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Title: Physical Behavior Profiles Among Older Adults and Their Associations With Physical Capacity and Life-Space Mobility

Year: 2024

Version: Accepted version (Final draft)

Physical behavior profiles among older adults and their associations with physical capacity and life-space mobility

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Running head: Physical behavior profiles in old age

Abstract

We identified data-driven multidimensional physical activity (PA) profiles using several novel accelerometer-derived metrics.

Participants aged 75, 80, and 85 (n=441) wore tri-axial accelerometers for 3-7 days. PA profiles were formed with k-means cluster analysis based on PA minutes, intensity, fragmentation, sit-to-stand transitions, and gait bouts for men and women. Associations with physical capacity and life-space mobility were examined using age-adjusted general linear models.

Three profiles emerged: "Exercisers" and "actives" accumulated relatively high PA minutes, with actives engaging in lighter intensity PA. "Inactives" had the highest activity fragmentation and lowest PA volume, intensity, and gait bouts. Inactives showed lower scores in physical capacity and life-space mobility compared to exercisers and actives. Exercisers and actives had similar physical capacity and life-space mobility, except female exercisers had higher walking speed in the 6-minute walk test.

Our findings demonstrate the importance of assessing PA as multidimensional behavior rather than focusing on a single metric.

Keywords: physical function, physical activity, cluster analysis, aging

Introduction

Physical activity (PA) can be defined as any bodily movement produced by skeletal muscles that results in energy expenditure (Caspersen et al., 1985). PA is a known modifiable behavior that can decrease the risk for several chronic conditions and maintain physical capacity (Paterson & Warburton, 2010; Warburton et al., 2006), defined as individual's ability to execute a task or an action in a standard environment (World Health Organization, 2001). The use of accelerometry in assessing free-living PA among older adults has increased over the past decade, but most studies assess PA and sedentary behavior using single metrics such as daily total volumes or step counts (Schrack et al., 2016; Shiroma et al., 2018). PA, however, is multidimensional and it is likely that no single metric can adequately describe individual's PA (Thompson et al., 2015). For instance, physical behavior characteristics such as hour-by-hour accumulation patterns, bouts of PA and sedentary behavior and activity fragmentation are associated with health-related outcomes (Bellettiere et al., 2017; Brady et al., 2022; Palmberg et al., 2020; Schrack et al., 2019). Building daily physical behavior profiles using a combination of several accelerometer-derived metrics could better capture the multidimensional nature of daily activity.

Data-driven, person-centered approaches such as mixture modelling and cluster analysis allow for the use of multiple variables of PA in the analyses and can provide a better understanding on how these are combined in older individuals' everyday life. These approaches for device-based physical behavior profiling have been increasingly used among different populations including children (Verswijveren et al., 2020), adult population (Farrahi et al., 2021; Gupta et al., 2020; von Rosen et al., 2020) and clinical subgroups (Geidl et al., 2019; Mesquita et al., 2017). Data-driven daily physical behavior profiling focusing on older people remains largely unexplored. A few previous studies investigated the associations of physical behavior clusters with health also among older people, but these studies focused on the total volumes and patterns of sedentary time rather than PA patterns (Laudani et al., 2013; Manta et al., 2019; O'Regan et al., 2021).

Physical behavior assessment in old age has its unique challenges and thus, there is a need to move beyond PA metrics describing solely total volume (Shiroma et al., 2018). While there is a need to explore data-driven physical behavior profiles in old age, consideration should also be given into which metrics to use among older people. For instance, cut-points based on absolute PA intensity may not accurately describe PA among older adults with more heterogeneity in physical capacity than their younger counterparts. With declining physical capacity, the relative intensity of physical activities may become higher, despite the decline in absolute intensity (Kujala et al., 2017; Schrack et al., 2018). In the AGNES study, our aim has been to develop PA assessment methods that may be able to overcome these challenges. The methods include individually scaled cut-points for PA based on preferred walking speed that showed promise as an assessment method for relative PA (Karavirta et al., 2020). We also identified free-living sit-to-stand (STS) transitions and their intensity, which are commonly performed among older people and are essential for independence in daily life (Löppönen et al., 2022). In addition, we have used other novel promising physical behavior metrics such as active-to-sedentary transition probability, an indicator of activity fragmentation (Schrack et al., 2019). In our earlier study, we found that activity fragmentation was associated with greater physical fatigability even beyond total PA volume (Palmberg et al., 2020). In addition, we identified gait bouts and their intensity from free-living accelerometer data and developed cut-points for higher risk of walking difficulty (Skantz et al., 2021).

