr Diet. 2015;115(9):1417-46.e2.

190. Compher C, Frankenfield D, Keim N, Roth-Yousey L, and Evidence Analysis Working G. *Best Practice Methods to Apply to Measurement of Resting Metabolic Rate in Adults: A Systematic Review*. J Am Diet Assoc. 2006;106(6):881-903.

191. Popp CJ, Tisch JJ, Sakarcan KE, Bridges WC, and Jesch ED. *Approximate Time to Steady-State Resting Energy Expenditure Using Indirect Calorimetry in Young, Healthy Adults*. Front Nutr. 2016;3:49.

192. Borges JH, Langer RD, Cirolini VX, Pascoa MA, Guerra-Junior G, and Goncalves EM. *Minimum Time to Achieve the Steady State and Optimum Abbreviated Period to Estimate the Resting Energy*

Expenditure by Indirect Calorimetry in Healthy Young Adults. Nutr Clin Pract. 2016;31(3):349-54.

193. Crouter SE, LaMunion SR, Hibbing PR, Kaplan AS, and Bassett DR, Jr. *Accuracy of the Cosmed K5 Portable Calorimeter*. PLoS One. 2019;14(12):e0226290.
194. Perez-Suarez I, Martin-Rincon M, Gonzalez-Henriquez JJ, Fezzardi C, Perez-Regalado S, Galvan-Alvarez V, et al. *Accuracy and Precision of the Cosmed K5 Portable Analyser*. Front Physiol. 2018;9:1764.
195. Weir JB. *New Methods for Calculating Metabolic Rate with Special Reference to Protein Metabolism*. J Physiol. 1949;109(1-2):1-9.
196. Hirschi S, and Huber M. *Erfassung des Energieverbrauchs am Arbeitsplatz Mittels Beschleunigungs- und Muskelsensoren*. Zurich University of Applied Sciences. 2018 (unpublished bachelor thesis).
197. Cain KL, Conway TL, Adams MA, Husak LE, and Sallis JF. *Comparison of Older and Newer Generations of ActiGraph Accelerometers with the Normal Filter and the Low Frequency Extension*. Int J Behav Nutr Phys Act. 2013;10:51.
198. Winkler EA, Bodicoat DH, Healy GN, Bakrania K, Yates T, Owen N, et al. *Identifying Adults' Valid Waking Wear Time by Automated Estimation in activPAL Data Collected with a 24h Wear Protocol*. Physiol Meas. 2016;37(10):1653-68.
199. Lyden K, John D, Dall P, and Granat MH. *Differentiating Sitting and Lying Using a Thigh-Worn Accelerometer*. Med Sci Sports Exerc. 2016;48(4):742-7.
200. Amirfaiz S, and Shahril MR. *Objectively Measured Physical Activity, Sedentary Behavior, and Metabolic Syndrome in Adults: Systematic Review of Observational Evidence*. Metab Syndr Relat Disord. 2019;17(1):1-21.
201. Dohrn IM, Sjostrom M, Kwak L, Oja P, and Hagströmer M. *Accelerometer-Measured Sedentary Time and Physical Activity - a 15 Year Follow-up of Mortality in a Swedish Population-Based Cohort*. J Sci Med Sport. 2018;21(7):702-7.
202. Kelly P, Fitzsimons C, and Baker G. *Should We Reframe How We Think About Physical Activity and Sedentary Behaviour Measurement? Validity and Reliability Reconsidered*. Int J Behav Nutr Phys Act. 2016;13:32.
203. Garner JB. *The Standard Error of Cohen's Kappa*. Stat Med. 1991;10(5):767-75.
204. Landis JR, and Koch GG. *The Measurement of Observer Agreement for Categorical Data.* Biometrics. 1977;33(1):159-74.
205. Bland J, and Altman D. *Measuring Agreement in Method Comparison Studies*. Stat Methods Med Res. 1999;8(2):135-60.
206. Endo K, Suzuki H, Nishimura H, Tanaka H, Shishido T, and Yamamoto K. *Sagittal Lumbar and Pelvic Alignment in the Standing and Sitting Positions*. J Orthop Sci. 2012;17(6):682-6.
207. Vähä-Ypyä H, Husu P, Suni J, Vasankari T, and Sievanen H. *Reliable Recognition of Lying, Sitting, and Standing with a Hip-Worn Accelerometer*. Scand J Med Sci Sports. 2018;28(3):1092-102.
208. Huberty J, Ehlers DK, Kurka J, Ainsworth B, and Buman M. *Feasibility of Three Wearable Sensors for 24 Hour Monitoring in Middle-Aged Women*. BMC Womens Health. 2015;15:55.
209. Kerr J, Marinac CR, Ellis K, Godbole S, Hipp A, Glanz K, et al. *Comparison of Accelerometry Methods for Estimating Physical Activity*. Med Sci Sports Exerc. 2017;49(3):617-24.
210. Bastian T, Maire A, Dugas J, Ataya A, Villars C, Gris F, et al. *Automatic Identification of Physical Activity Types and Sedentary Behaviors from Triaxial Accelerometer: Laboratory-Based Calibrations Are Not Enough*. J Appl Physiol (1985). 2015;118(6):716-22.
211. Gyllensten IC, and Bonomi AG. *Identifying Types of Physical Activity with a Single Accelerometer: Evaluating Laboratory-Trained Algorithms in Daily Life*. IEEE Trans Biomed Eng. 2011;58(9):2656-63.

