Latent profiles analysis of physical activity and sedentary behaviour with mortality risk: a 15-year follow-up

Running head: Latent profiles analysis of physical activity

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Abstract
By exploring multiple characteristics of physical activity and sedentary behaviour (SB), different physical activity profiles could be obtained, which may be beneficial for health and targeted physical activity interventions. The aim of this study was to identify distinct physical activity profiles based on accelerometer-derived activity characteristics, and to determine whether these profiles are associated with all-cause mortality. Eight hundred fifty-one participants (56% women, mean age 53 years) provided objectively assessed physical activity data using an Actigraph accelerometer and were followed for 15 years. Physical activity profiles were determined using latent profile analyses of 14 derived activity variables, resulting in that three profiles were identified; “Low Active” (n=147), “Average Active” (n=397), “High Active” (n=307). “Low Active” was characterized by participants with low absolute, relative and limited variation of time spent in physical activity, and high time spent in SB. “Average Active” had the most balanced movement behaviour with values close to the mean for all activity variables. “High Active” was characterised by participants with high absolute, relative and great variation of time spent in physical activity. Overall, a potentially non-linear pattern between multiple activity variables and all-cause mortality was found as “Low Active” was significantly (p<0.05) positively associated with all-cause mortality, and no difference in mortality risk was found between “High Active” and “Average Active”. Our data suggest that day-to-day variation in SB is not associated with all-cause mortality. The important message is to keep the overall time spent in SB low and replace this behaviour with physical activity.

Keywords: accelerometry, latent class analysis, movement behaviour

INTRODUCTION
Across a day, individuals spend time in diverse activities, representing a wide range of physical activity profiles, associated to health and all-cause mortality. The physical activity profiles could be described based on intensity, duration, and variation of time in different movement behaviours, such as time in light or vigorous activity. For instance, the “weekend warrior”, associated with reduced risks for all-cause mortality and cardiovascular disease, is described as a physical activity profile where individuals perform all their exercise in one or two sessions per week. In physical activity research, typically only a few characteristics of physical activity and sedentary behaviour (SB) are used, such as time in SB, light intensity physical activity (LIPA) and moderate-to-vigorous physical activity (MVPA), which may limit the conclusions. By exploring different physical activity profiles the complex relationship between health and physical activity behaviours may be determined, which may be beneficial for health and targeted physical activity interventions.

Traditionally, physical activity and SB different movement behaviours have been measured using accelerometer devices across a time period and classified according to time in different intensities different. These movement behaviours have then been associated with health outcomes and all-cause mortality. For instance, more time spent in LIPA and MVPA has been associated with lower risk of all-cause mortality, while more time spent in SB (e.g. activities with < 1.5 MET) with increased risk of all-cause mortality. However, since an individual could reach the total number of minutes in a specific behaviour in many different combinations, e.g. through day to day variation, time in a specific intensity represents only part of a complete physical activity profile.

Although time in SB, LIPA and MVPA provide valuable information about physical activity profiles, other characteristics such as bout duration, total activity, variation of time in different behaviours across a time period and the relative time spent in different movement behaviours may also be important for health. For instance, bouts of time in SB or MVPA has been suggested to be associated with health outcomes, even if the evidence is insufficient. Variation in physical activity between days has been explored and individuals with a low level and limited day-to-day variation of physical activity across a week has been associated with increased risk for all-cause mortality.
To identify discrete, mutually exclusive groups of physical activity profiles, latent profile analysis is a statistical method that group individuals based on response patterns for multiple indicators. This method has recently been used in physical activity research in young adults, Danish workers, and US citizens associating the identified groups with different health outcomes. However, more data are needed on different profiles’ effects on all-cause mortality. By exploring multiple characteristics of physical activity and SB, such as time and the relative time in different movement behaviours, bout duration, variation of time and total activity, different physical activity profiles could be obtained and associations to all-cause mortality could be determined. Therefore, this study aims to use latent profile analysis to identify distinct physical activity profiles based on accelerometer-derived activity characteristics, and to determine whether these profiles are associated with all-cause mortality, in a cohort with 15 years follow-up time.

