



Exposure to useable green space and physical activity during active travel: A longitudinal GPS and accelerometer study before and after retirement

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ABSTRACT

Green spaces may serve as population level interventions encouraging active travel. We examined the associations between exposure to useable green space (CORINE Land Cover categories) and physical activity during active travel (GPS and accelerometer) among late middle-aged participants from the Finnish Retirement and Aging study (n = 102). Greater proportion of useable green space was associated with higher physical activity during active travel on days off (+11 min/day per 1 SD increase in exposure) and on retirement days (+12 min/day), but not on workdays. Thus, it appears that in leisure time, people prefer to engage into active travel in green spaces.

1. Introduction

Physical activity behavior is determined by several psychosocial, cognitive and health-related factors at the individual level (Bauman et al., 2012), but social and physical environments can also promote or prevent physical activity (Sallis et al., 2006). Green space is of interest for physical activity researchers, because it has been associated with health benefits, such as better cardiometabolic (Kivimäki et al., 2021; Liu et al., 2022), brain (Besser, 2021; Jimenez et al., 2022) and mental (Gonzales-Inca et al., 2022; Liu et al., 2023) health as well as maintaining healthy weight (Halonen et al., 2014; Kim et al., 2021). Several mechanisms may explain these positive associations. For example, the proximity and access to green spaces may encourage physical activity (Jimenez et al., 2021).

Accelerometer-based measurements capture physical activity intensity and duration with a higher accuracy than self-reported methods, which are also prone to recall and social desirability bias (Schrack et al., 2016; Strath et al., 2013). The use of GPS-based methodology on the other hand enables geographic momentary assessment, providing

detailed information on the locations where people have stayed during their daily activities and the routes between these locations (Chaix, 2018). Consequently, simultaneously measured GPS and accelerometer data with a linkage to geographic and environmental characteristics provide objective and detailed insights into individual's physical activity and the physical activity environments, without relying on memory or subjective reporting.

Researchers in a US study (Boakye et al., 2021), using GPS and waist-worn accelerometer devices, reported that higher level of greenness during physical activities as well as visiting the parks were associated with more total physical activity and moderate-to-vigorous physical activity (MVPA) among middle-aged adults. Similarly, a Belgian study (Dewulf et al., 2016) using GPS in combination with waist-worn accelerometers reported that spending more time in green space was associated with more MVPA among late middle-aged adults.

Active travel (i.e., making journeys in a physically active ways) is one context in which daily physical activity accumulates. In a GPS and waist-worn accelerometer-based study among older adults from Canada, Luxembourg and France, it was observed that the physical activity

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recorded during transport corresponded 21% of the daily total physical activity (Brondeel et al., 2019). The results of one study from the UK, based on GPS information combined with accelerometer and heart rate measurement, using a device attached to the chest, indicated that walking and cycling or multimodal journeys resulted higher standard metabolic equivalents (MET) values than motorized transport (Costa et al., 2015). The role of environmental characteristics may be more meaningful for physical activity behavior during active travel than e.g., in the home environment, which many previous studies have focused on.

In a Finnish physical activity intervention, grounded on the use of a commercial activity tracker, the participants residing in areas with the highest level of greenness had a higher level of waist-worn accelerometer-measured light and total physical activity at baseline, and their daily MVPA increased more over a 1-year follow-up, when compared to the participants residing in areas with the lowest level of greenness. It was also observed that the increase in MVPA occurred during GPS-detected active travel or at home, rather than at non-home locations or during non-active travel (Pasanen et al., 2022). Likewise, Marquet et al. (2022) from the US observed, among middle-aged women, that higher greenness in participants' activity spaces assessed along their daily path area was associated with a greater number of steps taken per week, based on waist-worn accelerometer measurements.

A previous GPS and accelerometer-based study among the US adults has shown that the association between greenness and physical activity varies between weekdays and weekends (James et al., 2017), with stronger associations on weekends. This suggests that the possible encouraging effect of greenness on physical activity may relate more to leisure time physical activities. However, separating between weekdays and weekends may not accurately describe the leisure time among people outside the workforce or shift workers, thus, we compared workdays and days off for workers as well as retirement days. Active travel behavior may also change when retiring, as retirement allows more diversity in the spatiotemporal patterns of daily activities. To the best of our knowledge, the associations between green space and active travel has not been studied separately for workdays, days off and retirement days.

