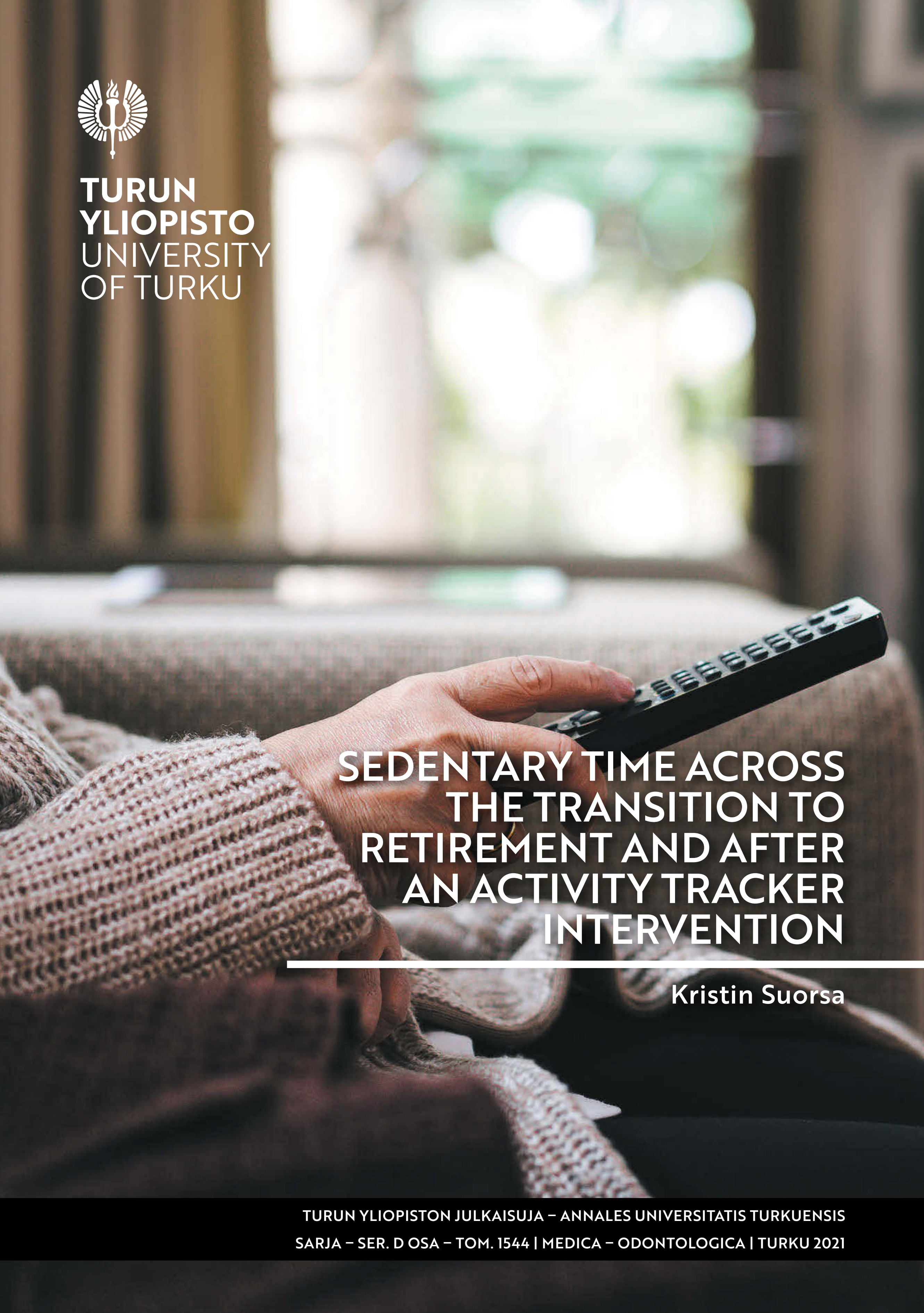

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SEDENTARY TIME ACROSS THE TRANSITION TO RETIREMENT AND AFTER AN ACTIVITY TRACKER INTERVENTION

Kristin Suorsa

TURUN YLIOPISTON JULKAISUJA – ANNALES UNIVERSITATIS TURKUENSIS
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To my family

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ABSTRACT

This study aimed to examine how accelerometer-measured daily total and prolonged sedentary time change across the transition to retirement using annual measurement data from the Finnish Retirement and Aging (FIREA) study (n=689). Another aim was to examine the effect of a 12-month activity tracker-based intervention on sedentary time among recent retirees using data from the REACT trial (n=231). The final aim was to compare sedentary time estimates of the wrist-worn accelerometers used in both studies to the estimates obtained by a more reliable method, a thigh-worn accelerometer.

Daily total sedentary time only changed among women retiring from manual occupations. Their daily total sedentary time increased by 54 minutes immediately after the transition to retirement. Prolonged sedentary time increased by half an hour across gender and occupational groups. The timing of the changes in relation to retirement differed between genders, as women's prolonged sedentary time increased immediately after the transition to retirement, whereas the increase in men's prolonged sedentary time was more gradual from the last years at work to a few years after retirement. The activity tracker-based intervention targeted at the first years after retirement did not elicit changes in daily total or prolonged sedentary time over 12 months in comparison to the controls. The wrist-worn accelerometer either underestimated or overestimated daily total sedentary time in comparison to the thigh-worn accelerometer, depending on the method used. However, within-individual differences in sedentary time were similarly captured by each method, suggesting that the observed changes in sedentary time across retirement and the intervention were reliable.

This study indicates that interventions to reduce sedentary time may be the most effective when targeted at the first years after retirement among women, but that the benefit for men may be highest during the last years in work life. As an activity tracker alone was insufficient to reduce sedentary time in the long term, other approaches or additional intervention components may be needed to attain long-term changes in sedentary time

KEYWORDS: sedentary time, prolonged sedentary time, retirement, work, aging worker, occupation, accelerometer, activity tracker

TURUN YLIOPISTO
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Väitöskirja, 148 s.
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Huhtikuu 2021

TIIVISTELMÄ

Tämän tutkimuksen tavoitteena oli selvittää, miten liikemittarilla mitattu päivän paikallaanoloaika ja pitkittynyt paikallaanolo muuttuvat eläköidyttäessä käyttäen Finnish Retirement and Aging (FIREA)-tutkimuksen vuosittain toistettuja mittauksia (n=689). Tavoitteena oli myös tutkia, onko aktiivisuusrannekkeella vaikutusta paikallaanoloon juuri eläköityneillä henkilöillä käyttäen koe- ja kontrolliasetelmaa REACT-interventiotutkimuksen aineistossa (n=231). Tutkimuksessa mitattiin paikallaanoloa ranteessa pidettävällä liikemittarilla, minkä vuoksi tavoitteena oli myös vertailla rannemittarilla saatuja paikallaanolon estimaatteja reisimittarilla saatuihin luotettavampiin paikallaanolon estimaatteihin.

Päivän kokonaispaikallaanolo muuttui ainoastaan naisilla, jotka eläköityivät fyysisistä ja palveluammateista. He lisäsivät paikallaanoloaikaansa 54 minuutilla päivässä heti eläköitymisen jälkeen. Pitkittynyt paikallaanolo lisääntyi sen sijaan noin puolella tunnilla päivässä sekä naisilla että miehillä ammatista riippumatta. Muutosten ajoittuminen eläköitymiseen nähden erosi naisten ja miesten välillä, koska naisilla pitkittyneen paikallaanoloajan lisääntyminen tapahtui heti eläköitymisen jälkeen, kun taas miehet lisäsivät pitkittynyttä paikallaanoloa tasaisesti viimeisistä työvuosista ensimmäisiin eläkevuosiin. Eläköitymisen jälkeiselle ajalle kohdistettu vuoden kestoinen aktiivisuusrannekeinterventio ei saanut aikaan muutoksia kokonaispaikallaanoloajassa eikä pitkittyneessä paikallaanoloajassa kontrolliryhmään nähden. Verrattuna reisimittariin, rannemittarilla saadut tulokset joko aliarvioivat tai yliarvioivat paikallaanoloa kiihtyvyysmittaridatan prosessointimenetelmästä riippuen. Havaitut paikallaanoloajan muutokset olivat kuitenkin samanlaisia menetelmästä riippumatta, joten paikallaanolon muutoksia koskevat tulokset ovat todennäköisesti luotettavia.

Tämän tutkimuksen tulokset osoittavat, että interventiot paikallaanolon vähentämiseksi ovat perusteltuja pian eläköitymisen jälkeen naisilla, kun taas miehillä suurimmat hyödyt voidaan mahdollisesti saavuttaa jo viimeisinä työvuosina. Aktiivisuusrannekkeen käyttö ei riittänyt vähentämään paikallaanoloa pitkällä aikavälillä, minkä vuoksi rannekkeen lisäksi voidaan tarvita muita keinoja.

AVAINSANAT: paikallaanolo, pitkittynyt paikallaanolo, eläköityminen, työ, ikääntyvä työntekijä, ammattiryhmä, liikemittari, aktiivisuusranneke

Table of Contents

Abbreviations

BCT	behavioral change technique
BMI	body mass index
CI	confidence interval
ENMO	Euclidean Norm Minus One
FIREA	Finnish Retirement and Aging (study)
ISCO	International Standard Classification of Occupations
LPA	light physical activity
MET	metabolic equivalent
MPA	moderate physical activity
MVPA	moderate-to-vigorous physical activity
REACT	Enhancing physical activity and healthy aging among recent retirees – Randomized controlled in-home physical activity trial (study)
SD	standard deviation
SES	socioeconomic status
VPA	vigorous physical activity
WHO	World Health Organization

List of Original Publications

This dissertation is based on the following original publications, which are referred to in the text by their Roman numerals:

I Suorsa K, Pulakka A, Leskinen T, Heinonen I, Heinonen OJ, Pentti J, Vahtera J & Stenholm S. Objectively Measured Sedentary Time Before and After Transition to Retirement: The Finnish Retirement and Aging Study. *J Gerontol A Biol Sci Med Sci*, 2020; 75(9):1737–1743.

II Suorsa K, Pulakka A, Leskinen T, Pentti J, Vahtera J & Stenholm S. Changes in prolonged sedentary behaviour across the transition to retirement. *Occup Environ Med,* 2020. doi: 10.1136/oemed-2020-106532.

III Suorsa K, Leskinen T, Pulakka A, Pentti J, Löyttyniemi E, Heinonen I, Vahtera J & Stenholm S. The effect of a consumer-based activity tracker intervention on accelerometer-measured sedentary time among retirees: a randomized controlled REACT trial. *J Gerontol A Biol Sci Med Sci.* doi: 10.1093/gerona/glab107.

IV Suorsa K*, Pulakka A*, Leskinen T, Pentti J, Holtermann A, Heinonen OJ, Sunikka J, Vahtera J, & Stenholm S. Comparison of Sedentary Time Between Thigh-Worn and Wrist-Worn Accelerometers. *Journal for the Measurement of Physical Behaviour*, 2020; 3(3): 234–243.

* These authors shared equal contribution.

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1 Introduction

Retirement is an important life transition that frees working hours for other activities. Work-related activities are an important determinant of daily physical behaviors (Prince et al., 2019) and thus, retirement may considerably affect daily physical behaviors. Those retiring from physical work do not seem to compensate the removal of work-related physical activity with increased leisure-time physical activity after retirement (Pulakka et al., 2020). In contrast, there is some indication that those retiring from sedentary occupations increase physical activities after retirement (Barnett et al., 2012; Pulakka et al., 2020).

Sedentary behavior refers to any waking behavior while sitting, lying down or reclining and is characterized by low energy expenditure (Tremblay et al., 2017). Sedentary behavior is a relatively newly recognized health risk and has been associated with several adverse health outcomes, such as compromised cardiometabolic health (Powell et al., 2018) and a higher risk of type 2 diabetes (Patterson et al., 2018) and mortality (Ekelund et al., 2019). Recent studies have indicated that prolonged uninterrupted sedentary time in particular is negatively associated with cardiometabolic outcomes (Bellettiere, LaMonte et al., 2019; Bellettiere, Healy et al., 2019) and mortality (Diaz, Howard et al., 2017). Current evidence implies that it may not be enough for a person to fulfil physical activity recommendations, and that attention should also be paid to sedentary time and breaking up prolonged sedentary time (Katzmarzyk et al., 2019).

Sedentary behavior can be assessed using self-report or device-based methods. The most common device-based method has been an accelerometer, which can be used to estimate sedentary time on the basis of low movement of the body part to which it is attached (Healy, Clark et al., 2011). Accelerometers have been attached to several body parts, and wrist placement seems to be the most comfortable for study participants and enables using the same device to examine both waking behavior and sleep (Schrack et al., 2016; Troiano et al., 2014). However, since wrist movements can be independent of whole body movements, for instance while doing handcrafts, a wrist-worn accelerometer generally underestimates sedentary time in comparison to more reliable methods (Flórez-Pregonero et al., 2018; Koster et al., 2016). The accuracy of the current methods that use a wrist-worn accelerometer to estimate sedentary time warrants further research.

To date, it is not known how sedentary time changes across the transition to retirement. Studies have suggested that self-reported daily sitting time decreases after retirement (Clark et al., 2014; Sprod et al., 2017), although increases have also been reported (Menai et al., 2014). Some studies have shown consistent findings of increased self-reported leisure-time sitting (Leskinen, Pulakka et al., 2018; Van Dyck et al., 2016), which is somewhat logical, as retirement involves increased leisure time in general. Due to recall and information bias related to self-reported measures (Prince, Cardilli et al., 2020), more reliable accelerometer-based examinations of sedentary time around retirement are warranted. Moreover, a more comprehensive consideration of the complexity of the phenomenon, such as taking occupational characteristics into account, may be necessary to explain some of the contradictory findings.

Sedentary time increases with advancing age (Loyen et al., 2017). Aging-related mobility limitations and diagnosed morbidities may decrease the ability and willingness to engage in physical activity and thus inevitably increase sitting (Chastin, Fitzpatrick et al., 2014). These findings highlight the need for effective ways to reduce sedentary time among older adults. Activity trackers may offer a cost-effective and personalized tool for reducing sedentary time in everyday life (Stockwell et al., 2019). Only a few randomized controlled trials (RCT) have evaluated the effect of activity trackers on sedentary time. These trials have reported that self-monitoring of sedentary time reduces sedentary time in the short term (Barwais et al., 2013), but that self-monitoring of physical activity has no effect on sedentary time (Jauho et al., 2015; Sloan et al., 2018). However, activity trackers can be harnessed to deliver a greater number of evidence-based behavioral change techniques (BCT) to change sedentary behavior. One possible technique is prompts, which remind the user to break up sedentary time. These have shown potential to reduce habit-like sedentary behavior at workplaces (Elavsky et al., 2019; Evans et al., 2012). Recent retirees may adopt the use of an activity tracker with high compliance, because retirement is often seen as an opportunity to make better health choices and the increased availability of time offers the possibility to move and sleep more. Therefore, the true potential of an activity tracker to reduce sedentary time during this important life transition needs to be evaluated.

The aim of this study was to examine how accelerometer-measured sedentary time changes across the transition to retirement and how these changes differ according to gender and occupation. It also aimed to examine how an activity tracker-based intervention affects sedentary time among recent retirees. Finally, the study aimed to compare estimates of sedentary time from a wrist-worn accelerometer to more reliable estimates of sedentary time from a thigh-worn accelerometer.

2 Review of the Literature

2.1 Retirement as a life transition

Retirement is a significant life transition, because for most retirees it leads to definite, full removal of work-related activities (Finnish Centre of Pensions, 2020). Work does not only determine physical behaviors during working hours (Prince et al., 2019); it also affects daily physical behaviors through commuting (Yang, X. et al., 2014) and may influence sleep timing and duration (Basner et al., 2014). The influence of work may also extend to leisure time because the need for recovery from physical and mental strain related to work may affect leisure-time activities (Holtermann et al., 2019). For some people, leisure-time physical activity may be a tool for coping with stress while others may perceive it as an additional burden after demanding working hours (Stults-Kolehmainen & Sinha, 2014).

Retirees report more leisure-time physical activity after their transition to retirement (Stenholm et al., 2016). Accelerometer-based findings have shown that changes in daily total physical activity depend on occupation: the daily total physical activity of those retiring from manual occupations decreases, whereas the opposite is seen among those retiring from non-manual occupations (Pulakka et al., 2020). Retirement seems to bring a physical activity peak, especially among those retiring from non-manual occupations (Barnett et al., 2012; Pulakka et al., 2020). However, the peak is only temporary, as physical activity seems to normalize and begin to decline as time passes after retirement (Stenholm et al., 2016).

Other changes in health-related behaviors have also been observed after retirement. Increased time availability and the removal of possible work-related stress seem to influence sleep, as retirees report having less sleep difficulties (Myllyntausta, Salo, Kronholm, Pentti et al., 2017) and sleeping more (Myllyntausta, Salo, Kronholm, Aalto et al., 2017), which is also confirmed by accelerometer-based findings (Myllyntausta et al., 2020). Moreover, retirement is often viewed as a "window of opportunity" to change course (Stenholm & Vahtera, 2017), retiring people become more aware of their own aging and want to make better health choices to improve their health and well-being and to engage in activities that were not possible during work life due to time limits (Barnett et al., 2012). Retirement has even been associated with higher odds of smoking cessation (Oshio & Kan, 2017; Pulakka et al., 2019). However, for some individuals, retirement may cause stress due to major life change and loss of income and social interactions (van Solinge & Henkens, 2008). Some retirees increase their consumption of alcohol to risky levels after retirement (Halonen et al., 2017).

Maintaining a physically active lifestyle with advancing age is the main strategy for suppressing aging-related physical decline and to promoting healthy aging (Angulo et al., 2020). Thus, it is important to support the sustainability of retirement-related positive changes in health behaviors and to simultaneously counteract aging-related deterioration.

2.2 Sedentary behavior

Sedentary behavior is defined as any waking behavior with an energy expenditure of no more than 1.5 metabolic equivalents (METs) in a sitting, reclining or lying posture (Tremblay et al., 2017). Sedentary behavior interplays with other daily physical behaviors, that is, sleep, light physical activity (LPA), moderate physical activity (MPA) and vigorous physical activity (VPA) constituting a 24-hour day (Figure 1). In the 24-hour energy expenditure circle, daily physical behaviors are classified on the basis of wakefulness and energy expenditure. The energy expenditure of sleep and sedentary behavior is almost the same; the only difference is that sedentary behavior is waking behavior. Daily waking physical behaviors can be classified on the basis of energy expenditure as sedentary time, LPA, MPA and VPA (Figure 1). Standing is defined as stationary, non-sedentary activity because although its energy expenditure may be lower or higher than 2.0 METs, it does not fulfil the postural definition of sedentary behavior. Standing, sitting and reclining without an energy expenditure specification are defined as stationary behaviors (Tremblay et al., 2017).

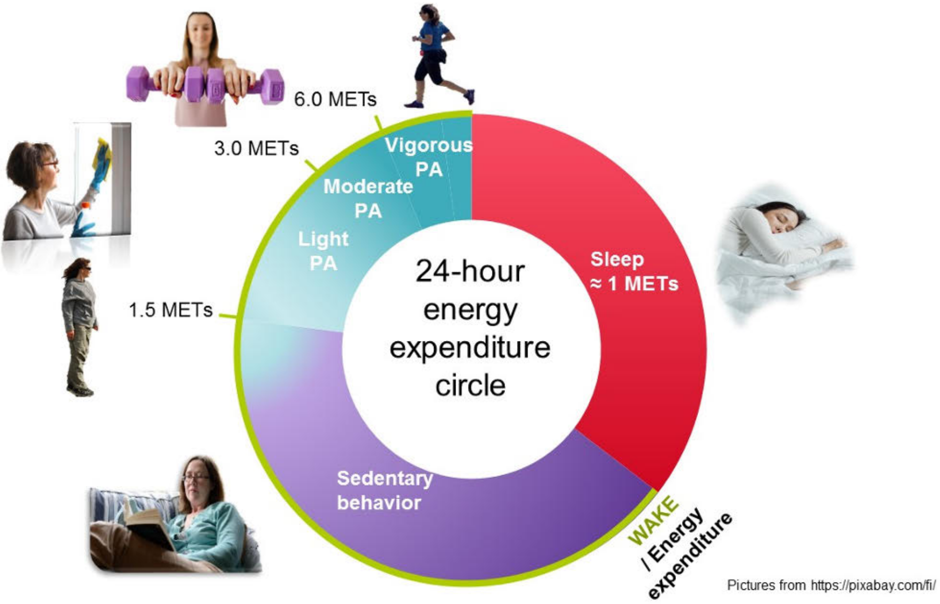

Figure 1. Energy expenditure circle over 24 hours. MET=metabolic equivalent.

As the number of hours in a day is fixed, the duration of daily physical behaviors are co-dependent. Thus, spending more time in sedentary activities means that the same amount of time is subtracted from physical activity or sleep. The proportion of sedentary behavior during the 24-hour day is considerable, because sedentary behavior takes place in several daily contexts: at work, while watching television or multimedia and using a computer, driving a vehicle and eating and reading. Indeed, Finnish adults aged 60–69 spend 60% of their waking hours sedentary, corresponding to approximately nine hours per day (Husu et al., 2018). Similar levels have also been observed among older adults in other high-income countries (Giné-Garriga et al., 2020; Harvey et al., 2015; Loyen et al., 2017). Moreover, according to some recent indications, increasing daily sedentary time may be at the cost of physical activity (Ng & Popkin, 2012). During the 19th century, an overall trend of increased time spent using a computer in all age groups and increased time spent watching TV among older adults has been observed (Yang, L. et al., 2019).