MATERIALS AND METHOD

Study population and design
This study use data from the 2001-2002 Sweden Attitude Behaviour and Change (ABC) study. The ABC study is a prospective cohort study, where a random sample of 3300 adults of age 18–75 years was selected from the Swedish population register, of which 2262 adults were reached. A total of 1556 (69%) individuals gave oral informed consent and 1221 (55% women) provided objective physical activity data. This sample was evenly distributed across Sweden, but the proportions of participants under 24 years and over 65 years were slightly lower than in the general population. In this study, only participants ≥50 years at follow-up in 2015 with objectively measured physical activity data at baseline were included, resulting in a final sample of 851 participants, mean age 53 years at baseline. The included participants, compared with the individuals that provided objective physical activity data, had higher BMI values (25.6 vs. 23.9), proportion smokers (27% vs. 20%), but similar distribution of sex (56% vs. 52%) and proportion with a university degree (31% vs. 31%). The study was approved by the Regional Ethical Review Board at the Karolinska Institute (Dnr 378/02, 2012/707 31/1, 2015 1578/32). Detailed information about the survey has previously been described.
Data collection

A uniaxial ActiGraph accelerometer model 7164 (ActiGraph, Pensacola, FL, US) was used to capture time in different behaviours, measuring time-varying acceleration in the vertical axis expressed as counts. The participants were instructed to wear the accelerometer on the lower back for seven consecutive days. The device was set to sampling counts per 1-minute epochs. Non-wear time were defined as periods of at least 60 consecutive min of zero counts, allowing for 2 min of counts between zero and 100. Data from participants with at least one valid day, including 10 hours or more of wear time, were included. Epochs were classified into intensity levels using validated cut-points chosen in accordance with previous population-based studies: SB (0-99 counts/min), LIPA (100-1951 counts/min) and MVPA (≥ 1952 counts/min). Performed time in ≥ 60-minutes bouts of SB and performed time in ≥10-minutes bouts of MVPA, was calculated. Number of SB bouts (lasting ≥ 60-minutes) and MVPA bouts (lasting ≥ 10-minutes) were estimated. Zero values of MVPA (n=5) were imputed based on maximum likelihood estimation. In average, the participants had 6.4 days of accelerometer data. The software ActiLife 6 (ActiGraph, Pensacola, FL, US) was used to extract and process the accelerometer data.

Demographic and anthropometric data were self-reported and collected from a baseline questionnaire sent by mail to the participants. Baseline data used in this study consists of data on sex, age, BMI, education (University, High school, Primary school), self-rated health (excellent, alright, poor), smoking status (never/former or current), and history of chronic disease (hypertension, heart disease, diabetes, and cancer). Register data of mortality of 2002–2015 were collected from the National Board of Health and Welfare’s Cause of Death Register and the Swedish Cancer Registry in 2016. The registers have a high completeness and a high accuracy due to the unique personal identity number assigned to all individuals registered in Sweden.

Data analysis

Since time spent in movement behaviours represent relative information of the complete day, the composition nature of daily time data needs to be acknowledged. Therefore, for each participant, time spent in SB, LIPA and MVPA was transformed into isometric log-ratio (ilr) coordinates. Since we use a 3-part composition (SB, LIPA, MVPA), each movement behaviour is then
represented by two ilr-variables. Therefore, a set of six ilr-variables were constructed with pair of two variables for each component (SB, LIPA, MVPA).

For the latent profile analysis, a total of 14 activity variables based on previous literature, were derived from the accelerometer data to capture a wide range of characteristics of physical activity and SB. These were time spent in different intensities (SB, LIPA, MVPA) variation of time spent in different intensities (standard deviation of time spent in SB, LIPA, MVPA), total time of sedentary bouts, total time of MVPA bouts, number of sedentary and MVPA bouts, total counts and the relative time spent in one behaviour relative to the two remaining behaviours (e.g. SB vs LIPA, MVPA). The activity variables were calculated across the days the participants had at least 10 hours of wear time For instance, if an participant spent 6,6,8,7,8 hours per day of time in SB across five days, the standard deviation of time spent in SB across the valid days was calculated as 1 hour of SB for that participant. All activity variables were transformed into z-scores. Spearman correlations between the 14 variables were used to identify multicollinearity, which resulted in that the relative time for LIPA and MVPA, number of sedentary and MVPA bouts, were excluded from the latent profile analysis.