The aim of this study was to identify data-driven physical behavior profiles among community-dwelling older people including novel accelerometer-based metrics describing the volume, intensity and accumulation patterns of PA. Furthermore, we studied the utility of the profiles by examining whether older people with different physical behavior profiles differ in terms of physical capacity and life-space mobility (ie. the spatial area where the person moves through in daily life), known correlates of PA.

Methods

This study forms a part of the “Active Aging—resilience and external support as modifiers of the disablement outcome” (AGNES) project (Portegijs et al., 2019; Rantanen et al., 2018). Briefly, participants were community-dwelling 75-, 80-, and 85-year-old people living in the Jyväskylä area, Finland and the initial sample was recruited from the Digital and Population Data Services Agency. Eligibility criteria included willingness to participate and residing in the study area. A total of 1021 people participated in a home interview in 2017-2018, of whom 495 agreed to wear a tri-axial accelerometer (Portegijs et al., 2019). Participants with valid data on all accelerometer-derived metrics on at least three complete days were included in the present analyses (n=441). Days with complete data, including no non-wear, from midnight to midnight based on visual inspection were considered valid.

Ethics

The study protocol followed the principles laid down by the Declaration of Helsinki. The study has been approved by the the Ethical Committee of the Central Finland Health Care District. All participants signed a written informed consent.

Accelerometer-assessed physical behavior

The accelerometers (range ±16 g, 13-bit analog-to-digital conversion, sampled at 100 Hz, UKK RM42; UKK Terveyspalvelut Oy, Tampere, Finland) were attached on participants’ dominant thigh using a waterproof film for 7–10 consecutive days following a home interview (Portegijs et al., 2019). The resultant accelerations were calculated for sampling instants and mean amplitude deviation (MAD, in g) calculated for non-overlapping 5-second epochs (Portegijs et al., 2019). Posture estimation was done following the approach by Vähä-Ypyä and colleagues (Vähä-Ypyä et al., 2018). Posture categories (sitting/lying down or upright) for each 5-second epoch were identified, and the median category for each minute of recording was used to calculate mean daily minutes in an upright posture. All epochs of a minimum duration of 20 seconds, upright posture and acceleration between 0.035 g and 1.2 g were identified as gait bouts based on laboratory experimentation, and mean number of gait bouts, mean gait bout intensity and mean duration of gait bouts were then calculated (Skantz et al., 2021). Furthermore, activity fragmentation was assessed as Active-to-Sedentary Transition Probability (ASTP) (Schrack et al., 2019). ASTP was calculated separately for mean daily minutes based on MAD values > 0.0167 g classified as at least light activity and mean daily minutes spent in an upright posture by dividing the mean active daily bouts by the mean sum of active daily minutes (Palmberg et al., 2020).

Minutes spent in different PA intensities were categorized with the following cut points originally developed for high-pass filtered vector magnitude: any minute with a MAD value below 0.0420 g as non-movement time, from 0.0420 g to 0.2375 g as light activity, ≥0.2375 g to < 0.6285 g as moderate activity and ≥ 0.6285 g as vigorous activity. These cut points corresponded to 1.5, 3 and 6 METs, respectively, following a linear equation by White and colleagues (White et al., 2019). Relative PA was then calculated as the number of epochs above or equal to the mean acceleration calculated during a laboratory-measured 6-minute walk test (6MWT) (Karavirta et al., 2020).

Daily STS transitions were detected from the accelerometer data using an open-access algorithm whose structure, code and properties are described elsewhere (Löppönen et al., 2022). The volume of the STS transitions was determined as the number of transitions per monitoring day.