212. Montoye AHK, Clevenger KA, Pfeiffer KA, Nelson MB, Bock JM, Imboden MT, et al. *Development of Cut-Points for Determining Activity Intensity from a Wrist-Worn ActiGraph Accelerometer in Free-Living Adults*. J Sports Sci. 2020;38(22):2569-78.

213. Edwardson CL, Henson J, Biddle SJH, Davies MJ, Khunti K, Maylor B, et al. *activPAL and ActiGraph Assessed Sedentary Behavior and Cardiometabolic Health Markers*. Med Sci Sports Exerc. 2020;52(2):391-7.

214. Plasschaert F, Jones K, and Forward M. *Energy Cost of Walking: Solving the Paradox of Steady State in the Presence of Variable Walking Speed*. Gait Posture. 2009;29(2):311-6.

215. Plasschaert F, Jones K, and Forward M. *Energy Cost of Walking: A Comparison of Two Recognised Methods for Defining Steady State in a Group of Unimpaired Children and Children with Cerebral Palsy*. Gait Posture. 2010;31(4):537-9.

216. Crowley P, Skotte J, Stamatakis E, Hamer M, Aadahl M, Stevens ML, et al. *Comparison of Physical Behavior Estimates from Three Different Thigh-Worn Accelerometers Brands: A Proof-of-Concept for the Prospective Physical Activity, Sitting, and Sleep Consortium (ProPASS)*. Int J Behav Nutr Phys Act. 2019;16(1):65.

217. Wu Y, Johns JA, Poitras J, Kimmerly DS, and O'Brien MW. *Improving the Criterion Validity of the activPAL in Determining Physical Activity Intensity During Laboratory and Free-Living Conditions*. J Sports Sci. 2020:1-9 (Online ahead of print).

218. Lyden K, Keadle SK, Staudenmayer J, and Freedson PS. *The activPAL Accurately Classifies Activity Intensity Categories in Healthy Adults*. Med Sci Sports Exerc. 2017;49(5):1022-8.

219. Stevens ML, Gupta N, Inan Eroglu E, Crowley PJ, Eroglu B, Bauman A, et al. *Thigh-Worn Accelerometry for Measuring Movement and Posture across the 24-Hour Cycle: A Scoping Review and Expert Statement*. BMJ Open Sport Exerc Med. 2020;6(1):e000874.

220. van der Ploeg HP, and Hillsdon M. *Is Sedentary Behaviour Just Physical Inactivity by Another Name?* Int J Behav Nutr Phys Act. 2017;14(1):142.

221. Duvivier B, Bolijn JE, Koster A, Schalkwijk CG, Savelberg H, and Schaper NC. *Reducing Sitting Time Versus Adding Exercise: Differential Effects on Biomarkers of Endothelial Dysfunction and Metabolic Risk*. Sci Rep. 2018;8(1):8657.

222. Arvidsson D, Fridolfsson J, Borjesson M, Andersen LB, Ekblom O, Dencker M, et al. *Re-Examination of Accelerometer Data Processing and Calibration for the Assessment of Physical Activity Intensity*. Scand J Med Sci Sports. 2019;29(10):1442-52.

223. Crouter SE, Kuffel E, Haas JD, Frongillo EA, and Bassett DR, Jr. *Refined Two-Regression Model for the ActiGraph Accelerometer*. Med Sci Sports Exerc. 2010;42(5):1029-37.

224. O'Driscoll R, Turicchi J, Beaulieu K, Scott S, Matu J, Deighton K, et al. *How Well Do Activity Monitors Estimate Energy Expenditure? A Systematic Review and Meta-Analysis of the Validity of Current Technologies*. Br J Sports Med. 2020;54(6):332-40.

225. Piercy KL, Troiano RP, Ballard RM, Carlson SA, Fulton JE, Galuska DA, et al. *The Physical Activity Guidelines for Americans*. JAMA. 2018;320(19):2020-8.