To identify discrete, mutually exclusive latent profiles, several consecutive latent models with two to five profile solutions were performed using latent profile analysis (package “tidyLPA”). The optimal number of profiles were evaluated using criteria described by Nylund et al. We evaluated the fit statistic for each model from a two-profile model to a five profile model and the final model was chosen based on the following fit statistics: 1) Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), 2) Entropy values, 3) Probability of profile membership, 4) Group size of profiles, 5) Meaningfulness of profile membership. Lower AIC and BIC values were found for more complicated models (higher number of profiles). Both the 5-profile and 4-profile model had quite few number of participants in at least one of the profiles (8.9-9.8% of all participants). We therefore decided to choose a simpler model (3 profiles), as it made sense theoretically with distinct different patterns of physical activity and SB, and meaningful differences between the three profiles. The results of the different consecutive latent profile models with 2 to 5-profile solutions is presented in Table 1.
To explore profiles, adjusted linear regression models to allow for potential confounder variables such as sex, age, education, smoking, hypertension, heart disease, cancer, diabetes, were fitted for the activity variables. Effect sizes using Hedges’ g and Cramer’s V for continuous and categorical data, was calculated.

Cox proportional-hazard model was conducted to estimate hazard ratios (HRs) of all-cause mortality with 95% confidence intervals (CIs). Participants were followed from the first day of accelerometer assessment until the date of death or censoring on December 31, 2015, with no deaths recorded during the first year. The profile variable along with covariates, considered as possible confounders (age, sex, smoking, history of chronic disease and education) were entered in a cox proportional-hazard model. Selection of these confounders was based on assumed association between these specific variables and mortality risk. Diagnostics in terms of testing the proportional hazards assumption, influential observations and detecting nonlinearity in relationship between the log hazard and the covariates were performed. Final model was stratified for age tertiles (1) age ≤47, (2) age 48-57, (3) age ≥58) to fulfil the proportional-hazard assumption. In sensitivity analysis, deaths occurring within the first three years were excluded, and another cox proportional-hazard model were run. A p value ≤ 0.05 was considered as statistically significant and all analyses were conducted using the R statistical system version 3.5.2 (R Core Team 2018).

Results
The three profiles are presented in Figure 1 and Table 2. Profile 1 was named “Low Active” to reflect participants with low absolute, relative and limited variation of time spent in physical activity, along with high absolute and relative time spent in SB. Profile 2 was named “Average Active” since individuals in that profile has the most balanced movement behaviour with values close to the mean (<0.5 z-score) of the 14 activity variables. Profile 3 was named “High Active” since individuals in this profile had the opposite movement behaviour as “Low Active” with high
absolute, relative and great variation of time spent in physical activity and low time spent in SB. The “Low Active” was older (age 58 vs. 51, 53), had a higher BMI (unit 27 vs. 25, 26), proportion with chronic diseases (29% vs. 15%, 18%) and mortality (20% vs. 8%, 6%), compared with “Average Active” and “High Active” profile.

Significant and large effect sizes (> 0.80) between “Low vs. Average Active” and “Low vs. High Active” were found for all activity variables except for time in sedentary bouts, number of sedentary bouts and variation of time spent in SB and LIPA (Table 3), adjusted for potential confounders. Large effect size differences between “Average vs. High Active” were found for all activity variables except for time spent in sedentary bouts, number of sedentary bouts, variation of time spent in SB and LIPA and relative time spent in LIPA and MVPA.

Over an average of 5197 days, a total of 79 deaths had occurred. The cox proportional-hazard regression model, adjusted for sex, education, self-rated health, smoking, hypertension, heart disease, cancer, diabetes, with stratification by age tertiles, showed that the profile “High Active” (HR 0.47, 95% CI 0.25-0.88, p=0.017) and “Average Active” (HR 0.60, 95% CI 0.36-0.998, p=0.049) was significantly negatively associated with all-cause mortality, compared to “Low Active” (Figure 2). No difference in all-cause mortality was found between “High Active” and “Average Active”. In sensitivity analysis, excluding deaths (n=3) within the first three years, showed that the profile “High Active” (HR 0.48, 95% CI 0.26-0.89, p=0.020) and “Average Active” (HR 0.55, 95% CI 0.33-0.93, p=0.026) was still significantly negatively associated with all-cause mortality, compared to the “Low Active” profile.
Discussion

In a national sample of adults, this study identified three distinct physical activity profiles derived from accelerometer data using latent profile analysis. The “High Active” profile, characterized by participants with high absolute and relative time spent in physical activity, and the “Average Active” profile, consisting of participants with average values for most of the activity variables, were negatively associated with all-cause mortality, compared to participants with high absolute and relative time spent in SB identified in the “Low Active” profile.