Descriptive and outcome measures

Education was assessed by a single question asking participants to report their total years of education. Participants were asked about their living situation (alone, with spouse, with children or grandchildren, with relatives, siblings or other people), and dichotomized into alone vs. with others. Willingness and perceived opportunities for PA participation were asked using two single questions (Rantanen et al., 2018). Cognitive function was assessed using mini mental state examination (MMSE) (Folstein et al., 1975) and depressive symptoms were assessed using Centre for Epidemiologic studies Depression Scale (CES-D) (Radloff, 1977).

Lower-extremity physical performance was assessed during the home interview by trained a researcher using the Short Physical Performance Battery (SPPB) (Guralnik et al., 1994). Maximal knee extension force of the dominant lower leg (knee at 60 degrees) was measured in a sitting position using an adjustable dynamometer chair (Metitur LTD, Jyväskylä, Finland). The highest force of at least three attempts was selected for analysis (Rantanen et al., 1997). Self-reported habitual PA was assessed using the eight-item Yale Physical Activity Survey for older adults (YPAS, range 0-137, higher scores indicate higher PA) (Dipietro et al., 1993). Finally, life-space mobility was assessed using 15-item University of Alabama at Birmingham Study of Aging Life-Space Assessment (LSA, range 0-120, higher scores indicate higher life-space mobility) (Baker et al., 2003).

Statistical methods

Profiles with similar physical behavior characteristics were identified separately for men and women using k-means clustering algorithm (Hartigan & Wong, 1979). The k-means clustering was used instead of model-based methods due to the violation of conditional independence assumption caused by the strong direct relationships between the features (Oberski, 2016). All participants with valid accelerometer measurements and no missing values

(177 men, 264 women) were included in the cluster analyses. The cluster analyses were carried out in R (Team, 2013).

First, correlation-based principal component analysis (Hotelling, 1933) was carried out to deal with multicollinearity. For both men and women, three principal components were chosen based on the scree test (Cattell, 1966). They explained 74.9 and 73.6% of the variance, respectively. For k-means clustering, the similarity of clusters was assessed using Euclidian distance and number of clusters was determined based on the "elbow method" using the "factoextra" package (Kassambara & Mundt, 2020). The optimal number of clusters was three for both sexes. Clusters were validated using graphical inspection and studying the cluster-wise stability by assessing the bootstrap distribution of the Jaccard coefficient (Hennig, 2007). The bootstrapping with 100 resamples was conducted using the "fpc" package (*Fpc*, n.d.).

Descriptive characteristics according to the physical behavior clusters were studied with means or percentages. Group differences were assessed with the chi-square test for categorical variables and the Kruskal-Wallis test for continuous variables. Age-adjusted group differences were assessed using general linear models. To account for multiple testing, the p-values were corrected using the Bonferroni method. Analyses were conducted using data from the participants with no missing data in the variables of interest. The percentage of missing data varied from 0 to 2% across the variables used in the analyses. All other analyses were performed using IBM SPSS Statistics 26 (IBM Corp, Armonk, NY, USA). The level of statistical significance was set to $p<0.05$.

Results

Identification of physical behavior profiles

The independent clustering analyses for men and women resulted in three clusters that were similar between the sexes. The bootstrap distribution of the Jaccard coefficients were 0.67, 0.76, and 0.86 in men and 0.86, 0.91, and 0.91 in women indicating high cluster-wise stability for most clusters (Hennig, 2008). The clusters were labelled as “the exercisers”, “the actives” and “the inactives” based on their physical behavior characteristics (Table 1 for women and Table 2 for men). Due to the similarity of clusters in men and women, the same labels were used for both sexes.

The exercisers included 22.7% of women and 10.7% of men. The exercisers accumulated the highest moderate PA minutes, highest relative PA minutes, the longest duration of gait bouts and highest mean daily acceleration compared to the actives and the inactives ($p<0.05$ for all). The difference was especially notable concerning relative PA minutes which the exercisers accumulated 227% more compared to the actives and 319% more compared to the inactives among women ($p<0.001$ for both), and 373% and 525% more among men ($p<0.001$ for both). The actives and the inactives accumulated similar relative PA in both sexes.