2.2.1 Association between sedentary time and health outcomes

The most pronounced adverse health consequences of sedentary time concern cardiometabolic health. Accelerometer-based findings from a recent meta-analysis show negative associations between sedentary time and fasting glucose, insulin, triglycerides, high-density lipoprotein cholesterol, and waist circumference (Powell et al., 2018). Other accelerometer-based studies have suggested that sedentary time accumulation patterns also matter, as accumulating sedentary time for long, uninterrupted bouts is associated with impaired glucose regulation (Diaz, Goldsmith et al., 2017) and a higher risk of cardiovascular diseases and type 2 diabetes (Bellettiere, LaMonte et al., 2019; Bellettiere, Healy et al., 2019). Experimental studies have shown that limiting the longest uninterrupted sedentary bout to 30 minutes or less has favorable effects on cardiometabolic markers in comparison to accumulating sedentary time for longer uninterrupted bouts (Loh et al., 2020). Systematic reviews based mostly on survey findings have reported associations between long sedentary time and the risk of cardiovascular mortality (Ekelund et al., 2018; Patterson et al., 2018).

In addition to cardiovascular health, sedentary time has been associated with cancer incidence (colon, colorectal endometrial, epithelial ovarian cancers) (Biswas et al., 2015; Mahmood et al., 2017), cancer mortality (Ekelund et al., 2018), lower cognitive performance (Falck et al., 2017), sleep disturbances (Yang, Y. et al., 2017) and low back pain (De Carvalho et al., 2020), although this research evidence is somewhat less convincing than that for cardiovascular health.

Meta-analyses have shown a dose-response association with sedentary time and all-cause mortality, especially when accelerometer-measured daily sedentary time exceeds 9.0 hours (Ekelund et al., 2019; Ku et al., 2019). However, physical activity seems to attenuate the health risks of excessive sedentary behavior. Ekelund and colleagues (2016) showed in their harmonized meta-analysis of over one million adults that 60–75 minutes of self-reported daily moderate-to-vigorous physical activity (MVPA) is needed to attenuate the health risks associated with high self-reported daily sitting time.

2.2.2 Correlates of sedentary behavior

Current evidence of the intrapersonal, social environment, physical environment, and policy-level factors associated with sedentary behavior relies mostly on cross-sectional findings rather than longitudinal studies that examine factors that predict changes in sedentary time (Chastin et al., 2015; O'Donoghue et al., 2016; Prince et al., 2017). Thus, it is more appropriate to discuss the correlates rather than determinants of sedentary behavior (Bauman et al., 2002). Occupational class, education and income/socioeconomic status (SES) have shown to be important correlates of sedentary behavior among adults (Jelsma et al., 2019; Prince et al., 2017). On the other hand, age, working status, obesity and health status seem to be the most pronounced correlates of sedentary behavior among older adults aged 65 or over (Chastin et al., 2015). Accelerometer-based cross-sectional studies among westerners aged 60 or over have also highlighted gender as a correlate of sedentary behavior, as men have been observed to be more sedentary than women (Giné-Garriga et al., 2020; Harvey et al., 2015).

Occupation is an important correlate of sedentary time, because it determines the type of activities done at work. Moreover, work constitutes a major part of waking hours (Statistics Finland, 2018). In recent decades, sedentary work, i.e. work done in a sitting position, has become more common, while physically strenuous work has decreased due to technological advances (Ng & Popkin, 2012).

The majority of the studies examining the differences between the sedentary time of occupational groups are based on relatively small samples and comparisons of specific groups such as office workers, health care workers, laborers and drivers (Prince et al., 2019). Findings on Australian and American workers show that office workers in particular are the most sedentary occupational group both at work and during wakeful time (Prince et al., 2019). Office workers' high sedentary time accumulates mainly from working hours, as working hours involve considerably more total sedentary time and prolonged sedentary time than non-working hours (Clemes et al., 2014; Kurita et al., 2019; Parry & Straker, 2013; Thorp et al., 2012). In contrast, working hours are less sedentary than non-working hours among those whose working hours mostly include standing, walking or physical tasks (Kurita et al., 2019). Moreover, findings on middle-aged and aging Dutch workers in various occupations show that most differences are on weekdays, as those in lower-level, i.e. occupations that do not require special skills (e.g. cleaners, waitresses), have less sedentary time than those with intermediate- and higher-level occupations (Pulakka, Stenholm et al., 2018).

Occupation does not seem to determine sedentary time on days off as clearly as on working days. Accelerometer-based studies have found no differences between daily total sedentary time or prolonged sedentary time on the days off of those who mostly sit at work and those with more physically active job types (Kurita et al., 2019) or according to occupational group (Pulakka, Stenholm et al., 2018). Studies comparing the sedentary time during non-working hours on working days of different occupational groups are limited to two studies among Japanese workers, which indicate that non-working hours on working days do not differ in terms of sedentary time between desk-based occupations and other types of occupations (Kurita et al., 2019; Shibata et al., 2020). Thus, it seems that work-related activities are the main factor contributing to differences between the sedentary behavior of different occupational groups.

Occupation is often used as an indicator of SES. When occupation is classified into groups according to required skills, duties and education, it is usually referred to as occupational status and used as an indicator of SES (Braveman et al., 2005; Statistics Finland, 2010). Work tasks and SES are linked so that those with high SES typically do sedentary work, whereas those with low SES usually have more occupational physical activity (Bauman et al., 2011; Loyen et al., 2016). Using education or income as an indicator of SES has resulted in consistent findings of higher accelerometer-based sedentary time and self-reported total sitting time among higher SES groups than among lower SES groups (Prince et al., 2017; Prince, Roberts et al., 2020). Survey studies using occupation, education or income as an indicator of SES have suggested that there may be differences between the sitting domains of SES groups, as those with higher SES report more occupational sitting time (Beenackers et al., 2012) and time spent using a computer (Prince, Roberts et al., 2020), but on the other hand, less time spent watching TV (Mackenbach et al., 2019; Prince, Roberts et al., 2020) than in the low SES groups.

Systematic reviews have associated several health-related factors with sedentary time, including obesity, functional limitations and subjective well-being (Chastin et al., 2015; Prince et al., 2017). As regards health-related behaviors, some studies suggest that smoking is associated with higher levels of sedentary time (Shiroma et al., 2013; van Ballegooijen et al., 2019).

Accelerometer-based cross-sectional studies have shown positive association between daily sedentary time and age (Chastin et al., 2015; Loyen et al., 2017; Prince et al., 2017). A few longitudinal studies have shown that sedentary time among older adults tends to continuously increase every year, but that the increase is most pronounced among adults aged 65 or over (Hajna et al., 2018; Smith et al., 2015). The underlying reasons for increasing sedentary time may be aging-related mobility limitations, diagnosed morbidities, pain, and fatigue (Chastin et al., 2014; Schrack et al., 2014). Age-related differences in sedentary time seem to be especially prominent during evenings. A comparison of adults of retirement age (60–69 years) and older adults (>70 years) revealed that the lowest point of sedentary time among all adults aged >60 is in the late morning and at midday, but age-related differences were observed in the afternoons and evenings, as sedentary time is higher among older age groups (Schrack et al., 2014; Yerrakalva et al., 2017). It has been suggested that longer sedentary time in the evenings is caused by older adults' diurnal patterns, as chores are typically done during the morning and at midday, and evenings are reserved for rest (Yerrakalva et al., 2017).

2.2.3 Sedentary behavior assessment methods

Sedentary behavior began to be assessed on a large-scale in the early 2000s, using self-report methods that focused on determining sitting time (Owen et al., 2020). The first self-report methods were based on single-item questions on time spent watching TV or overall sitting (Atkin et al., 2012; Owen et al., 2020). Later on, self-report methods were developed to include multiple domains of sitting, such as computer use, reading and sitting in a vehicle, and diaries and short-term recalls to include all sitting activities in a day (Atkin et al., 2012; Healy, Clark et al., 2011). Self-report methods provide information on the domains and contexts of sedentary behavior (Healy, Clark et al., 2011). However, these methods only focus on sitting (i.e. not the actual sedentary behavior) and are subject to information and recall bias, often leading to underestimation of sedentary time in comparison to accelerometer measurements (Chastin, Culhane et al., 2014; Dyrstad et al., 2014; Harvey et al., 2015). Due to the habitual nature of sedentary behaviors, sedentary time is often difficult to recall and quantify (Prince, Cardilli et al., 2020; Wullems et al., 2016). Another reason for underestimating sedentary time may be social desirability bias, because individuals may report lower levels of sitting than in reality due to a desire to present themselves in a more positive light (Chastin, Culhane et al., 2014).

Attempts have been made to overcome the limitations related to self-report methods by using devices that enable the assessment of daily total sedentary time and that are not affected by recall or information bias. Furthermore, device-based methods have enabled in-depth examinations of sedentary accumulation patterns in the everyday lives of a large study populations (Schrack et al., 2016). Device-based methods include wearable devices that assess sedentary time by low acceleration, posture or both (Rosenberger et al., 2016). Some of these methods are based on electromyography (EMG), utilizing muscle activity information to estimate not only the postural component but also the metabolic component of sedentary time (Kuster et al., 2018).

In epidemiological studies, the most common device-based method for quantifying sedentary time has been an accelerometer that measures movements of the body or body parts in terms of acceleration, i.e. change in speed with respect to time (Chen & Bassett, 2005; Healy, Clark et al., 2011). Acceleration is detected by piezoelectronic sensors, on one to three axes (anteroposterior, mediolateral and vertical) (Chen & Bassett, 2005). Acceleration information has been used to detect low movement periods, which are, after taking into account sleep and accelerometer non-wear time, assumed to be sedentary time. To date, several accelerometer brands are available that can be used in different body placements, such as the hip, wrist, thigh, back, and ankle.

Data collection using device-based methods requires consideration of accelerometer placement (Heesch et al., 2018; Migueles et al., 2017). The placement of an accelerometer naturally affects sedentary time estimates because movement of certain body parts such as the wrist can be independent of the rest of the body which may remain sedentary. In general, when researchers choose the placement of an accelerometer, they have to weigh up different aspects. Depending on the research question, researchers may aim to estimate either only sedentary time or the whole composition of 24-hour physical activities (sedentary time, LPA, MVPA, sleep) with the highest possible accuracy. Furthermore, researchers have to consider feasibility and participant burden; the participation rate and the accelerometer wear time must be sufficient to provide reliable results. Based on studies evaluating wrist- and hip-worn accelerometers among middle-aged and older adults, at least three to five measurement days with a minimum of 10 hours of accelerometer wear time per participant are needed to attain acceptable test-retest reliability in the estimation of sedentary behavior (Dillon et al., 2016; Hart et al., 2011). In addition to device placement, an important choice is the data processing software, as different types of software have been developed to process either acceleration data or the combination of acceleration and postural data from accelerometers worn in different body locations.

The most popular accelerometer location has been the hip (Healy, Clark et al., 2011), because hip placement enables the estimation of whole body movements due to its location close to the center of the mass (Shiroma et al., 2016). Recently, large scale observational studies such as the National Health and Nutrition Examination Survey (NHANES) (Healy, Matthews et al., 2011) and the UK Biobank (Plotz et al., 2017) have employed wrist-worn accelerometers, mainly due to increased participant compliance and being able to estimate sleep using the same device (Freedson & John, 2013; Quante et al., 2015; Schrack et al., 2016). However, wrist movements are not likely to correspond with whole body movements as well as hip-worn accelerometers (Shiroma et al., 2016). Given that the most common methods for drawing sedentary time estimates from accelerometers are based on low acceleration values recorded by hip- and wrist-worn accelerometers, their capability of distinguishing standing from sitting and lying down is limited. Thus, a growing number of research groups have adopted thigh-worn accelerometers, combining acceleration and postural detection and providing more reliable estimates of not only sedentary behavior but also other types of physical behavior (Stamatakis et al., 2020).

Because hip- and wrist-worn accelerometers produce data in units of acceleration, their data processing methods are basically similar. The most common data processing method, originally developed for hip-worn accelerometers, but later also used with wrist-worn accelerometers, has been converting “raw” acceleration data, expressed as gravitational acceleration (*g*), into activity counts that are unitless numerical values for the acceleration of movement intensity (Watson et al., 2014).

Activity counts have been used to develop cutpoints that reflect specified levels of activity, typically against energy expenditure values (Crouter et al., 2006). Count-based cutpoints for sedentary behavior have been created to reflect waking activities in a sitting, reclining or lying posture with an energy expenditure of no more than 1.5 METs. A few cutpoints for wrist-worn accelerometers have been developed for adults and older adults, by comparing them to a thigh-worn accelerometer in free-living conditions (Koster et al., 2016) and video observations in semi-controlled conditions (Flórez-Pregonero et al., 2018). However, this approach has limitations: cutpoints that are usually developed in controlled conditions may not be easily transferred to free-living conditions and other study populations (Koster et al., 2016). Only in a study by Koster and colleagues (2016) were the developed count-based cutpoints evaluated in free-living conditions. A wrist-worn accelerometer was found to underestimate daily sedentary time by approximately 23 minutes in comparison to a thigh-worn accelerometer. As a further limitation in the count-based approach, activity counts are primarily used with ActiGraph accelerometers, thus making data harmonization with other accelerometer brands challenging (Rosenberger et al., 2016).

In recent years, new methods for obtaining sedentary time estimates directly from raw acceleration data, without the step of converting raw data into activity counts, have been developed (Migueles et al., 2019). Operating with raw data facilitates data harmonization between different accelerometer brands, as commonly used accelerometer brands all provide raw data in SI units, which means that data from these different accelerometers can be pooled and processed using the same procedures (Rowlands, Mirkes et al., 2018). One of the commonly used methods is the open-source R-package GGIR, which was developed to convert raw data from wrist-worn accelerometers into estimates of sedentary behavior, physical activity and sleep. The GGIR package enables researchers to make their own data processing choices related to, for instance, an estimation of non-wear and sleep time (Migueles et al., 2019). It also employs the ENMO method, i.e. the calculation of the average magnitude of dynamic acceleration expressed as ENMO (Euclidean norm minus one). The ENMO method relies on the previously mentioned cutpoint approach, as sedentary time estimates are produced on the basis of the threshold values corresponding to sitting and lying postures, which are assumed to reflect activities with no more than 1.5 METs of energy expenditure. Several threshold values for sedentary behavior have been developed among adults in laboratory conditions (Hildebrand et al., 2017) and in semi-controlled free-living conditions (Rowlands, Mirkes et al., 2018). Only Hildebrand and colleagues (2017) have evaluated the developed ENMO cutpoint in free-living conditions and have observed great overestimation (approximately 140 minutes) of daily sedentary time by a wrist-worn accelerometer in comparison to a thigh-worn accelerometer.

Recent software for processing data from thigh-worn accelerometers have been developed to process both acceleration and postural data. The PAL Technologies software designed for the thigh-worn activPAL accelerometer and the Acti4 software suitable for several accelerometer brands such as ActiGraph and Axivity have shown high accuracy in the detection of time spent sitting and lying down (Crowley et al., 2019; Kozey Keadle et al., 2011; Lyden et al., 2012; Skotte et al., 2014; Stemland et al., 2015). Basically, this software offers a similar data processing template, such as the GGIR package for wrist-worn accelerometers.

2.2.4 Sedentary behavior and retirement

Because work-related activities, which are a major contributor to daily sedentary time levels, change to leisure-time activities in the transition to retirement, changes in sedentary time can be expected. Accelerometer-based findings on changes in sedentary time across the transition to retirement are limited to cross-sectional studies (Table 1). Findings from a large British study population (n=3705) showed that total daily sedentary time and prolonged sedentary time were higher among retired adults than among non-retired adults (Yerrakalva et al., 2017), although another smaller study from the UK (n=98) suggests the opposite (Godfrey et al., 2014). Due to the cross-sectional study design it is unclear whether the differences between the sedentary time of the non-retired and retired adults are due to retirement or some other participant characteristic, such as health status.

To reliably examine how sedentary time changes across the transition to retirement, we need longitudinal studies to follow the same individuals from work to retirement. Longitudinal studies have mainly examined changes in self-reported time spent watching TV and other domains of leisure-time sitting (Table 1). Because watching TV, using a computer or multimedia have become the most common leisure-time activities in recent decades (Ng & Popkin, 2012) and work-related activities change to leisure-time activities in the transition to retirement, it can be expected that retirement induces an increase in leisure-time sitting. The survey study by Touvier and colleagues (2010) was the first to show an increase in time spent watching TV after retirement. Later, other survey studies have confirmed this increasing trend and have included other domains of leisure-time sitting, observing an increase in sitting when using a computer at home (Leskinen, Pulakka et al., 2018; Menai et al., 2014; Van Dyck et al., 2016). The survey study by Leskinen and colleagues (2018) was the first to find that changes in self-reported leisure-time sitting took place immediately after the transition to retirement, and no notable changes were observed years before or after retirement. The only domain of leisure-time sitting that decreases after retirement is passive transport (Leskinen, Pulakka et al., 2018; Van Dyck et al., 2016).

Survey studies have also shown that changes in leisure-time sitting differ according to gender, occupation, level of education, and health status. Increased leisure-time sitting behaviors, especially watching TV, have been observed among women more than among men (Leskinen, Pulakka et al., 2018; Van Dyck et al., 2016). Differences between occupational and educational groups seem to depend on the domain of sedentary behavior. Watching TV increases most among the less educated and among those retiring from manual occupations (Barnett et al., 2014; Touvier et al., 2010; Van Dyck et al., 2016), whereas computer use at home increases most among those retiring from occupations with long sitting times (Leskinen, Pulakka et al., 2018). Moreover, the highest increases in leisure sedentary time have been observed among those reporting low physical activity levels, sleep difficulties, mental disorders, and poor health before retirement (Leskinen, Pulakka et al., 2018).

Although longitudinal survey studies examining changes in leisure-time sitting across the transition to retirement provide some indication of how working hours are replaced after retirement, they do not provide knowledge on how daily total sedentary time changes in the transition to retirement. Three survey studies have examined daily total sitting time before and after retirement by summing up the domains of sitting: a nine-year survey study among Australian women (Clark et al., 2014), a six-year survey study among French women and men (Menai et al., 2014) and a one-year time use survey among a small group of retiring Australian women and men (Sprod et al., 2017) (Table 1). These studies provided inconsistent findings. Clark and colleagues (2014) and Sprod and colleagues (2017) suggested that self-reported daily total sitting time actually decreases in the transition to retirement, mainly due to reduced time spent sitting at work and in vehicles, which after retirement is replaced by indoor and outdoor chores, sleep, screen time, and physical activity. In contrast, Menai and colleagues (2014) found that self-reported daily total sitting time increased after retirement. These studies were unable to fully examine the role of occupation, which is likely to be an important factor affecting changes in sedentary behavior in the transition to retirement.

To fully understand overall changes in sedentary time in the transition to retirement, we need longitudinal studies that evaluate changes in daily total sedentary time and prolonged sedentary time using accelerometers, taking into account occupational sedentary time and examining the role of occupation. Depending on whether an individual retires from a sedentary or physical occupation, retirement may take daily total sedentary time in different directions. Retiring from physically demanding occupations may result in a highly sedentary lifestyle because active working hours are not necessarily replaced by eight hours of leisure-time physical activity. Longitudinal survey studies partly support this hypothesis, as it seems that time spent watching TV increases among those retiring from manual occupations (Barnett et al., 2014; Touvier et al., 2010; Van Dyck et al., 2016). In contrast, for those with sedentary occupations, retirement may bring positive changes to sedentary behavior because sitting time at the office is freed for other activities. Previously described cross-sectional studies among office workers give an indication that this hypothesis may hold up, because these studies show that non-working hours include less sedentary time and prolonged sedentary time than working hours (Clemes et al., 2014; Kurita et al., 2019; Parry & Straker, 2013; Thorp et al., 2012). Moreover, studies focusing on changes in self-reported physical activity have shown that physical activity increases after the transition to retirement especially among those who retire from higher-level occupational groups (Barnett et al., 2012). Thus, it is possible that those retiring from sedentary occupations, which usually correspond to higher-level occupations, replace occupational sitting with health-promoting physical activity and that this may be reflected in decreased daily total sedentary time after retirement.

Table 1. Studies on the association between retirement and sedentary time.

AUTHOR, PUBLICATION YEAR	STUDY POPULATION	PARTICIPANTS	STUDY DESIGN	ASSESSMENT OF SEDENTARY TIME	MAIN FINDINGS
SELF-REPORTED SITTING TIME					
Touvier et al. 2010	N=1389 Age range 45–64 France	Employees from the SU.VI.MAX cohort	Prospective three-year cohort study	Self-reported daily time spent watching TV. Assessed during work life and three years after.	Those who retired from physically demanding jobs increased their time spent watching TV by 46 min/day.
Barnett et al. 2014	N=3334 Age range 45–79 UK	Employees from the EPIC-Norfolk study cohort	Prospective 7.6-year cohort study	Self-reported weekly time spent watching TV. Assessed during work life, and 4 and 7.6 years after	Participants in the manual class increased watching their time spent watching TV by 6.6 h/week, and those from the non-manual class by 5.4 h/week after retirement.
Clark et al. 2014	N=6973 Mean age 52.5 Australia	ALSWH cohort	Prospective nine-year cohort study	Self-reported daily sitting time (sitting while visiting friends, driving, reading, watching TV, using a computer, occupational sitting). Assessed in four study waves, every three years.	Women who reported retirement were more likely to decrease their daily sitting time in comparison to those who continued working.
Menai et al. 2014	N=2841 Mean age 57.3 France	SU.VI.MAX cohort	Prospective six-year cohort study	Self-reported weekly total sitting time (watching TV/video, using a computer, playing video games, reading, occupational and sitting at home). Assessed at baseline and six years later.	Retiring adults increased their total sitting time by 8.4 h/week, considerably more than the retirees (4.2 h/week). The highest increase was observed in time spent using a computer.
Van dyck et al. 2016	N=446 Mean age 62.4 Belgium	Random sample of municipal workers planning to retire or recently retired.	Prospective two-year cohort study	Self-reported weekly leisure-time sitting including passive transport, watching TV, using a computer, sitting during hobbies, household chores and meals. Assessed at baseline and two years later.	Retiring adults increased their time spent using a computer more than retirees (98 vs. 65 min/week). Computer use increased the most among women and low-educated and watching TV among low-educated adults.