Previous findings from the same cohort as in this study have showed an inverse relationship between MVPA and mortality, and replacing SB with time spent in LIPA and MVPA has been found to have beneficial effect for all-cause mortality. This study adds to the existing literature by showing that multiple activity variables differ between physical activity profiles associating with different mortality risk. It also demonstrates considerably larger effect sizes than in previous reports on the same population. Even if this study cannot for sure identify which physical characteristics are most important for decreasing all-cause mortality, the correlation between the
characteristics suggest a complex interplay. For example, the correlation between z-scores of total time of sedentary bouts and time spent in LIPA, and between time spent in MVPA and relative time spent in SB, was -0.66 and -0.70, respectively, indicating that multiple physical characteristics are closely related.

The study also confirms previous findings that high time spent in MVPA,28,29 high time spent in LIPA,10,30 reduced time spent in SB31-33 and shorter time spent in sedentary bouts,34 are associated with lower risk of all-cause mortality. However, the latent profile analysis provides additional information of other physical characteristics’ importance for all-cause mortality. For example, comparison of the “Low Active” profile, which has the highest absolute and relative time in SB and highest proportion of events (20%), with the “Average Active” or the “High Active” profile, showed no difference in variation of SB across profiles. Consequently, the three profiles changed time spent in SB to a similar extent across the week they were followed. Even if the latent profile analysis cannot identify which of the 14 activity variables that is most important for all-cause mortality, our results indicate that all-cause mortality is not influenced by a high variation in SB as the three profiles showed similar pattern of variation in SB. On the contrary, very large effect sizes (>1.4) were observed for relative time spent in SB and MVPA between “Low Active” and “Average Active” profile, suggesting that the relative time spent in SB and MVPA may have greater impact on all-cause mortality since the effect size, comparing “Low Active” and “Average Active” profile, were greatest for these two measures.

Even if large effect sizes were observed for many of the activity variables, the mortality risk did not differ between “High Active” and “Average Active” profile. Accordingly, a participant, with high time spent in SB and little time spent in MVPA/LIPA, changing towards the “Average Active” profile, is likely associated with greater risk reduction in terms of mortality risk, compared to a participant shifting from the profile “Average Active” to “High Active”. This propose a potentially non-linear pattern between activity variables and all-cause mortality, in line with previous findings.5,35

Based on our findings, the important message is to promote relative time in MVPA and limit time spent in SB. Day-to-day variation in SB does not seem to affect mortality, instead it is more important to keep the overall time spent in SB low and replace this behaviour with time in LIPA or
MVPA. Still, we did not find any benefits on all-cause mortality, changing from “Average Active” towards the “High Active” profile, however, a “High Active” profile is likely associated with reduced risk of several diseases such as breast cancer, colon cancer, diabetes, ischemic heart disease, and ischemic stroke events.\textsuperscript{36}

The strength of this study is related to the prospective cohort design and the objectively measured physical activity in a large nationally representative sample with 15 years’ follow-up. Meaningfully interpretable physical activity profiles were derived from latent profile analysis based on 14 activity variables, including variables that acknowledged the compositional nature of time-use data.\textsuperscript{37} The study design allows direction of causality between physical activity profiles and all-cause mortality. Data on mortality and cause of death were collected from reliable register and no deaths were related to accidents. However, residual confounding may still exist, even though the analysis was adjusted for multiple covariates. In addition, participants with subclinical diseases may report low levels of physical activity and due to subclinical diseases have an increased mortality risk, that is not caused by physical activity levels. However, the sensitivity analysis, where deaths within the first three years were excluded, showed our findings to be robust which suggest that the impact of this bias from undiagnosed disease is relatively limited.\textsuperscript{38}