To fill these evidence gaps, this study examines the association between exposure to useable green space, e.g., forests and parks, and accelerometer-measured physical activity during GPS-detected active travel. The associations are examined separately for workdays, days off and retirement days among participants in their retirement age. We hypothesize that there is more physical activity during trips with a higher exposure to useable green space, particularly on days off and after retirement.

2. Methods

2.1. Study population

The study population consists of participants in the Finnish Retirement and Aging Study (FIREA), which is a longitudinal study established in 2013 that examines changes in the health and health behavior of retiring Finnish public sector employees. The FIREA study includes public sector employees who worked in one of the 27 municipalities of Southwest-Finland in 2012, or in selected nine cities or five hospital districts across Finland and whose personal retirement date was between 2014 and 2019 (Stenholm et al., 2023). The FIREA study includes the FIREA study cohort, the FIREA activity sub-study and the FIREA clinical sub-study. This study is based on the FIREA clinical sub-study, which was conducted between 2015 and 2022.

The study population was identified and the timing of data collection was planned based on the estimated retirement days received from the insurance institution Keva (2024), which is Finland's largest pension provider that also administers public sector pensions. All participants were contacted with a questionnaire 18 months before their estimated

retirement date. After answering the questionnaire ($n = 6783$), Finnish-speaking participants who lived in Southwest-Finland, were still working, and whose estimated retirement time was between 2017 and 2019 ($n = 773$) were invited to the FIREA clinical sub-study. Of these, 290 (38%) returned written informed consent and were included in the study. The participants were thereafter followed with annual measurements across the retirement transition. Annual combined GPS and accelerometer measurement with the SenseDoc device was added to the protocol of the FIREA clinical sub-study in March 2016. Actual date of retirement to full-time statutory retirement was inquired at each stage of data collection, and the information was used to identify pre- and post-retirement measurements. Detailed information on the selection of the analytical sample can be found in the flowchart (Supplemental Fig. 1).

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. Collecting GPS and accelerometer data

We used a waist-worn SenseDoc 2.0 device (Mobysens Technologies Inc, Canada) which includes a GPS sensor and a tri-axial accelerometer to collect data on intensity and location of physical activity. The device was initialized 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).

The participants received the device during annual clinical examination visit. They were asked to wear the device during waking hours, but to remove it during bathing or water sports, for at least two workdays and two days off when still working, and minimum of four days when the measurement was conducted after retirement. Thus, before retirement, the length of the measurement phase varied according to the order of the participant's workdays and days off being 4 day at minimum. The participants were also asked to fill in a diary in which they reported their work days and days off when still working, as well as their bedtimes. This information was used to separate the measurement days. The device and the diary were returned by mail after the measurement. The measurements were completed on all four seasons of the year, and the repeated measurements of each participant were performed at the same season.

2.3. Processing GPS and accelerometer data

Detecting physical activity during trips. A published algorithm of Thierry et al. (2013) was used to identify different intensities of physical activity at different locations and during the trips between locations. In this work, we focus on physical activity accumulated during trips, in accordance with the study aims. SenseAnalytics (versions 1.9 and 1.10) was used to connect to SenseDoc devices to download 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 the algorithm (Thierry et al., 2013), which runs as a Python (version 3.6.6) script. 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 stops 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 provide convergent validity of the GPS activity locations with self-reported VERITAS map-based questionnaire locations.

Estimating physical activity intensity. An algorithm developed by Brønd et al. (2017) was used to convert the raw accelerometer data to ActiGraph equivalent counts using R (version 3.5.3) (for details see R package from GitHub (2022)). PostgreSQL (version 11.1) with PostGIS

extension were used to merge the GPS and accelerometry datastreams and produce the aggregated metrics. Counts per second were aggregated to counts per minute, and commonly used thresholds were applied for light physical activity (>100 and ≤ 2020 counts/min) (Loprinzi and Brosky Jr, 2014; Wolff-Hughes et al., 2015) and MVPA (>2020 counts/min) (Troiano et al., 2008).