Sprod et al. 2017	N=124 Mean age 62.3 Australia	Life After Work Study cohort	Prospective one-year cohort study	Self-reported daily quiet time (reading, non-reading), screen time (watching TV, playing video games), time spent on self-care (eating, grooming), passive transport, computer use at work. Assessed during work life and 3, 6, 12 months after.	Screen time, mostly watching TV, increased by 32 min/day soon after retirement, but remained fairly stable after three months among all participants.
Jones et al. 2018	N=6814 Age range 45–84 US	MESA cohort	Prospective nine-year cohort study	Self-reported weekly time spent watching TV in five study waves every two years.	Retirement was associated with a 15% increase in TV watching.
Leskinen et al. 2018	N=2011 Mean age 63.2 Finland	FIREA study cohort	Prospective 3.4-year cohort study	Self-reported daily time spent sitting at the office and total non-occupational sitting including time spent watching TV or videos at home, using a computer at home, being in a vehicle and other sitting. Assessed one and two years before, and one, two and three years after retirement.	Non-occupational sitting time, especially watching TV and other sitting time, increased by 73 min/day in the transition to retirement and 18 min/day after retirement. Highest increases were observed among women and those with high pre-retirement occupational sedentary time, low pre-retirement physical activity level, sleep difficulties, chronic diseases, mental disorders, poor self-reported health and psychological distress.
ACCELEROMETER-MEASURED SEDENTARY TIME					
Godfrey et al. 2014	N=98 Mean age 69.1 UK	Healthy age-matched controls for larger ICICLE-PD GAIT Study	Cross-sectional	A thigh-worn accelerometer worn for seven days to produce percentage of sedentary time and prolonged sedentary time (>55 min).	Being retired was associated with lower percentage of sedentary time and prolonged sedentary time in comparison to working adults.
Yerrakalva et al. 2017	N=3705 Median age 69.5 UK	EPIC-Norfolk Study cohort	Cross-sectional	A hip-worn accelerometer for seven days to produce estimates of total daily sedentary time and breaks from sedentary time.	Retired participants had more sedentary time and fewer breaks every hour of the day in comparison to non-retired participants.

2.2.5 Interventions to reduce sedentary time among retirees

Given that retirement seems to be a susceptible time point for changes in sedentary behavior and that sedentary behavior tends to increase with advancing age, actions to attenuate or reverse the increasing trend of sedentary behavior are needed. To date, no interventions have targeted the time window immediately after the transition to retirement (Baxter et al., 2016), which could be a potential time point for modifying sedentary behavior, as new routines are often adopted after retirement.

In general, interventions to reduce sedentary time can be divided into sedentary behavior-focused, physical activity-focused and combination (focus on both sedentary behavior and physical activity) interventions. Sedentary behavior-specific interventions have mainly utilized sit-stand workstations at workplaces (Prince et al., 2014). Physical activity interventions have attempted to reduce sedentary time by replacing it with increasing physical activity by exercise protocols or pedometers, while combination interventions have added a few sedentary behavior-specific components such as counseling on the health consequences of sedentary behavior (Compernolle et al., 2019; Prince et al., 2014). Meta-analyses have shown that sedentary behavior-specific interventions are superior to physical activity and combination interventions in reducing sedentary time (Compernolle et al., 2019; Martin et al., 2015; Prince et al., 2014), possibly due to their higher number of sedentary behavior-specific intervention components (Martin et al., 2015). Moreover, people who manage to increase their physical activity by taking part in exercise sessions may feel that they no longer need to be physically active for the rest of the day, leading to high daily sedentary levels (Prince et al., 2014). However, given that there is a fixed number of hours in a day and that both increasing physical activity and reducing sedentary time induce health effects, combining intervention components to reduce sedentary time and increase physical activity may be the most optimal from the public health perspective (Compernolle et al., 2019).

Interventions to reduce sedentary time have mostly been conducted at workplaces (Shrestha et al., 2018) and fewer studies have attempted to reduce sedentary time during leisure time (Shrestha et al., 2019). Leisure time offers several possibilities for sedentary behavior such as watching TV and using multimedia and a computer. Thus, targeting sedentary behavior during leisure time may be more complex and challenging than in work environments, which are characterized by relatively stable routines and environments. In their meta-analysis, Shrestha et al. (2019) showed that most interventions targeting leisure sedentary time have been multicomponent lifestyle interventions aiming to change sedentary behavior and/or physical activity along with diet. These interventions have employed traditional methods, i.e. face-to-face counseling, education and exercise programs, and have resulted in a reduction of self-reported leisure-time sitting of approximately 30 minutes per day for up to six months (Shrestha et al., 2019). All of these interventions have targeted working-age adults, so it is not known how these methods apply to retirees. Concerns about the cost-effectiveness of these traditional methods have arisen, because traditional methods require a relatively high number of resources in terms of time and personnel (Stockwell et al., 2019).

Activity trackers may offer a cost-effective tool for intervening in sedentary behavior in retirees' everyday lives, i.e. non-occupational contexts. Activity trackers are considered a less resource-intensive and more scalable, practical and personalized method to elicit behavior changes than traditional face-to-face and counseling interventions (Brickwood, Watson et al., 2019; Stockwell et al., 2019). Activity trackers can be harnessed to change both sedentary behavior and physical activity through multiple evidence-based BCTs such as self-monitoring, feedback, prompts, and goal-setting (Duncan et al., 2017; Michie et al., 2013; Shin, Jarrahi et al., 2019). Moreover, activity trackers have been reported as feasible among middle-aged and older adults (Brickwood, Williams et al., 2019; Lyons et al., 2017). A recent meta-analysis by Brickwood and colleagues (2019) showed that activity trackers have mainly been employed in short- and medium-term (≤6 months) physical activity interventions, either as a primary component or as one part of multicomponent interventions to increase physical activity. These interventions have resulted in a mean increase in MVPA of 75 minutes. Only a minority of these studies have included sedentary behavior as an outcome.

To date, activity trackers have mainly been used as one component in multicomponent interventions to reduce sedentary time. No activity tracker-based multicomponent interventions have targeted retirees. Table 2 presents the rare RCTs that have evaluated multicomponent interventions that have utilized an activity tracker and targeted adults close to retirement age (50–65 years) (Ashe et al., 2015; Li et al., 2018; Lynch et al., 2019a; Lyons et al., 2017). These interventions have mostly been pilot/feasibility studies with small sample sizes, lasted up to six months, and focused mainly on physical activity (Table 2). The main sedentary behavior-specific BCTs have been activity tracker-delivered prompts, counseling on the health consequences of sedentary behavior, feedback, and goal-setting. A study by Lynch and colleagues (2019a) found that a three-month intervention resulted in a 30-minute greater reduction in accelerometer-measured sedentary time per day than among the controls. Slight attenuation was observed three months after the end of the intervention (7 min/day) (Lynch et al. 2019b). A quite similar but shorter intervention by Li and colleagues (2018) did not gain statistically significant reductions in accelerometer-measured sedentary time over one month, possibly due to a small sample size (n=34) and the absence of prompts. Other multicomponent interventions targeted at a general population did not result in significant changes in sedentary time in comparison to controls over three months (Lyons et al., 2017) or over six months (Ashe et al., 2015).

Only a small number of RCTs have evaluated the effect of interventions that have delivered all BCTs to target sedentary behavior by an activity tracker (Table 2). These interventions have been conducted among adults with a mean age of 18–36 years, none have been conducted among adults of retirement age (Barwais et al., 2013; Jauho et al., 2015; Sloan et al., 2018). Barwais and colleagues (2013) evaluated the effect of an activity tracker that enabled self-monitoring of sedentary behavior and physical activity. This one-month intervention resulted in two hours less self-reported sitting time among the intervention group than among the controls who were middle-aged adults. The rest of the activity tracker-based interventions have focused on physical activity and have not included sedentary behavior-specific BCTs (Jauho et al., 2015; Sloan et al., 2018). Self-monitoring of physical activity neither reduced accelerometer-measured sedentary time nor increased physical activity over three months among young men (Jauho et al., 2015), or over six months among 800 working-age adults (Sloan et al., 2018).

Based on the existing literature, interventions need to use activity trackers that have more features to address specifically habit-like sedentary behavior. Recent systematic reviews suggest that computer- or phone-delivered prompts, mainly utilized at the workplace, that remind the user to break up sitting time, are promising tools to reduce sedentary time (Elavsky et al., 2019; Hardeman et al., 2019; Stephenson et al., 2017). For instance computer software that reminded the user to break up occupational sitting every 30 minutes reduced worktime accelerometer-measured prolonged sedentary time by one hour more among the intervention group than among the controls during a usual working week (n=28, aged 40–50 years, UK) (Evans et al., 2012). There is a dearth of information on how prompts apply to non-occupational contexts, because only a few multicomponent interventions have utilized activity trackers with inactivity alerts, and the majority of the study participants have been in work life. The results have been conflicting, as one study found no effect on accelerometer-based sedentary time among healthy adults over three months (Lyons et al., 2017), but another found a significant effect on both accelerometer-based daily total sedentary time and prolonged sedentary time among cancer survivors over three months (Lynch et al., 2019a). One recent short-term RCT among obese older adults (n=60, mean age 68 years, US) evaluated an intervention that utilized an activity tracker to only deliver inactivity alerts; the other features of the tracker were not utilized (Rosenberg et al., 2020). The inactivity alerts were combined with face-to-face meetings and telephone calls to support goal-setting, feedback and identifying barriers and strategies to reduce sedentary time. The intervention resulted in a 58-minute greater reduction in accelerometer-measured sedentary time than among controls over three months.

Table 2. Randomized controlled trials utilizing activity trackers to reduce sedentary time.

AUTHOR PUBLICATION YEAR	PARTICIPANTS	INTERVENTION		CONTROL GROUP	SEDENTARY OUTCOMES	MAIN FINDINGS
		DURATION (MONTHS)	TECHNIQUES			
MULTICOMPONENT INTERVENTIONS						
Ashe et al. 2015 (pilot study)	N=25 Mean age 64 Healthy, inactive Canada	6	Fitbit: self-monitoring and feedback on physical activity, social support. Other: information on health consequences, action and coping planning, social support.	Monthly education sessions	Accelerometer-based (hip) daily sedentary time at 0, 3 and 6 months.	Intervention group reduced daily sedentary time from 68% to 66%, but the change did not differ from that of controls.
Lyons et al. 2017 (Pilot study)	N=40 Mean age 61 Healthy USA	3	Jawbone: prompts, self-monitoring and feedback on physical activity and inactivity bouts, social support. Other: action and coping planning, goal-setting.	Delayed intervention	Accelerometer-based (thigh) daily sedentary time at 0, 6 and 12 weeks.	Indication of larger decrease in sedentary time among intervention group but the change did not differ from that of controls.
Li et al. 2018 (pilot study)	N=34 Mean age 56 Diagnosed with knee osteoarthritis Canada	1	Fitbit: self-monitoring and feedback on physical activity and daily activity goal. Other: information on health consequences, action and coping planning, goal-setting.	Delayed intervention	Accelerometer-based (wrist) daily prolonged sedentary time (≥20 min) at 0, 1 and 2 months.	Sedentary time decreased in the intervention group by 25 min but the change did not differ from that of controls.
Lynch et al. 2019a	N=83 Mean age 62 Inactive breast cancer survivors Australia	3	Garmin: prompts, self-monitoring and feedback on physical activity. Other: information on health consequences, action and coping planning, goal-setting.	Delayed intervention	Accelerometer-based (thigh) daily sedentary time and prolonged sedentary time (≥20 min) at 0, 3 and 6 months.	The intervention group reduced sedentary time by 37 min and prolonged sedentary time by 42 min more than the controls.

Table 2—Continued

AUTHOR PUBLICATION YEAR	PARTICIPANTS	INTERVENTION		CONTROL GROUP	SEDENTARY OUTCOMES	MAIN FINDINGS
		DURATION (MONTHS)	TECHNIQUES			
ACTIVITY TRACKER-BASED INTERVENTIONS						
Barwais et al. 2013	N=33 Mean age 27 High self-reported sitting time (>7 h per day) Australia	1	Gruve: self-monitoring of sedentary time and physical activity, daily activity goal.	No intervention	Daily sitting time from a seven-day SLIPA log at baseline and at four weeks.	The intervention group reported two hours less sitting time after the intervention, while the controls reported no changes. Effect size was exceptionally high, Cohen *d*=1.30.
Jauho et al. 2015 (Pilot study)	N=276 Mean age 18 Healthy population Finland	3	Polar Active: self-monitoring of physical activity.	No intervention	Activity tracker-based daily sedentary time (blinded device among controls) over three months.	During the first two months, the intervention group reduced sedentary time more than the controls, but the effect did not last three months.
Sloan et al. 2018	N=800 Mean age 36 Healthy population Singapore	6	Fitbit: self-monitoring of physical activity.	No intervention	Accelerometer-based (hip) daily sedentary time and prolonged sedentary time (≥30 min) at baseline, six and twelve months.	No changes in total or prolonged sedentary time among the intervention group in comparison with the controls.

2.3 Gaps in previous research

Before the current PhD study, knowledge on changes in sedentary behavior across the transition to retirement was based on longitudinal survey studies (Barnett et al., 2014; Clark et al., 2014; Jones et al., 2017; Menai et al., 2014; Sprod et al., 2017; Touvier et al., 2010; Van Dyck et al., 2016). Because the evidence relied mostly on self-reported sitting time, it was unclear how daily total sedentary time and patterns of sedentary behavior, i.e. daily sedentary profiles and prolonged sedentary time, change in the transition to retirement. In 2018, a survey study by Leskinen and colleagues (2018) followed study participants with repeated surveys across the transition to retirement, enabling examination of both short- and long-term changes in leisure-time sitting across the transition to retirement. However, as self-report methods are prone to recall bias, due to the habitual nature of sedentary behavior, and also to information and social desirability bias, accelerometer-based examinations are warranted. Existing accelerometer-based findings are based solely on two cross-sectional studies comparing the accelerometer-measured daily total sedentary time and prolonged sedentary time of retired and non-retired adults, both in British study populations (Godfrey et al., 2014; Yerrakalva et al., 2017). Thus, there is a lack of knowledge on how accelerometer-measured sedentary time changes in the transition to retirement.

At the time the current PhD study began, no interventions aiming to reduce sedentary behavior had targeted the time window immediately after retirement. Retirement may be a potentially fruitful time for intervening in increasingly sedentary lifestyles. Activity trackers may offer a cost-effective solution to deliver multiple evidence-based BCTs, but their effect on sedentary time has been studied very little. Only three RCTs have evaluated the effect of an activity tracker as the core instrument of an intervention (Barwais et al., 2013; Jauho et al., 2015; Sloan et al., 2018) and none of these have targeted retirees. These studies provide heterogenous results, possibly due to one of them using self-reported daily sitting time as an outcome and due to differences in the number of sedentary behavior-specific BCTs, and the duration of the interventions and follow-up periods. Only multicomponent interventions have utilized activity trackers equipped with inactivity alerts, which may be effective in reducing habit-like sedentary behavior. Thus, the true potential of activity trackers for reducing sedentary time among recent retirees in the long term is not known.

Finally, studies evaluating the count- and ENMO-based cutpoints developed for a wrist-worn accelerometer in free-living conditions are scarce (Hildebrand et al., 2017; Koster et al., 2016). Cutpoints are often developed under laboratory conditions or video observation, and because these conditions may not represent free-living activities very well, further evaluation in free-living conditions and in other study populations is important. To date, only thigh-worn accelerometers provide a valid reference method for estimating sedentary time in free-living conditions, because they enable precise detection of sitting and lying postures. Given that the study populations of Koster and colleagues (2016) and Hildebrand and colleagues (2017) were relatively small and included only middle-aged adults or adults older than 70, it is not known how large the differences between thigh- and wrist-worn accelerometers can be expected to be among relatively healthy adults in their 60s in free-living conditions.

3 Aims

The overall aim of this PhD study was to examine changes in sedentary behavior across the transition to retirement. Another aim was to examine whether an activity tracker used in the everyday lives of retirees reduced sedentary behavior. As changes in sedentary time were captured by a wrist-worn accelerometer, the study also aimed to evaluate the accelerometer's accuracy in estimating sedentary time.

Thus the specific aims of this PhD thesis are:

1. To examine how accelerometer-measured daily total sedentary time, prolonged sedentary time and daily sedentary time profiles change across the transition to retirement according to gender and occupational status (Study I and II).

2. To investigate, using a randomized controlled trial, the effect of an activity tracker-based intervention on daily total sedentary time and prolonged sedentary time among recent retirees (Study III).

3. To compare sedentary time estimates from the movement-based methods applied to a wrist-worn accelerometer to daily sedentary time estimates from a posture-based thigh-worn accelerometer (Study IV).

4 Materials and Methods

4.1 Participants and study design

This PhD study is based on two larger studies: 1) a longitudinal observational study, the Finnish Retirement and Aging Study (FIREA) and 2) an RCT study, Enhancing physical activity and healthy aging among recent retirees – Randomized controlled in-home physical activity trial (REACT) study.

4.1.1 The FIREA study (Studies I, II, IV)

The FIREA study began in 2013 at the University of Turku with the aim of following aging workers from work to statutory retirement and to examine how health behaviors, clinical risk factors and health change across the transition to statutory retirement. The FIREA study was approved by the Ethics Committee of the Hospital District of Southwest Finland and all the participants gave their informed consent to participate in the study.

The eligible study population of the FIREA survey cohort included public sector workers who were working in one of the 27 municipalities in Southwest Finland or in one of the selected 11 towns or five hospital districts around Finland in 2012 and who retired on a statutory basis between 2014 and 2019 (N=10 629). The participants were first contacted 18 months prior to their estimated retirement date by sending them a questionnaire, after which questionnaires were sent annually, up to six times in total to gather data from at least two time points before and two time points after the transition to statutory retirement. Of the eligible study population, 5076 answered at least one questionnaire by December 2017, were still working at the time of the first survey, and thus, formed the FIREA survey cohort.

The Finnish-speaking FIREA survey cohort participants who were still working in 2016 and had an estimated statutory retirement date between 2016 and 2019 were considered to be eligible and were invited to participate in the FIREA activity sub-study (n=2663). Of these, 908 gave their informed consent and were followed via questionnaires and activity measurements annually, at the same time of the year, up to six times in total. Figure 2 shows how the samples in Studies I and II were comprised. Studies I and II consisted of participants who had participated in the accelerometer measurements immediately before and after retirement (one year between the measurements). In addition, valid measurements were restricted to those with at least four valid days of 10 or more hours of wake wear time for the accelerometer measurement. The final study population of Study I was 478, which was determined by the end of March 2019, and that of Study II 689, which was determined by the end of January 2020.

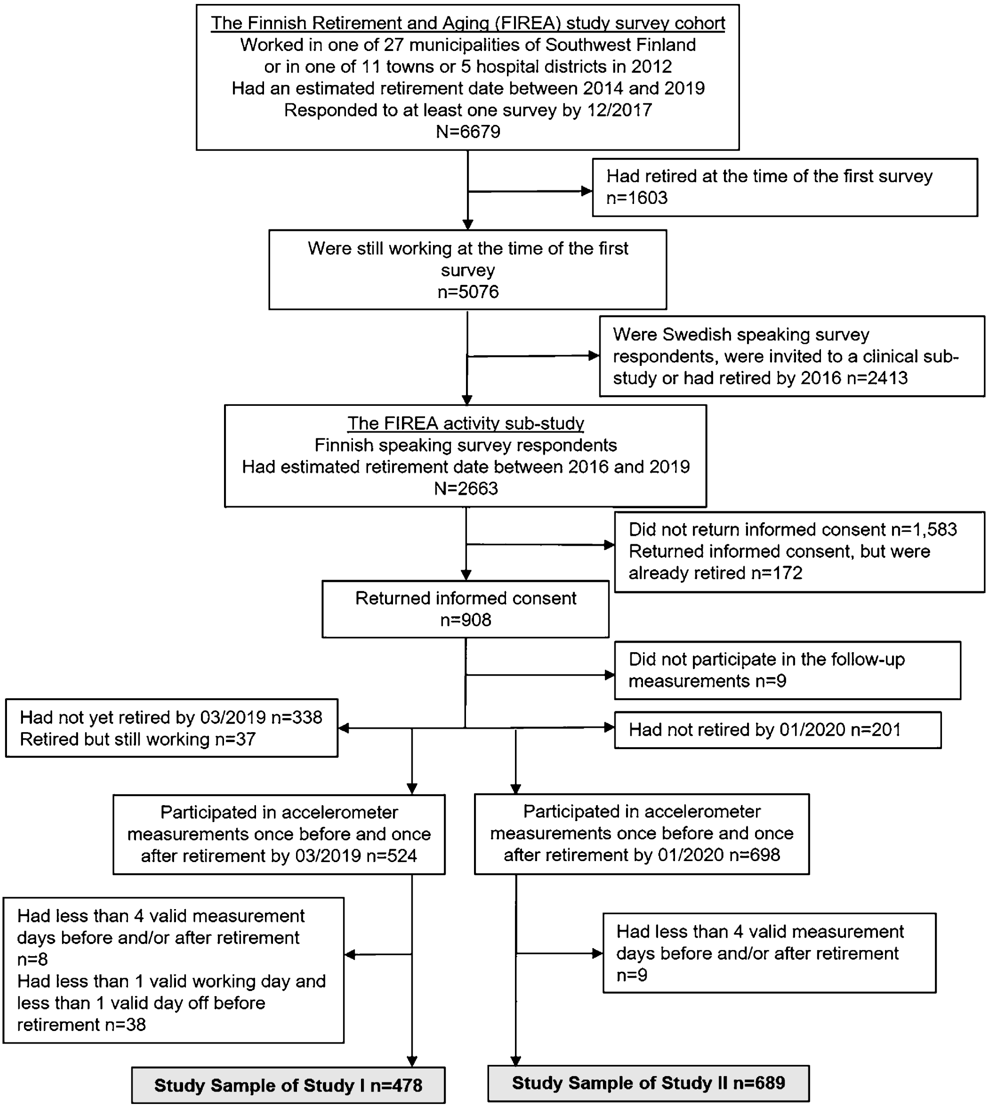

Figure 2. Flow chart of selection of samples for Studies I and II.

