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# The association between well-being and a large variation of accelerometer-assessed physical activity and sedentary behavior measures☆

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ABSTRACT

Higher well-being has been associated with more physical activity (PA) and less sedentary behavior (SB), both when assessed by self-report or accelerometers. Most studies using accelerometer data only examined estimates of total volume or daily average of PA/SB in relation to well-being. Taking into account the richness of accelerometer data, we investigated the association of different measures of SB, light PA (LPA) and moderate-to-vigorous PA (MVPA) and well-being including the combined effect and the PA/SB timing and patterns. We explored whether results differed between occupational and non-occupational time.

In an adult sample (n = 660, $M_{age}$: 30.4, $SD$ = 8.1, 74.5% female), we applied pre-registered analyses. First, we created different global scores of SB, LPA and MVPA based on 4 to 7-days of Actigraph data and investigated associations with well-being, i.e., defined as life satisfaction. These analyses were done using raw scores and transformed scores using compositional data analysis. Next, we applied multilevel models including time of the day and well-being as predictors of PA/SB. Finally, we clustered participants based on PA/SB intensity, timing and accumulation and explored differences in well-being across clusters.

In total wear time, there were no associations between different measures of SB/LPA/MVPA and well-being. Restricting to non-occupational wear time, less total SB and more total LPA were associated with higher well-being, both in absolute and relative sense. Well-being was not associated with the PA/SB timing or patterns. In conclusion, beyond the association between total non-occupational SB and LPA and well-being, the PA/SB timing or patterns had no added value in explaining the association between PA/SB and well-being.

## 1. Background

On average, higher levels of well-being have been associated with more time spent being physically active, and less time spent in sedentary behavior (Pengpid & Peltzer, 2019; Richards et al., 2015; Zhang & Chen, 2019). Well-being can be defined as high levels of positive affect, low levels of negative affect, and a positive subjective evaluation of life satisfaction (i.e, subjective well-being, Diener et al., 2018) or as thriving, positive functioning, and judgments about the meaning and purpose of an individual's life (i.e., psychological well-being, Ryff, 1989). Physical activity (PA) can be defined as "any bodily movement produced by the skeletal muscle that results in energy expenditure" (Caspersen et al., 1985). Based on the intensity of PA, a distinction between light PA (LPA) and moderate to vigorous PA (MVPA) is often made. LPA includes activities such as light walking, gardening or household activities, whereas MVPA includes for example brisk walking, running, or heavy lifting. Sedentary behavior (SB) can be defined as "any waking behavior characterized by an energy expenditure of less than 1.5 metabolic equivalents (METs), either in a sitting, reclining or lying posture" (Tremblay et al., 2017). Sedentary activities include watching television or sitting in a chair. SB is not simply the lack of PA and is often reported to be independent of (moderate-to-vigorous) PA (Hamilton et al., 2008; Owen et al., 2010). Therefore, the associations between SB, LPA or MVPA and well-being may differ.

☆ The corresponding author confirms that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted. All authors read and approved the final manuscript.

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A recent meta-analysis reported a positive association between self-reported PA and well-being overall (Cohen's $d = 0.36$). The intensity of PA (i.e., light, moderate, vigorous) or exercise type (i.e., aerobic vs non-aerobic) did not moderate this relation. Furthermore, when only including experimental studies that directly manipulated MVPA, the meta-analysis showed a small positive effect of MVPA on well-being (Buecker et al., 2020). Regarding SB, a recent review on the relation between different indices of SB (i.e., device-measured, self-report or screen time) and well-being reported inconsistent associations (Sui et al., 2021). Based on self-report, the associations were mixed and dependent of the SB measure. Based on a limited number of device-based SB measures, SB was either negatively or not significantly associated with well-being. Larger systematic reviews and meta-analyses reported positive associations between self-reported SB and the risk of depression (Rodriguez-Ayllon et al., 2019; Teychenne et al., 2010). As depression is strongly associated with well-being (Baselmans et al., 2018; Greenspoon & Saklofske, 2001; Koivumaa-Honkanen et al., 2004), these findings suggest that SB could be negatively associated with well-being as well.

In the above-mentioned meta-analyses and reviews, the included studies mostly used self-reports to assess PA. Using self-reports, participants typically report their daily or weekly PA or SB, e.g., sitting or watching television. However, PA and SB can also be assessed more directly, for example using accelerometers. Participants wear an accelerometer on their hip or wrist that continuously records movement for a number of days and measures of PA and SB are extracted from the raw data. Correlations between self-report and direct measures of PA are mostly low-to-moderate (Prince et al., 2008). Direct measures of PA and SB are believed to result in more precise estimates as recall or social desirability biases are avoided. However, accelerometer data only give an estimation of movement and is less accurate in for example identifying posture, i.e., sitting or standing (but see Grant et al., 2006).

