Health & Place 81 (2023) 103025

Contents lists available at ScienceDirect

Health and Place

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

Does work-related and commuting physical activity predict changes in physical activity and sedentary behavior during the transition to retirement? GPS and accelerometer study

S. Pasanen [a,b,*], J.I. Halonen [c], K. Suorsa [a,b], T. Leskinen [a,b], Y. Kestens [d,e], B. Thierry [d], J. Pentti [a,b,f], J. Vahtera [a,b], S. Stenholm [a,b]

[a] Department of Public Health, University of Turku and Turku University Hospital, Turku, Finland
[b] Centre for Population Health Research, University of Turku and Turku University Hospital, Turku, Finland
[c] Department of Health Security, Finnish Institute for Health and Welfare, Helsinki, Finland
[d] Centre de Recherche en Santé Publique (CReSP), Montreal, Canada
[e] Department of Social and Preventive Medicine, Université de Montréal, Montréal, Canada
[f] Clinicum, Faculty of Medicine, University of Helsinki, Helsinki, Finland

ARTICLE INFO

Keywords:
Physical activity
Retirement
Activity locations
Occupational physical activity
Active commute

ABSTRACT

We examined how GPS and accelerometer measured work-related and commuting physical activity contribute to changes in physical activity and sedentary behavior during the retirement transition in the Finnish Retirement and Aging study (n = 118). Lower work-related activity was associated with a decrease in sedentary time and an increase in light physical activity during retirement. Conversely, higher work-related activity was associated with an increase in sedentary time and a decrease in light physical activity, except among those active workers who also were active commuters. Thus, both work-related and commuting physical activity predict changes in physical activity and sedentary behavior when retiring.

1. Introduction

Regular and adequate amount of physical activity provides health benefits by reducing risk of chronic diseases, maintaining physical and cognitive functioning, and improving quality of life among older adults (Bauman et al., 2016). High level of sedentary time has been associated with higher risk of several chronic diseases and increased all-cause mortality (De Rezende et al., 2014). Physical activity levels tend to decline (Bauman et al., 2016; Caspersen et al., 2000) and sedentary time to increase (Harvey et al., 2015) towards old age, which underlines the importance of promoting physical activity among older adults. Retirement, a common life transition in late middle-age, can lead to either positive or negative changes in physical activity and sedentary behavior (Gropper et al., 2020; Sprod et al., 2015; Vansweevelt et al., 2022). Prior studies using self-reported measures of physical activity have reported that the transition to statutory retirement often increases leisure and domestic physical activity, but reduces work- and transportation related physical activity, as well as total physical activity (Gropper et al., 2020).

Pre-retirement occupation seems to have a marked role on the changes in physical activity and sedentary behavior when retiring. Several studies have shown that self-reported physical activity tend to decrease during retirement transition among those with physically demanding pre-retirement work or manual occupation, whereas sedentary work or higher occupational position is associated with an increase in physical activity (Celidoni and Rebba, 2017; Chung et al., 2009; Stenholm et al., 2016). To our knowledge, changes in accelerometer-measured physical activity and sedentary behavior during retirement transition have so far been reported only from the Finnish Retirement and Aging study (FIREA). Largest decrease in total physical activity was observed among women retiring from manual, i.e. physically active occupations (Pulakka et al., 2020), and total and prolonged sedentary time was found to increase particularly among women retiring from manual occupations (Suorsa et al., 2019, 2021, 2022). Moreover, the pre-retirement mode of commute to work has been found to predict changes in physical activity during the transition to retirement. Cycling to work was associated with a higher level of accelerometer measured total physical activity both before and after retirement, and with a better maintenance of the level of physical

* Corresponding author. Public Health, Kiinamyllynkatu 10, Medisiina A, FI-20014, University of Turku, Finland.
E-mail address: sanna.pasanen@utu.fi (S. Pasanen).

https://doi.org/10.1016/j.healthplace.2023.103025
Received 15 December 2022; Received in revised form 31 March 2023; Accepted 5 April 2023
Available online 26 April 2023
1353-8292/

activity during the transition to retirement (Pulakka et al., 2020).

However, a major limitation of the previous studies is related to the measurement of physical activity at work. In prior studies the occupational activity has been estimated using self-reported or register-based information on job titles (Barnett et al., 2014; Pulakka et al., 2020; Suorsa et al., 2019, 2021, 2022), which are not accurate measures of physical activity. Similarly, commuting physical activity has mostly been measured by self-reports (e.g. Pulakka et al., 2020; Van Dyck et al., 2016), that are prone to measurement and recall biases. These limitations can be overcome by utilizing simultaneous GPS and accelerometer measurements, which enable to distinguish physical activity and sedentary time that occurs at workplace and during commute.

The aim of this study was to examine how pre-retirement physical activity at work and during commute associates with the changes in physical activity and sedentary behavior during the transition to retirement. The level of physical activity intensity and daily total sedentary time were measured with accelerometer both before and after retirement. GPS measurements were utilized to identity the contexts of pre-retirement physical activity and sedentary time, that is, the workplace and commuting trips.

2. Methods

2.1. Study population

The study population consists of people who participated in the Finnish Retirement and Aging study (FIREA), which is a longitudinal study established in 2013 examining the changes in health and health behaviors around retirement transition among public sector workers in Finland. The FIREA study includes public sector employees who worked in 2012 in one of the 27 municipalities of Southwest-Finland, or in the nine selected cities, or in the five hospital districts around Finland, and whose personal retirement date was between 2014 and 2019 (Leskinen et al., 2018).

The FIREA study includes FIREA survey cohort, FIREA activity sub-study (Pulakka et al., 2020), and a FIREA clinical sub-study. The present study is based on the FIREA clinical sub-study, which was conducted between 2015 and 2022. All participants were first contacted 18 months before their estimated retirement date with a questionnaire. After responding to the survey ($n = 6783$), the Finnish-speaking participants who lived in the Southwest Finland and were still working and whose estimated retirement date was between 2017 and 2019 were invited to participate in the FIREA clinical sub-study ($n = 773$). Of these, 290 (38%) returned written informed consent and were included.

In the FIREA clinical sub-study, annual clinical examination visit included fasting blood sample, hair sample, measurements of anthropometry, body composition, cardiovascular function, physical function and cognitive function (Karelius et al., 2023; Stenholm et al., 2021; Teräs et al., 2020). Measurements were conducted by trained study nurses. Annual combined GPS and accelerometer measurement with SenseDoc device were added to the FIREA clinical sub-study protocol in March 2016, and the device was given during the clinical examination visit.

The FIREA study has been approved by the Ethics Committee of the Hospital District of Southwest Finland (ETMK: 84/1801/2014), and it is conducted in accordance with the ethical principles of the Helsinki declaration.

2.2. Measurement of retirement

Estimated retirement times were obtained from Keva, which is an insurance institution that administers the pensions of the Finnish municipal sector, and were used to identify the study population and to plan the timing of data collection. The actual retirement day (for full-time statutory retirement) was inquired during each phase of the data collection and this information was used to identify pre- and post-retirement measurements.

In Finland, there is no single retirement age, but each age group has its own retirement age. The retirement age for each age group is based on their calculated life expectancy. Generally public sector employees can retire on statutory basis in the age of 63–68 years, but there are some occupations where the possible retirement age is lower.