The eligible study population of the FIREA clinical sub-study consisted of the Finnish-speaking FIREA survey cohort participants who lived in Southwest Finland, were still working in 2017 and had an estimated statutory retirement date between 2017 and 2019 (n=773). Those invited to participate in the FIREA activity sub-study were not included. The eligible study population was invited to participate in the FIREA clinical sub-study and 290 gave their informed consent, participated in the baseline measurement with wrist- and thigh-worn accelerometers and formed the study population of Study IV.

Of the 290 participants who participated in the baseline measurement, 18 were excluded due to device malfunctions or missing accelerometers or log data. To compare the valid measurement days during which the wrist- and thigh-worn accelerometers were worn for approximately the same time period, the analytical sample was first restricted to the measurement days with a difference in wake wear time between wrist- and thigh-worn accelerometers of 10 minutes or less. This resulted in the exclusion of 12 people from the first comparison of the count cutpoint method of the wrist-worn accelerometer and the thigh-worn accelerometer, 71 people from the second comparison of the ENMO cutpoint method with a 60-second bout restriction for the wrist-worn accelerometer and the thigh-worn accelerometer, and 69 people from the third comparison of the ENMO cutpoint method without a bout restriction for the wrist-worn accelerometer and the thigh-worn accelerometer. After this, the participants who had less than one valid day with a minimum of 10 hours of accelerometer wear time during waking hours were excluded (first comparison n=1, second comparison n=2, third comparison n=3), resulting in an analytical sample of 259 participants in the first comparison, 199 participants in the second comparison, and 200 participants in the third comparison.

4.1.2 The REACT trial (Study III)

The REACT trial was established in 2017 with the aim of evaluating a 12-month activity tracker-based intervention on accelerometer-measured physical activity as a primary outcome, and sedentary time, sleep, and other health-related outcomes as secondary outcomes among recent retirees. The REACT trial was approved by the Ethics Committee of the Hospital District of Southwest Finland.

The target study population for the REACT trial consisted of Finnish public sector employees who lived in Southwest Finland in 2017 and had an estimated retirement date between January 2016 and April 2019 (n=1475). FIREA study participants who had responded to at least one survey were not included. The researcher responsible for the implementation of the REACT trial contacted the target study population for the first time in January 2018, by mailing them an invitation letter to their home address. The letter included information on the REACT trial and inclusion criteria. The enrollment continued until March 2018. The inclusion criteria were the self-reported actual dates of retirement between January 2016 and December 2018, self-reported ability to walk 500 m without interruptions, no current post-operative state or no known surgery in the next six months, no malign cancer or recent myocardial infraction, basic knowledge of how to use a computer, and internet access at home.

The formation of the sample for Study III is illustrated in Figure 3. Overall, 272 individuals (18% of the target population) expressed an interest in taking part in the trial. The proportion of women and the highly educated was higher among the respondents than among the non-respondents (82% vs. 78%, 37% vs. 20%, respectively). Of the respondents, 252 fulfilled the inclusion criteria and were invited to participate in the REACT trial, 231 of whom gave their signed, informed consent and participated in the REACT trial. After the baseline measurements, a statistician not involved in the running of the REACT trial randomized the participants, stratified by gender, into intervention and control groups with an allocation ratio of 1:1.

Sample size was calculated so that, based on a power of 0.80 and a two-sided alpha of 0.05, 214 participants were required to detect a 12% unit difference (standard deviation 31) between the intervention and the control group in the primary outcome – accelerometer-measured wake-time physical activity at the 12-month time point (Wijsman et al., 2013). No separate sample size calculations were conducted for sedentary time.

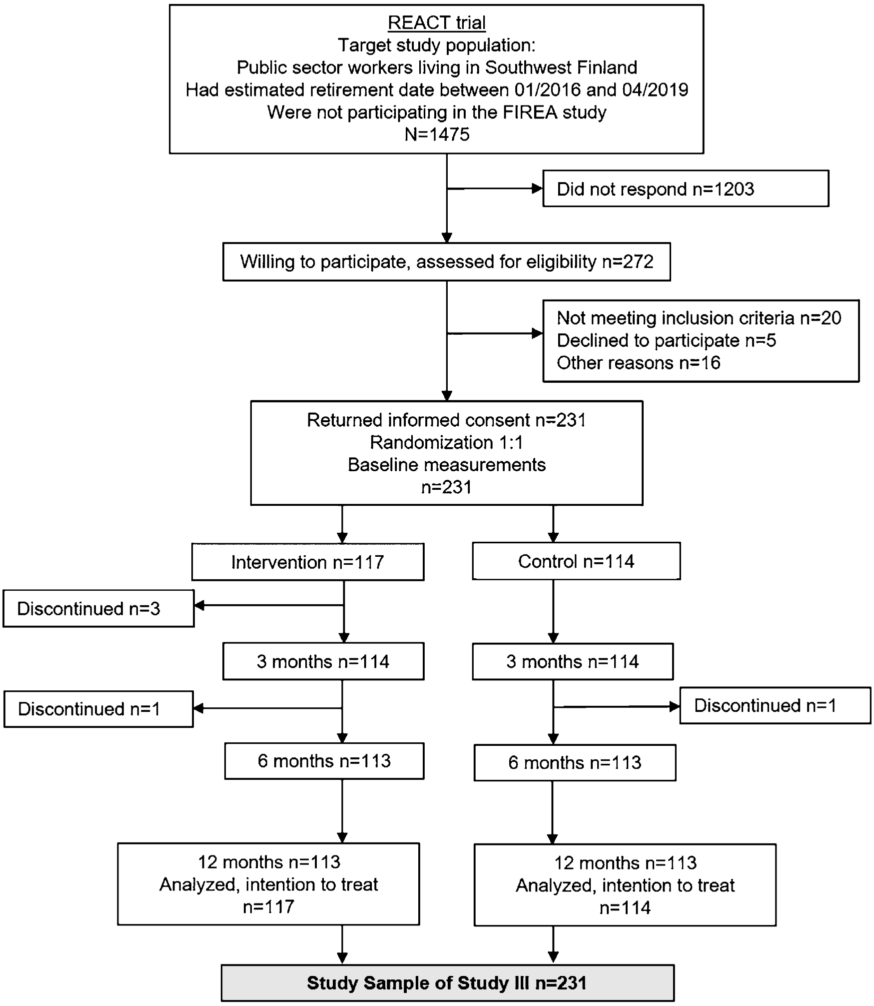

Figure 3. Flow chart of selection of sample for Study III.

After the baseline measurements and allocation into intervention and control groups, a commercial activity tracker (Polar Loop 2, Polar, Kempele, Finland) and its instructions were sent to the intervention group members. They were instructed to wear the activity tracker on their non-dominant at all times, day and night, over a 12-month period. The control group members were instructed to abstain from using any type of activity trackers during the 12-month follow-up. As an incentive to participate in the follow-up, the control group were informed that they will receive the Polar Loop 2 activity tracker and guidance for using it after the follow-up.

The Polar Loop 2 activity tracker was chosen to deliver multiple BCTs, and no other intervention components were used. Technical guidance on the use of the activity tracker was given if needed. The main functionalities of the Polar Loop 2 activity tracker were daily activity goals and inactivity alerts. At the beginning of the intervention, the participants were advised to aim to fulfil the daily activity goal that was initially set in Stage 1. Since the activity tracker had a built-in accelerometer, various kinds of activities contributed to achieving the daily activity goal: activities at higher intensities fulfilled the daily goal faster than activities at lower intensities. According to the tracker's manufacturer, to achieve 100% of the daily activity goal at Stage 1, the participant should for instance jog for ~1h/day or walk for ~2h/day or do household activities for ~7h/day or do a combination of these activities (Polar Electro, 2020). Based on the accumulated daily activity, the tracker provided real-time feedback and practical guidance on its screen on how to reach the daily goal; for example, "jog for 20 minutes" or "walk for 50 minutes". When the daily goal was fulfilled, the tracker notified and congratulated the user. If the participant frequently exceeded their daily activity goal at Stage 1, the researcher suggested Stage 2, which was comparable to, for instance 3h/day of walking, and ultimately Stage 3, which was comparable to, for instance 3.5h/day of walking, via email or text message. In some cases, the users changed stages themselves. The activity tracker also gave an inactivity alert as a vibration and the text "it's time to move" appeared on the screen of the tracker if the person had been still without interruptions for 55 minutes. If the person did not start to move within five minutes, the tracker saved an "inactivity stamp".

A researcher created personal accounts for the participants in the web-based Polar Flow program (Polar Electro, 2020). The participants were asked to upload their activity tracker data to Polar Flow at least once a week. The participants had unrestricted access to their personal Polar Flow accounts either via their computer or mobile phone app. Polar Flow displayed overviews and summaries of the data collected by the tracker (activity, sedentary time, sleep) on daily, weekly and monthly bases. It also provided feedback on the attainment of the daily activity goal, whether the tracker had been worn sufficiently, and detailed feedback on the health benefits of the accumulated activity and sedentary time, such as "You spent quite a lot of time sitting down. You'll see more health benefits if you reduce this". The participants gave the researcher permission to access their personal Polar Flow accounts. The researcher followed the data in Polar Flow every week and if a participant had not downloaded the data to the program, they were reminded to do so as soon as possible. Intervention adherence was assessed by following the participants' activity data in Polar Flow.

The daily activity goal and other physical activity-specific BCTs (Leskinen et al., 2021) were expected to reduce sedentary time by replacing it with physical activity. Moreover, the REACT trial included sedentary behavior-specific BCTs. According to the taxonomy of BCT Taxonomy v1 (Michie et al., 2013), the BCTs incorporated in the activity tracker that were expected to specifically target sedentary behavior were feedback on behavior [#2.2], self-monitoring of behavior [#2.3], information on health consequences [#5.1] and prompts/cues [#7.1]. It has been theorized that feedback on behavior supports behavior change by making the gap between an individual's behavior and the recommended behavior visible, which may in turn drive the individual's motivation to their change behavior (Gardner et al., 2010). Self-monitoring has been used to bring habitual behavior such as sedentary behavior into conscious awareness and to promote self-control (Bandura, 2004; Compernolle et al., 2019; Glanz & Bishop, 2010). Providing information on health consequences is believed to convince individuals of the health benefits of changing their behavior, which in turn may enhance their readiness to take action (Rosenstock et al., 1988). Prompts/cues act as essential external signals to trigger the recommended behavior among people convinced of the health benefits of reducing sedentary behavior (Glanz & Bishop, 2010; Rosenstock et al., 1988).

4.2 Accelerometer measurements

In Studies I─III, a wrist-worn accelerometer was used to estimate sedentary time by detecting time periods with no or little movement of the wrist. Study IV used both a wrist- and thigh-worn accelerometer to compare movement-based estimates from a wrist-worn accelerometer to posture-based estimates from a thigh-worn accelerometer.

Studies I and II measured sedentary time for seven days and nights using two compatible accelerometer models: triaxial ActiGraph wActiSleep-BT and wGT3X-BT accelerometers (ActiGraph, Pensacola, Florida, US (ActiGraph, 2020)) once a year across the transition to retirement. The accelerometer measurements were conducted during all four seasons, but approximately at the same time of the year for each study participant to minimize possible seasonal effects on the results. The consecutive measurement points were on average 361–364 days apart. Study I, had two measurement points (one before and one after retirement) and in Study II, the average number of measurement points was 3.4 (range 1–4; 1.7 before and 1.7 after retirement). In Study III, the ActiGraph wGT3X-BT accelerometer measured sedentary time at baseline, 3, 6 and 12 months after the initiation of the intervention in both the intervention and control groups. In Study IV, sedentary time was measured using two accelerometer models: a wrist-worn ActiGraph wActiSleep-BT and a thigh-worn Axivity AX3. Each of the accelerometer brands contained a three-axis MEMS accelerometer. None of the accelerometer brands used provided feedback for the users on their sedentary time, physical activity or sleep. Figure 4 illustrates the timeline of the accelerometer measurements in Studies I–IV.

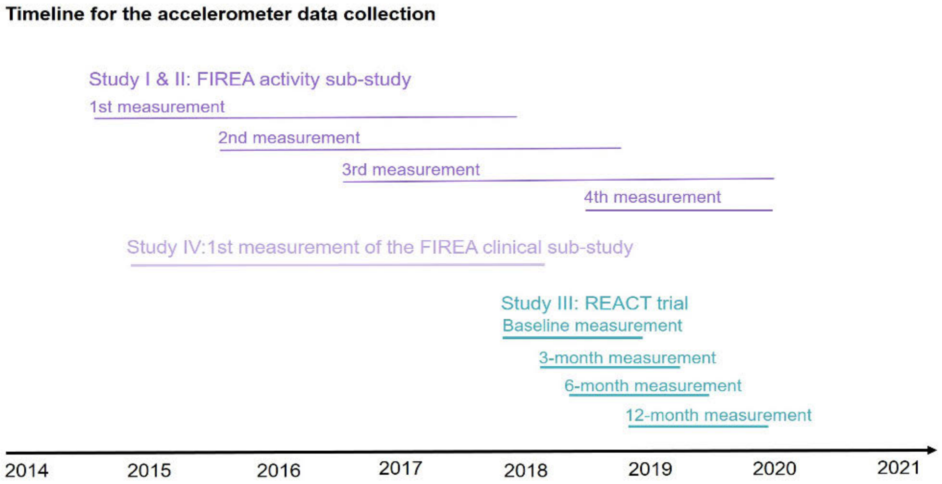

Figure 4. Timeline for accelerometer measurements conducted in Studies I–IV.

Before giving or mailing the accelerometers to the participants, the ActiGraph accelerometers with a dynamic range of +/- 8G were initialized to sample acceleration data by a 12-bit analog to digital converter at a sampling frequency of 80 Hz (ActiGraph, 2019). The ActiGraph accelerometers' sleep mode was also enabled. The Axivity accelerometers were initialized to sample acceleration data with a dynamic range of +/- 8G by a 13-bit analog to digital converter at 100 Hz (Axivity, 2021). For the Axivity accelerometers, recording was continuous, but no additional sleep mode was available (Axivity, 2021). In Studies I, II and IV, the ActiGraph accelerometers were also initialized to start recording at 05:00 on the first Saturday after the participants received them and the participants were instructed to attach the accelerometer to their non-dominant wrist as soon as they woke up on the given Saturday. If beginning the measurement on Saturday was not ideal due to, for instance, annual leave or travel abroad, i.e. an unusual week, the participants began the measurement later, nevertheless within two weeks. Accelerometers, wrist bands, instructions and daily logs, as well as pre-paid return envelopes were mailed to the participants. The instructions contained information on the data that the accelerometer collected from the participant and instructions on how to use the accelerometer, emphasizing that the measurement week should be as normal as possible. Participants were instructed to record the following information in a daily log each day that they wore the accelerometer until the last evening of the measurement: dates, in-bed and out-of-bed times, whether the day was a working day or a day off, start and end times of work shifts, and whether the day differed from a normal day in any way.

In Study III, the accelerometers, wrist bands, instructions, daily logs and postage-paid envelopes for return were given to the participants during a clinical visit at baseline, mailed at three- and six-month follow-up and given during a clinical visit at the 12-month measurement point. When the accelerometers were given to the participants during the clinical visits, they were initialized to start recording on the morning of the visit. When the accelerometers were mailed to the participants, they were initialized to start recording at 06:00 on the first Saturday after the participants received them. As in Studies I and II, the participants were instructed to attach the accelerometer to their non-dominant wrist as soon as they woke up on the given Saturday. They were also permitted to begin the measurement later, within two weeks, if they were sick or traveling during the planned measurement week. During the measurement weeks, the intervention group participants wore both the ActiGraph accelerometer and the Polar Loop 2 activity tracker on their non-dominant wrist. The daily log was almost the same as in Studies I and II, but working times were not included because the study participants were retired.

In Study IV, the participants received the ActiGraph accelerometers by mail a few days before the clinical visit, and the study nurse initialized the Axivity accelerometers to start recording at 08:00 on the clinical visit day and to stop recording exactly two weeks later at 08:00. During the clinical visit, the study nurse fastened the thigh-worn Axivity accelerometer with adhesive waterproof film dressing (Opsite, Smith & Nephew, London, England) directly to a standardized position, on the skin on the medial front of the right thigh, midway between the hip and knee joints (Skotte et al., 2014). After receiving the Axivity accelerometers, the participants continued the measurements of both the ActiGraph and Axivity accelerometers. The instructions and daily logs were almost the same as in Studies I and II, but they also included information on the synchronization procedures between the wrist- and thigh-worn accelerometers. The participants were instructed to synchronize the wrist- and thigh-worn accelerometers by taking them off and waiving them five times at the beginning and the end of the measurement and every day during the measurement week by standing still for 15 seconds. In addition, the participants were instructed to enter the synchronization times into the daily log.

The participants were asked to wear the accelerometers for seven consecutive days and nights in Studies I and II; eight consecutive days and nights in Study III; and for a minimum of four days and nights, including at least one working day and one day off in Study IV at all times, including during water-based activities, but to remove the accelerometers while showering or having a sauna.

Table 3 presents an overview of the accelerometer measurement and data processing procedures used in Studies I–IV.

Table 3. Accelerometer measurements and data processing methods used in Studies I–IV.

	STUDY I & II	**STUDY III**	**STUDY IV**	
ACCELEROMETER	ActiGraph on wrist	ActiGraph on wrist	ActiGraph on wrist	Axivity on thigh
DATA PROCESSING				
SOFTWARE	ActiLife	ActiLife, GGIR	ActiLife, GGIR	Open Movement
SAMPLING FREQUENCY	80 Hz	80 Hz	80 Hz	100 Hz
EPOCH LENGTH	60 sec	5 sec	5 sec, 60 sec	5 sec
NON-WEAR TIME	Choi algorithm	SD^{A} of acceleration <13 m*g* or value range <50 m*g* for 60 min	1) Choi algorithm 2) SD^{A} of acceleration <13 m*g* or value range <50 m*g* for 60 min	0 G for >60 min and SD$^{A}_{x}$, SD$^{A}_{y}$ and SD$^{A}_{z}$ >0.5 G for 10–60 min
SLEEP TIME	Cole–Kripke's algorithm & ActiGraph algorithm	Daily log and changes of ≤5º in arm angle within daily log-defined sleep	1) Daily log 2) Daily log and changes of ≤5º in arm angle within daily log-defined sleep	Daily log
SEDENTARY TIME	VM CPM^{B} <1853	Acceleration <30 m*g*	1) VM CPM^{B} <1853 2) Acceleration <30 m*g*	Thigh inclination <45°
SEDENTARY TIME VARIABLES	Daily total & hourly sedentary time Prolonged sedentary time	Daily total & hourly sedentary time Prolonged sedentary time	Daily total sedentary time	Daily total sedentary time
CHARACTERISTICS OF THE MEASUREMENTS				
ACCELEROMETER WEAR TIME DURING WAKING HOURS	953 min (SD^{A} 67)	937 min (SD^{A} 52)	Count cutpoint vs. thigh: 945 min (SD 100) ENMO 5-s vs. thigh: 942 min (SD 106) ENMO 60-s vs. thigh: 940 min (SD 102)	
NUMBER OF VALID DAYS PER PARTICIPANT	6.8 (range 4–8)	6.8 (range 4–8)	Count cutpoint vs. thigh: 3.2 (range 1–9) ENMO 5-s vs. thigh: 1.9 (range 1–5) ENMO 60-s vs. thigh: 2.0 (range 1–5)	

^{A} SD = Standard deviation
^{B} VM CPM = Vector magnitude counts per minute

In all Studies I–IV, the data from the ActiGraph accelerometers were downloaded onto the ActiLife software, version 6.13 (ActiGraph, Pensacola, Florida, US) as soon as the accelerometers were returned by the participants via mail. In Studies I and II, the accelerometer data were first converted into 60-second epochs in the ActiLife software. To capture the sedentary time from the 24 hours/day accelerometer data, sleep and non-wear time had to be first estimated and then excluded from the analyses. The detection of sleep and non-wear time is crucial for accurate sedentary time estimations, because sleep, non-wear time and sedentary time are all determined by low acceleration values (Pulakka, Shiroma et al., 2018; Quante et al., 2018). The ActiLife software estimated sleep periods using validated algorithms that estimate sleep time based on wrist movements, the Cole–Kripke algorithm (Cole et al., 1992; Quante et al., 2018) and the ActiGraph algorithm (ActiGraph, 2018). Non-wear time was estimated by R statistical software, version 3.5.1 (R Foundation for Statistical Computing, Vienna, Austria, https://cran.r-project.org/) using the validated Choi algorithm (Choi et al., 2011). The Choi algorithm determines non-wear time as 90 consecutive minutes of vector magnitude zero counts, allowing for two minutes of non-zero counts, providing that there are 30 minutes of zero counts before or after the non-zero counts (Choi et al., 2011; Choi et al., 2012). After the exclusion of sleep and non-wear time, leaving only wake wear time in the analyses, sedentary time was defined as <1853 vector magnitude counts per minute (CPM), which is validated for accelerometers worn on the non-dominant wrist by older adults against a thigh-worn activPAL accelerometer (Koster et al., 2016).