An advantage of accelerometer data is the richness of the available data, since data are collected continuously. Until recently, many studies using accelerometer data included only the total activity count or average daily time engaged in SB or a specific PA intensity. Recently, focus has shifted towards investigating more detailed aspects and the daily or weekly patterns of PA and SB instead of total volumes. For example, investigating the association between well-being and SB/PA in different day segments (morning, afternoon, evening) can lead to information on when people are engaging in more or less PA and SB during the day and how this timing affects well-being. Furthermore, the same total time in PA or SB may be accumulated in different patterns (Chinapaw et al., 2019). For example, if someone walks for an hour and another person walks 6 times per day for 10 min, they have the same total time of walking, but the accumulation over the day differs considerably. Moreover, the combination of different intensities of PA and SB could lead to different results. Thus, accumulation patterns of PA and SB jointly could be more predictive of (mental) health and well-being outcomes than total PA/SB time separately.

In addition, combining accelerometer data with daily diaries, it is possible to make a distinction between PA and SB during work hours, i.e., occupational time and during non-occupational time. Non-occupational PA/SB includes PA/SB during leisure time, transport, household activities and education. A recent meta-analysis summarized the associations between PA in the different domains and mental (ill-) health and suggests slightly different associations between well-being and occupational versus non-occupational PA (White et al., 2017). PA during leisure time or transport was significantly associated with better mental health ($r = 0.13$, 95%CI: 0.08-0.18 and $r = 0.13$, 95%CI: 0.02-0.23), while occupational PA was associated with ill-health (i.e., symptoms of depression or anxiety) ($r = 0.09$, 95%CI: 0.03-0.15) (White et al., 2017). However, all associations were small and based on self-reported PA.

In the current study, we investigated the association between different measures of SB, LPA and MVPA and well-being (i.e., defined as life satisfaction) going beyond simple averages. More specifically, in a 4-step approach, we first investigated the association of well-being with the different well-known summary measures. Next, we investigated if the timing of SB or PA is related to well-being. Third, we clustered participants based on the timing and amount of SB or PA and compared the well-being of the different clusters. Finally, we clustered participants based on both SB and PA behaviors and compared the clusters on well-being (see Table 1). For all research questions, we explored whether results differed between occupational and non-occupational PA and SB.

## 2. Method

### 2.1. Sample

Participants were voluntary members of the Netherlands Twin Register (NTR). The NTR was established by the Department of Biological Psychology, Vrije Universiteit Amsterdam more than 30 years ago (Ligthart et al., 2019). Every two/three years, longitudinal survey data about lifestyle, personality, psychopathology, and well-being in twins and their families are collected. The NTR sample is a population-wide, non-clinical sample.

Accelerometer data were collected in three separate studies (n total = 800), (1) a study in 2013 on the determinants of voluntary PA in 98 participants, i.e., young adult monozygotic twins discordant for PA, (2) a study in 2014–2015 in 30 participants, i.e., female monozygotic twins discordant for body mass index (BMI), and (3) a study on the heritability of SB that ran in 2016–2017 in 672 participants, both twins and non-twin siblings. Accelerometer data were collected using the same protocol in the three studies with the same instructions for every participant (for more details see Schutte et al., 2020).

Well-being data were collected in various survey waves of the NTR preceding or during the accelerometer studies. For every participant, if multiple well-being scores were available, we included the well-being score closest in time to the accelerometer data collection.

We only included participants for who the well-being and accelerometer data was collected within maximally 5 years of each other. In the final sample ($n = 660$), the average length between the measurements was 2.2 years (range: −0.4 to +4.9 years), with well-being assessed mostly before the accelerometer data. In a sensitivity analysis, including time between the measurements as covariate, we found that the time between the well-being and accelerometer measurements did not affect the results (see Supplementary Table S1).

Participants ($n = 660$) were on average 30.4 years old ($SD = 8.2$, range = 18–65). The number of participants in the different analyses differed due to availability of the required data. For example, not all participants completed a daily dairy indicating their working hours. Therefore, we had to exclude these participants from the occupational and non-occupational time analyses, leaving 553 participants.

The data collection was approved and declared to be of low risk and exempt of formal medical ethical risk assessment by the METc of the Vrije Universiteit Medical Center Amsterdam and performed in accordance with the Declaration of Helsinki. All participants provided written informed consent.