The actives included 37.9% of women and 43.5% of men. The actives formed the intermediate profile in terms of moderate PA minutes and mean acceleration but accumulated 22% and 59% higher light-intensity PA minutes compared to the exercisers and the inactives among women, and 34% and 65% higher among men ($p<0.001$ for all), respectively. In addition, the women actives accumulated 22% and 70% higher number of gait bouts compared to the exercisers and the inactives ($p<0.001$ for both), and the men actives 32% ($p=0.002$) and 70% ($p<0.001$) higher, respectively.

The inactives included 39.4% of women and 45.8% of men. While non-movement time between the exercisers and the actives was similar among both women and men, the inactives accumulated 5-6% higher non-movement time among women ($p<0.001$ for both) and 7% higher among men ($p<0.001$ for both) compared to the exercisers and the actives. Overall, the inactives formed the most inactive profile, accumulating the least PA minutes and 33% higher activity fragmentation compared to the actives and 60% higher compared to the exercisers among women (p<0.001), and 31% and 42% higher among men, respectively. Among men the actives had slightly higher vigorous PA minutes and mean gait bout duration compared to the inactives, while no difference was observed among women.

Associations with demographic characteristics and measures of mobility and health

Among men, the inactives had the fewest years of education, but among women there was no statistically significant difference. Among women, the inactives reported more depressive symptoms, but similar difference was not observed among men. There were no statistically significant differences in cognitive function or living situation. Among women, over 70% of the actives and the inactives reported that they wanted to be more physically active (vs. 39% in the exercisers). Similarly, among men over 70% of the inactives reported a willingness to increase PA (vs. 50% in actives and 35% in exercisers) (Table 3).

Among women, the inactives had 27.9% (p<0.001) and 14.3% (p=0.013) lower self-reported PA scores compared to the exercisers and the actives, respectively. In addition, women actives had 15.9% lower self-reported PA compared to the exercisers (p=0.004). Among men, the inactives had 33.5% and 22.5% lower self-reported PA compared to the exercisers and the actives (p<0.001 for both), but the difference between the exercisers and actives did not reach statistical significance. Among women, the inactives had 15.4% and 12.7% (p<0.001 for both) lower scores in life-space mobility compared to the exercisers and the actives, respectively. Among men, the inactives had 10.3% lower scores in life-space mobility compared to the actives (p=0.004), but the other differences did not reach statistical significance (Table 3). In the age-adjusted models, the findings did not materially change (Table 4).

Associations with demographic characteristics and physical capacity

Among women, the inactives had 9.2% (p=0.002) and 6.6% (p=0.011) lower SPPB scores, and 15.4% (p<0.001) and 10.1% (p=0.019) lower maximal knee extension force compared to the exercisers and the actives, respectively. The differences did not reach statistically significance between the women exercisers and the women actives. Concerning walking speed, the women inactives had 23.1% and 16.7% slower walking speed in the 6MWT, and 15.8% and 11.1 slower in the 10-m test (p<0.001 for all) compared to the exercisers and the actives. The women exercisers had higher walking speed in the 6MWT compared to the women actives (p=0.013) but did not differ in 10-m walking speed.

Among men, the exercisers and the actives did not differ in any of the indicators of physical capacity. The men inactives had 11.4% (p=0.011) and 7.3% (p=0.013) lower SPPB scores compared to the exercisers and the actives, respectively. Furthermore, the men inactives had 11.3% lower maximal knee extension force than the actives (p=0.009) but no statistically significant difference compared to the exercisers. Concerning walking speed, the men inactives had 15.4% slower 6MWT speed compared to both the exercisers and the actives (p=0.001). In the 10-m test, the men inactives had 14.3% slower walking speed compared to the actives (p<0.001) but no difference compared to the exercisers. In the age-adjusted models (Table 4), the findings remained materially unchanged.

Discussion

In the present study, we identified three physical behavior profiles among community-dwelling older people, characterizing different phenotypes of physical activity behavior in old age. Similar profiles emerged for women and men, separately. Parallel to earlier research findings, we found that compared to the two more physically active profiles, the inactives were characterized by lower life-space mobility, self-reported PA, and physical capacity. In women, walking speed in 6MWT/10 m and self-reported PA differed statistically between the exercisers and the actives, but in men significant differences were not observed between these two groups. These findings indicate that PA profiling can be a useful method for research aiming to combine multiple dimensions of physical activity in old age. The novelty of the present study is utilizing a data-driven, person-centered approach to assess the multidimensional physical activity combining a range of novel accelerometer-based metrics among older people.