In Study III, accelerometer data was processed using the open-source R-package GGIR version 1.7-1 (R Foundation for Statistical Computing, Vienna, Austria, https://cran.r-project.org/) (Migueles et al., 2019) in R statistical software, version 3.5.1. The R-package GGIR script is shown in Appendix 1. In the R-package, GGIR accelerometer data are processed by autocalibration according to local gravity, the detection of sustained abnormally high values and non-wear time and the calculation of ENMO values over either one- or five-second epochs with negative values rounded to zero (Migueles et al., 2019). The five-second epoch value was chosen because it is the default value in the GGIR package and has been used in several previous studies using the GGIR package to process data from a wrist-worn accelerometer (Cabanas-Sánchez et al., 2020; Rowlands et al., 2016; van Hees, 2018). Sleep time was defined as periods of time within the in-bed and out-of-bed times reported in the daily logs during which there was no change larger than 5° in the arm angle over at least five minutes (Migueles et al., 2019; van Hees et al., 2015). The sleep time estimation method has been validated against polysomnography data from adults (van Hees et al., 2015). If the in-bed and/or out-of-bed times were missing from the daily log, new in-bed and out-of-bed times were manually added on the basis of the visual inspection of the accelerometer data to improve the performance of the sleep algorithm. Non-wear time was classified using 15-minute time blocks based on the characteristics of the 60-minute time window centered on these 15 minutes. A block was classified as non-wear time if the standard deviation of the 60-minute window was less than 13.0 m*g* for at least two out of the three axes or if the value range for at least two out of three axes was less than 50 m*g* (van Hees et al., 2013). The detection of non-wear and abnormally high acceleration values in the GGIR package has been developed using robot experiments as the reference method and by evaluating the method in free-living conditions (van Hees et al., 2013). After the definition and exclusion of sleep and non-wear time, sedentary time was defined from wake wear time using a previously proposed threshold of 30 m*g* that was developed among adults in semi-standardized conditions (Rowlands, Mirkes et al., 2018).

In Study IV, two movement-based data processing methods for a wrist-worn accelerometer, defined as “the count cutpoint method” and “the ENMO cutpoint method” were compared to the posture-based daily sedentary time estimates from a thigh-worn accelerometer. The count cutpoint method basically corresponded to the data processing method used in Studies I and II, but sleep time was estimated by self-reported in-bed and out-of-bed times in the daily log instead of the Cole–Kripke and ActiGraph algorithms in the ActiLife software. Daily logs were used to estimate sleep time in order to harmonize the sleep estimation methods of the wrist- and thigh-worn accelerometers. The ENMO cutpoint method corresponded to the data processing method in Study III. Sedentary time was additionally estimated from bouts of a minimum of 60 seconds, in which a minimum of 90% time met the threshold criteria for sedentary time, to increase correspondence to the previously suggested and commonly used 60-second epoch length for a wrist-worn accelerometer in sedentary time estimations (Heesch et al., 2018).

In Study IV, data from thigh-worn Axivity accelerometers were downloaded, processed and analyzed using Open Movement software (version 1.0.0.37; Open Movement, Newcastle University, UK) and customized MATLAB software, Acti4, which determines the type and duration of different activities and body postures with a high sensitivity and specificity (Skotte et al., 2014; Stemland et al., 2015). In the Acti4 software, the epoch length for sedentary time was set at five seconds. Sleep time was estimated on the basis of the self-reported in-bed and out-of-bed times reported in the daily log. Non-wear time was defined on the basis of the definition of the Acti4 software: periods longer than 60 minutes without movement and also periods between 10 and 60 minutes if the standard deviation (SD) in the x, y, and z axes were higher than 0.5 *g* for any second during a five-second interval immediately before the period without movement (raw and unfiltered data were used) (Skotte et al., 2014). Sleep and non-wear time were then excluded, leaving only wake wear time for the analyses. The Acti4 software estimates sitting and lying postures on the basis of the inclination of the x-axis, as the x-axis is parallel to the thigh axis, and the inclination provides the angle between the vertical line and the thigh axis, as a positive value ranging from 0–180° (Skotte et al., 2014). A thigh inclination above 45° was identified as sitting or lying down, and as sedentary time (Stemland et al., 2015).

After processing the sedentary time from the accelerometer data, the following parameters were obtained: daily total sedentary time (Studies I─IV), hourly sedentary time (Studies I and III) and prolonged sedentary time (Studies II and III). Daily total sedentary time was calculated as the sum of the sedentary minutes for each day and the sum was averaged across all days. In addition, daily total sedentary time was calculated separately for working days and days off in Studies I and IV. Hourly sedentary time was calculated as sums of sedentary minutes for each waking hour from 7:00 to 22:00 each day and the sums were averaged across all days. In Study I, hourly sedentary time was also calculated separately for working days, days off and all days after retirement. In Study II, daily time spent in sedentary bouts of ≥30 minutes and ≥60 minutes were calculated as sums of daily sedentary minutes and averaged across all days, and further defined as prolonged (≥30 min) and highly prolonged (≥60 min) sedentary time. Sedentary bout was defined as consequent minutes spent sedentary ending in a ≥1 min break spent in non-sedentary activity. In Study III, daily time spent in sedentary bouts of ≥60 minutes was calculated from sedentary bouts derived from five-second time epochs, allowing breaks from sedentary behavior lasting less than one minute but requiring at least 90% of the sedentary bout to be below the sedentary threshold (<30 m*g)* (van Hees, 2018).

4.3 Assessment of retirement

In Studies I─III, information on individual estimated retirement dates was obtained from the pension insurance institute for the municipal sector in Finland (Keva) which administers the pensions of municipal employees. In Studies I and II, the participants reported the actual date of full-time statutory retirement in their daily logs during the accelerometer measurement weeks. The first accelerometer measurement time point when a participant reported being retired in their daily log was considered the retirement year. If a participant reported being on annual leave during the accelerometer measurement week and continuing on annual leave until transition to full-time statutory retirement, they were considered retired at the time of the accelerometer measurement.

In Study I, as the aim was to compare sedentary time not affected by work-related activity before and after the transition to retirement, those who reported being full-time retired but having occasional working days were excluded from the final study population (n=55). In Study II the focus was on examining the changes in sedentary time across the transition to retirement so those who reported having occasional working days after transition to full-time retirement were included (n=78). In the final study population, 77 participants (11.0%) had working days during the measurement weeks after retirement (mean 2.7 working days per week, range 1─7).

4.4 Assessment of pre-retirement factors and covariates

In Studies I─IV, the following demographic factors were obtained from the Keva registers: gender, date of birth, and occupational status. Participants' age was used as a continuous variable. Occupational status was categorized according to the International Standard Classifications of Occupations (ISCO) (Statistics Finland, 2010) and the occupational titles of the last known occupation preceding retirement. In Studies I and II, occupational status was categorized into two groups: non-manual (ISCO classes 1–4) and manual workers (ISCO classes 5–9). In Studies III and IV, occupational status was categorized into three groups: managers and professionals (ISCO classes 1–2), associate professionals and office workers (ISCO classes 3–4), and service and manual workers (ISCO classes 5–9).

Health-related factors were used as covariates and derived from the last questionnaires prior to retirement in Studies I and II, before initiation of the intervention in Study III, and in the same year as the initial accelerometer measurement in Study IV. The covariates were chosen because they have been reported as being associated with sedentary behavior (Chastin et al., 2015). Smoking status was categorized into non-smokers (never and former) and current smokers. The number of chronic diseases was calculated, and participants were categorized as having 0, 1 or ≥2 doctor-diagnosed chronic diseases (angina pectoris, claudication, myocardial infarction, cerebrovascular disease, diabetes, osteoarthritis, osteoporosis, sciatica, fibromyalgia, rheumatoid arthritis, asthma, chronic bronchitis, or depression or other mental disorder). Body mass index (BMI) was calculated from self-reported weight and height in Studies I, II and IV, and in Study III from measured weight and height, and categorized into under/normal weight (<25.0 kg/m^2), overweight (25 to <30 kg/m^2) and obese (≥30 kg/m^2) (World Health Organisation, 2000). As the study population only had 0.4%–1.7% of underweight participants, these were included in the same category as the normal weight study participants. Physical functioning was evaluated using the validated RAND-36 Health Survey (identical with the Short Form SF-36) (Aalto et al., 1995; Hays et al., 1993). Information on mobility limitation was based on the question on difficulties walking 2.0 km and categorized as no/yes. Self-reported physical activity level was determined on the basis of self-reported weekly duration and intensity of leisure and commuting physical activity during the past year and categorized as “low” i.e. not meeting physical activity recommendations (<14 MET hours per week) or “moderate to high” i.e. meeting physical activity recommendations (≥14 MET hours per week) (Leskinen, Stenholm et al., 2018; Physical Activity Guidelines Advisory Committee, 2008). Self-reported daily sitting time was determined as the sum of sitting at the office, when watching TV or using a computer, being in a vehicle, and other sitting.

4.5 Statistical analyses

Because the aim was to examine changes in sedentary time across the transition to retirement (Study I and II) using an activity tracker (Study III), hierarchical linear mixed models were used as the main statistical analysis tool. Linear mixed models are suitable for longitudinal data analyses because they control for the intraindividual correlation between repeated measurements by using an exchangeable correlation structure and are not sensitive to measurements missing completely at random (Burton et al., 1998). Linear mixed models were also used in Study IV, to examine intraindividual differences between sedentary time estimates from wrist- and thigh-worn accelerometers.

In Study I, the analyses targeted the transition phase from work life to retirement, thus the time points immediately before and after the transition to retirement were chosen. Daily total sedentary time on all days before retirement was compared to all days after retirement. To further examine changes in daily sedentary time which were not affected by work-related activity, daily total sedentary time on days off only was compared to that on all days after retirement. The results of the comparisons were expressed as means and their 95% confidence intervals (CI). The first model was adjusted for the wear time of the accelerometer during waking hours, pre-retirement age, gender and occupational status and additional analyses were also adjusted for pre-retirement smoking, body mass index, number of chronic diseases and mobility limitations. Analyses were also conducted separately by gender (interaction term gender*time p=0.0005) and occupational status (interaction term occupation*time for women p<.0001, for men p=0.16). To illustrate daily sedentary patterns, mean hourly sedentary time was expressed as the mean sums of minutes and their 95% CIs per hour from 7:00 to 22:00 by gender and occupation on working days before retirement, days off before retirement, and all days after retirement.

In Study II, accelerometer data were first centered around the transition to retirement and daily total sedentary time, prolonged and highly prolonged sedentary time were calculated in each study wave before (wave -1, wave -2) and after (wave +1, wave +2) the transition to retirement. Analyses were conducted by gender (interaction term gender*time p=0.0001, p=0.03 and p=0.0007, respectively) and further illustrated as means and their CIs. In addition, daily total, prolonged and highly prolonged sedentary time immediately after retirement (wave +1) were compared to those immediately before retirement (wave -1) by gender and occupational status (daily total sedentary time: the interaction term time*gender p=0.0001, time*gender*occupation p=0.03, prolonged sedentary time: time*gender p=0.03 and time*gender*occupation p=0.6, highly prolonged sedentary time: time*gender p=0.0007 and time*gender*occupation p=0.09). Analyses were initially adjusted for the wear time of the accelerometer during waking hours and age and the second set of analyses were also adjusted for pre-retirement smoking, body mass index, number of chronic diseases, and mobility limitations.

In Study III, daily total sedentary time and prolonged sedentary time were calculated at baseline and 3-, 6- and 12-month follow-up time points and expressed as means and their CIs. The changes and differences in daily total sedentary time and prolonged sedentary time of the intervention and control groups were compared. The model was adjusted for the wear time of the accelerometer during waking hours. As a post hoc analysis, changes in daily total and prolonged sedentary time of the intervention and control groups were also compared in the short term (≤3 months) and the medium term (≤6 months). Moreover, the study participants were stratified into tertiles according to the baseline proportion of prolonged sedentary time of daily total sedentary time (%) and changes in the intervention and control group by tertiles were compared. In the intervention group, the mean number of inactivity stamps were calculated per month and changes in the number of inactivity stamps per month were examined across the intervention.

Study IV used a thigh-worn accelerometer as the reference, and the relative agreement between the wrist- and thigh-worn accelerometers was examined using Pearson correlations and Bland-Altman plots. The Bland-Altman analysis (Bland & Altman, 2007) was used to visualize the magnitude of the pairwise differences and to compare the daily sedentary time estimates from the thigh- and wrist-worn accelerometers. The results were expressed as mean differences and 95% limits of agreement. To examine the accuracy of the wrist-worn accelerometer in estimating within-individual differences in sedentary time, the difference between the daily sedentary time on working days and days off was calculated and the results of the wrist- and thigh-worn accelerometers compared. In addition, correlations were examined separately for working days and days off. All the analyses were performed for both data processing methods of the evaluated wrist-worn accelerometers, i.e. the count cutpoint method and the ENMO cutpoint method. For the ENMO cutpoint method, the analyses of sedentary time were performed separately, derived directly from the five-second epochs and with bout restriction (60-second bouts).

All statistical analyses were performed using SAS statistical software, version 9.4 (SAS Institute, Inc., Cary, North Carolina).

5 Results

5.1 Characteristics of study participants

Table 4 shows the characteristics of the participants in Studies I–IV. In Studies I and II, the mean age in the last measurement before retirement was 63.2 years (SD 1.6-1.7). As Study III targeted recent retirees, the participants were slightly older, on average 65.2 years old (SD=1.1) at baseline. In Study IV, the mean age was 62.8 years (SD=1.0). In all the studies, the majority of the study participants were women, 83% in Studies I and II, and 85% in Studies III and IV; and retiring or retired from non-manual occupations, ranging from 65% to 69%.

Comparison of the last measurement before retirement of the FIREA activity sub-study participants (Study I and II) and the FIREA survey cohort (n=3426) revealed no marked differences in participant characteristics. The only exception was smoking, which was less prevalent in Studies I and II (5–6% vs. 9%).

Table 4. Characteristics of participants in Studies I–IV.

CHARACTERISTICS	**STUDY I** (N=478) N (%) / MEAN (SD)	**STUDY II** (N=689) N (%) / MEAN (SD)	**STUDY III** (N=231) N (%) / MEAN (SD)	**STUDY IV** (N=290) N (%) / MEAN (SD)
AGE	63.2 (1.7)	63.2 (1.6)	65.2 (1.1)	62.8 (1.0)
GENDER				
MEN	70 (15)	102 (15)	40 (17)	50 (17)
WOMEN	408 (85)	587 (85)	191 (83)	240 (83)
OCCUPATIONAL STATUS				
UPPER/LOWER-GRADE NON-MANUAL	325 (68)	457 (66)	151 (65)	201 (69)
SERVICE AND MANUAL	153 (32)	232 (34)	80 (35)	89 (31)
BODY MASS INDEX				
NORMAL WEIGHT	178 (38)	252 (38)	81 (35)	122 (43)
OVERWEIGHT	199 (42)	270 (40)	88 (38)	117 (41)
OBESE	94 (20)	145 (22)	62 (27)	44 (16)
SMOKING				
NO	447 (95)	620 (94)	222 (97)	269 (95)
YES	22 (5)	40 (6)	8 (3)	14 (5)
NUMBER OF CHRONIC DISEASES[A]				
0	114 (25)	151 (27)	55 (24)	74 (30)
1	164 (36)	191 (34)	83 (36)	80 (32)
≥2	175 (39)	226 (40)	93 (40)	96 (38)
LIMITATIONS IN WALKING 2 KM				
NO	413 (87)	583 (87)	215 (93)	263 (91)
YES	64 (13)	90 (13)	15 (7)	26 (9)
SELF-REPORTED PHYSICAL ACTIVITY LEVEL				
LOW	175 (37)	247 (37)	55 (24)	75 (26)
MODERATE/HIGH	302 (63)	424 (63)	176 (76)	213 (74)
SELF-REPORTED DAILY SITTING TIME (HOURS)	8.1 (3.0)	8.3 (3.1)	7.8 (3.3)	8.2 (2.8)

[A] The following doctor-diagnosed chronic diseases: angina pectoris, claudication, myocardial infarction, cerebrovascular disease, diabetes, osteoarthritis, osteoporosis, sciatica, fibromyalgia, rheumatoid arthritis, asthma, chronic bronchitis, and depression or other mental disorder.

5.2 Changes in sedentary time across transition to retirement (Study I and II)

Figure 5 illustrates the changes in daily total sedentary time, prolonged and highly prolonged sedentary time across the transition to retirement by gender, adjusted for accelerometer wear time during waking hours. In the first measurement, approximately 18 months before the transition to retirement, women had 8.1 hours of sedentary time, of which 1.7 hours was prolonged sedentary time (≥30 min) and 0.6 hours was highly prolonged sedentary time (≥60 min). The levels were higher among men, at 9.5 hours, 2.3 hours and 0.8 hours, respectively.

Sedentary time among women did not change before retirement, but among men daily total sedentary time increased by 18 minutes (95% CI 2 to 34), prolonged sedentary time by 19 minutes (95% CI 6 to 31) and highly prolonged sedentary time by 11 minutes (95% CI 2 to 19). Women showed considerable changes in sedentary time during the transition to retirement, from approximately six months before retirement to six months after retirement. Daily total sedentary time increased by 22 minutes (95% CI 16 to 28), prolonged sedentary time by 32 minutes (95% CI 27 to 37) and highly prolonged sedentary time by 15 minutes (95% CI 12 to 18). Men showed changes in prolonged sedentary time only, as prolonged sedentary time increased by 16 minutes (95% CI 5 to 28) during the transition to retirement. After retirement, daily total sedentary time and highly prolonged sedentary time stabilized, a small increase was only observed in prolonged sedentary time among women (6 minutes, 95% CI 1 to 12).

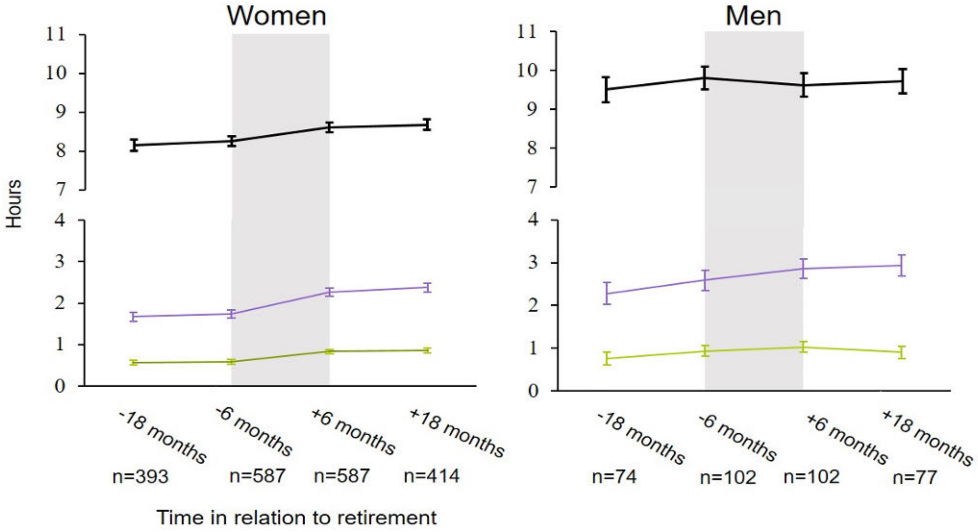

Figure 5. Changes in daily total sedentary time (black line), prolonged (≥30 min) (purple line) and highly prolonged (≥60 min) (green line) sedentary time by gender across the transition to retirement, the transition from work to retirement represented by the gray area, adjusted for accelerometer wear time during waking hours.

As both gender and occupation moderated the changes in sedentary time (interaction time*gender p=.0001, time*gender*occupation p=0.03), and the main changes were observed immediately after retirement, Table 5 presents the gender and occupation-specific results in the transition to retirement. The greatest increases in sedentary time in the transition to retirement were observed among women retiring from manual occupations: 54 minutes (95% CI 42 to 65) in daily total sedentary time, 41 minutes (95% CI 32 to 51) in prolonged sedentary time, and 17 min (95% CI 11 to 23) in highly prolonged sedentary time. Daily total sedentary time did not change among women retiring from non-manual occupations (7 min, 95% CI -2 to 15), but prolonged sedentary time increased by 28 minutes (95% CI 21 to 35) and highly prolonged sedentary time by 14 minutes (95% CI 10 to 18). Among men, the only statistically significant change in sedentary time in the transition to retirement was observed among those retiring from manual occupations: their prolonged sedentary time increased by 27 minutes (95% CI 4 to 50). In addition to adjustment for accelerometer wear time during waking hours and age, additional adjustments for pre-retirement smoking, body mass index, number of chronic diseases and mobility limitations did not notably alter the interpretation of the results.

Table 5. Changes in daily total sedentary time, prolonged (≥30 min) and highly prolonged (≥60 min) sedentary time in the transition to retirement by gender and occupational status.