### 2.2. Measures

#### 2.2.1. Accelerometer data

Participants were instructed to wear an Actigraph accelerometer (Actigraph GT3X+, Actigraph LLC) attached to an elastic belt on the right hip during waking hours for 7 consecutive days, except during water-based activities. Count data were processed and statistics were computed using the Actilife software (version 6.10.4). We used the Actigraph activity count data of the vertical axis. The raw data was converted into 60-s epoch data. Non-wear time was excluded and defined as zero counts during an uninterrupted time of at least 60 min with allowance of 2 min with counts between 0 and 100 within that time

**Table 1**
Overview of the different analyses.

| Part | Research question | | Analysis | Accelerometer measure | | Result |
|---|---|---|---|---|---|---|
| 1 | Is WB associated with the (relative) time spent in.. | SB? | Regression well-being on average SB/PA measures | Percentage of total time in | SB | Non-working days: ↑ WB →↓ SB |
| | | LPA? | | | LPA | Non-working days: ↑ WB →↑ LPA |
| | | MVPA? | | | MVPA | - |
| | Is WB associated with the average bout length of.. | SB? | | Mean length of bouts of | SB | - |
| | | LPA? | | | LPA | - |
| | | MVPA? | | | MVPA | - |
| | Is WB associated with the time spent in bouts of.. | SB? | | Percentage of total time in bouts of | SB | Non-working days: ↑ WB →↓ SB |
| | | LPA? | | | LPA | Non-working days: ↑ WB →↑ LPA |
| | | MVPA? | | | MVPA | - |
| | Is WB associated with the fragmentation of.. | SB? | | Fragmentation of | SB | - |
| | | LPA? | | | LPA | - |
| | | MVPA? | | | MVPA | - |
| 2 | Is WB associated with the timing of.. | SB? | Multilevel model including well-being and day segments (*morning, afternoon and evening*) predicting SB/PA measures | Per day segment, percentage of total time in | SB | *↑ WB → ↓ SB in evening* |
| | | LPA? | | | LPA | *↑ WB → ↑ LPA in evening* |
| | | MVPA? | | | MVPA | - |
| | Is WB associated with the timing of.. | SB bouts? | | Per day segment, percentage of time in bouts of | SB | *↑ WB → ↓ SB in evening* |
| | | LPA bouts? | | | LPA | *↑ WB → ↑ LPA in evening* |
| | | MVPA bouts? | | | MVPA | - |
| 3 | Do participants in the different SB clusters differ on WB? | | Comparing different SB or PA clusters on well-being | Cluster on amount and timing of | SB | |
| | Do participants in the different LPA clusters differ on WB? | | | | LPA | *Non-working days: ↑ WB →↑ LPA* |
| | Do participants in the different MVPA clusters differ on WB? | | | | MVPA | - |
| 4 | Do participants in the different clusters differ on WB? | | Comparing different clusters on well-being | Cluster on intensity and timing of SB and PA | | - |

***Note***: SB= Sedentary behavior, LPA= light physical activity, MVPA= moderate-vigorous physical activity, WB = well-being.

range. Wear time was considered acceptable when there was a minimum of 4 days of 10 h of wear time per day.

Standard cut-points were used to define SB (<100 counts/min), light (100-<2020 counts/min), moderate (2020–5998 counts/min), and vigorous (>5999 counts/min) intensity PA (Troiano et al., 2008). Moderate and vigorous intensity PA were combined in a MVPA category. Below we describe the various metrics of SB, LPA and MVPA extracted from the accelerometer data.

During the accelerometer data collection, participants were asked to indicate (using a paper-pencil diary) each day whether it was a workday or not and if so, the start and end time. These time-points were used to classify SB/LPA/MVPA in occupational time and non-occupational time. Furthermore, we classified days on which participants worked part of the day as working days, and days on which participants did not work as non-working days. On average, the participants indicated 4.2 working days ($SD$ = 1.7, range = 0–8) and 3.0 ($SD$ = 1.2, range = 1–7) non-working days.

### 2.2.2. Well-being

Well-being was assessed with the Satisfaction with Life scale (Diener et al., 1985). This scale consists of five items with a 7-point Likert scale, ranging from 1 = *strongly disagree* to 7 = *strongly agree*. An example question is '*In most ways my life is close to ideal*'. Items were summed to calculate a score ranging from 0 to 35, with higher scores indicating higher levels of satisfaction with life.