Our findings demonstrate the relevance of assessing multiple PA dimensions among older people, rather than focusing on simple PA metrics such as activity minutes. An important observation was that although the exercisers and the actives accumulated similar total activity minutes, they did differ in several other PA characteristics such as relative PA minutes, gait bouts and mean intensity contributing towards a substantially different physical activity phenotype. These differences were also seen among women in walking speed and self-reported physical activity. The findings indicate that the use of distinctive multidimensional profiles has the potential to demonstrate differences in PA beyond what is captured by single PA metrics, and reducing accelerometer-based data into a simple physical activity metric may present a missed opportunity. Earlier studies identifying physical behavior clusters among older people found four distinct physical behavior clusters (Manta et al., 2019; O'Regan et al., 2021). Compared to these earlier studies, we used a wider range of PA metrics that address the common pitfalls of assessing PA among older adults, and capture accumulation patterns in addition to commonly used metrics of volume and intensity. Due to the differences in PA metrics, our findings are not comparable to these previous studies profiling physical activity in old age, and thus, future studies are needed to see whether similar profiles can be found among other older adult populations using a similar set of PA metrics.

The differences in physical capacity and life-space mobility between the inactives and the more active profiles were comparable with earlier research showing associations of higher PA levels, lower activity fragmentation and higher PA complexity with better physical function

(Paterson & Warburton, 2010; Rantalainen et al., 2022; Schrack et al., 2019; Simonsick et al., 2005) and higher life-space mobility (Portegijs et al., 2015; Tsai et al., 2016). We found that among both men and women, those who accumulated the least PA and had highest activity fragmentation (the inactives) had poorer physical capacity and lower life-space mobility compared to the more physically active profiles. Poorer physical capacity and health can limit the opportunities for PA among older people (Rai et al., 2020), while engaging in PA can also help in maintaining physical capacity in old age (Paterson & Warburton, 2010; Simonsick et al., 2005). Given the cross-sectional nature of our findings, future prospective studies are needed to confirm the predictive validity of the profiles in predicting changes in physical capacity and life-space mobility.

Interestingly, between the two more active profiles, we observed no differences in terms of physical capacity, besides the difference in walking speed among women. This finding is in line with earlier dose-response observations where the steepest risk reduction occurs at low volumes of PA, indicating that some activity is much better than none. This is important as there was a rather large difference in the amount of relative PA i.e. activity beyond the intensity of 6MWT between these profiles among both men and women. This finding is consistent with the growing research evidence that older people can benefit from a wide range of PA behaviors, including light-intensity activities, as already stated in the new World Health Organization 2020 guidelines on health-enhancing PA and sedentary behaviour (Bull et al., 2020). Future prospective research is, however, needed to confirm whether older people with high activity levels can maintain their physical capacity and life-space mobility regardless of lower intensity levels.

The difference in the results among men and women concerning walking speed may be explained by lower robustness in the clusters among men or by overall higher walking speed among men. This would have allowed them to accumulate higher time in moderate and vigorous PA. Furthermore, it may be that among highly functioning older people, the differences in higher intensity PA may rather be explained by individual preferences, than differences in physical function and health (Rai et al., 2020). The findings that the difference in relative PA was rather large between these profiles, and that the actives accumulated more light PA, can be interpreted in a way that the exercisers may be more likely to walk more for exercise, while the actives may be more likely to accumulate PA while doing household chores or running errands. This is also supported by differences in self-assessed PA (YPAS), suggesting that actives reported less walking and vigorous PA, and accumulated PA in activities that they did not perceive as PA or were not able to recall.