	DAILY TOTAL SEDENTARY TIME				**DAILY PROLONGED SEDENTARY TIME**				**DAILY HIGHLY PROLONGED SEDENTARY TIME**			
	Before retirement Mean (hours) 95% CI		Change Mean (minutes) 95% CI		Before retirement Mean (hours) 95% CI		Change Mean (minutes) 95% CI		Before retirement Mean (hours) 95% CI		Change Mean (minutes) 95% CI	
WOMEN[A]	8.2	8.1 to 8.4	23	16 to 30	1.7	1.6 to 1.8	33	27 to 39	0.6	0.5 to 0.6	15	12 to 19
MANUAL[B]	7.7	7.5 to 7.9	54	42 to 65	1.7	1.5 to 1.8	41	32 to 51	0.6	0.5 to 0.7	17	11 to 23
NON-MANUAL[B]	8.5	8.4 to 8.7	7	-2 to 15	1.8	1.6 to 1.9	28	21 to 35	0.6	0.5 to 0.6	14	10 to 18
MEN[A]	9.8	9.5 to 10.1	-9	-24 to 5	2.6	2.3 to 2.8	17	5 to 29	0.9	0.8 to 1.1	7	-1 to 14
MANUAL[B]	9.2	8.6 to 9.7	-1	-27 to 27	2.1	1.7 to 2.6	27	4 to 50	1.0	0.8 to 1.1	3	-11 to 18
NON-MANUAL[B]	10.1	9.7 to 10.4	-13	-31 to 5	2.8	2.5 to 3.0	12	-3 to 27	0.8	0.6 to 1.1	7	-3 to 16

[A] Adjusted for accelerometer wear time during waking hours, age and occupational status.

[B] Adjusted for accelerometer wear time during waking hours and age.

In Study I, usual days after retirement were compared to days off before retirement to examine the changes in daily total sedentary time that were not affected by work-related activity. Daily total sedentary time on usual days after retirement increased by 19 minutes from days off before retirement among women retiring from non-manual occupations (95% CI 9 to 29). Women retiring from manual occupations and men regardless of occupational group showed no statistically significant changes in sedentary time.

Daily sedentary profiles from working days and days off before retirement were compared to the usual days after retirement according to gender and occupation in Study I (Figure 6). The main differences were seen between the profiles during usual working hours (from 8:00 to 16:00) and working days before retirement and the usual days after retirement. Among women in manual occupations, usual working hours were more sedentary after retirement than before retirement. In contrast, among women and men in non-manual occupations usual working hours were less sedentary after retirement than before retirement. Daily sedentary profiles on days off before retirement and on usual days after retirement were very similar. Evenings were the most sedentary time both before and after retirement among all the study participants.

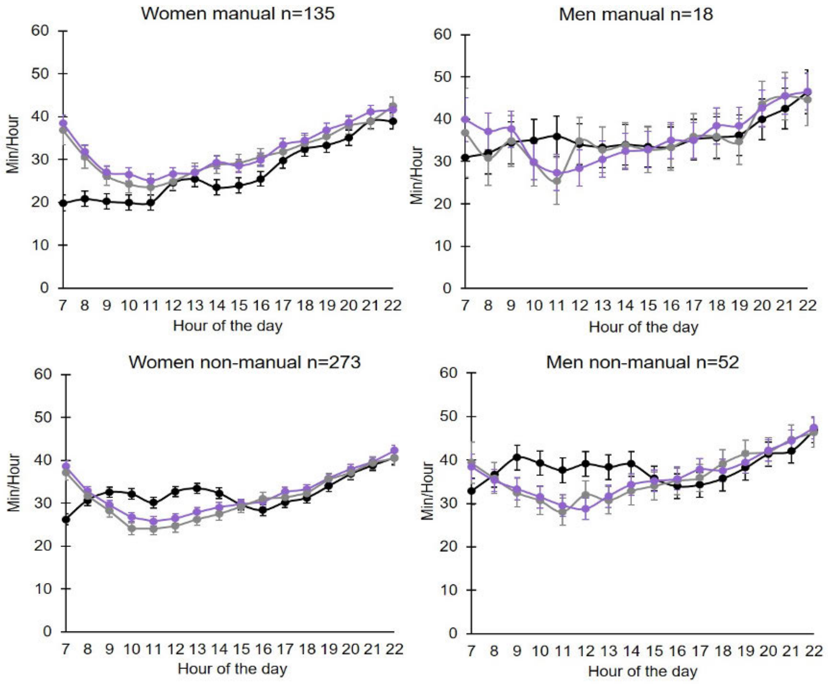

Figure 6. Daily sedentary profiles by gender and occupation. Working day before retirement (black line), day off before retirement (gray line) and usual day after retirement (purple line).

5.3 Effect of activity tracker intervention on sedentary time (Study III)

Figure 7 and Table 6 show the daily total sedentary time and prolonged sedentary time among the intervention and control groups across the follow-up. At baseline, the intervention group had 10.9 hours (95% CI 10.7–11.2) of daily total sedentary time, of which 4.0 hours (95% CI 3.6–4.4) accrued from bouts of ≥60 minutes. The control group was slightly more sedentary at baseline, as they had 11.1 hours (95% CI 10.8–11.4) of daily total sedentary time and 4.2 hours (95% CI 3.7–4.6) of prolonged sedentary time. Both daily total and prolonged sedentary time decreased among the intervention group during the first six months of the intervention, whereas the control group showed a decrease in only daily total sedentary time. During the last six months of the intervention, daily total and prolonged sedentary time increased close to baseline levels among both groups. Thus, the intervention had no effect on daily total sedentary time (time*group interaction p=0.39) or on prolonged sedentary time (time*group interaction p=0.27).

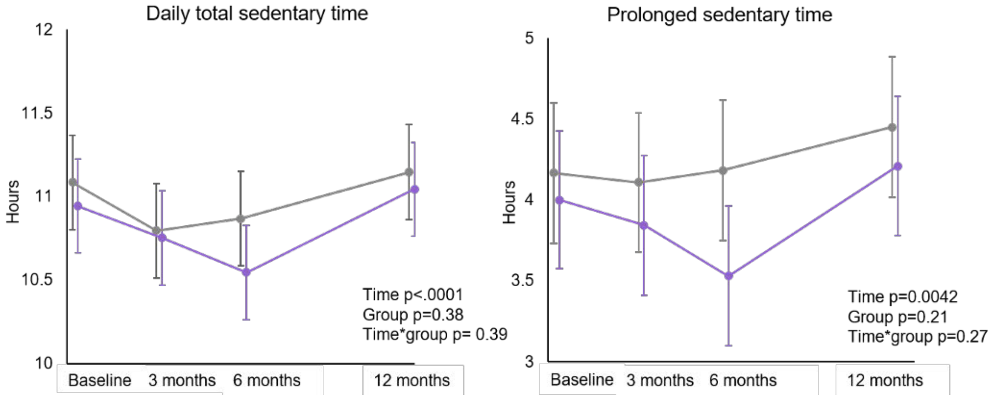

Figure 7. Changes in daily total and prolonged sedentary time among intervention group (purple line) and control group (gray line).

As a post hoc analysis, the short-term (3 months) and medium-term (6 months) effects of the intervention were also examined. As seen in Table 6, in the short term, both the intervention and control group showed a decrease in daily total sedentary time, with no marked differences between the groups (mean difference in changes 6 min, 95% CI -14 to 26). No significant changes were observed in prolonged sedentary time over the first three months. From baseline to six months, the intervention group's daily total sedentary time decreased by 24 minutes (95% CI -38 to -10), but this change did not differ from that among the controls (-13 min, 95% CI -27 to 1, mean difference -11 min, 95% CI -31 to 9). During the first six months of follow-up, the intervention group's prolonged sedentary time decreased by 28 minutes (95% CI -51 to -6), but no changes were observed in the control group (1 min, 95% CI -21 to 24). However, the difference between the changes in the groups did not reach statistical significance, the mean difference in the changes being -29 minutes (95% CI -61 to 2).

Table 6. Changes in daily total sedentary time and prolonged sedentary time by randomization group (intention to treat analysis).

	INTERVENTION		**CONTROL**		**MEAN DIFFERENCE**	
	Mean	95% CI	Mean	95% CI	Mean	95% CI
DAILY TOTAL SEDENTARY TIME						
Baseline (hours)	10.9	10.7 to 11.2	11.1	10.8 to 11.4	-0.1	-0.5 to 0.3
Change at 3 months (min)	-11	-26 to 3	-17	-31 to -3	6	-14 to 26
Change at 6 months (min)	-24	-38 to -10	-13	-27 to 1	-11	-31 to 9
Change at 12 months (min)	7	-8 to 20	4	-10 to 18	2	-18 to 22
DAILY PROLONGED SEDENTARY TIME						
Baseline (hours)	4.0	3.6 to 4.4	4.2	3.7 to 4.6	-0.2	-0.8 to 0.4
Change at 3 months (min)	-9	-32 to 13	-3	-26 to 19	-6	-38 to 26
Change at 6 months (min)	-28	-51 to -6	1	-21 to 24	-29	-61 to 2
Change at 12 months (min)	13	-10 to 35	17	-5 to 40	-4	-36 to 27

In the supplemental analyses, the reduction in prolonged sedentary time from baseline to the six-month time point was the highest among those with the highest baseline proportion of prolonged sedentary time. The individuals with the highest proportion of prolonged sedentary time in the intervention group showed a gradual reduction of 120 minutes of sedentary time from baseline to the six-month time point (95% CI -166 to -73), but this change did not differ from that among the controls (-77 min, 95% CI -124 to -31, p-value 0.20).

Figure 8 illustrates the daily sedentary profiles of the intervention and control group at all four measurement points. The daily sedentary profiles of the intervention and control group were very similar at baseline, 3-month and 12-month time points, but differed at the 6-month follow-up time point, as the intervention group showed slightly lower sedentary minutes per hour from midday to late evening.

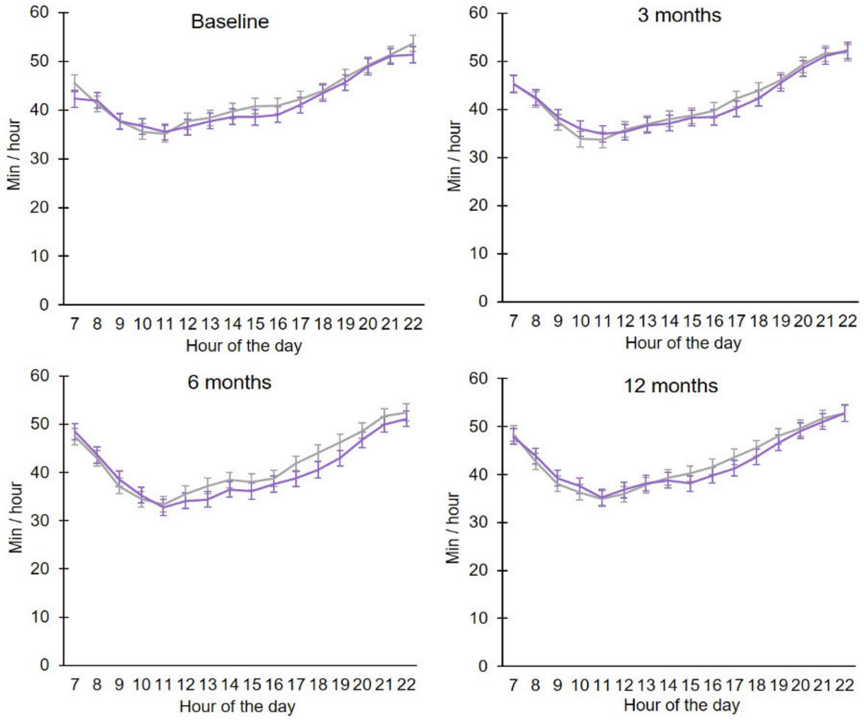

Figure 8. Daily sedentary profiles of intervention (purple line) and control group (gray line) at baseline, 3-month, 6-month and 12-month follow-up time points.

5.4 Comparison of sedentary time measured by wrist- and thigh-worn accelerometers (Study IV)

The mean daily sedentary time measured by the thigh-worn accelerometer was 556 min (95% CI 543 to 569). Compared to the thigh-worn accelerometer, the count cutpoint method underestimated mean daily sedentary time by 63 minutes (95% CI -73 to -53), the ENMO cutpoint method utilizing 60-second bouts underestimated sedentary time by 50 minutes (95% CI -67 to -34), and the ENMO cutpoint method utilizing five-second epochs overestimated sedentary time by 59 minutes (95% CI 43 to 76).

Figure 9 illustrates the correlations between the daily sedentary time estimates obtained from the thigh- and wrist-worn accelerometer. The correlation between the daily sedentary time estimates obtained from the thigh-worn accelerometer and the count cutpoint method for the wrist-worn accelerometer was high: 0.78 (95% CI 0.75 to 0.80). For the ENMO cutpoint methods, using the 60-second bout restriction or deriving the estimates directly from the five-second epoch values, the correlations were moderate, 0.62 (95% CI 0.56 to 0.68) and 0.60 (95% CI 0.54 to 0.66), respectively.

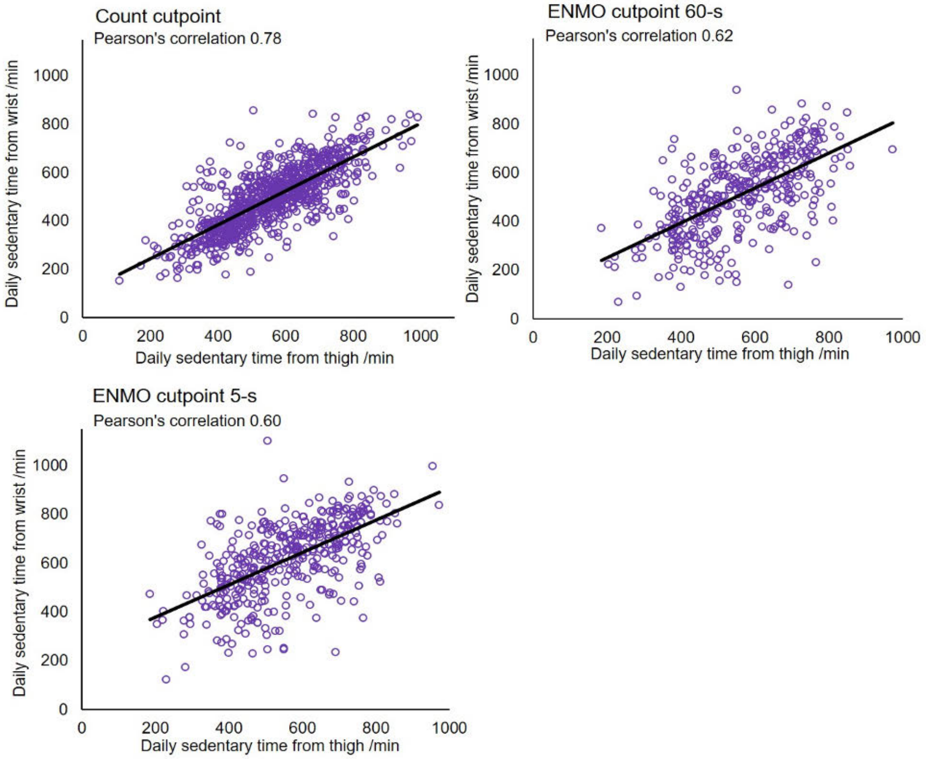
Count cutpoint
Pearson's correlation 0.78
ENMO cutpoint 60-s
Pearson's correlation 0.62
ENMO cutpoint 5-s
Pearson's correlation 0.60

Figure 9. Correlation between daily sedentary time estimates from thigh-worn and wrist-worn accelerometer using count cutpoint method, ENMO cutpoint method with 60-second bout restriction and ENMO cutpoint method with five-second epoch length.

The relative agreement between the thigh- and wrist-worn accelerometers was examined using the Bland-Altman analysis, which plots the differences between the measurement methods against their average. As seen in Figure 10, the 95% limits of agreement were relatively large for all the methods applied to the wrist-worn accelerometer. The count cutpoint method for the wrist-worn accelerometer had the narrowest 95% limits of agreement, from -117 minutes to +243 minutes, and the corresponding levels were from -212 minutes to +313 minutes for the ENMO cutpoint method utilizing 60-second bouts, and from -323 minutes to +205 minutes for the ENMO cutpoint method utilizing five-second epochs.

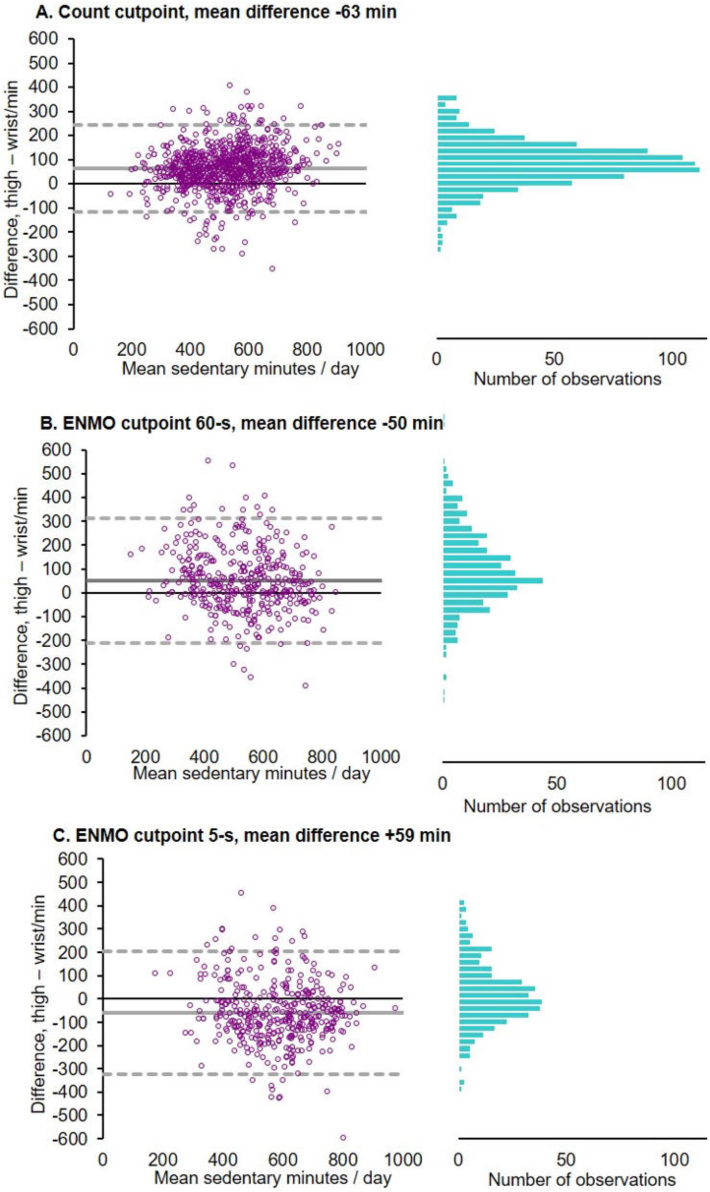

Figure 10. Bland-Altman plots describing level of agreement between daily sedentary time estimates of thigh-worn accelerometers and (A) count cutpoint, (B) ENMO cutpoint using 60-second bout restriction and (C) ENMO cutpoint using five-second epochs. Solid gray line is zero bias line representing mean difference, and dashed lines represent 95% limits of agreement. The histogram describes the number of observations (i.e., number of days for each value of difference between daily sedentary time estimates obtained from thigh- and wrist-worn accelerometers).

The mean differences between the methods' estimated sedentary times were also examined on working days and days off, and the results are shown in Table 7. The mean difference between sedentary time on working days and days off, approximately 50 minutes, was detected by both the count cutpoint method and the thigh-worn accelerometer. The ENMO cutpoint method utilizing 60-second bouts detected a slightly smaller difference (34 min) and the ENMO cutpoint method utilizing five-second epochs a slightly larger difference (54 min) than those found by the thigh-worn accelerometer.

Table 7. Differences between sedentary time on working days and days off by methods applied to the wrist-worn accelerometer and thigh-worn accelerometer.

	DIFFERENCE BETWEEN WORKING DAYS AND DAYS OFF	
	Mean (minutes)	95% CI
COUNT CUT POINT (WRIST) VS. THIGH		
THIGH (REF)	48	30 to 67
WRIST	49	33 to 64
DIFFERENCE	0	-12 to 14
ENMO CUT POINT 60-S (WRIST) VS. THIGH		
THIGH (REF)	49	21 to 76
WRIST	34	3 to 65
DIFFERENCE	-11	-40 to 17
ENMO CUT POINT 5-S (WRIST) VS. THIGH		
THIGH (REF)	46	18 to 73
WRIST	54	25 to 84
DIFFERENCE	-12	-41 to 17

6 Discussion

Daily total sedentary time increased among women retiring from manual occupations, but an increase in prolonged sedentary time was observed across gender and occupational groups. The timing of the changes in sedentary time differed between genders. The increase found in sedentary time was immediately after the transition to retirement among women, whereas the increase in prolonged sedentary time was more gradual among men. After retirement, an activity tracker-based intervention was insufficient to elicit changes in sedentary time over 12 months. Given that sedentary time was estimated by a wrist-worn accelerometer, these estimates were compared to those made by a more reliable method, a posture-based thigh-worn accelerometer. The comparison indicated considerable differences between the absolute estimates of daily sedentary time. However, the wrist- and thigh-worn accelerometers detected similar within-individual differences between sedentary time on working days and days off, suggesting that the changes during retirement transition and intervention were captured reliably.

6.1 Changes in sedentary time across the transition to retirement

Before the current PhD study, knowledge of the changes in daily total sedentary time across the transition to retirement was based on a few longitudinal survey studies. The Australian ALSWH cohort study (Clark et al., 2014) and the Life After Work Study cohort study (Sprod et al., 2017) showed a decrease in self-reported daily total sitting time, whereas an increase was observed in the French SU.VI.MAX cohort (Menai et al., 2014). Accelerometer-based findings were limited to cross-sectional studies (Godfrey et al., 2014; Yerrakalva et al., 2017). In Studies I and II, the same individuals were followed repeatedly, and the accelerometer measurements from the last years at work to a few years after the transition to retirement provided more accurate information on how daily total sedentary time changed across the transition to retirement. The general trend in daily total sedentary time over 3.5 years across the transition to retirement was increasing.