### 2.2.3. Covariates

Body Mass Index (BMI) and educational attainment (EA) were included as covariates as both are associated with PA, SB, and well-being (Beenackers et al., 2012; Cooper et al., 2000; Gidlow et al., 2006; Hemmingsson & Ekelund, 2007). BMI was calculated for every participant by dividing the self-reported weight by the squared self-reported height, i.e., BMI = $kg/m^2$.

Educational attainments was enquired with the question "What is the highest educational level you have completed?". The educational attainment variable was recoded in four categories: primary education only (1), lower vocational school and lower secondary school (2), intermediate vocational school and intermediate or higher secondary school (3) and higher vocational school and university (4).

## 2.3. Statistical analyses

This study was a secondary data analysis of previously collected data in the Netherlands Twin Register. The analyses were pre-registered before data analysis at https://osf.io/rxafd. We created different indicators of SB, LPA and MVPA and divided the analyses in four different parts (see Table 1 for an overview).

We used a significance threshold that is corrected for multiple testing using a Bonferroni correction. The number of main tests is 66 ((12 (summary)+6 (multilevel)+3 (cluster 1)+1 (cluster 2)) x3 (total wear time, occupational and non-occupational). Therefore, the threshold of significance is $p$ = .05/66 = .00076.

### 2.3.1. Part 1: Summary scores

Summarizing all accelerometer data per participant, we computed four different summary scores of SB, LPA and MVPA.

First, we computed the total time of SB/LPA/MVPA as the percentage of total wear time for each participant.

Second, we calculated the average length of bouts in which SB/LPA/MVPA were accumulated. A bout of SB and LPA was defined as at least 10 consecutive minutes and a bout of MVPA was defined as at least 5 consecutive minutes followed by a different intensity (Chinapaw et al., 2019).

Third, we calculated the percentage of the total time spent in SB/LPA/MVPA bouts, using the above definition of a bout.

Fourth, we computed the fragmentation index of SB/LPA/MVPA, by dividing the number of bouts by the total SB/LPA/MVPA time. A higher number reflects more fragmentation of that particular intensity (Chastin & Granat, 2010).

Using Generalized Estimating Equation (GEE) (Minică et al., 2015) to correct for familial relatedness, well-being was associated with the four summary scores, adjusting for covariates, i.e., sex, age, BMI and educational attainment.

**Occupational vs non-occupational time.** Next, we computed the four different summary measures for participants that categorized their accelerometer wear time in occupational and non-occupational time (n = 553) and repeated the GEE analyses separately for occupational and non-occupational time.

**Compositional data analysis.** As exploratory (not-preregistered) analysis, we redid the GEE analyses according to compositional data analysis procedures to explore the combined effects of SB and PA. Accelerometer data is compositional by nature, since the different behaviours add up to the total accelerometer wear time. We created three sets of two isometric log-ratio (ilr) partitions of SB, LPA, and MVPA (Dumuid et al., 2020). The first ilr predictor of each set reflects one activity relative to the other two activities, i.e., SB relative to LPA and MVPA, LPA relative to SB and MVPA, and MVPA relative to SB and LPA. The second ilr predictor of each set reflects then the ratio of the other activities in the denominator of $ilr_1$, i.e., respectively LPA relative to MVPA, SB relative to MVPA, and SB relative to LPA. See the equations for $ilr_1$ and $ilr_2$ below for the computation for one set of predictors.

$$ilr_1 = \sqrt{\frac{2}{3}}\ln\left(\frac{SB}{\sqrt[2]{LPA*MVPA}}\right)$$

$$ilr_2 = \sqrt{\frac{1}{2}}\ln\left(\frac{LPA}{MVPA}\right)$$

Next, in three separate models, we included the set of composition predictors, i.e., $ilr_1$ and $ilr_2$ in the models to predict well-being, adjusting for covariates, i.e., sex, age, BMI and educational attainment.

#### 2.3.2. *Part 2: Time of the day*

In part 2, we investigated the patterns of SB, LPA and MVPA over the day in relation to well-being. We divided the day in three segments (morning: 7:00–12:59/midday: 13:00–17:59/evening: 18:00–23:00) to investigate if well-being is differently associated with SB/LPA/MVPA in different day segments. We applied a multilevel model where the day segments (level 1: morning/afternoon/evening) were clustered in participants (level 2) and participants in families (level 3). Participants were clustered in families, since the sample consists of twins and siblings.