Despite the strengths of this study, this study has also several limitations. Physical activity was only assessed at baseline and therefore no data was collected on if any participants changed their behaviour over the course of the study period. However, a previous report on the same cohort, with six years follow-up, showed only small changes in physical activity composition.\textsuperscript{39} Multiple activity variables were used in latent profile analysis, however there are other potential variables (e.g. daily time of different behaviours in parts of the day, different lengths of bouts) that could have been derived from accelerometer data to describe the physical activity profiles. A larger sample size might have resulted in that a higher number of physical activity profiles could be identified. In addition, the accelerometers may undercount some activities important for health (e.g., bicycling, strength training, water-based activities). Only accelerometer data of awake time was explored and not for all 24 hours of a given day. Number of events were quite few compared to other population-based studies,\textsuperscript{39,40} and a higher number would have resulted in more accurate estimates of all-cause mortality across physical activity profiles. In addition, the covariates were self-reported, which may bias the estimates. Future studies should monitor time spent sleeping/in...
bed to capture all 24 hours of a day, explore other activity variables and monitor activities (e.g., bicycling) that is not captured well by accelerometers.

**PERSPECTIVE**

Across a day, individuals spend time in diverse activities, representing a wide range of physical activity profiles, associated to health and all-cause mortality. Based on a national sample of adults aged ≥ 50 years at 15 years follow-up, three distinct physical activity profiles derived from accelerometer data were identified, associating with different mortality risk. Adjusted for the covariates, the “High Active” and “Average Active” had a reduced hazard of all-cause mortality with 54%, 41%, respectively, compared to the “Low Active” profile. A potentially non-linear pattern between multiple activity variables and all-cause mortality was identified, where the greatest effect on all-cause mortality may be achieved for the participants that are most inactive. The important message is to keep the overall time spent in SB low and replace this behaviour with time in LIPA or MVPA.

**References**


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**Table 1.** Fit indices of the 2 to 5-profile latent models.

<table>
<thead>
<tr>
<th>Profiles</th>
<th>AIC</th>
<th>BIC</th>
<th>Probability minimum for profile membership</th>
<th>Entropy</th>
<th>Smallest group size</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>17116</td>
<td>17272</td>
<td>0.92</td>
<td>0.84</td>
<td>0.32</td>
</tr>
<tr>
<td>3</td>
<td>16188</td>
<td>16426</td>
<td>0.92</td>
<td>0.84</td>
<td>0.17</td>
</tr>
<tr>
<td>4</td>
<td>15517</td>
<td>15835</td>
<td>0.89</td>
<td>0.87</td>
<td>0.10</td>
</tr>
</tbody>
</table>
Table 2. Baseline characteristics of the study population by profile, with mean (SD) or number (%). Last three columns present effect sizes (Hedges’ g, Cramer’s V) for profile differences.