The observed changes in daily total sedentary time were moderated by gender, as daily total sedentary time only increased among women. Previous studies have also shown a greater increase in leisure-time sitting among women than among men (Leskinen, Pulakka et al., 2018; Van Dyck et al., 2016), but it was not known whether gender differences also exist in changes in daily total sedentary time. There are several possible explanations for the observed gender differences. The greater increase in sedentary time among women than among men may be related to the fact that the women had considerably lower sedentary levels than the men before retirement due to differences in occupational characteristics. One explanation for the occupational differences between genders may be the gender-based segregation of occupations in the public sector in Finland (Statistics Finland, 2016). Women's most common occupations may be less sedentary than those of men; for instance teachers vs. technicians in the non-manual occupational group, and nurses vs. drivers in the manual occupational group. Moreover, active commuting has shown to be more common for women than for men among 60–64-year-old Finns (Koponen et al., 2018). The removal of relatively active working hours and active commuting may also explain the greater increase in daily total sedentary time among women than among men. However, gender differences in daily total sedentary time were also observed on days off before retirement and on usual days after retirement, which may be related to domestic physical activity. Although the traditional gender roles have diminished over the years in the Nordic countries, in this age group women seem to engage more in domestic physical activity than men (Fahlen, 2016).

In addition to gender, occupational status also moderated the changes in daily total sedentary time across the transition to retirement. Previous knowledge on changes in sedentary time in the transition to retirement according to occupational status was limited to self-reported leisure-time sitting (Leskinen, Pulakka et al., 2018). Thus, it was not known how the removal of working hours affects daily total sedentary time in different occupations. Studies I and II only found an increase in daily total sedentary time among women retiring from manual occupations; they had the least sedentary working days before retirement, and thus, it was not surprising that the removal of physically active working hours led to increased levels of daily total sedentary time. Daily sedentary profiles also indicated that usual working hours were more sedentary after retirement. Occupational differences were closely related to work, as there were no occupational differences in days off either before retirement or after retirement.

Regarding non-manual occupations, it was hypothesized that people retiring from higher-level occupations may see retirement as an opportunity to make better health-related choices, to increase physical activity, and by doing so, also reduce sedentary time as they are no longer obliged to sit at work. Interestingly, although usual working hours seemed to be less sedentary after retirement among non-manual workers, no great changes in daily total sedentary time across the transition to retirement were observed. The FIREA study also examined changes in physical activity in the transition to retirement (Pulakka et al., 2020), and observed that daily total physical activity, expressed as mean daily activity counts, increased only among men retiring from non-manual occupations (by approximately 5.0%). These findings suggest that although previous survey studies have indicated an increase in leisure-time physical activity among higher-level occupations after retirement (Barnett et al., 2012), it is not reflected in higher levels of accelerometer-measured daily total physical activity nor in lower levels of daily total sedentary time. It is possible that leisure-time physical activity increases after retirement, but it has no marked effect on daily total sedentary time, because at the same time, work-related active commuting and light activity are removed from daily activities. Resistance training as leisure-time physical activity, which typically includes slow, static movements, may be poorly captured by accelerometers. Moreover, higher intensity leisure physical activity is often performed in short bursts, which may not notably affect daily total sedentary time.

Studies I and II fill in the gaps in the previous literature regarding how patterns of sedentary behavior change in the transition to retirement. Prolonged sedentary time increased among most of the retiring individuals. Surprisingly, prolonged sedentary time also increased among those retiring from non-manual occupations, although previous studies have shown that office workers have less prolonged sedentary time during non-working time than during working time (Clemes et al., 2014; Kurita et al., 2019; Parry & Straker, 2013; Thorp et al., 2012). There are some possible explanations for the increase in prolonged sedentary time among retiring individuals. Previous survey studies have shown a consistent increase in screen time (Sprod et al., 2017), especially in watching TV after retirement (Barnett et al., 2014; Jones et al., 2017; Leskinen, Pulakka et al., 2018; Touvier et al., 2010; Van Dyck et al., 2016). Thus, it is probable that after retirement some of the working time is reallocated to watching TV. Watching TV may be more prolonged than other sedentary activities, such as using a computer (Ekelund et al., 2016). Retirement may also lead to reduced social interaction and among those who do not maintain a social role or activity after retirement, retirement may increase time spent at home watching TV (Chastin et al., 2015; Van Cauwenberg et al., 2014). Moreover, the removal of active commuting to work and active breaks from work, for instance walking to a lunch spot, coffee room or printer, may increase prolonged sedentary time. It can be speculated that after retirement, household chores may not break sedentary time as often as before retirement, because the usual amount of household chores can be distributed to a longer time period (the whole week) than during work life (leisure time on working days and weekends). The distribution of household chores to a longer period of time may also explain the finding that daily total sedentary time also increased from days off before retirement to usual days after retirement among women but not among men (Fahlen, 2016). However, it is possible that retirees also increase their total time spent on household chores (Sprod et al., 2017).

Study II also showed relevant findings on the timing of these changes. Leskinen and colleagues (2018) were the first to show that the main changes in self-reported leisure-time sitting are immediately after retirement. Similarly, accelerometer-measured daily total sedentary time mainly increased immediately after the transition to retirement. Study II expands on previous knowledge, as the timing of the changes differed between genders. Among women, increases in daily total, prolonged and highly prolonged sedentary time were observed immediately after the transition to retirement, otherwise sedentary time remained relatively stable. In contrast, men showed a gradual increase in prolonged sedentary time from the last years at work to a few years after the transition to retirement. It is not known why the timing of the changes differed between genders, but it may be related to the fact that women appeared to have a much less sedentary work life during the last years of work than men.

6.2 Sedentary time after activity tracker intervention

Study III evaluated the effect of an activity tracker-based intervention, which was easy to implement in the everyday lives of recent retirees. Although some favorable changes in sedentary time were observed among the intervention group during the first six months of the intervention, an activity tracker was insufficient to reduce sedentary time in the long term.

Study III reported findings from the first RCT to examine the effect of an activity tracker-based intervention on physical activity and sedentary time that was targeted at the time window immediately after the transition to retirement. Based on previous studies, retirement is often seen as a window of opportunity to make better health choices and concentrate on well-being (Barnett et al., 2012; Pulakka et al., 2019; Stenholm et al., 2016; Stenholm & Vahtera, 2017). An activity tracker with several features to address both physical activity and sedentary behavior was seen as a potential method to intervene in retirees' everyday lives and support changes in sedentary behavior among users that were already motivated to change their activity behaviors. However, despite its potential, the use of an activity tracker was insufficient to overcome the increasing trend of sedentary behavior after retirement. There was room for changes in sedentary behavior, because the study participants had high baseline levels of daily sedentary time, approximately 11 hours per day. As sedentary behavior after retirement has several different contexts, such as watching TV, using a computer and reading, and a sitting/lying posture is only subservient to these activities, intervention components to target these context-specific activities instead of sedentary behavior in general may be needed (Gardner et al., 2019).

Study III provided novel findings on the long-term effect of an activity tracker that was harnessed to deliver prompts and self-monitoring of sedentary behavior as the main sedentary behavior-specific BCTs. A previous activity tracker-based trial suggested that self-monitoring of sedentary behavior by an activity tracker was effective in reducing self-reported sitting in the short term (Barwais et al., 2013). In the REACT trial, sedentary time, mainly prolonged sedentary time, decreased during the first six months of the intervention, but the change did not differ from that among the controls. Reduction in prolonged sedentary time was seen particularly among those with the highest levels of prolonged sedentary time at baseline. Being able to set more frequent inactivity alerts may have resulted in more robust changes in prolonged sedentary time. Personal modifications to and goal-setting for the activity tracker's inactivity alert feature may also have enhanced the effect of the activity trackers (Duncan et al., 2017). Some participants may have experienced initial interest in the use of an activity tracker that nevertheless attenuated toward the end of the intervention (Shin, Feng et al., 2019). Recent qualitative studies have given an insight into older adults' experiences in the long-term use of activity trackers. Older adults seem to become more conscious of their activity patterns when using an activity tracker. However, the use of a tracker alone does not necessarily affect older adults' internal motivation to change activity behavior in the long term (Brickwood, Williams et al., 2019; Kononova et al., 2019).

The aim of Study III was to evaluate the independent effect of an activity tracker on sedentary time. Therefore, the intervention relied on the BCTs delivered by the activity tracker and the web-based program. All other sedentary behavior-specific BCTs except for prompts were delivered by the web-based program. The program enabled participants to self-monitor their daily sedentary levels and number of inactivity stamps and to obtain information on the health benefits of reducing sedentary time. The role of program-delivered BCTs probably remained small, because the intervention participants were not asked to follow the information provided in the program. It is not known how many of the intervention group participants followed the information. Among those who did, self-monitoring and information on the activity benefits may have increased their awareness of their own sedentary levels, made them more conscious of the health benefits of reducing sedentary time, and strengthened their responsiveness to the other BCTs such as inactivity alerts (Compernolle et al., 2019; Glanz & Bishop, 2010; Rosenstock et al., 1988). Given that internal motivation is important for attaining long-term changes in health behaviors (Teixeira et al., 2012), more emphasis on users' perceptions of the long-term benefits of reducing sedentary time may have been needed to drive their internal motivation to change their sedentary behavior. However, given that sedentary behavior is so strongly habitual (Conroy et al., 2013), self-monitoring and information on health consequences alone are unlikely to lead to any considerable long-term reductions in sedentary behavior.

The aim of Study III was also to reduce sedentary time by encouraging the tracker users to increase their daily total physical activity levels. However, the use of an activity tracker did not elicit notable changes in either LPA or MVPA (Leskinen et al., 2021). Consistent with these findings, a recent meta-analysis by Brickwood and colleagues (2019) indicated that the use of an activity tracker alone to self-monitor daily activity levels and to encourage reaching daily activity goals may be sufficient to elicit a small increase in daily steps, but not in MVPA. Moreover, the meta-analysis was based on mainly short-term findings, suggesting that a long-term effect may be even more difficult to obtain. Multicomponent activity tracker-based physical activity interventions combining activity tracker use, counseling and education have reported greater short-term increases in daily steps and MVPA (Brickwood, Watson et al., 2019), suggesting that additional intervention components such as support from a health professional in the form of counseling, education or exercise sessions may be needed. It has been suggested that an activity tracker may be the optimal monitoring tool for a health professional to follow participants outside counseling, education and/or supervised exercise sessions (Brickwood, Watson et al., 2019).

Determining a cost-effective intervention requires identifying the most effective BCTs and their ideal number and combination. Previous multicomponent interventions utilized activity trackers that delivered sedentary behavior-specific BCTs such as prompts and self-monitoring of sedentary behavior (Ashe et al., 2015; Li et al., 2018; Lynch et al., 2019a; Lyons et al., 2017). In addition to the activity tracker, these interventions included counseling on the health benefits of reducing sedentary time and the identification of possible strategies and goal-setting to reduce sedentary time. These BCT combinations resulted in reductions in sedentary time for up to six months, but these reductions were mostly non-significant in comparison to the controls. A recent RCT by Rosenberg and colleagues (2020) reported a marked reduction in sedentary time of approximately one hour per day after a three-month health coaching and activity tracker intervention. An activity tracker was only used to deliver inactivity alerts after 15 minutes of inactivity, and the main focus was on coaching which delivered feedback and helped older adults develop strategies and goals to break up sedentary time, especially in the home environment. Based on the findings of these RCTs and Study III, more robust changes in sedentary time may be achieved with a combination of sedentary behavior-specific BCTs such as prompts, self-monitoring, counseling on the health benefits of reducing sedentary time and how to develop strategies to change sedentary time, feedback, and setting attainable and specific goals. Social support may also be an effective addition. Many of these

BCTs could be included in the activity tracker and the synchronized program (Duncan et al., 2017). However, the human contact in counseling and feedback may be important, since multicomponent interventions utilizing face-to-face counseling and feedback have attained more robust short-term reductions in sedentary time than activity tracker-delivered information on the health consequences and feedback on sedentary behavior utilized in Study III.

6.3 Comparison of sedentary time measured by wrist- and thigh-worn accelerometers

In Study IV, comparison of the movement-based cutpoint methods applied with a wrist-worn accelerometer and a posture-based thigh-worn accelerometer showed considerable differences between the absolute values of daily sedentary time on these device-based methods. The count cutpoint-based method used in Studies I and II, resulted in underestimation of daily sedentary time of 63 minutes in comparison to the thigh-worn accelerometer. The ENMO cutpoint method used in Study III, with a five-second epoch length, resulted in overestimation of daily sedentary time by 59 minutes. The ENMO cutpoint method was also evaluated by deriving sedentary time estimates from bouts of a minimum of 60 seconds, instead of the five-second epochs, which resulted in underestimation of daily sedentary time by 50 minutes.

The current methods applied to a wrist-worn accelerometer to estimate sedentary time were expected to differ from those of a thigh-worn accelerometer, because these methods estimate different constructs of sedentary behavior. The evaluated methods for a wrist-worn accelerometer are based on the detection of low acceleration values of the wrist, whereas thigh-worn accelerometer-based methods rely on the detection of both low acceleration values of the thigh and sitting/lying postures based on the thigh inclination. The thigh-worn accelerometer provides accurate estimates of time spent sitting and lying down (Skotte et al., 2014; Stemland et al., 2015), but its accuracy in detecting actual sedentary behavior with both a postural and metabolic component is poorly examined. Nevertheless, compared to a thigh-worn accelerometer, a wrist-worn accelerometer provides less accurate estimates of sedentary time because of its limited ability to separate standing from sitting and to detect sedentary behaviors that involve arm movements, for instance doing handcrafts in a sitting position.

Of the cutpoint-based methods applied to a wrist-worn accelerometer, the count cutpoint method was found to have the highest correlation and the narrowest 95% limits of agreement in daily sedentary time estimates with a thigh-worn accelerometer. The count cutpoint-based method for a wrist-worn accelerometer was developed by Koster and colleagues (2016), who evaluated it against a thigh-worn accelerometer among older adults in free-living conditions. Koster and colleagues also found that the developed count cutpoint-based method underestimated daily total sedentary time, but to a smaller extent than in Study IV (23 min vs. 63 min). This difference may be related to the study populations, because the study population in Study IV consisted of working adults with a mean age of 63 years, whereas the study population of Koster and colleagues included older and retired adults (mean age 78 years). Work-related activities may include more time spent using a computer i.e. sitting with arm movements, which may in turn increase the false-negative classifications of sedentary time when using a wrist-worn accelerometer. Other explanations may be differences in data processing and epoch lengths. Koster and colleagues applied 60-second epochs to both wrist- and thigh-worn accelerometers, whereas in Study IV a five-second epoch length was applied to a thigh-worn accelerometer and 60-second epoch length to a wrist-worn accelerometer. Shorter epoch lengths have generally been used with thigh-worn accelerometers (Crowley et al., 2019), but the epoch length of 60-seconds has shown to the most accurate for a wrist-worn accelerometer, when evaluated against a thigh-worn accelerometer (Koster et al., 2016) and using video observation (Flórez-Pregonero et al., 2018).

The ENMO cutpoint method applied to a wrist-worn accelerometer did not show as good an agreement with a thigh-worn accelerometer as the count cutpoint-based method. Deriving daily sedentary time estimates from bouts of a minimum of 60 seconds resulted in somewhat similar findings as with the count cutpoint-based method, and an underestimation of daily sedentary time of 50 minutes in comparison to a thigh-worn accelerometer. However, the GGIR package enables choosing either one-second or five-second epoch values, the latter being the default value (van Hees, 2018) and the five-second epoch length in the ENMO cutpoint-based method resulted in an overestimation of daily sedentary time by one hour in comparison to a thigh-worn accelerometer. Marked overestimation was also observed in another study employing a one-second epoch length and comparing daily sedentary time estimates of the ENMO cutpoint-based method for a wrist-worn accelerometer to that of a thigh-worn accelerometer (Hildebrand et al., 2017). Because the GGIR package was developed to convert raw data from wrist-worn accelerometers into estimates of not only sedentary time, but also of sleep, LPA and MVPA, it is of interest to choose the most optimal epoch length to draw reliable estimates from all physical behaviors. The 60-second epoch length seems to be the most accurate in terms of sedentary time (Heesch et al., 2018; Koster et al., 2016), but it is not known whether it is the optimal choice for the whole composition of daily physical behaviors.

In Study IV, information on whether the measurement day was a working day or a day off enabled relevant and unique comparisons of how similarly each method detects the difference between sedentary time on working days and days off. Previous studies have shown that working days and days off differ in terms of sedentary time (Clemes et al., 2014; Kurita et al., 2019; Parry & Straker, 2013; Thorp et al., 2012). The movement-based methods applied to a wrist-worn accelerometer and posture-based thigh-worn accelerometer were found to detect very similar differences in sedentary time between the same individuals' working days and days off. This finding suggests that although absolute values from a wrist-worn accelerometer should be interpreted with caution, this accelerometer can be used to reliably examine within-individual changes in sedentary time.

6.4 Methodological considerations

6.4.1 Study populations

A relatively large, representative sample of the target population of Finnish public sector workers is one of the strengths of the current PhD study. There were no marked differences between the study population in Study I and II and that of the FIREA survey cohort. Participant compliance was very good in the FIREA study and the REACT trial. The dropout rates were low, from 1.6% to 2.8% in the accelerometer measurements (Studies I and II) and 2.0% in the activity tracker-based intervention (Study III). Thus, the findings are generalizable to aging public sector workers in Finland as well as in other countries with similar statutory retirement ages and pension systems. Moreover, due to the high diversity of occupations among public sector workers, the findings may be generalized to people retiring from a variety of occupations. In all the studies of this thesis, the majority of the participants were women, and because there were large differences between the sedentary time of genders, the analyses were conducted separately for women and men. However, in the REACT trial, the analyses were not separated by gender, and thus it is not known how well the findings of the REACT trial can be generalized to men. One of the eligibility criteria for the REACT trial was having no major functional limitations, which may explain the lower level of functional limitations in Study III in comparison to Studies I and II. There might also have been selection bias in Study III, given that mainly physically active and healthy individuals are interested in following and improving their health-related behavior (Baker et al., 2015).

As the study populations included only full-time statutory retirees, further examinations of partial and disability retirees may be needed. It is probable that sedentary time would increase among part-time retirees, but to a lesser extent, because they still have working days after retirement. Sedentary levels may be higher and more stable among disability retirees because the transition to disability retirement is commonly preceded by a reduced ability to work and sickness absences due to somatic or mental disorders (Finnish Centre of Pensions, 2020; Salonen et al., 2020). Moreover, a decline in self-reported leisure-time physical activity has been reported after retirement among disability retirees, possibly due to the fact that reduced capacity to work also means a limited ability to engage in physical activity (Stenholm et al., 2016).

The populations in Studies I and II, with a high diversity of occupations, were crudely categorized into two occupational groups: non-manual and manual occupational groups. Due to the small number of men in the samples of Studies I and II, dividing men into more than two occupational groups would have weakened statistical power and resulted in non-significant findings. There may have been heterogeneity within the occupational groups in terms of sedentary time, especially in the manual occupational group, because it included workers in physically demanding occupations (e.g. maintenance work) and workers who mainly sit at work (drivers etc.). Within the non-manual group, dividing women into upper-grade and lower-grade non-manual workers showed that there were no actual differences between these groups. This suggests that heterogeneity was not so significant within the non-manual occupational group. Moreover, despite the possible heterogeneity in terms of sedentary time, clear differences were seen between sedentary time among the non-manual and manual occupational groups. Therefore, although the occupational categorization was crude, it enabled separating two occupational groups that had clearly different levels of sedentary time. Nonetheless, future examinations with more detailed occupational categorizations and more specific categorization by work-related physical demands are warranted.

The actual retirement date was based on the information that the study participants reported in their daily logs. Some participants reported being full-time retired but having occasional working days, and a few participants reported being retired in one measurement and working in the following measurement. However, because comparing working days before retirement and usual days after retirement was one of the interests of this PhD study (Study I), information on whether a measurement day was a working day or a day off was utilized and only “true” retirement days were included in the analyses.

6.4.2 Accelerometer measurements

The main strength of the current study is the estimation of sedentary time by accelerometers, which are not subject to recall and information bias, like self-reports (Chastin et al., 2014; Dyrstad et al., 2014; Harvey et al., 2015). In each study, the annual accelerometer measurements were conducted using a similar protocol in the data collection and processing of the accelerometer data. In Studies I and II, the effect of seasonal variation was minimized by conducting the measurements at the same time of the year for each individual. In Study III, the effect of seasonal variation was taken into account by conducting the measurements in five groups, both the intervention and control group starting their follow-up in the same seasons: spring, winter and autumn. Therefore, the effects of changes in methodology and seasonal variation were minimized. Accelerometer measurements may be subject to measurement reactivity, that is, study participants may increase their physical activity during the measurement because they are aware that their activity is being monitored (Baumann et al., 2018). It is likely that the effect of measurement reactivity was constant over the follow-up, and thus did not affect the findings on the changes in sedentary time. However, it can be speculated that measurement reactivity may be stronger during the first measurements and attenuate after participants become more familiar with the monitoring. It is not known how well the measurement weeks corresponded to a participants' usual weeks, but the variation in the results could be reduced by a larger number of participants and measurement days.

In addition, it is not yet quite clear how many days of accelerometer data are required to produce reliable estimates of a participant's usual sedentary levels (Heesch et al., 2018) and moreover, how many working days and days off are required to reliably estimate a participant's usual sedentary level at work and during leisure time. Dillon and colleagues (2016) showed that at least three measurement days with a minimum of 10 hours of accelerometer wear time are needed to attain acceptable test-retest reliability in sedentary time estimations from a wrist-worn GENEActiv accelerometer among middle-aged adults. A higher requirement of at least five measurement days with a minimum of 10 hours of accelerometer wear time has been reported in another study evaluating a hip-worn ActiGraph accelerometer among older adults (Hart et al., 2011). The majority of the study participants in the FIREA study wore accelerometers with a high compliance and the mean number of valid days was over five days in each measurement year in Studies I–III. The mean number of working days before retirement was 4.3 days (range 1–7) and for days off 2.5–2.7 days (range 1–7) in Studies I and II, implying that for most of the participants the measurement week represented a usual working week, at least in terms of the number of working days and days off. Based on the available evidence, the number of working days (over 4) was likely sufficient, but more days off may be needed to attain reliable estimates of sedentary time during work and leisure time (Pedersen et al., 2016).