2.3. GPS and accelerometer measurements

We used a waist-worn SenseDoc 2.0 device (Mobysens Technologies Inc, Canada), which includes GPS sensor and a tri-axial accelerometer. We initialized the device to record GPS coordinates once per second and collected the simultaneous accelerometer data at a sampling rate of 80 Hz. A detailed description of the features of the device has been reported previously (Brondeel et al., 2019). A study nurse instructed the participants of the use of the device during the clinical examination visit. The participants were asked to wear the SenseDoc device during waking hours, but to remove it while bathing or doing water sports, for at least two workdays and two days off when still working, and after retirement a minimum of any four days. The participants were also asked to fill in a diary, where they provided daily information about their workdays and days off, and about their bedtimes and modes of commute. Only the GPS and accelerometer data that according to the diary were within a measurement phase were used in the formation of the analytical sample. In our study, the wake time activity behavior at different locations and during trips is examined day-by-day, based on the bedtime recorded in the diary. The device and diary were returned by mail after the measurement phase.

The following software were needed to export and process the raw GPS and accelerometer data: SenseAnalytics (versions 1.9 and 1.10) connects to SenseDoc devices and downloads the raw binary data stored on the device into CSV files readable by the remaining of the processing pipeline. ArcGIS (version 10.3.1) was used to segment the GPS track into visited locations and trips, using a published algorithm (Thierry et al., 2013), which runs as a Python (version 3.6.6) script. R (version 3.5.3) was used to convert the raw accelerometer measurements into ActiGraph equivalent counts leveraging the activityCounts package (GitHub, 2022). PostgreSQL (version 11.1) and PostGIS were used to merge the GPS and accelerometry datastreams and produced the aggregated metrics.

We used an algorithm developed by BrØnd et al. (2017) to convert raw accelerometer data to ActiGraph equivalent counts (for details see R package from GitHub (2022)). We aggregated the counts per second to counts per minute, and applied commonly used thresholds for sedentary time (≤100 counts/minute) (Ekelund et al., 2020; Matthews et al., 2016), light physical activity (>100 and ≤ 2020 counts/minute) (Loprinzi and Brosky Jr, 2014; Wolff-Hughes et al., 2015) and moderate-to-vigorous physical activity (MVPA) (>2020 counts/minute) (Troiano et al., 2008). The average minutes of daily total sedentary time, light physical activity and MVPA were calculated for workdays, days off, and retirement days. Physical activity before retirement was calculated as a weighted average ($(5 \times PA_{work\ day} + 2 \times PA_{day\ off})/7$), and physical activity after retirement as an average of the physical activity of at least two retirement days. In our analytical sample, most participants (78%) worked full-time before retirement, while 22% were part-time workers. Device wear time was assessed with the accelerometer signal, using Choi's method which flags as non-wear time any measure within a 90-min time window of consecutive zero counts, allowing 2-min interval of non-zero counts with the up or downstream in 30 min consecutive zero counts window (Choi et al., 2011, 2018).

Flow chart for the selection of the analytical sample is in Supplemental Fig. 1. Briefly, we included those participants who provided at least two valid measurement days, both before and after retirement. Before retirement, one valid day had to be a working day and another a valid day off. A valid measurement day was defined with commonly used criteria of wear time of ≥10 h or more during waking hours

(Aadland and Ylvisåker, 2015; Schrack et al., 2016). We excluded the participants whose workplace or commuting trip could not be identified. Consequently, the final analytical sample consisted of 118 participants with 585 valid measurement days before retirement and 561 after retirement. The mean number of valid measurement days was 5.0 (standard deviation (SD) 2.2) before and 4.8 (SD 2.2) after retirement. On average, the participants provided GPS and accelerometer measurement data in 2.9 phases (range 2–4). The average time between before and after retirement measurements was 1.60 years (SD 0.34). The data were collected during all seasons of the year, but the measurements for each individual were conducted at the same time each year. The information of the measurement seasons overall and by the activity group is provided in Table 1.

2.4. Identification of home, workplace and commuting trips

To identify physical activity at different locations and during trips between locations, we utilized an algorithm developed by Thierry et al. (2013). The algorithm operates globally by computing a kernel density surface from the GPS points, then derives stop locations by identifying local maxima. Finally, the track is segmented into stop and trip bouts by allocating GPS points to either a local peak or a trip segment. For further details and validity statistics, see Thierry et al. (2013) and Kestens et al. (2018), which further document convergent validity of GPS activity locations with self-reported VERITAS map-based questionnaire locations.

To identify the participants' home, workplace and commuting trips to work and back home, we made the following assumptions regarding our GPS data. The detected location, which was the nearest to and within 100 m of the participant's registered home address was marked as the participant's *home*. For those participants who did not have a registered home address or the distance between the home address and the nearest identified location was more than 100 m, home was determined to be the location where the participant spent most time (8% of all homes). All other identified locations were interpreted as non-home locations.

Workplace was identified to be a non-home location within 100 km from home, where the participant had the longest device wear time on workdays. We chose the 100 km range, because we wanted to focus on daily commute and exclude days when a person had business trips etc. Wear time at workplace was required to be at least 4 h continuously or accumulating from shorter time periods spent at the workplace.

To recognize *commuting* to work and back home, we detected the time of day when the participant was at the workplace for the first time on a working day, then we identified the previous departure from home, and collected all trips between these times. The return journey from work was identified using the same protocol, but in the opposite direction.

2.5. Determination of work-related and commuting physical activity

For the analyses, we formed four activity groups defined by work-related and commuting physical activity: 'Non-active workers and commuters', 'Non-active workers but active commuters', 'Active workers but non-active commuters', and 'Active workers and commuters'.

Work-related physical activity was measured as an average of total physical activity (light physical activity + MVPA) accumulated during time accumulated at workplace. Participants were categorized as 'non-active worker' or 'active worker' by using median (123 min) as a divider.

Commuting physical activity was defined based on the average speed of the detected trips to work and back home. Each detected trip between home and workplace was categorized as active or non-active trip. A trip which average speed was less than 20 km/h was categorized as 'active' and a trip with an average speed of at least 20 km/h as 'non-active'. The participants who had higher number of active trips than non-active trips were categorized as active commuters, and participants having as much or higher number of non-active trips than active trips were categorized as non-active commuters. Previous information (Aittasalo et al., 2019; Oja et al., 1998) on the walking and cycling speeds of the adult population (walking from 5.8 to 6.2 km/h and cycling from 14 to 20 km/h) was used to define the cut off speed for active and non-active commuting.

We examined the validity of our cut-off speed for commuting categories by comparing the GPS-measured commuting physical activity classification (active vs. non-active) and self-reported type of commute (walk, bicycle vs. bus, car). In this analysis we included 603 commuting trips for which there was a travel mode reported in the diaries. The agreement percent was 90% and kappa coefficient 0.78 (95% confidence limit 0.73–0.83). There are good sidewalks almost everywhere in urban areas in Finland. Thus, walkability and possibilities for active travel are good. In 2016, 9% of commutes was done by foot, 10% by bike and 12% by public transportation in Finland (Finnish Transport Infrastructure Agency, 2018).