The strengths of the study include a continuous 3–7-day accelerometer recording, which allowed us to account for day-to-day variations in PA. Another strength is the availability of several novel metrics of physical behavior, that can together provide a more comprehensive description of the physical behavior of older people. There are also limitations that should be taken into account when interpreting the findings. First, the cross-sectional study setting does not allow conclusions about causality, and future longitudinal studies are needed. Second, the physical behavior clusters for older men were less robust, which may explain why we observed no differences between exercisers and actives among men. Third, we were not able to differentiate between sedentary time and sleep and thus, differences in non-movement time could also be explained by differences in sleep duration. Finally, it should be noted that the participants agreeing to participate in the PA monitoring had better health and higher PA than participants who only participated in the home interview (Portegijs et al., 2019), and hence the present sample underrepresented the less healthy and the less physically active part of the population.

Conclusions

The findings of this study demonstrate the importance of assessing multidimensional PA rather than focusing merely on single metrics. We were able to identify distinct activity phenotypes among older people which provide a more comprehensive picture of the volume, patterns and intensity of PA in which older people engage in during their everyday lives. Notably, although the two more physically active profiles had similar total activity minutes, they exhibited notable differences in various other PA characteristics, contributing to distinct PA phenotypes. This observation underscores the importance of recognizing that studying PA minutes alone is not sufficient when investigating the PA behavior of older adults. Instead, researchers should place greater emphasis on carefully selecting PA characteristics according to the context and purpose of their studies. In addition, similar profiles arose from both the women and the men independently, further supporting the utility of the profiles in characterizing PA behavior. Although these profiles showed associations with known correlates of physical activity in a cross-sectional study setting, the predictive validity of these profiles needs to be confirmed in future prospective studies.

Acknowledgments

The Gerontology Research Center is joint effort between the University of Jyväskylä, Finland and the University of Tampere, Finland.

Funding:

This work was supported by the European Research Council (693045 to Ta.R.); the Academy of Finland (339391 and 346462 to L.K., 321336 and 328818 to Ti.R. and 310526 to Ta.R.) and the University of Jyvaskyla. The content of this manuscript does not reflect the official opinion of the European Union. Responsibility for the information and views expressed in the manuscript lies entirely with the authors.

Conflict of interest:

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Table 1. Included variables in the cluster analysis according to physical behavior clusters among women (n=264)

	Exercisers n=60	Actives n=100	Inactives n=104	P-values*		
	Mean (SD)	Mean (SD)	Mean (SD)	E vs. A	A vs. I	E vs. I
Non-movement time (min)	1255.2 (44.1)	1262.7 (32.9)	1330.7 (23.2)	1.000	<0.001	<0.001
Light PA (min/day)	122.9 (29.5)	149.5 (29.1)	93.8 (20.8)	<0.001	<0.001	<0.001
Moderate PA (min/day)	58.7 (22.6)	27.7 (13.0)	15.2 (10.7)	<0.001	<0.001	<0.001
Vigorous PA (min/day)	2.9 (5.8)	0.15 (0.35)	0.27 (0.84)	<0.001	1.000	<0.001
Relative PA (min/week)	138.3 (92.7)	42.2 (42.9)	33.0 (40.0)	<0.001	0.246	<0.001
No of sit-to-stand transitions	41.4 (13.4)	44.0 (17.3)	37.9 (15.4)	1.000	0.023	0.253
Mean gait bout duration (min)	1.17 (0.21)	0.82 (0.13)	0.78 (0.13)	<0.001	0.098	<0.001
SD of gait bout duration	2.83 (0.97)	1.11 (0.49)	1.05 (0.59)	<0.001	0.868	<0.001
Mean gait bout intensity (g)	0.13 (0.02)	0.12 (0.02)	0.11 (0.02)	0.010	0.013	<0.001
Mean no of gait bouts	114.1 (34.6)	139.2 (29.1)	82.1 (20.1)	<0.001	<0.001	<0.001
Mean MAD (g)	0.03 (0.007)	0.02 (0.004)	0.02 (0.003)	<0.001	<0.001	<0.001
Fragmentation (posture)	0.10 (0.02)	0.12 (0.04)	0.16 (0.05)	0.018	<0.001	<0.001
Fragmentation (MAD)	0.22 (0.05)	0.22 (0.04)	0.29 (0.05)	1.000	<0.001	<0.001

Note; PA=physical activity, MAD=mean amplitude deviation, E vs. A = exercisers vs. actives, A vs. I = actives vs. inactives, E vs. I = exercisers vs. inactives, *Bonferroni-corrected p-values