2.4. Identification of active travel

We defined active travel as a trip with an average speed of less than 20 km/h and non-active travel as a trip with an average speed of 20 km/h or higher. The cut-off speed for active travel was based on the previous results of average walking (5.8–6.2 km/h) and cycling (14–20 km/h) speed among adult populations (Aittasalo et al., 2019; Oja et al., 1998). The validity of the 20 km/h cut-off speed has also been tested by comparing the GPS-measured classification (active vs. non-active travel) and self-reported type of commute to work (walk, bicycle vs. bus, car): The agreement percent was 90% and kappa coefficient 0.78 (95% confidence interval (CI) 0.73–0.83) for 603 commuting trips (Pasanen et al., 2023). Prior study (Pasanen et al., 2021) has also completed sensitivity analysis investigating the influence of different speed thresholds between 16 and 24 km/h to dichotomize the trips to active and non-active travel, which resulted in similar findings as main analysis using 20 km/h threshold.

2.5. Determination of exposure to useable green space during active travel

We used data provided by SYKE (2018), utilizing the 2018 CORINE Land Cover data with 20m \times 20m grid size, to identify useable green space, which was used as the exposure in this study, and linked the information with GPS data using ArcGIS (version 10.3.1) and PostgreSQL (version 11.1) with PostGIS extension. Because not all green spaces are accessible and suitable for physical activities and leisure, we only selected certain CORINE Land Cover categories, e.g., green urban areas, forests and vegetated sport and leisure facilities, to define useable green space. All other categories included, as well as the categories excluded from the useable green space definition, are presented in Supplemental Table 1. Excluded categories included e.g., areas with urban fabric, industrial or commercial units, plantations, pastures and marine areas. Detailed description of land included in each CORINE Land Cover category can be found from Copernicus Land Monitoring Service (2024). We determined exposure to useable green space as computing the percentage of an average daily active travel time that occurred within useable green space. The calculations were made separately for workdays, days off and retirement days.

2.6. Selection of the analytical sample

A flowchart of the selection of the analytical sample is shown in Supplemental Fig. 1. In short, we included those participants who provided at least two valid measurement days before and after retirement. Before retirement, at least one valid day had to be a workday and the other a day off. A valid measurement day was defined by commonly used requirement of 10 h or more device wear time during waking hours (Aadland and Ylvisåker, 2015; Schrack et al., 2016). Device wear time was assessed from 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 within the up or downstream in 30-min consecutive zero counts window (Choi et al., 2011, 2021). Participants with active travel on workdays, days off or retirement days and who had information about exposure to useable green space during active travel were included in the analytical sample. Consequently, the final analytical sample consisted of 102 participants with 804 valid measurement days including 236 workdays, 232 days off and 336 retirement days.

2.7. Assessment of participant characteristics and covariates

Date of birth, gender, and occupational status were obtained from the register maintained by Kevala (2024). Occupational status was used as an indicator of socioeconomic status and was categorized according to 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). Body weight and height were measured at the clinical examination and body mass index (BMI) was calculated as weight in kg divided by height in meters squared. Mobility limitations were asked as difficulty of walking 2 km; no limitations (no difficulties) and limitations (some or marked difficulties) using the validated RAND-36 Health Survey, which is identical to the Short Form SF-36 (Aalto et al., 1995, 1999; Hays et al., 1993). Self-reported leisure-time physical activity was used to examine possible selection bias. For that, 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 (Kujala et al., 1998). The time spent on activities on each intensity level was multiplied by the average energy expenditure of each activity and expressed in MET values (Ainsworth et al., 2011).

2.8. Statistical analyses

The characteristics of the study participants, from the nearest measurement point before retirement, are presented as mean values with standard deviation (SD) for continuous variables and as frequencies with percentages for categorical variables. First, an average daily total physical activity minutes (including light physical activity and MVPA) accrued during active travel was calculated separately for workdays, days off and retirement days, and compared between the days. Similarly, the percentage of the minutes of exposure to useable green space during active travel was presented for workdays, days off and retirement days, and compared between the days.