2.6. Assessment of participant characteristics and covariates

Information about the date of birth, gender, and occupational status was obtained from the Keva register. Occupational status was used as an indicator of socioeconomic status and was categorized based on the International Standard Classification of Occupations (ISCO) to non-manual (ISCO classes 1–4, e.g. managers and professionals, associate professionals and office workers) and manual (ISCO classes 5–9, e.g. service and manual workers). The neighborhood socio-economic disadvantage was based on the share of low-educated adults, the unemployment rate and the median household income (inversed) in the 250 × 250 m map grid around the home address. The information was obtained from Statistics Finland and used as another indicator for socioeconomic status. Higher scores in the continuous standardized index indicate greater socioeconomic disadvantage (Halonen et al., 2020). Body mass index (BMI) was calculated as weight in kg/height in meters squared using measured body weight and height. Mobility limitations were asked as difficulties in walking 2 km; no limitations (no difficulties) and limitations (some or marked difficulties) using validated RAND-36 Health Survey, identical with the Short Form SF-36 (Aalto et al., 1995, 1999; Hays et al., 1993). For self-reported leisure-time physical activity, which was used to examine possible selection bias, respondents were asked to estimate their weekly hours of leisure-time physical activity (including commuting) in walking, brisk walking, jogging and running or their equivalent activities, within the previous year. The time spent on activities on each intensity level was multiplied by the average energy expenditure of each activity and expressed in metabolic-equivalent (MET) (Ainsworth et al., 2011).

2.7. Statistical analyses

Participants' characteristics before retirement are reported as mean values with SD or median values with lowest and highest quartiles for continuous variables, or as frequencies and percentages for categorical variables. For comparison between the activity groups, Analysis of Variance was used for mean values, Median test for median values, and Chi-squared test for percentages.

To investigate changes in sedentary time, light physical activity and MVPA during the transition to retirement by pre-retirement work-related and commuting physical activity, we used linear regression analysis with generalized estimating equations (GEE) and exchangeable correlation structure, which take into account the intra-individual correlation between repeated measurements. The GEE method fits a marginal model to longitudinal data, and the regression parameters in the marginal model are interpreted as population-averaged (Liang and Zeger, 1986). We conducted the analysis by using information from all available measurements, including 1–2 measurements before and 1–2 after retirement, depending on the participant's retirement date. As results of GEE models, we obtained the mean values for sedentary time and physical activity before and after retirement. To examine whether the changes in sedentary time, light physical activity and MVPA varied between the activity groups, the model included an interaction term 'activity group * time'. The differences between the activity groups were examined using contrast statements. The results are presented as a mean change in minutes of sedentary time, light physical activity and MVPA with 95% confidence intervals (CI).

We adjusted the models for age, gender, BMI and mobility limitations, as these factors have been associated with the level of physical activity (Choi et al., 2017; Trost et al., 2002). We also controlled the analyses for occupational status, which gives us indications of the content and physical demand of the job, but also of participants' socioeconomic status (SES), which is well-known determinant for physical activity (Trost et al., 2002). As an additional SES variable we used socioeconomic disadvantage of the neighborhood (Halonen et al., 2020). In addition, we adjusted the models for device wear time and measurement season. All covariates were obtained from the last pre-retirement measurement.

To examine the selection of the analytical sample, we compared the characteristics of our analytical sample to the FIREA clinical sub-study participants as an eligible sample, and also to the FIREA survey cohort. As sensitivity analysis we ran the analyses using only minimal adjustments (age, gender and device wear time), and examined how our results would change if merely the participants with less than 10 km commuting length would be included in the analysis. We used SAS statistical software, version 9.4 (SAS Institute, Inc. Cary, North Carolina) to conduct our analyses.

3. Results

The pre-retirement characteristics of the study population are shown in Table 1 overall and by the activity group. The mean age of the participants was 62.9 years (SD 1.1) and most of them were women (82%). Mean BMI was 25.5 kg/m^2 (SD 4.6), only 8% of the participants reported mobility limitations, and 69% of the participants were in non-manual occupations.

On average, the daily device wear time was 13 h and 37 min (SD 1 h and 49 min) before, and 13 h and 33 min (SD 1 h and 8 min) after retirement. Before retirement, the participants spent on average of 6 h and 48 min (SD 1 h and 23 min) at the workplace. In general, active workers spent more time at the workplace than non-active workers. The median length of one-way commuting to work or back home was 9.9 km (Q1 4.4 km, Q3 17.8 km) and one-way commuting took 26 min (SD 15 min) on average. The median speed for active travel was 12.3 km/h (Q1 8.2, Q3 15.8 km/h) and non-active travel 38.9 km/h (Q1 32.4, Q3 48.7 km/h). The participants with non-active work had more often non-manual than manual occupational status. The active workers groups included both manual and non-manual occupations.

Fig. 1 shows the average levels and Table 2 the mean changes for daily total sedentary time, light physical activity, and MVPA before and after retirement by the activity group. Before retirement, non-active workers, regardless of commuting activity, accumulated clearly more sedentary time ($P < 0.004$) and less light physical activity ($P < 0.008$) than active workers. The most active group 'Active workers and commuters' had higher level of MVPA before retirement, compared to 'Non-active workers and commuters' ($P = 0.034$) and to 'Non-active workers but active commuters' ($P = 0.023$).

During the retirement transition, no overall changes were observed in sedentary time and light physical activity. However, the changes in sedentary time (P for interaction 'activity group * time' 0.0002) and light physical activity (P for interaction 'activity group * time' <0.0001) varied by the activity group. Among the non-active workers, sedentary time decreased, and light physical activity increased in the 'Non-active workers and commuters' group. These changes in the 'Non-active workers but active commuters' were indicative, but not statistically

Table 1
Characteristics of the study population before retirement (n = 118).

	Overall	Non-active workers and commuters	Non-active workers but active commuters	Active workers but non-active commuters	Active workers and commuters	P-value for group differences
n (%)	118 (100)	41 (34.8)	18 (15.3)	40 (33.9)	19 (16.1)	
Age mean (SD)	62.9 (1.1)	63.1 (0.9)	62.8 (0.9)	62.6 (1.2)	63.2 (1.1)	0.12
Gender n (%)						0.98
Men	21 (17.8)	8 (19.5)	3 (16.7)	7 (17.5)	3 (15.8)	
Women	97 (82.2)	33 (80.5)	15 (83.3)	33 (82.5)	16 (84.2)	
BMI (kg/m2) mean (SD)	25.5 (4.6)	26.4 (5.6)	23.7 (3.5)	26.1 (4.3)	24.1 (3)	0.08
Mobility limitations n (%)						0.18
No	109 (92.4)	35 (85.4)	17 (94.4)	38 (95)	19 (100)	
Yes	9 (7.6)	6 (14.6)	1 (5.6)	2 (5)	0 (0)	
Occupational status n (%)						<.0001
Non-manual	82 (69.5)	35 (85.4)	18 (100)	16 (40)	13 (68.4)	
Manual	36 (30.5)	6 (14.6)	0 (0)	24 (60)	6 (31.6)	
Measurement season n (%)						0.16
Spring	42 (35.6)	14 (34.2)	5 (27.8)	12 (30)	11 (57.9)	
Summer	19 (16.1)	5 (12.2)	5 (27.8)	6 (15)	3 (15.8)	
Autumn	28 (23.7)	7 (17.1)	4 (22.2)	14 (35)	3 (15.8)	
Winter	29 (24.6)	15 (36.6)	4 (22.2)	8 (20)	2 (10.5)	
Neighborhood disadvantage mean (SD)	−0.1 (0.6)	−0.1 (0.5)	0 (0.7)	−0.2 (0.7)	−0.1 (0.5)	0.84
Time (min) spent at workplace mean (SD)	407.8 (82.7)	375.8 (80.7)	393.2 (68.2)	443.2 (81.2)	416.2 (76.6)	0.002
Time (min) spent on commuting mean (SD)[a]	25.5 (15.3)	26.1 (15.8)	24.5 (15.2)	26.7 (14.6)	22.8 (16.7)	0.81
Commute length km median (Q1,Q3)	9.9 (4.4, 17.8)	12.9 (7.9, 20)	3.7 (1.9, 4.9)	16.9 (9.4, 27.5)	2.9 (0.8, 8.0)	<.0001
Commute speed km/h median (Q1,Q3)	32.5 (16.8, 44.4)	37 (32.3, 45.3)	12.5 (6.7, 16.8)	41.8 (33.2, 58.3)	11.9 (8.2, 15.8)	<.0001
Valid days (≥600 min wear time/day) mean (SD)						
Before retirement	5.0 (2.2)	5 (2.4)	4.4 (1.9)	5.3 (2.3)	4.7 (1.7)	0.50
After retirement	4.8 (2.2)	5.4 (2.5)	4.7 (1.9)	4.5 (2.2)	4 (1)	0.09