Table 2. Included variables in the cluster analysis according to physical behavior clusters among men (n=177)

Men N=177	Exercisers n=19	Actives n=77	Inactives n=81	P-values		
	Mean (SD)	Mean (SD)	Mean (SD)	E vs. A	A vs. I	E vs. I
Non-movement time (min)	1233.6 (51.1)	1228.7 (35.7)	1315.0 (31.0)	1.000	<0.001	<0.001
Light PA (min/day)	127.6 (40.4)	171.3 (35.7)	103.8 (28.2)	<0.001	<0.001	0.104
Moderate PA (min/day)	68.6 (27.4)	38.4 (15.9)	20.4 (10.5)	<0.002	<0.001	<0.001
Vigorous PA (min/day)	10.2 (9.8)	1.59 (2.95)	0.57 (1.79)	0.011	<0.001	<0.001
Relative PA (min/week)	230.1 (167.2)	48.6 (66.5)	36.8 (44.4)	<0.001	0.989	<0.001
No of sit-to-stand transitions	52.6 (20.9)	52.8 (15.7)	42.3 (14.7)	1.000	<0.001	0.054
Mean gait bout duration (min)	1.29 (0.29)	0.94 (0.15)	0.87 (0.19)	<0.001	0.027	<0.001
SD of gait bout duration	3.22 (1.21)	1.33 (0.61)	1.22 (0.79)	<0.001	0.493	<0.001
Mean gait bout intensity (g)	0.14 (0.02)	0.13 (0.02)	0.12 (0.02)	0.543	0.002	0.002
Mean no of gait bouts	117.2 (37.0)	154.2 (36.1)	91.1 (26.1)	0.002	<0.001	0.035
Mean MAD (g)	0.04 (0.007)	0.03 (0.005)	0.02 (0.004)	0.015	<0.001	<0.001
Fragmentation (posture)	0.12 (0.03)	0.13 (0.04)	0.17 (0.06)	1.000	<0.001	0.001
Fragmentation (MAD)	0.22 (0.05)	0.19 (0.03)	0.27 (0.06)	0.128	<0.001	0.001

Note; PA=physical activity, MAD=mean amplitude deviation, E vs. A = exercisers vs. actives, A vs. I = actives vs. inactives, E vs. I = exercisers vs. inactives, *Bonferroni-corrected p-values

Table 3. Participant characteristics according to physical behavior profiles

	Women				Men			
	Exercisers	Actives	Inactives		Exercisers	Actives	Inactives	
	Mean (SD)	Mean (SD)	Mean (SD)	p	Mean (SD)	Mean (SD)	Mean (SD)	p
Age	78.0 (3.2)	77.7 (3.3)	78.8 (3.7)	0.094	77.7 (3.0.)	78.2 (3.4)	79.0 (3.5)	0.019
Years of education	11.2 (4.0)	12.5 (4.3)	11.4 (4.0)	0.092	12.2 (3.4)	12.4 (4.5)	11.0 (4.7)	0.016
MMSE score	27.7 (2.2)	27.7 (2.0)	27.6 (2.0)	0.872	26.8 (2.2)	27.3 (2.5)	27.0 (2.9)	0.758
CES-D score	6.5 (6.0)	7.7 (5.8)	9.0 (7.0)	0.028[c]	7.6 (8.0)	6.5 (5.8)	7.8 (7.2)	0.581
SPPB score	10.9 (1.3)	10.6 (1.6)	9.9 (1.9)	0.002 [b,c]	11.4 (0.8)	10.9 (1.6)	10.1 (1.8)	<0.001[b,c]
YPAS score	70.0 (22.5)	58.9 (1.1)	50.5 (18.8)	<0.001[a,b,c]	79.9 (27.3)	68.5 (22.4)	53.1 (21.6)	<0.001[b,c]
LSA score	75.0 (13.5)	72.7 (15.1)	63.9 (16.9)	<0.001 [b,c]	82.8 (15.8)	85.0 (14.5)	76.3 (17.1)	<0.001[b]
6MWT walking speed (m/s)	1.3 (0.2)	1.2 (0.2)	1.0 (0.2)	<0.001[a,b,c]	1.3 (0.2)	1.3 (0.2)	1.1 (0.2)	<0.001[b,c]
10m walking speed (m/s)	1.9 (0.3)	1.8 (0.3)	1.6 (0.3)	<0.001[b,c]	2.0 (0.3)	2.1 (0.4)	1.8 (0.4)	<0.001[b]
Max. knee extension force (N)	318.5 (70.3)	299.8 (79.0)	269.5 (81.3)	<0.001[b,c]	445.8 (92.8)	457.1 (91.4)	405.6 (114.4)	0.004[b]
	%	%	%		%	%	%	
Living alone	56.7	40.4	51.9	0.203	15.8	19.7	12.5	0.468
Wants to be more physically active	38.6	70.7	72.6	<0.001	35.3	50.0	72.0	0.003
Good perceived opportunities for PA	88.1	69.7	50.0	<0.001	78.9	84.9	69.6	0.078