Second, we examined the associations between exposure to useable green space and total physical activity during active travel between workdays, days off and retirement days using linear regression analysis with generalized estimating equations (GEE) and exchangeable correlation structure, which take into account the intra-individual correlation between repeated measurements (Liang and Zeger, 1986). The percentage of daily active travel time in useable green space as an exposure variable was standardized, and thus the results show an effect of one additional SD in exposure on physical activity during active travel. To examine whether the association between exposure to useable green space and total physical activity during active travel differed between workdays, days off and retirement days, the model included an interaction term 'day type*useable green space'. We adjusted Model 1 for age, gender and occupational status and Model 2 additionally for BMI, mobility limitations and measurement season, as these factors have been associated with the level of physical activity (Choi et al., 2017; Trost et al., 2002; Tucker and Gilliland, 2007).

As supplementary analyses, we repeated the analysis by examining the associations between exposure to useable green space and light physical activity and MVPA accumulated during active travel on workdays, days off and retirement days. This was done since prior evidence suggests an association between MVPA and healthier aging (Menai et al., 2017), and MVPA is included in the global recommendations for health enhancing physical activity among both adults and older adults (WHO, 2016). In addition, we conducted sensitivity analysis including also those participants with only one measurement day ($n = 132$) and repeated analyses for physical activity during non-active travel. Moreover, we conducted an additional analysis presenting how the mean total physical activity minutes is distributed between speed categories. We used SAS statistical software, version 9.4 (SAS Institute, Inc. Cary, North Carolina) to conduct all analyses.

3. Results

The pre-retirement characteristics of the study population are shown in [Table 1](#). The mean age of the participants was 63.3 years and most of them (82%) were women. Of the participants, 68% were in non-manual and 32% in manual occupations when still working. Only 4% of the participants had mobility limitations and the mean BMI was 25.4 kg/m². The valid measurement days ranged from 2 to 11 (mean 4.6) at pre-retirement and 1 to 9 (mean 3.3) at post-retirement phase. More measurements were completed during spring (34%) than summer (23%), autumn (21%) or winter (23%). The average time spent in active travel was 38 min/day on workdays, 48 min/day on days off, and 51 min/day on retirement days. Most of the total physical activity minutes accumulated at travel speeds of <20 km/h ([Supplemental Fig. 2](#)).

As shown in [Table 2](#), more total physical activity during active travel was accumulated on days off (34 min/day, 95% CI 28–39) and on retirement days (37 min/day, 95% CI 32–42) than on workdays (23 min/day, 95% CI 19–27). There was no difference in total physical activity during active travel between days off and retirement days. Exposure to useable green space during active travel was higher on days off (29%, 95% CI 25–34) and on retirement days (28%, 95% CI 24–32) than on workdays (19%, 95% CI 16–22), and exposure to useable green space during active travel was very similar on days off and on retirement days ([Table 2](#)).

Associations between exposure to useable green space and total physical activity during active travel on workdays, days off and retirement days are shown in [Fig. 1](#) and [Table 3](#). When adjusted for age, gender, and occupational status (Model 1), one SD addition to useable green space exposure was associated with 11 min/day (95% CI 7–15) of additional total physical activity during active travel on days off and 12 min/day (95% CI 9–16) on retirement days. No association was observed between exposure to useable green space and total physical

Table 1

Pre-retirement characteristics and physical activity levels of the study population.

Variable	
n	102
Age mean (SD)	63.3 (1.0)
Gender n (%)	
Men	18 (17.7)
Women	84 (82.4)
Occupational status n (%)	
Non-manual	69 (67.7)
Manual	33 (32.4)
BMI (kg/m²) mean (SD)	25.4 (4.2)
Mobility limitations n (%)	
No	98 (96.1)
Yes	4 (3.9)
Measurement season n (%)	
Spring	35 (34.3)
Summer	23 (22.6)
Autumn	21 (20.6)
Winter	23 (22.6)
Light physical activity per day (min) mean (SD)	
Workday	279.6 (94.1)
Day off	258.9 (67.3)
Retirement	272.4 (88.2)
Moderate-to-vigorous physical activity per day (min) mean (SD)	
Workday	28.4 (19.2)
Day off	39.1 (24.6)
Retirement	36.0 (22.9)
Total physical activity per day (min) mean (SD)	
Workday	308.0 (95.5)
Day off	298.0 (71.9)
Retirement	308.4 (95.3)
Active travel duration per day (min) mean (SD)	
Workday	37.9 (33.9)
Day off	47.6 (38.2)
Retirement	50.7 (33.0)

activity during active travel on workdays. P-value for interaction indicating the difference between the days was 0.003. Further adjustment for BMI, mobility limitations and measurement season (Model 2) did not change the results.