[a] One way to work or back home.

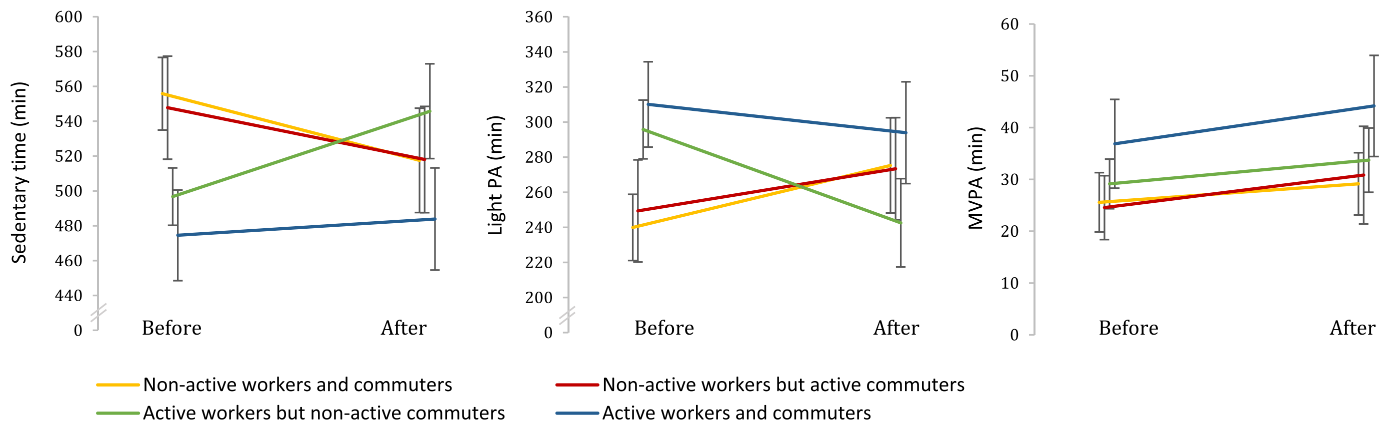

Fig. 1. Mean sedentary time, light physical activity (Light PA) and moderate-to-vigorous physical activity (MVPA) before and after retirement by work-related and commuting physical activity groups, with 95% confidence limits. Estimates adjusted for age, gender, BMI, mobility limitations, occupational status, neighborhood disadvantage, wear time and measurement season.

Table 2
Mean change for sedentary time, light physical activity (Light PA), moderate-to-vigorous physical activity (MVPA) by work-related and commuting physical activity.

Intensity (min)	Group	Before retirement mean (min)	95% CL		Mean change (min)	95% CL		P*
Sedentary time	Overall	521.0	509.6	532.4	1.2	−18.3	20.8	
	Non-active workers and commuters	555.8	535.0	576.6	−38.3	−69.1	−7.4	0.0002
	Non-active workers but active commuters	547.8	518.2	577.3	−29.7	−60.6	1.2	
	Active workers but non-active commuters	496.7	480.2	513.2	49.0	23.6	74.5	
	Active workers and commuters	474.6	448.5	500.6	9.3	−28.1	46.8	
Light PA	Overall	272.1	261.2	282.9	−5.4	−23.1	12.3	
	Non-active workers and commuters	240.0	221.1	258.8	35.3	7.7	63.0	<.0001
	Non-active workers but active commuters	249.4	220.2	278.5	24.0	−2.4	50.5	
	Active workers but non-active commuters	295.8	279.0	312.6	−53.2	−76.9	−29.6	
	Active workers and commuters	310.1	285.8	334.4	−16.1	−48.4	16.2	
MVPA	Overall	28.5	25.5	31.5	4.5	0.5	8.6	
	Non-active workers and commuters	25.6	19.9	31.3	3.6	−3.4	10.5	0.91
	Non-active workers but active commuters	24.6	18.4	30.7	6.3	−2.4	14.9	
	Active workers but non-active commuters	29.1	24.3	33.9	4.6	−1.0	10.1	
	Active workers and commuters	36.9	28.3	45.5	7.3	−2.5	17.2	

Adjusted for age, gender, BMI, mobility limitations, occupational status, neighborhood disadvantage, wear time and measurement season.
Mean change: after vs. before retirement.
*P for interaction activity group * time.

significant. Among the active workers, 'Active workers but non-active commuters' group increased sedentary time and decreased light physical activity, but 'Active workers and commuters' group maintained their rather low level of sedentary time and high level of light physical activity during retirement. Overall, mean MVPA increased by 4.5 min, but no differences were observed across activity groups (P for interaction 'activity group * time' = 0.91). Sensitivity analyses adjusted with merely age, gender and device wear time showed similar effect estimates (Supplemental Fig. 2 and Supplemental Table 1). The analysis including merely the participants whose commute length was less than 10 km replicated the results (Supplemental Fig. 3).

Retirement partly evened out the differences in sedentary time and light physical activity between the activity groups. However, after retirement 'Active workers and commuters' remained markedly less sedentary compared to 'Active workers but non-active commuters' (P = 0.019). Also, the level of light physical activity among 'Active workers and commuters' remained higher than among 'Active workers but non-active commuters' (P = 0.008), and the MVPA of 'Active workers and commuters' remained higher compared to 'Non-active workers and commuters' (P = 0.009).

The selection bias in the present study population was examined by comparing the characteristics of our analytical sample to all participants in the FIREA clinical sub-study as an eligible sample, and to the FIREA survey cohort (Supplemental Table 2). There were no notable differences between the current analytical sample and the FIREA clinical sub-study sample, except that BMI was lower in the analytical sample. However, the participants in our analytical sample had higher occupational status, higher self-reported physical activity, fewer mobility limitations, and lower BMI than the participants in the FIREA survey cohort.

4. Discussion

In this study, we used a wearable device combining GPS and accelerometer sensors to measure physical activity and sedentary behavior throughout the day. The measurements were conducted both before and after the transition to statutory retirement among Finnish public sector workers. This enabled us to investigate how pre-retirement work-related and commuting physical activity was related to the changes in physical activity and sedentary behavior during the transition to retirement. We observed that 'Non-active workers and commuters' decreased their sedentary time and increased their light physical activity during retirement transition. Indication of a similar trend was seen among 'Non-active workers but active commuters'. Among 'Active workers but non-active commuters' the results were opposite as they increased their sedentary time and decreased light physical activity during retirement transition, whereas 'Active workers and commuters' maintained their rather low level of sedentary time and high level of physical activity.