Note; SD=Standard deviation, PA=Physical activity, 6MWT=6-minute walk test, MMSE=Mini Mental State Examination, CES-D= Centre for Epidemiologic studies Depression Scale, SPPB=Short Physical Performance Battery, YPAS=Yale Physical Activity Survey, LSA= University of Alabama at Birmingham Study of Aging Life-Space Assessment (LSA) questionnaire, [a]Bonferroni-corrected p<0.05 between the exercisers and the actives, [b] Bonferroni-corrected p<0.05 between the actives and the inactives, [c] Bonferroni-corrected p<0.05 between the exercisers and the inactives

Table 4. Age-adjusted associations between the physical behavior profiles, physical capacity, life-space mobility and self-reported physical activity

	Exercisers (E)	Actives (A)	Inactives (I)	P-values*		
Women n=264	EMM (SE)	EMM (SE)	EMM (SE)	E vs. A	A vs. I	E vs. I
10m walking speed (m/s)	1.9 (0.04)	1.8 (0.03)	1.6 (0.03)	0.071	0.001	<0.001
6MWT walking speed (m/s)	1.3 (0.02)	1.2 (0.02)	1.1 (0.02)	0.004	<0.001	<0.001
Max. knee extension force (N)	317.4 (9.70)	296.7 (7.54)	273.0 (7.44)	0.281	0.080	0.001
SPPB	10.8 (0.21)	10.6 (0.16)	10.0 (0.16)	0.877	0.041	0.004
CES-D	6.6 (0.81)	7.9 (0.64)	8.9 (0.63)	0.628	0.805	0.079
YPAS	69.9 (2.67)	58.6 (2.08)	50.9 (2.04)	0.003	0.027	<0.001
LSA	74.9 (1.97)	72.5 (1.54)	64.3 (1.50)	1.000	<0.001	<0.001
Men n=177						
10m walking speed (m/s)	2.0 (0.09)	2.0 (0.04)	1.8 (0.04)	1.000	0.001	0.274
6MWT walking speed (m/s)	1.3 (0.04)	1.3 (0.02)	1.1 (0.02)	1.000	<0.001	0.001
Max. knee extension force (N)	438.7 (22.84)	452.9 (11.11)	411.1 (10.79)	1.000	0.023	0.829
SPPB	11.3 (0.37)	10.9 (0.18)	10.2 (0.18)	0.856	0.027	0.021
CES-D	7.8 (1.53)	6.5 (0.77)	7.7 (0.75)	1.000	0.965	1.000
YPAS	79.7 (5.21)	68.4 (2.62)	53.2 (2.54)	0.166	<0.001	<0.001
LSA	81.9 (3.55)	84.5 (1.77)	76.9 (1.72)	1.000	0.009	0.646

Note; EMM=Age-adjusted estimated marginal means, SE=Standard error, 6MWT=6-minute walk test, CES-D= Centre for Epidemiologic studies Depression Scale, SPPB=Short Physical Performance Battery, YPAS=Yale Physical Activity Survey, LSA= University of Alabama at Birmingham Study of Aging Life-Space Assessment (LSA) questionnaire, E vs. A = exercisers vs. actives, A vs. I = actives vs. inactives, E vs. I = exercisers vs. inactives, *Bonferroni corrected p-values