<table>
<thead>
<tr>
<th></th>
<th>Low Active (n=147)</th>
<th>Average Active (n=397)</th>
<th>High Active (n=307)</th>
<th>Low vs. Average Active effect size</th>
<th>Low vs. High Active effect size</th>
<th>Average vs. High Active effect size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female (%)</td>
<td>84 (57)</td>
<td>224 (56)</td>
<td>168 (55)</td>
<td>0.023</td>
<td>0.006</td>
<td>0.017</td>
</tr>
<tr>
<td>Age (SD)</td>
<td>58.1 (10.0)</td>
<td>52.5 (10.2)</td>
<td>50.5 (9.5)</td>
<td>0.783</td>
<td>0.554</td>
<td>0.197</td>
</tr>
<tr>
<td>BMI (SD)</td>
<td>27.0 (4.3)</td>
<td>25.6 (3.4)</td>
<td>24.9 (3.1)</td>
<td>0.578</td>
<td>0.378</td>
<td>0.196</td>
</tr>
<tr>
<td>Smoker (%)</td>
<td>53 (36)</td>
<td>103 (26)</td>
<td>71 (23)</td>
<td>0.136</td>
<td>0.101</td>
<td>0.031</td>
</tr>
<tr>
<td>Chronic disease (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Any</td>
<td>42 (29)</td>
<td>72 (18)</td>
<td>45 (15)</td>
<td>0.165&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.114&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.046&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>Hypertension</td>
<td>32 (27)</td>
<td>54 (16)</td>
<td>31 (12)</td>
<td>5 (2)</td>
<td>12 (5)</td>
<td></td>
</tr>
<tr>
<td>Heart disease</td>
<td>8 (7)</td>
<td>16 (5)</td>
<td>5 (2)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Diabetes</td>
<td>-</td>
<td>5 (1)</td>
<td>5 (2)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cancer</td>
<td>3 (3)</td>
<td>8 (2)</td>
<td>12 (5)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary school</td>
<td>56 (38)</td>
<td>91 (23)</td>
<td>77 (25)</td>
<td>0.140</td>
<td>0.164</td>
<td>0.036</td>
</tr>
<tr>
<td>High school</td>
<td>59 (40)</td>
<td>169 (43)</td>
<td>132 (43)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>University</td>
<td>32 (22)</td>
<td>136 (34)</td>
<td>95 (31)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deaths (%)</td>
<td>29 (20)</td>
<td>33 (8)</td>
<td>17 (6)</td>
<td>0.220</td>
<td>0.160</td>
<td>0.054</td>
</tr>
<tr>
<td>Days followed (SD)</td>
<td>5025 (873)</td>
<td>5193 (751)</td>
<td>5285 (509)</td>
<td>0.401</td>
<td>0.213</td>
<td>0.141</td>
</tr>
<tr>
<td>Accelerometer wear time, h/day (SD)</td>
<td>13.8 (1.5)</td>
<td>14.5 (1.2)</td>
<td>14.7 (1.3)</td>
<td>0.656</td>
<td>0.545</td>
<td>0.161</td>
</tr>
<tr>
<td>Days with accelerometer data (SD)</td>
<td>6.1 (1.4)</td>
<td>6.5 (0.9)</td>
<td>6.4 (1.1)</td>
<td>0.317</td>
<td>0.396</td>
<td>0.050</td>
</tr>
</tbody>
</table>

<sup>a</sup>Calculated for “any” category.
Table 3. Descriptive data (mean (SD)) for activity variables by profile. Last three columns present effect sizes (Hedges’ g) and p-value in parenthesis for differences between profiles. Bold numbers indicate large effect sizes (>0.80).