We observed increased sedentary time among 'Active workers but non-active commuters', which complements the findings by Suorsa et al. (2022, 2019) among Finnish retiring public sector workers, where they similarly observed an increase in accelerometer measured sedentary time among manual workers. However, Suorsa et al. (2022, 2019) used occupational titles as proxies for occupational activity, while we were able to quantify work-related physical activity objectively. Sedentary time may increase during the transition to retirement particularly among active workers because some occupational activity is likely replaced with more sedentary activities, such as watching TV (Leskinen et al., 2018; Sprod et al., 2015). On the contrary, we observed reduced sedentary time among 'Non-active workers and commuters', which is in line with previous findings among non-manual workers (Suorsa et al., 2022). Reduced sedentary time may result from replacing some work-time sedentary behavior, e.g., sitting at the office, with more active behaviors after retirement.

Our finding on decreased light physical activity among 'Active workers but non-active commuters' is in line with the results of Pulakka et al. (2020), where the largest decrease in accelerometer measured total physical activity was observed among women retiring from manual occupations. For those having active work, occupational activity accounts a large part of daily light physical activity (Prince et al., 2019). It may therefore be demanding to maintain the same level of activity after retirement, thus leading to a decrease in light physical activity.

Our result concerning the increase in light physical activity among 'Non-active workers and commuters' also complements the previous findings by Pulakka et al. (2020), where an increase in accelerometer measured total physical activity during retirement was reported among non-manual workers, albeit only among men. However, the study of Pulakka et al. (2020) used the type of occupation as a proxy for occupational physical activity instead of device-measured activity at work. Non-active workers often have a job where they need to be stationary, but after retirement they can choose whether to spend time in sedentary or physically active ways. For this reason, total physical activity may increase and sedentary time decrease after retirement among non-active workers. However, in the current study we focused on the retirement transition phase and did not follow the participants for post-retirement years. Previous long-term studies based on self-reported physical activity suggest that an increase in physical activity after retirement may be temporary (Holstila et al., 2017; Stenholm et al., 2016).

Interesting finding of our study was that 'Active workers and commuters' did not show clear changes in their rather low level of sedentary time and high level of physical activity during retirement transition. The finding is supported by previous findings from the FIREA study, where the participants who self-reported walking or cycling to work were more active before retirement than car drivers, and they also maintained their total physical activity level during retirement (Pulakka et al., 2020). Concerning the maintained lower sedentary time among 'Active workers and commuters', a similar trend has been reported in the longitudinal analyses of Foley et al. (2019) among middle-aged participants from the U.K., where the maintenance of active commuting over time was associated with a relative reduction in screen-time. However, their study population was younger than ours and the setting did not include follow-up over retirement transition. Nevertheless, these results together suggests that active mode of commute might support or indicate an active lifestyle, which may attenuate the otherwise observed increase in sedentary time and a decrease in light physical activity among retiring active workers.

Our results showed an overall increase in MVPA, but statistically non-significant differences were observed across the activity groups. The results are somewhat contradictory to a recent findings from the FIREA study, which observed a decline in wrist-accelerometer measured MVPA during retirement transition (Suorsa et al., 2022). These conflicting findings may be related to different study populations, measurement device (SenseDoc vs. ActiGraph) and device wear location (waist vs. wrist), and to the fact that absolute changes in MVPA were small in both studies.

Retirement seems to even the differences in sedentary time and light physical activity between the activity groups. However, our results show that 'Active workers and non-active commuters' group significantly increased their sedentary time and decreased light physical activity during retirement transition, and thus may be at a particular risk of low level of physical activity and high sedentary time after retirement, and might benefit from targeted interventions. However, a longer follow-up time after retirement is necessary to see how the observed decline in daily physical activity persists.

To the best of our knowledge, this is the first study to utilize GPS and accelerometer measurements to objectively estimate work-related and commuting physical activity, and examine how they associate with changes in physical activity and sedentary time during the transition to retirement. Previous studies in this field have mainly relied on occupational titles or self-reported data to estimate work-related and commuting activity. Thus, a major strength of this study is the longitudinal study design and repeated device-based measurements around statutory retirement. Another strength of our study is the relatively healthy and age-homogeneous study population retiring on statutory basis, so the changes are unlikely to be explained by changes in health status.

However, our study has also limitations. To limit the number of excluded participants, we required merely two valid measurement days (with a minimum wear time of 10 h) before and after retirement, instead of four or more, which is commonly used in device-based physical activity research (Aadland and Ylvisåker, 2015; Schrack et al., 2016). Reflecting the gender distribution of labor force in the Finnish public sector (Statistics Finland, 2016), the majority of our study population were women, which limits possible additional analyses on gender differences and narrows the generalizability of the results. The number of participants in the final analytical sample of our study ($n = 118$) is clearly smaller than the number of participants eligible to the FIREA clinical sub-study. Of the invited 773 people, 290 (38%) agreed to participate in the clinical sub-study. The relatively low participation rate may be explained by experienced participation burden as the study included several different measurements and clinical visits. Relatively similar participation rates have been observed in other studies including accelerometer and clinical measurements, such as the UK biobank study (44.8%) (Doherty et al., 2017). In addition, GPS measurements were introduced one year later to the study protocol and therefore not all the participants received the device in the first visit. Many participants were also excluded due various requirements for data, such as sufficient device wear time. To explore potential selection bias, we compared our analytical sample to the FIREA clinical sub-study participants as an eligible sample and to the FIREA survey cohort. There were no major differences between the analytical and the eligible sample. However, the participants in the analytical sample had less mobility limitations and had higher level of self-reported leisure-time physical activity than the participants of the FIREA survey cohort. Thus, the results cannot directly be generalized to all retiring Finnish workers of this age. It also needs to be noted that we used the median of work-related physical activity to categorize non-active vs. active workers, which is relative only to our study population. In addition, the follow-up time after retirement was rather short in our study, so that we were able to capture only the immediate effects of retirement on physical activity and sedentary behavior.

Our findings may also be affected by socioeconomic differences between active and non-active workers, because SES relates to physical activity and sedentary behavior. The groups with lower SES are typically more active at work but more sedentary during leisure-time than the groups with higher SES, and vice-versa; the groups with higher SES are more sedentary at work but more active during leisure-time than the lower SES groups (Beenackers et al., 2012; Loyen et al., 2016; O'Donoghue et al., 2018). As SES indicators, we controlled for occupational status and neighborhood socioeconomic disadvantage. These adjustments had only small effect on the effect estimates. Future studies might need to consider including other indicators of socioeconomic background to further elaborate the role of SES on the changes in physical activity and sedentary behavior when retiring.