[Supplemental Fig. 3](#) and [Supplemental Table 2](#) show the associations between exposure to useable green space and light physical activity and MVPA during active travel. While no association was observed between exposure to useable green space and light physical activity during active travel on any days, one SD addition to useable green space exposure was associated with 8 min/day (95% CI 4–11) of additional MVPA during active travel on days off, and 9 min/day (95% CI 6–13) on retirement days, when adjusted for age, gender, occupational status, BMI, mobility limitations and measurement season (Model 2).

Results of the sensitivity analysis, including all participants who had even only one measurement day, replicated the results of the main models ([Supplemental Table 3](#)). Sensitivity analyses also showed that the level of physical activity was lower during non-active than active travel ([Supplemental Table 4](#)), and there were no associations between exposure to useable green space and total physical activity during non-active travel between workdays, days off and retirement days ([Supplemental Table 5](#)). The possible selection bias was examined by comparing the characteristics of the analytical sample to all participants in the FIREA clinical sub-study as an eligible sample, and to the FIREA survey cohort ([Supplemental Table 6](#)). There were no major differences between the analytical and the eligible sample. However, in the larger FIREA survey cohort, there were less participants in non-manual occupations (63%) and their self-reported leisure time physical activity was lower (23.6 MET hours/week) than in the analytical sample (68%, 29.9 MET hours/week) and in the FIREA clinical sub-study population (69%, 28.8 MET hours/week).

4. Discussion

In this study, we used a waist-worn wearable device collecting GPS and accelerometry data to investigate the relationship between exposure to useable green space and physical activity during active travel among late middle-aged Finns. The measurements were conducted both before and after the transition from full-time work to statutory retirement, and the associations were examined separately for workdays, days off and retirement days. Overall, our results showed more total physical activity accumulating during active travel on days off and after retirement, than on workdays before retirement. Our results show that retirement does not necessarily mean giving up active travel, which is often considered as primarily relating to commuting, and ending when retiring. We observed a positive association between exposure to useable green space and total physical activity during active travel on days off and on retirement days, but not on workdays. We also observed a positive association between exposure to useable green space and MVPA on days off and on retirement days.

Our findings are in line with a previous intervention study grounded on the use of a commercial activity tracker ([Pasanen et al., 2022](#)), showing that the participants (mean age 64.8) who lived in areas with high level of greenness increased their daily waist-worn accelerometer-measured MVPA more than the participants living in areas with low level of greenness, and the observed increase occurred during GPS-detected active travel. Further, our results are in line with the GPS and waist-worn accelerometer-based results of [Marquet et al. \(2022\)](#), where a positive association was observed between greenness and number of steps taken among adult women (mean age 55.3). Moreover, our results support the previous results based on self-reported physical activity among adults (mean age 56.5) from the UK ([Sarkar, 2017](#)), which showed an association between greater greenness around participants' home and increased odds of engaging in active travel for non-work trips and walking for physical activity for more than 30 min/day.

The positive association between exposure to useable green space

Table 2

Unadjusted mean level of total physical activity during active travel and exposure to useable green space between workdays, days off and retirement days.