<table>
<thead>
<tr>
<th></th>
<th>Low Active (n=147)</th>
<th>Average Active (n=397)</th>
<th>High Active (n=307)</th>
<th>Low vs. Average Active</th>
<th>Low vs. High Active</th>
<th>Average vs. High Active</th>
</tr>
</thead>
<tbody>
<tr>
<td>SB min/day</td>
<td>618.1 (96.0)</td>
<td>539.4 (65.3)</td>
<td>447.6 (74.5)</td>
<td><strong>0.94</strong> (p &lt;10^{-15})</td>
<td><strong>3.48</strong> (p &lt;10^{-15})</td>
<td><strong>1.08</strong> (p &lt;10^{-15})</td>
</tr>
<tr>
<td>LIPA min/day</td>
<td>233.5 (73.4)</td>
<td>309.7 (59.3)</td>
<td>385.3 (82.6)</td>
<td><strong>0.91</strong> (p &lt;10^{-15})</td>
<td><strong>2.69</strong> (p &lt;10^{-15})</td>
<td><strong>0.90</strong> (p &lt;10^{-15})</td>
</tr>
<tr>
<td>MVPA min/day</td>
<td>7.2 (6.6)</td>
<td>23.9 (10.7)</td>
<td>48.2 (21.0)</td>
<td>0.78 (p &lt;10^{-15})</td>
<td><strong>4.01</strong> (p &lt;10^{-15})</td>
<td><strong>1.39</strong> (p &lt;10^{-15})</td>
</tr>
<tr>
<td>SB variation</td>
<td>90.1 (51.6)</td>
<td>93.2 (34.5)</td>
<td>95.4 (42.5)</td>
<td>0.01 (p=0.952)</td>
<td>0.04 (p=0.731)</td>
<td>0.03 (p=0.697)</td>
</tr>
<tr>
<td>LIPA variation</td>
<td>76.5 (43.8)</td>
<td>94.0 (42.9)</td>
<td>99.9 (51.7)</td>
<td>0.38 (p &lt;10^{-3})</td>
<td>0.51 (p &lt;10^{-3})</td>
<td>0.12 (p=0.115)</td>
</tr>
<tr>
<td>MVPA variation</td>
<td>6.1 (7.0)</td>
<td>16.7 (7.8)</td>
<td>27.5 (13.6)</td>
<td><strong>0.88</strong> (p &lt;10^{-15})</td>
<td><strong>2.77</strong> (p &lt;10^{-15})</td>
<td><strong>0.96</strong> (p &lt;10^{-15})</td>
</tr>
<tr>
<td>Total time of sedentary bouts min/day</td>
<td>235.7 (127.6)</td>
<td>157.8 (61.2)</td>
<td>102.6 (56.2)</td>
<td><strong>1.12</strong> (p &lt;10^{-15})</td>
<td><strong>2.33</strong> (p &lt;10^{-15})</td>
<td><strong>0.60</strong> (p &lt;10^{-15})</td>
</tr>
<tr>
<td>Number of sedentary bouts</td>
<td>4.6 (1.8)</td>
<td>3.1 (1.1)</td>
<td>2.1 (1.0)</td>
<td><strong>0.99</strong> (p &lt;10^{-15})</td>
<td><strong>2.41</strong> (p &lt;10^{-15})</td>
<td><strong>2.01</strong> (p &lt;10^{-15})</td>
</tr>
<tr>
<td>Total time of MVPA bouts min/day</td>
<td>1.4 (3.5)</td>
<td>8.0 (8.5)</td>
<td>19.0 (15.7)</td>
<td>0.57 (p &lt;10^{-10})</td>
<td><strong>1.96</strong> (p &lt;10^{-15})</td>
<td><strong>0.99</strong> (p &lt;10^{-15})</td>
</tr>
<tr>
<td>Number of MVPA bouts</td>
<td>0.1 (0.2)</td>
<td>0.4 (0.4)</td>
<td>1.0 (0.8)</td>
<td>0.52 (p &lt;10^{-10})</td>
<td><strong>1.68</strong> (p &lt;10^{-15})</td>
<td><strong>0.87</strong> (p&lt;10^{-15})</td>
</tr>
<tr>
<td>Total counts</td>
<td>133911.5 (47988.3)</td>
<td>249352.6 (51686.6)</td>
<td>401495.1 (99437.8)</td>
<td><strong>0.97</strong> (p &lt;10^{-15})</td>
<td><strong>2.00</strong> (p &lt;10^{-15})</td>
<td><strong>1.58</strong> (p &lt;10^{-15})</td>
</tr>
<tr>
<td>Relative time SB</td>
<td>2.5 (0.8)</td>
<td>1.5 (0.2)</td>
<td>1.0 (0.2)</td>
<td><strong>1.93</strong> (p &lt;10^{-15})</td>
<td><strong>5.57</strong> (p &lt;10^{-15})</td>
<td><strong>0.92</strong> (p &lt;10^{-15})</td>
</tr>
<tr>
<td>Relative time LIPA</td>
<td>1.2 (0.5)</td>
<td>0.8 (0.3)</td>
<td>0.8 (0.3)</td>
<td><strong>0.91</strong> (p &lt;10^{-15})</td>
<td><strong>1.03</strong> (p &lt;10^{-15})</td>
<td><strong>0.09</strong> (p=0.198)</td>
</tr>
<tr>
<td>Relative time MVPA</td>
<td>-3.7 (1.1)</td>
<td>-2.4 (0.4)</td>
<td>-1.8 (0.4)</td>
<td><strong>1.85</strong> (p &lt;10^{-15})</td>
<td><strong>2.13</strong> (p &lt;10^{-15})</td>
<td><strong>0.68</strong> (p &lt;10^{-15})</td>
</tr>
</tbody>
</table>

LIPA, light intensity physical activity; MVPA, moderate-to-vigorous physical activity; SB, sedentary behaviour.
Figure legends

Figure 1. z-Values for different physical activity profiles. LIPA, light intensity physical activity; MVPA, moderate-to-vigorous physical activity; SB, sedentary behaviour.

Figure 2. Odds ratio with error bars (95% CI) for all-cause mortality for the profiles “High Active” and “Average Active”, compared to the “Low Active” profile, in fully adjusted cox regression model (adjusted for sex, education, self-rated health, smoking, hypertension, heart disease, cancer, diabetes and stratification by age tertiles). Model I includes all observations and in model II deaths within the first three years were excluded. Dashed reference line marks no difference in all-cause mortality between groups.