By combining GPS and accelerometer measurements, detailed information on spatial location, speed of locomotion and the physical activity can be collected. This offers wide opportunities to study physical activity in different places and during travel. However, combined GPS and accelerometer data are usually collected for a short measurement period, partly because limited data storage space may restrict the duration of possible data collection. The devices have limited battery life and the participants may forget to recharge them, while losing GPS signal is also possible (Shareck et al., 2013; Thierry et al., 2013). Waist-worn accelerometers' incapability to detect certain types of physical activity, e.g. cycling, swimming, yoga, or strength training, may underestimate the total physical activity (Schrack et al., 2016). The threshold values that we applied to define sedentary time and light physical activity from acceleration data have been widely used in earlier studies (Ekelund et al., 2020; Loprinzi and Brosky Jr, 2014; Matthews et al., 2016; Wolff-Hughes et al., 2015). However, these threshold values applied to waist-worn accelerometry data have been observed to underestimate sedentary time by 4.9% and the error marginals in real-life conditions are somewhat high (Kozey-keadle et al., 2011). Further, the Troiano cut point, which we applied to MVPA (Troiano et al., 2008), is determined in laboratory conditions with a small group of young adults, which may limit the applicability in real-life conditions or among different age groups (Brage et al., 2003; Freedson et al., 1998; Leenders et al., 2001; Yngve et al., 2003). However, the Troiano cut points are widely used in various population-based studies among adult populations. Since our participants were in their early 60s and their health was relatively good and mobility limitations rare, using Troiano cut point for the MVPA also in the current study is justified.

Further, we used information from GPS detected workplaces to estimate work-related physical activity, and when doing this we made several assumptions to identify workplace from other GPS detected locations. It is possible that some workplaces were not identified correctly. Also, our reasoning does not allow us to identify physical activity related to remote work, or a work completed in several locations. Finally, we estimated active commuting based on the speed of the GPS detected trips, which is a crude indicator, and there is a possibility of misclassification.

5. Conclusions

Our results among retiring workers suggest that work-related physical activity is the main determinant for retirement-induced changes in light physical activity and sedentary time, whereas commuting physical activity before retirement was associated with better maintenance of light physical activity during the transition to retirement. People with physically active job and who do not engage in active commuting, may be at particular risk for decreasing physical activity and increasing sedentary time after retirement, and thus a possible target group for future interventions. Studies having longer follow-up times after retirement are warranted to see whether the observed changes are persistent.

Declaration of competing interest

Yan Kestens and Benoit Thierry are co-founders of Mobysens Inc., which developed and markets the SenseDoc device. Other authors have no competing interests.

Acknowledgements

The study has been supported by the Academy of Finland (grants 286294, 294154, 319246, 332030 to SS, and 321409 329240 to JV), Finnish Ministry of Education and Culture, Juho Vainio Foundation, and Competitive State Research Financing of the Expert Responsibility Area of the Turku University Hospital. SP was supported by the Emil Aaltonen Foundation, the Juho Vainio Foundation, and the Turku University Foundation. The authors would like to thank all the participants who took part in the FIREA-study and the research staff members for their contribution in the data collection.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2023.103025.

References

Aadland, E., Ylvisåker, E., 2015. Reliability of objectively measured sedentary time and physical activity in adults. PLoS One 10. https://doi.org/10.1371/journal.pone.0133296.

Aalto, A.-M., Aro, A.R., Teperi, J., 1999. RAND-36 Terveyteen Liittyvän Elämänlaadun Mittarina. Mittarin luotettavuus ja suomalaiset väestöarvot., Helsinki: Stakes, Tutkimuksia.

Aalto, A.-M., Aro, S., Aro, A.R., Mähönen, M., 1995. Rand 36-item Health Survey 1,0 : Suomenkielinen Versio Terveyteen Liittyvän Elämänlaadun Kyselystä : Kyselylomake Ja Käyttöohjeet (Stakes).

Ainsworth, Barbara E., Haskell, William L., Herrmann, Stephen D., Meckes, Nathanael, Bassett, David R., Tudor-Locke, Catrine, Greer, Jennifer, L., Vezina, Jesse, Whitt-Glover, Melicia, C., Leon, Arthur S., Ainsworth, B.E., Haskell, W.L., Herrmann, S.D., Meckes, N., Bassett, D.R., Tudor-Locke, C., Greer, J.L., Vezina, J., Whitt-Glover, M. C., Leon, A.S., 2011. Compendium of physical activities: a second update of codes and MET values. Med. Sci. Sports Exerc. 43, 1575–1581. https://doi.org/10.1249/MSS.0b013e31821ece12.

Aittasalo, M., Tiilikainen, J., Tokola, K., Suni, J., Sievänen, H., Vähä-Ypyä, H., Vasankari, T., Seimelä, T., Metsäpuro, P., Foster, C., Titze, S., 2019. Socio-ecological natural experiment with randomized controlled trial to promote active commuting to work: process evaluation, behavioral impacts, and changes in the use and quality of walking and cycling paths. Int. J. Environ. Res. Publ. Health 16, 1661. https://doi.org/10.3390/ijerph16091661.

Barnett, I., van Sluijs, E., Ogilvie, D., Wareham, N.J., 2014. Changes in household, transport and recreational physical activity and television viewing time across the transition to retirement: longitudinal evidence from the EPIC-Norfolk cohort. J. Epidemiol. Community Health 68, 747–753. https://doi.org/10.1136/JECH-2013-203225.

Bauman, A., Merom, D., Bull, F.C., Buchner, D.M., Fiatarone Singh, M.A., 2016. Updating the Evidence for Physical Activity: Summative Reviews of the Epidemiological Evidence, Prevalence, and Interventions to Promote "Active Aging. Gerontologist. https://doi.org/10.1093/geront/gnw031.

Beenackers, M.A., Kamphuis, C.B.M., Giskes, K., Brug, J., Kunst, A.E., Burdorf, A., van Lenthe, F.J., 2012. Socioeconomic inequalities in occupational, leisure-time, and transport related physical activity among European adults: a systematic review. Int. J. Behav. Nutr. Phys. Activ. 9 https://doi.org/10.1186/1479-5868-9-116.

Brage, S., Wedderkopp, N., Franks, P.W., Andersen, L.B., Froberg, K., 2003. Reexamination of validity and reliability of the CSA monitor in walking and running. Med. Sci. Sports Exerc. 35, 1447–1454. https://doi.org/10.1249/01.MSS.0000079078.62035.EC.

BrØnd, J.C., Andersen, L.B., Arvidsson, D., 2017. Generating ActiGraph counts from raw acceleration recorded by an alternative monitor. Med. Sci. Sports Exerc. 49, 2351–2360. https://doi.org/10.1249/MSS.0000000000001344.

Brondeel, R., Wasfi, R., Perchoux, C., Chaix, B., Gerber, P., Gauvin, L., Richard, L., Gaudreau, P., Thierry, B., Chevrier, M., Hoj, S., Kestens, Y., 2019. Is older adults' physical activity during transport compensated during other activities? Comparing 4 study cohorts using GPS and accelerometer data. J. Transport Health 12, 229–236. https://doi.org/10.1016/J.JTH.2019.02.006.

Caspersen, C.J., Pereira, M.A., Curran, K.M., 2000. Changes in physical activity patterns in the United States, by sex and cross-sectional age. Med. Sci. Sports Exerc. 32, 1601–1609. https://doi.org/10.1097/00005768-200009000-00013.

Celidoni, M., Rebba, V., 2017. Healthier lifestyles after retirement in Europe? Evidence from SHARE. Eur. J. Health Econ. 18, 805–830. https://doi.org/10.1007/s10198-016-0828-8.

Choi, J., Lee, M., Lee, J., Kang, D., Choi, J.-Y., 2017. Correlates associated with participation in physical activity among adults: a systematic review of reviews and update. BMC Publ. Health 17, 356. https://doi.org/10.1186/s12889-017-4255-2.