Outcome	Day type	Mean	95% CI	Mean difference	95% CI	Mean difference	95% CI
Total physical activity during active travel (min)	Workday	22.9	18.9 26.9	0 (Ref)			
	Day off	33.8	28.4 39.1	10.9	5.0 16.8	0 (Ref)	
	Retirement	36.7	31.6 41.7	13.8	8.6 18.9	2.9	-2.8 8.7
Useable green space during active travel (%)	Workday	19.0	16.2 21.9	0 (Ref)			
	Day off	29.3	25.0 33.7	10.3	5.5 15.0	0 (Ref)	
	Retirement	27.8	24.1 31.6	8.8	4.3 13.3	-1.5	-6.7 3.8

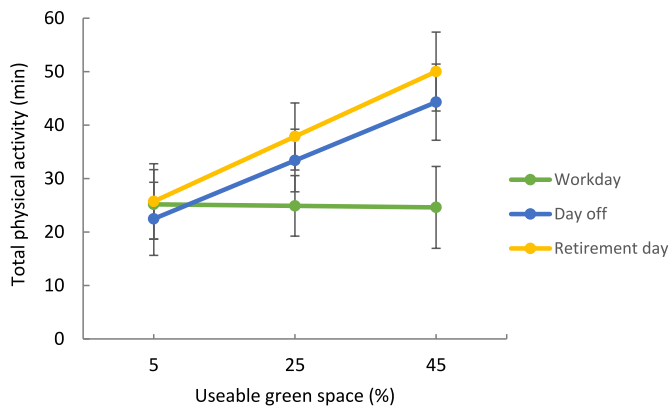


Fig. 1. Association between exposure to useable green space (mean 25%, SD = 20%) and total physical activity during active travel on workdays, days off and retirement days. Adjusted for age, gender, occupational status, BMI, mobility limitations and measurement season. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

and total physical activity during active travel (including both light physical activity and MVPA) appears to be more related to MVPA, as no positive association between exposure to useable green space and light physical activity during active travel was observed in our study. Prior studies, based on GPS and waist-worn accelerometer data, have also demonstrated the association between time spent in green space or general greenness and increased MVPA among the US adults (mean age 46) (Boakye et al., 2021) and among Belgian adults in their 60s (Dewulf et al., 2016).

The observed positive associations between exposure to useable green space and total physical activity and MVPA during active travel on days off and after retirement, but not on workdays, indicate that during leisure time people prefer to engage into active travel along routes with more green spaces. Thus, motivational determinants could offer an explanation to our findings, as active travel in green spaces seems to be what people like and choose to do. Our results suggest that urban planning promoting the construction and maintenance of green spaces around light traffic lanes might encourage active travel among late middle-aged people.

It has also been shown in prior studies that adults and late middle-

aged people accumulate generally more MVPA on days off than on workdays (Mutikainen et al., 2014; Pasanen et al., 2021; Pulakka et al., 2019), and that green space is a favored context for physical activity, as almost 70% of the Finnish adults mentioned parks and outdoors as places for their exercise (it was possible to select multiple answers) (European Commission, 2022). On workdays however, the choice of routes and the modes of commuting are perhaps often more constrained by, e.g., the location of the workplace, the schedule of the travel, the length of the work-related trip, the pedestrian and bicycle path network, or the chores to be completed during the travel to work or back. Future research is needed to examine which other environmental factors might support active travel particularly on workdays, as we did not observe an association between exposure to useable green space and physical activity during workday active travel. An interesting finding is also the similarity of observed positive associations between useable green space and total physical activity and MVPA during active travel on days off and on retirement days.

A major strength of this study is the applied longitudinal with-in individual high-resolution study design using repeated GPS and accelerometer-measurements before and after statutory retirement. We were able to measure both the exposure to useable green space and the minutes of different intensity physical activity during the trips using sensor-based measures. However, exposure to useable green space and different physical activity intensity levels may not fully coincide, as both were measured for each entire trip but are not necessarily accumulated exactly at the same time. Nevertheless, our study took a step forward from using fixed buffers, defining often merely an area around, e.g., home address with various radius (e.g., 500 m), that may not describe the area where physical activity takes place. Such a transition to more dynamic measures has been encouraged when investigating environmental exposures in health research (Laatikainen et al., 2018).