Accelerometer measurements over 24 hours bring challenges to analyzing the data, because all low movement periods, that is, sedentary time, sleeping and non-wear time have to be detected and distinguished from each other (Meredith Jones et al., 2016; Pulakka, Shiroma et al., 2018). All the studies used validated methods to estimate sleep and non-wear time. However, as sleep algorithms estimate sleep based on wrist movements, their capacity to detect actual wakefulness during the sleep period is limited (Slater et al., 2015). It is possible that short periods of sleep, for instance daytime napping, were detected as sedentary time. Especially in Study III, the sleep algorithm only detected sleep periods within the timeframe of the in-bed and out-of-bed times reported in the daily logs, thus daytime napping was not detected as sleep. Moreover, the Choi algorithm used in Studies I and II to detect non-wear time recognizes only relatively long periods of time, 90 minutes, of zero counts as non-wear time. Thus, it is probable that short periods of non-wear time such as when taking a shower, were also detected as sedentary time. These limitations in separating sleep and non-wear time from sedentary time may affect the absolute levels of sedentary time. However, any measurement errors were likely to be small, because several valid measurement days were used to calculate the means of daily sedentary time.

Another important methodological consideration in the estimations of sedentary time from accelerometer data is the developed cutpoint for sedentary time. Cutpoints are usually developed in laboratories or in other circumstances that do not correspond to free-living conditions. The validation study by Koster and colleagues (2016) clearly showed that the cutpoint that was developed in the laboratory conditions did not perform as well as that developed in free-living conditions. Moreover, cutpoints that are developed among young adults may not easily be transferred to other study populations, such as older adults who may have different movement patterns and gait speed (Heesch et al., 2018). In Studies III and IV, the ENMO cutpoint used to define sedentary time was actually developed among a small group of young adults (N=20, mean age 23 years) in supervised free-living conditions (Rowlands, Mirkes et al., 2018), as no available ENMO cutpoints had been developed among older adults.

Given that the same validated methods for estimating sedentary time were used in each follow-up time point in Studies I–III, it was expected that the within-individual changes in sedentary time would be captured with adequate accuracy. However, as the methods used were developed and validated in different settings (small study populations, different age groups, partly in laboratory conditions), it was not known how they would perform in free-living conditions or among the age groups of Studies I–III. Thus, a relevant strength of the current study is that Study IV enabled obtaining insights into how reliable the findings of Studies I–III are. Study IV showed that the methods applied to the wrist-worn accelerometer detected within-individual differences in sedentary time between working days and days off as accurately as the thigh-worn accelerometers. These findings suggest that the within-individual changes in sedentary time in Studies I–III can be considered reliable. However, absolute values of sedentary time should be interpreted with caution. It is likely that these were underestimated in Studies I and II and overestimated in Study III, at least when compared to the thigh-worn accelerometer. Nevertheless, the main focus of Studies I, II and III was to examine within-individual changes between the sedentary levels of the groups rather than absolute levels of sedentary time.

It should be noted that the count cutpoint method evaluated in Study IV was not exactly the same method as that used in Studies I and II. Study IV used a daily log to estimate sleep time, whereas Studies I and II used the Cole–Kripke and ActiGraph algorithms. Study IV used a daily log to harmonize the sleep detection of the wrist-worn and thigh-worn accelerometers. In Studies I and II, algorithms were used instead of daily logs to increase the accuracy of the sleep time estimations. However, the influence of the different sleep estimation methods on the results is likely to be minimal, because the sleep estimates from daily logs and the combination of the Cole–Kripke and Actigraph sleep algorithms have shown to be very close to each other (Pulakka, Shiroma et al., 2018).

Several methodological aspects need to be considered when interpreting the findings of Study IV. Firstly, the thigh-worn Axivity AX3 accelerometer and the Acti4 software were chosen as a reference measurement method because processing data from a thigh-worn accelerometer (independently of the accelerometer brand) in the Acti4 software has shown to produce reliable estimates of time spent sitting and lying down (Crowley et al., 2019; Skotte et al., 2014; Stemland et al., 2015). However, it should be noted that the Acti4 software has not been validated to detect the metabolic component of sedentary behavior.

Secondly, because the aim was to compare the currently established methods applied to a wrist-worn accelerometer to the more reliable method applied to a thigh-worn accelerometer, there were also other differences than the device location between the methods, sleep and non-wear time detection being the most important. Therefore, several possible factors may explain the observed differences between the absolute levels of sedentary time of the methods. Given that it is easier for a participant to remove a wrist-worn accelerometer than a thigh-worn accelerometer attached by tape to skin, the accelerometers may have had different wear times for some part of the measurement days. Therefore, due to the different sleep and non-wear time estimates of the methods, only days with a maximum of 10 minutes difference in wear time were included in the comparative analyses of the methods. Consequently, the comparison between the movement-based count cutpoint method and the thigh-worn accelerometer found no differences in sleep time estimates due to the same sleep detection method (daily logs), but it did find slight differences in wear time (<10 min). The comparison between the movement-based ENMO cutpoint method and the thigh-worn accelerometer showed slight differences between both the sleep time and non-wear time of the methods (3 min, SD 61 min, 4 min, SD 60 min, respectively).

Thirdly, another methodological choice that seemed to affect the sedentary time estimates of the wrist-worn accelerometer was epoch length. When the same epoch length was used for the thigh-worn accelerometer and the ENMO cutpoint method applied to the wrist-worn accelerometer, the wrist-worn accelerometer overestimated sedentary time by one hour. In contrast, when using the five-second epoch length for the thigh-worn accelerometer and the 60-second epoch length or 60-second bout restriction for the wrist-worn accelerometer, the wrist-worn accelerometer underestimated sedentary time by 50–60 minutes in comparison with the thigh-worn accelerometer. Given that wrist movements are more frequent than thigh movements, longer epoch lengths for the wrist seem to produce more accurate estimates of sedentary time (Heesch et al., 2018). Finally, as a minor factor, the methods' sample frequencies also differed slightly (thigh: 100 Hz, wrist: 80 Hz). As sample frequency has been reported to affect the generation of counts (Brønd & Arvidsson, 2016), it may play a minor role in the observed differences between the absolute levels of sedentary time of the methods.

6.5 Implications and future directions

The clinical relevance of the findings on the changes in sedentary time across the transition to retirement can be evaluated on the basis of a few longitudinal studies. In a longitudinal cohort study of 65-year-old participants with known risk factors for type 2 diabetes, reallocating from sedentary time to physical activity every 30 minutes over 12 months was associated with improved cardiometabolic health; reduction in waist circumference (LPA: 0.21-cm, MVPA: 1.23-cm), two-hour glucose (LPA:0.09-mmol/l, MVPA:0.23-mmol/l), triglycerides (LPA:0.02-mmol/l, MVPA:0.04-mmol/l) and cardiometabolic risk score (LPA:0.02, MVPA:0.07) (Yates et al., 2020). Moreover, a greater increase in sedentary time over six years among middle-aged adults was associated with a greater increase in cardiometabolic risk score and a less than two-hour increase in sedentary time was associated with an almost 0.2 increase in cardiometabolic risk score (Wijndaele et al., 2014). Based on these findings, the increase of 54 minutes in daily total sedentary time among women retired from manual occupations that was observed in the current PhD study is most likely clinically relevant. No longitudinal studies have examined how changes in prolonged sedentary time are associated with health outcomes, but cross-sectional studies have shown dose-dependent associations with prolonged sedentary time and risk of cardiovascular diseases and type 2 diabetes (Bellettiere, LaMonte et al., 2019; Bellettiere, Healy et al., 2019).

Meta-analyses based on hip-worn accelerometer data have suggested an increase in mortality risk when daily total sedentary time exceeds nine hours (Ekelund et al., 2019; Ku et al., 2019), whereas new Canadian 24-hour movement behavior guidelines recommend limiting daily sedentary time to eight hours per day (Ross et al., 2020). Absolute levels of sedentary time from a wrist-worn accelerometer are not fully comparable to levels of sedentary time from a hip-worn accelerometer. However, as the estimates of sedentary time from hip-worn accelerometers among Finnish adults aged 60–69 (approximately 9 hours) (Husu et al., 2018) are close to the absolute levels of sedentary time observed after retirement in the current PhD study (8.5 hours among women and 9.6 hours among men), it is likely that recently retired adults, especially men, are close to the risky levels of sedentary time. The findings of the current PhD study indicate a need for interventions to reduce sedentary time among retiring individuals.

The findings of the current study imply that interventions to reduce sedentary time among aging workers should be tailored to gender- and occupation-specific needs. Men appeared to be considerably more sedentary than women before and after retirement. Men also showed a constant increase in prolonged sedentary time from pre-retirement years to post-retirement years, whereas among women, an increase in prolonged sedentary time was only observed during the transition to retirement. These findings suggest that men may benefit from interventions to reduce sedentary time already during work life, while the benefit for women may be highest during the transition to retirement. Given that the daily sedentary levels were distinctly higher among the non-manual workers than among the manual workers before retirement, and that working hours were the main contributor to high sedentary levels, workplace interventions would probably be the most optimal strategy to reduce sedentary time among non-manual workers. Workplace interventions have been reported to also decrease sedentary time during leisure time, possibly due to increasing awareness of the health hazards of sedentary time (Shrestha et al., 2019). Regarding manual workers' sedentary behavior, leisure time is more important than working hours. Helping manual workers adopt a physically active lifestyle in their leisure time before retirement could possibly attenuate an increase in sedentary time after retirement. As prolonged sedentary time increased after retirement among both non-manual and manual workers, interventions that promote breaking up sedentary time during leisure-time sedentary activities are needed. The findings of the current study indicate that sedentary behavior is most common during evening hours both before and after retirement. Therefore, breaking up sedentary time with LPA or MVPA during early evenings and LPA during late evenings, so that falling asleep is not disturbed (Stutz et al., 2019), may be effective to reduce sedentary time during leisure time.

The focus of the current PhD study was on changes in sedentary time, but it would be relevant for future research to examine how the whole 24-hour physical behavior composition changes after retirement or during an intervention. Health consequences may be different depending on whether sedentary time increases at the expense of sleep, LPA or MVPA (Grgic et al., 2018). Given that sleep time increased among most retirees after the transition to retirement (Myllyntausta et al., 2020), increasing sedentary time most likely replaces LPA or MVPA after retirement. In general, the research field is shifting toward the 24-hour perspective, because all physical behaviors – sedentary behavior, LPA, MVPA and sleep – are interrelated (Dumuid et al., 2020). Several countries have included sedentary behavior recommendations in their national physical activity guidelines (Stamatakis et al., 2018) and recently, some have launched new national 24-hour movement recommendations, including guidelines on physical activity, sedentary behavior and sleep (Canadian Society for Exercise Physiology, 2020; UKK-instituutti, 2019). However, whether more research taking into account the whole 24-hour physical behavior composition is needed to produce more precise and evidence-based 24-hour physical behavior guidelines is still under debate (Stamatakis et al., 2018; Stamatakis & Bauman, 2020; Tremblay et al., 2020). Therefore, longitudinal examinations of how the 24-hour composition of physical behaviors changes after retirement and how these changes associate with health outcomes later in life would provide important information on the optimal composition of physical behaviors.

The current PhD study focused on examining the role of gender and occupation in changes in sedentary time across the transition to retirement. The role of other factors such as obesity, chronic pain and chronic diseases, which may affect the changes in sedentary time across the transition to retirement should be examined in larger study samples. To date, factors determining the changes in sedentary time in the transition to retirement have only been examined comprehensively in relation to self-reported leisure-time sitting (Leskinen, Pulakka et al., 2018). Therefore, accelerometer-based findings on the determinants of changes in sedentary time are warranted.

One of the interests of this PhD study was changes in prolonged sedentary bouts across the transition to retirement and during an activity tracker intervention, but it would also be relevant to examine how breaks in sedentary time, their frequency, intensity and duration change and how different breaks from sedentary behavior affect health outcomes. These types of examinations would benefit the development of more robust guidelines regarding prolonged sedentary time, as no consensus or recommendations exist on how sedentary time should be broken up and the current knowledge is mostly based on short-term experimental studies (Loh et al., 2020).

This PhD study evaluated one possible tool to reduce sedentary time among retirees, an activity tracker, and its findings suggest that such a tracker may not be sufficient to elicit long-term changes in sedentary time. Qualitative examinations of the intervention participants' experiences and challenges related to the activity tracker use would be beneficial and would help us understand why long-term changes were not achieved. Future examinations of effective ways to reduce sedentary time in the long term, especially during leisure time, are warranted. Leisure time seems to be a challenging target, because it includes so many different contexts of sedentary behavior – watching TV, using a computer, eating and reading, to name the most common behaviors. It has been suggested that each of these contexts should be taken into account when planning interventions to reduce sedentary time, because people primarily engage in meaningful activities for different reasons such as using a computer for work or reading for leisure, and sitting simply comes along with these activities. Furthermore, some contexts of sedentary behavior, such as watching TV, may as a mentally passive activity be more harmful for health than other contexts, such as reading, which is considered a mentally active activity (Hallgren et al., 2020).

Future studies are needed to examine whether effective ways to increase physical activity at all intensities and effective ways to reduce sedentary time can be combined. Interventions that focus on sedentary time, mainly by breaking it up, are likely to induce increases in LPA but not in MVPA. Knowledge of the health benefits of LPA has accumulated in recent years and has also been noted in the new Canadian 24-hour movement guidelines (Canadian Society for Exercise Physiology, 2020) and WHO's guidelines on physical activity and sedentary behavior (World Health Organisation, 2020). Many older adults may face challenges in engaging in higher intensity physical activity due to chronic diseases and mobility limitations, and thus, limiting daily sedentary time by promoting LPA may be a more practical approach. Nevertheless, higher intensity physical activity seems to be safe and feasible even for 70-year-old adults (Stensvold, Viken et al., 2020). MVPA is needed in a healthy lifestyle, and seems to attenuate the health risks of high sedentary time (Ekelund et al., 2016). The core of an intervention that could possibly change sedentary time, LPA and MVPA at the same time might include a mixture of supervised exercise and self-directed physical activity to promote long-term physical activity habits (Stensvold, Wisloff et al., 2020; Stensvold, Viken et al., 2020), an activity tracker to provide long-term ongoing monitoring of self-directed physical activity at all intensities (Brickwood, Watson et al., 2019) and the activity tracker's inactivity alerts as reminders to break up sedentary time.

The aim of this PhD study was to examine how large the differences between the established methods of estimating sedentary time are, using a wrist-worn accelerometer and the more reliable sedentary time estimates of a thigh-worn accelerometer. Of the methods applied to the wrist-worn accelerometer, the count cutpoint-based method seemed to have the highest agreement with the thigh-worn accelerometer. However, the difference in the absolute levels of sedentary time was considerable. Even though a wrist-worn accelerometer has apparent limitations in detecting sedentary time, it has been employed in several large epidemiological studies because of its important strengths in 24-hour measurements, such as increased participant compliance, reliable detection of light physical activity related to daily tasks and the option of estimating sleep time (Freedson & John, 2013; Quante et al., 2015; Schrack et al., 2016). Therefore, further development of the data processing methods applied to wrist-worn accelerometers for detecting sedentary behavior as a part of the 24-hour composition is needed and would benefit further study.

Given that the most common methods for estimating sedentary time are based on the detection of low movement periods (i.e. periods with acceleration values lower than a certain cutpoint value) by wrist- or hip-worn accelerometers, the accuracy of these methods in differentiating a sitting posture from a standing posture is inherently limited (Berendsen et al., 2014; Mitchell et al., 2017). Thus, it may be more appropriate to define the low movement time they capture as stationary time rather than sedentary time (Flórez-Pregonero et al., 2018; Tremblay et al., 2017). Therefore, one possible future research direction might be the examination of stationary behaviors as a part of the 24-hour composition. The majority of the cutpoints for wrist-worn accelerometers have been developed to correspond to sitting and lying activities, assumed to have low energy expenditure (<1.5 METs). To date, only one research group has developed a wrist-accelerometer cutpoint for stationary time (Flórez-Pregonero et al., 2018). Furthermore, not much is known of the health associations of standing, but some evidence has shown that breaking up sedentary time by standing does not bring marked health benefits; light physical activity is also needed (Bailey & Locke, 2015). However, further research on standing and stationary behaviors may be needed.

Due to the known limitations of the cutpoint approach, mainly related to generalizability and using one single cutpoint whereas a range of cutpoints might be more optimal (Koster et al., 2016), suggestions to move away from this approach have been made (Montoye et al., 2020; Rowlands, Edwardson et al., 2018). Moreover, cutpoint-based methods utilize only acceleration information, whereas additional information on, for example, the orientation of the accelerometer device can be gleaned from the acceleration data. A promising future direction for accelerometer data processing is machine learning, which may offer more accurate information on physical behaviors than cutpoint-based methods. Models can be trained to detect specific behaviors from the data by more comprehensively utilizing the captured acceleration data. Machine learning models have already been developed in several datasets such as the UK Biobank study (Willetts et al., 2018) and the HUNT4 study (Krokstad et al., 2013). However, it is not known how models that are trained in a specific dataset perform in different datasets gathered from other study populations, implicating a need for more field-based evaluation for each target population (Heesch et al., 2018). Furthermore, one reason for the popularity of the cutpoint approach, despite its limitations, is that cutpoint-based methods are simpler to use than machine learning methods. Proper use of machine measuring methods requires expertise in 24-hour movement patterns and understanding of the techniques applied in machine learning methods (Montoye et al., 2020).

7 Conclusions

This PhD study examined changes in daily total and prolonged sedentary time and daily sedentary profiles across the transition to retirement according to gender and occupation. It also evaluated the effect of an activity tracker-based intervention on daily total and prolonged sedentary time among recent retirees. Finally, daily sedentary time estimates from the movement-based methods applied to a wrist-worn accelerometer were compared to the posture-based estimates from a thigh-worn accelerometer. The main findings of the PhD study were the following:

1. Daily total sedentary time only changed among women retiring from manual occupations, as they increased their daily total sedentary time immediately after the transition to retirement. Usual working hours in particular were more sedentary after retirement among women retiring from manual occupations. Prolonged sedentary time increased across gender and occupational groups. Prolonged sedentary time increased immediately after the transition to retirement among women, whereas among men it increased more gradually from the last years at work to the first years after retirement.
2. The activity tracker that encouraged users to fulfil their daily physical activity goal and reminded them to break up prolonged inactivity periods was insufficient to elicit changes in daily total or prolonged sedentary time over 12 months.
3. Compared to a posture-based thigh-worn accelerometer, the movement-based methods applied to a wrist-worn accelerometer either underestimated or overestimated daily sedentary time by 50–60 minutes, depending on the data processing method. However, similar within-individual differences between sedentary time on working days and days off were detected by wrist- and thigh-worn accelerometers, suggesting that the within-individual changes during retirement transition and the intervention were captured reliably.

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Appendices

Appedix 1. The GGIR script used in the Study III.

```
library(GGIR)

f0=1
f1=231

g.shell.GGIR(#=====================================
            mode=c(1,2,3,4,5),
            datadir="/wrk/data",
            outputdir="/wrk/results",
            f0=f0, f1=f1,
            daylimit=FALSE,
            #-------------------------------
            # Part 1:
            #-------------------------------
            windowsizes = c(5, 900, 3600),
            desiredtz="Europe/Helsinki",
            do.enmo = TRUE,          do.anglez=TRUE,
            chunksize=1,             printsummary=TRUE,
            overwrite=TRUE,
            #-------------------------------
            # Part 2:
            #-------------------------------
            strategy = 3,
            ndayswindow=9,
            winhr = c(5),
            qwindow=c(0,24),
            ilevels = c(seq(0,400,by=50),8000),
            mvpathreshold =c(100.6),
            bout.metric = 4,
            epochvalues2csv=FALSE,
            closedbout=FALSE,
            do.imp = FALSE,
            #-------------------------------
            # Part 3:
            #-------------------------------
            # Key functions: Sleep detection
            timethreshold= c(5),     anglethreshold=5,
            ignorenonwear = TRUE,
            desiredtz="Europe/Helsinki",
             #-------------------------------
             # Part 4:
             #-------------------------------
             excludefirstlast = FALSE,
             includenightcrit = 16,
```

```
def.noc.sleep = c(),
loglocation= c("/wrk/KL_log.csv"),
outliers.only = TRUE,
criterror = 4,
relyonsleeplog = FALSE,
sleeplogidnum = TRUE,
colid=1,
coln1=2,
do.visual = TRUE,
nnights = 9,
#-------------------------------
# Part 5:
# Key functions: Merging physical activity with sleep analyses
#-------------------------------
threshold.lig = c(30), threshold.mod = c(100.6),  threshold.vig = c(428.8),
boutcriter = 0.8,      boutcriter.in = 0.9,     boutcriter.lig = 0.8,
boutcriter.mvpa = 0.8, boutdur.in = c(1,30,60), boutdur.lig = c(1,10),
boutdur.mvpa = c(1,10),   timewindow = c("WW"), save_ms5rawlevels= TRUE,
#-----------------------------------
# Report generation
#-------------------------------
# Key functions: Generating reports based on meta-data
do.report=c(2,4,5),
visualreport=TRUE,     dofirstpage = TRUE,
viewingwindow=1)
```

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