Choi, L., Beck, C., Liu, Z., Matthews, C.E., Buchowski, M.S., 2018. Physical Activity: Process Accelerometer Data for Physical Activity Measurement. R Package Version 0, 2-2.

Choi, L., Liu, Z., Matthews, C.E., Buchowski, M.S., 2011. Validation of accelerometer wear and nonwear time classification algorithm. Med. Sci. Sports Exerc. 43, 357–364. https://doi.org/10.1249/MSS.0b013e3181ed61a3.

Chung, S., Domino, M.E., Stearns, S.C., Popkin, B.M., 2009. Retirement and physical activity. Analyses by occupation and wealth. Am. J. Prev. Med. 36, 422–428. https://doi.org/10.1016/j.amepre.2009.01.026.

De Rezende, L.F.M., Lopes, M.R., Rey-Loṕez, J.P., Matsudo, V.K.R., Luiz, O.D.C., 2014. Sedentary behavior and health outcomes: an overview of systematic reviews. PLoS One 9, 105620. https://doi.org/10.1371/JOURNAL.PONE.0105620.

Doherty, A., Jackson, D., Hammerla, N., Plötz, T., Olivier, P., Granat, M.H., White, T., van Hees, V.T., Trenell, M.I., Owen, C.G., Preece, S.J., Gillions, R., Sheard, S., Peakman, T., Brage, S., Wareham, N.J., 2017. Large scale population assessment of physical activity using wrist worn accelerometers: the UK biobank study. PLoS One 12, e0169649. https://doi.org/10.1371/journal.pone.0169649.

Ekelund, U., Tarp, J., Fagerland, M.W., Johannessen, J.S., Hansen, B.H., Jefferis, B.J., Whincup, P.H., Diaz, K.M., Hooker, S., Howard, V.J., Chernofsky, A., Larson, M.G., Spartano, N., Vasan, R.S., Dohrn, I.M., Hagströmer, M., Edwardson, C., Yates, T., Shiroma, E.J., Dempsey, P., Wijndaele, K., Anderssen, S.A., Lee, I.M., 2020. Joint associations of accelero-meter measured physical activity and sedentary time with all-cause mortality: a harmonised meta-analysis in more than 44 000 middle-aged and older individuals. Br. J. Sports Med. 54, 1499–1506. https://doi.org/10.1136/bjsports-2020-103270.

Finnish Transport Infrastructure Agency, 2018. Henkilöliikennetutkimus 2016, Työssäkäynti Ja Liikkuminen. Faktakortti [WWW Document]. URL. www.hlt.fi. (Accessed 17 March 2023).

Foley, L., Dumuid, D., Atkin, A.J., Wijndaele, K., Ogilvie, D., Olds, T., 2019. Cross-sectional and longitudinal associations between active commuting and patterns of movement behaviour during discretionary time: a compositional data analysis. PLoS One 14. https://doi.org/10.1371/journal.pone.0216650.

Freedson, P.S., Melanson, E., Sirard, J., 1998. Calibration of the computer science and applications, Inc. accelerometer. Med. Sci. Sports Exerc. 30.

GitHub, 2022. walkabillylab/activityCounts: creates ActiLife counts based on the raw acceleration data [WWW Document]. https://github.com/walkabillylab/activityCounts. (Accessed 3 January 2023).

Gropper, H., John, J.M., Sudeck, G., Thiel, A., 2020. The impact of life events and transitions on physical activity: a scoping review. PLoS One 15, e0234794. https://doi.org/10.1371/JOURNAL.PONE.0234794.

Halonen, J.I., Pulakka, A., Pentti, J., Kallio, M., Koskela, S., Kivimäki, M., Kawachi, I., Vahtera, J., Stenholm, S., 2020. Cross-sectional associations of neighbourhood socioeconomic disadvantage and greenness with accelerometer-measured leisure-time physical activity in a cohort of ageing workers. BMJ Open 10, 38673. https://doi.org/10.1136/bmjopen-2020-038673.

Harvey, J.A., Chastin, S.F.M., Skelton, D.A., 2015. How sedentary are older people? A systematic review of the amount of sedentary behavior. J. Aging Phys. Activ. https://doi.org/10.1123/japa.2014-0164.

Hays, R.D., Sherbourne, C.D., Mazel, R.M., 1993. The rand 36-item health survey 1.0. Health Econ. 2, 217–227. https://doi.org/10.1002/hec.4730020305.

Holstila, A., Mänty, M., Rahkonen, O., Lahelma, E., Lahti, J., 2017. Statutory retirement and changes in self-reported leisure-time physical activity: a follow-up study with three time-points. BMC Publ. Health 17. https://doi.org/10.1186/s12889-017-4455-9.

Karelius, S., Vahtera, J., Suorsa, K., Heinonen, O.J., Pentti, J., Niiranen, T.J., Stenholm, S., 2023. Changes in ambulatory blood pressure during the transition to retirement. J. Hypertens. 41, 187–193. https://doi.org/10.1097/HJH.0000000000003320.

Kestens, Y., Thierry, B., Shareck, M., Steinmetz-Wood, M., Chaix, B., 2018. Integrating activity spaces in health research: comparing the VERITAS activity space questionnaire with 7-day GPS tracking and prompted recall. Spat. Spatiotemporal. Epidemiol. 25, 1–9. https://doi.org/10.1016/j.sste.2017.12.003.

Kozey-keadle, S., Libertine, A., Lyden, K., Staudenmayer, J., Freedson, P.S., 2011. Validation of Wearable Monitors for Assessing Sedentary Behavior, pp. 1561–1567. https://doi.org/10.1249/MSS.0b013e31820ce174.

Leenders, N.Y.J.M., Sherman, W.M., Nagaraja, H.N., Kien, C.L., 2001. Evaluation of methods to assess physical activity in free-living conditions. Med. Sci. Sports Exerc. 33, 1233–1240. https://doi.org/10.1097/00005768-200107000-00024.

Leskinen, T., Pulakka, A., Heinonen, O.J., Pentti, J., Kivimäki, M., Vahtera, J., Stenholm, S., 2018. Changes in non-occupational sedentary behaviours across the retirement transition: the Finnish Retirement and Aging (FIREA) study. J. Epidemiol. Community Health 72, 695–701. https://doi.org/10.1136/jech-2017-209958.

Liang, K.-Y., Zeger, S.L., 1986. Longitudinal Data Analysis Using Generalized Linear Models 13–22.

Loprinzi, P.D., Brosky Jr., J.A., 2014. Objectively measured physical activity and balance among U.S. Adults. J. Strength Condit Res. 28, 2290–2296. https://doi.org/10.1519/JSC.0000000000000402.

Loyen, A., Van Der Ploeg, H.P., Bauman, A., Brug, J., Lakerveld, J., 2016. European sitting championship: prevalence and correlates of self-reported sitting time in the 28 European union member states. PLoS One 11, e0149320. https://doi.org/10.1371/JOURNAL.PONE.0149320.

Matthews, C.E., Keadle, S.K., Troiano, R.P., Kahle, L., Koster, A., Brychta, R., Van Domelen, D., Caserotti, P., Chen, K.Y., Harris, T.B., Berrigan, D., 2016. Accelerometer-measured dose-response for physical activity, sedentary time, and mortality in US adults. Am. J. Clin. Nutr. 104, 1424–1432. https://doi.org/10.3945/ajcn.116.135129.