However, there are also limitations in the present study. Our study population reflects the gender distribution of the labor force in the Finnish public sector occupations (Statistics Finland, 2016) and thus the majority of our study population were women, which limits the possible additional analyses by gender and narrows the generalizability of the results. Following our research aims, only those participants who had completed some active travel were included in the analyses, hence not representing those who did not complete any active travel. Moreover, participants were asked to wear the SenseDoc device for at least two workdays and two days off when still working and at least four days after retirement, which resulted in a relatively small number of valid measurement days, knowing that some measurement days were further

Table 3

Association between one standard deviation increase in exposure to useable green space and total physical activity during active travel between workdays, days off and retirement days.

Day type	Model 1.				Model 2.			
	Beta coefficient	95% CI		P for interaction*	Beta coefficient	95% CI		P for interaction*
Workday	-0.2	-4.4	4.0	0.003	-0.3	-4.6	4.0	0.003
Day off	10.8	7.0	14.5		10.9	7.1	14.7	
Retirement	12.4	8.8	16.0		12.1	8.6	15.7	

*day type*useable green space.

Model 1. Adjusted for age, gender and occupational status.

Model 2. Adjusted for age, gender, occupational status, BMI, mobility limitations and measurement season.

excluded due to various requirements, e.g., minimum wear time of 10 h per day. The incomplete measurements in our study can be due the common troubles when collecting sensor data, such as limited battery life if the participants forgot to recharge the devices or losing the GPS signal (Shareck et al., 2013; Thierry et al., 2013). A few participants were also excluded due to technical problems with some devices during the measurements. To limit the number of excluded participants in this study, we required merely two valid measurement days before and after retirement to be included in the analytical sample. This is less than four or more days, which is commonly thought to reflect usual physical activity levels of an individual (Aadland and Ylvisåker, 2015; Schrack et al., 2016) or 12 to 14 measurement days recommended for reliable GPS measurement of activity spaces (Holliday et al., 2017; Zenk et al., 2018). To explore potential selection bias in our analytical sample, we compared the analytical sample to the FIREA clinical sub-study participants as an eligible sample and to the larger FIREA survey cohort. There were no major differences between the analytical and the eligible sample, but the participants in the FIREA clinical sub-study population, and thus also in the analytical sample, had higher leisure time physical activity than the participants in the larger FIREA survey population. This kind of bias is common in studies that require more effort from the participants, such as using wearable devices, and it should be noted that the results of our study may not be representative especially among those who participate less often in leisure-time physical activity. Furthermore, waist-worn accelerometers' weakness to detect certain types of physical activity, particularly cycling, is commonly known (Schrack et al., 2016), and thus the physical activity accumulated during active travel might be underestimated in our study. Our results may also be affected by the selective daily mobility bias (Chaix et al., 2013), common when using GPS measures to explore environmental effects. That is, our participants with higher exposure to useable green space may have selected the type of environment, e.g., parks, for their intended use of the facilities, like walking for physical activity. Therefore, while there was a positive association observed between exposure to useable green space and total physical activity and MVPA during active travel, we cannot conclude that being exposed to more green space induces more physical activity.

5. Conclusions

Since we observed positive association between exposure to useable green space and total physical activity and MVPA during active travel on days off and after retirement, but not on workdays, our results suggest that people prefer to engage into active travel in green spaces during their leisure time. Encouraging active travel may be a feasible way to promote more strenuous physical activity among aging populations, and construction and maintenance of green spaces around light traffic lanes might be an efficient way to increase participation in active travel.

CRediT authorship contribution statement

S. Pasanen: Writing – original draft, Visualization, Investigation, Formal analysis. **J.I. Halonen:** Writing – review & editing, Supervision, Investigation, Formal analysis, Conceptualization. **K. Suorsa:** Writing – review & editing, Investigation. **T. Leskinen:** Writing – review & editing, Investigation. **C. Gonzales-Inca:** Writing – review & editing, Supervision, Investigation. **Y. Kestens:** Writing – review & editing, Software, Methodology, Investigation. **B. Thierry:** Writing – review & editing, Software, Methodology, Investigation. **J. Pentti:** Writing – review & editing, Investigation, Formal analysis, Data curation. **J. Vah-tera:** Writing – review & editing, Supervision, Investigation, Conceptualization. **S. Stenholm:** Writing – review & editing, Supervision, Investigation, Formal analysis, Conceptualization.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.healthplace.2024.103366>.

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