O'Donoghue, G., Kennedy, A., Puggina, A., Aleksovska, K., Buck, C., Burns, C., Cardon, G., Carlin, A., Ciarapica, D., Colotto, M., Condello, G., Coppinger, T., Cortis, C., D'Haese, S., De Craemer, M., Di Blasio, A., Hansen, S., Iacoviello, L., Issartel, J., Izzicupo, P., Jaeschke, L., Kanning, M., Ling, F., Luzak, A., Napolitano, G., Nazare, J.-A., Perchoux, C., Pesce, C., Pischon, T., Polito, A., Sannella, A., Schulz, H., Simon, C., Sohun, R., Steinbrecher, A., Schlicht, W., MacDonncha, C., Capranica, L., Boccia, S., 2018. Socio-economic determinants of physical activity across the life course: a "DEterminants of DIet and Physical ACtivity" (DEDIPAC) umbrella literature review. PLoS One 13, e0190737. https://doi.org/10.1371/journal.pone.0190737.

Oja, P., Vuori, I., Paronen, O., 1998. Daily walking and cycling to work: their utility as health-enhancing physical activity. Patient Educ. Counsel. 33, S87–S94. https://doi.org/10.1016/S0738-3991(98)00013-5.

Prince, S.A., Elliott, C.G., Scott, K., Visintini, S., Reed, J.L., 2019. Device-measured physical activity, sedentary behaviour and cardiometabolic health and fitness across occupational groups: a systematic review and meta-analysis. Int. J. Behav. Nutr. Phys. Activ. 16, 1–15. https://doi.org/10.1186/S12966-019-0790-9, 2019 161.

Pulakka, A., Leskinen, T., Suorsa, K., Pentti, J., Halonen, J.I., Vahtera, J., Stenholm, S., 2020. Physical activity across retirement transition by occupation and mode of commute. Med. Sci. Sports Exerc. 52, 1900–1907. https://doi.org/10.1249/MSS.0000000000002326.

Schrack, J.A., Cooper, R., Koster, A., Shiroma, E.J., Murabito, J.M., Rejeski, W.J., Ferrucci, L., Harris, T.B., 2016. Assessing daily physical activity in older adults: unraveling the complexity of monitors, measures, and methods. Journals Gerontol. - Ser. A Biol. Sci. Med. Sci. https://doi.org/10.1093/gerona/glw026.

Shareck, M., Kestens, Y., Gauvin, L., 2013. Examining the spatial congruence between data obtained with a novel activity location questionnaire, continuous GPS tracking, and prompted recall surveys. Int. J. Health Geogr. 12, 40. https://doi.org/10.1186/1476-072X-12-40.

Sprod, J., Ferrar, K., Olds, T., Maher, C., 2015. SYSTEMATIC REVIEW Changes in sedentary behaviours across the retirement transition: a systematic review. https://doi.org/10.1093/ageing/afv140.

Statistics Finland, 2016. Women and Men in Finland 2016 [WWW Document]. URL. https://www.stat.fi/tup/julkaisut/tiedostot/julkaisuluettelo/yyti_womefi_201600_2016_16133_net.pdf. (Accessed 12 January 2022).

Stenholm, S., Pulakka, A., Kawachi, I., Oksanen, T., Halonen, J.I., Aalto, V., Kivimäki, M., Vahtera, J., 2016. Changes in physical activity during transition to retirement: a cohort study. Int. J. Behav. Nutr. Phys. Activ. 13, 51. https://doi.org/10.1186/s12966-016-0375-9.

Stenholm, S., Pulakka, A., Leskinen, T., Pentti, J., Heinonen, O.J., Koster, A., Vahtera, J., 2021. Daily physical activity patterns and their association with health-related physical fitness among aging workers—the Finnish retirement and aging study. Journals Gerontol. Ser. A 76, 1242–1250. https://doi.org/10.1093/GERONA/GLAA193.

Suorsa, K., Leskinen, T., Pasanen, J., Pulakka, A., Myllyntausta, S., Pentti, J., Chastin, S., Vahtera, J., Stenholm, S., 2022. Changes in the 24-h movement behaviors during the transition to retirement: compositional data analysis. Int. J. Behav. Nutr. Phys. Activ. 19, 1–11. https://doi.org/10.1186/s12966-022-01364-3.

Suorsa, K., Pulakka, A., Leskinen, T., Heinonen, I., Heinonen, O.J., Pentti, J., Vahtera, J., Stenholm, S., 2019. Objectively measured sedentary time before and after transition to retirement: the Finnish retirement and aging study. Journals Gerontol. Ser. A XX, 1–7. https://doi.org/10.1093/gerona/glz127.

Suorsa, K., Pulakka, A., Leskinen, T., Pentti, J., Vahtera, J., Stenholm, S., 2021. Changes in prolonged sedentary behaviour across the transition to retirement. Occup. Environ. Med. 78, 409–412. https://doi.org/10.1136/oemed-2020-106532.

Teräs, T., Rovio, S., Spira, A.P., Myllyntausta, S., Pulakka, A., Vahtera, J., Stenholm, S., 2020. Associations of accelerometer-based sleep duration and self-reported sleep difficulties with cognitive function in late mid-life: the Finnish Retirement and Aging Study. Sleep Med. 68, 42–49. https://doi.org/10.1016/J.SLEEP.2019.08.024.

Thierry, B., Chaix, B., Kestens, Y., 2013. Detecting activity locations from raw GPS data: a novel kernel-based algorithm. Int. J. Health Geogr. 12, 14. https://doi.org/10.1186/1476-072X-12-14.

Troiano, R.P., Berrigan, D., Dodd, K.W., Mâsse, L.C., Tilert, T., Mcdowell, M., 2008. Physical activity in the United States measured by accelerometer. Med. Sci. Sports Exerc. 40, 181–188. https://doi.org/10.1249/mss.0b013e31815a51b3.

Trost, S.G., Owen, N., Bauman, A.E., Sallis, J.F., Brown, W., 2002. Correlates of adults' participation in physical activity: review and update. Med. Sci. Sports Exerc. 34, 1996–2001. https://doi.org/10.1097/00005768-200212000-00020.

Van Dyck, D., Cardon, G., De Bourdeaudhuij, I., 2016. Longitudinal changes in physical activity and sedentary time in adults around retirement age: what is the moderating role of retirement status, gender and educational level? BMC Publ. Health 16, 1–11. https://doi.org/10.1186/S12889-016-3792-4/TABLES/2.

Vansweevelt, N., Boen, F., Uffelen, J. van, Seghers, J., 2022. Socioeconomic differences in physical activity and sedentary behavior during the retirement transition: a systematic review of longitudinal studies. J. Phys. Activ. Health 19, 623–637. https://doi.org/10.1123/JPAH.2022-0196.

Wolff-Hughes, D.L., Fitzhugh, E.C., Bassett, D.R., Churilla, J.R., 2015. Waist-worn actigraphy: population-referenced percentiles for total activity counts in U.S. Adults. J. Phys. Activ. Health 12, 447–453. https://doi.org/10.1123/jpah.2013-0464.

Yngve, A., Nilsson, A., Sjöström, M., Ekelund, U., 2003. Effect of monitor placement and of activity setting on the MTI accelerometer output. Med. Sci. Sports Exerc. 35, 320–326. https://doi.org/10.1249/01.MSS.0000048829.75758.