The model included a level 1 fixed effect of day segment and we adjusted for the covariates at level 2. Relevant to the research question, fixed effects of well-being at level 2 and the cross-level interaction of day segment and well-being were included. We tested these effects separately for the average time in SB/LPA/MVPA and percentage time in bouts of SB/LPA/MVPA, resulting in 6 models.

**Workdays vs non-work days.** We repeated the above analyses for non-work days and workdays. In contrast to the summary scores for which we could split the total wear time directly into occupational and non-occupational time, note that non-work days are completely non-occupational time, whereas work days include both occupational time and non-occupational time.

#### 2.3.3. *Part 3: Clustering based on SB, LPA or MVPA*

To investigate in more detail if the patterns of SB, LPA or MVPA over the day is associated with well-being, we clustered participants based on these patterns and compared the well-being scores of the participants in the different clusters. We applied the two-phase clustering procedure of Reuter et al. (2020) separately per activity intensity, i.e., SB, LPA and MVPA. Participants are clustered on both the timing and duration of either SB, LPA or MVPA in two phases. In short, in phase 1, all days across all participants ($n_{days} = 4189$) are clustered based on similarities in within-day timing, i.e., the trajectories. In phase 2, participants ($n_{individuals} = 660$) are clustered on similarities in their between-day patterns, based on the proportion of their day trajectories of phase 1(see Fig. 1).

##### 2.3.3.1. *Phase 1.*

To be able to cluster day trajectories, the SB/LPA/MVPA minutes of each 1-h interval were summed per day. Then, we clustered all available days of the entire sample ($n_{days} = 4189$) based on similarities in the timing of SB/LPA/MVPA during the day using a cluster technique for longitudinal data, longitudinal k-means (*kml* function in R) (Genolini & Falissard, 2011) (see upper panel Fig. 1). Based on the convergence of the Calinski-Harabasz criteria and other criteria computed by the *kml* function (i.e. Ray & Turi and Davies & Bouldin criteria), the optimal number of clusters with different SB/LPA/MVPA trajectories was selected. The upper right panel of Fig. 1 shows examples of possible day trajectories.

##### 2.3.3.2. *Phase 2.*

In phase 2, the participants were clustered based on similarities in their between-day patterns, i.e., the proportion of the different phase 1 day trajectories (see lower panel of Fig. 1). For every participant, the number of days in each identified trajectory were summed. Since participants did not have an equal number of days, the proportion of days assigned to each trajectory was computed by dividing the number of the days per trajectory by the total number of days. For example, if the phase 1 results in four different day trajectories (i.e., A, B, C and D), the 7-day data for a participant might be ABACBAA, and this participant has 4 A days, 2 B days, 1 C day and no D days. This would result in: proportion A = 4/7, B = 2/7, C = 1/7 and D = 0/7. Next, using hierarchical clustering (*hclust* function in R), participants were clustered on the similarities of these proportions. The silhouette criterium was used to select the optimal number of clusters based on the maximum average silhouette width across observations (Maechler et al., 2019). The clusters will differ on the proportions and mixture of day trajectories (see Fig. 1 for an example). We compared the well-being scores of the participants in the different clusters.

**Workdays vs non-workdays.** We repeated the clustering analyses separately for non-work days and workdays. Since there were only a few workdays or non-workdays per participant, we did not apply the two-phase clustering, but we directly clustered participants based on their minutes of SB/LPA/MVPA per hour across the days.

For this analysis, participants needed to have a similar amount of accelerometer data. Participants varied in their number of working and non-working days, i.e., some participants worked 5 from the 7 days, whereas others worked less days or not at all. To create an as large as possible sample and similar amounts of data per participant, we included the first 4 or 5 working days or 2 non-working days per participant out of the maximum of 7 days. We then used dynamic time warping (DTW: R package *dtw* (Giorgino, 2009)) and hierarchical cluster analysis (function *hclust*) to cluster participants based on the similarities in the trajectories of SB/LPA/MVPA over the days. DTW tries to find trajectories, i.e., the underlying similarities, in temporal data. These sequences are allowed to vary in speed or length. Note that work days both include occupational time and non-occupational time, whereas non-work days only includes non-occupational time.

#### 2.3.4. *Part 4: Clustering based on sequence maps*

Lastly, we clustered the participants based on sequence maps of intensity and duration of SB and PA combined, using the methods and R functions of Chinapaw et al. (2019). Based on epochs of 60 s, we converted the accelerometer counts over all valid days into one sequence map per participant. This sequence map is based on a combination of intensity (from SB to VPA) and the duration of the intensity (shorter or longer bouts), resulting in 12 different states and a sequence of numbers

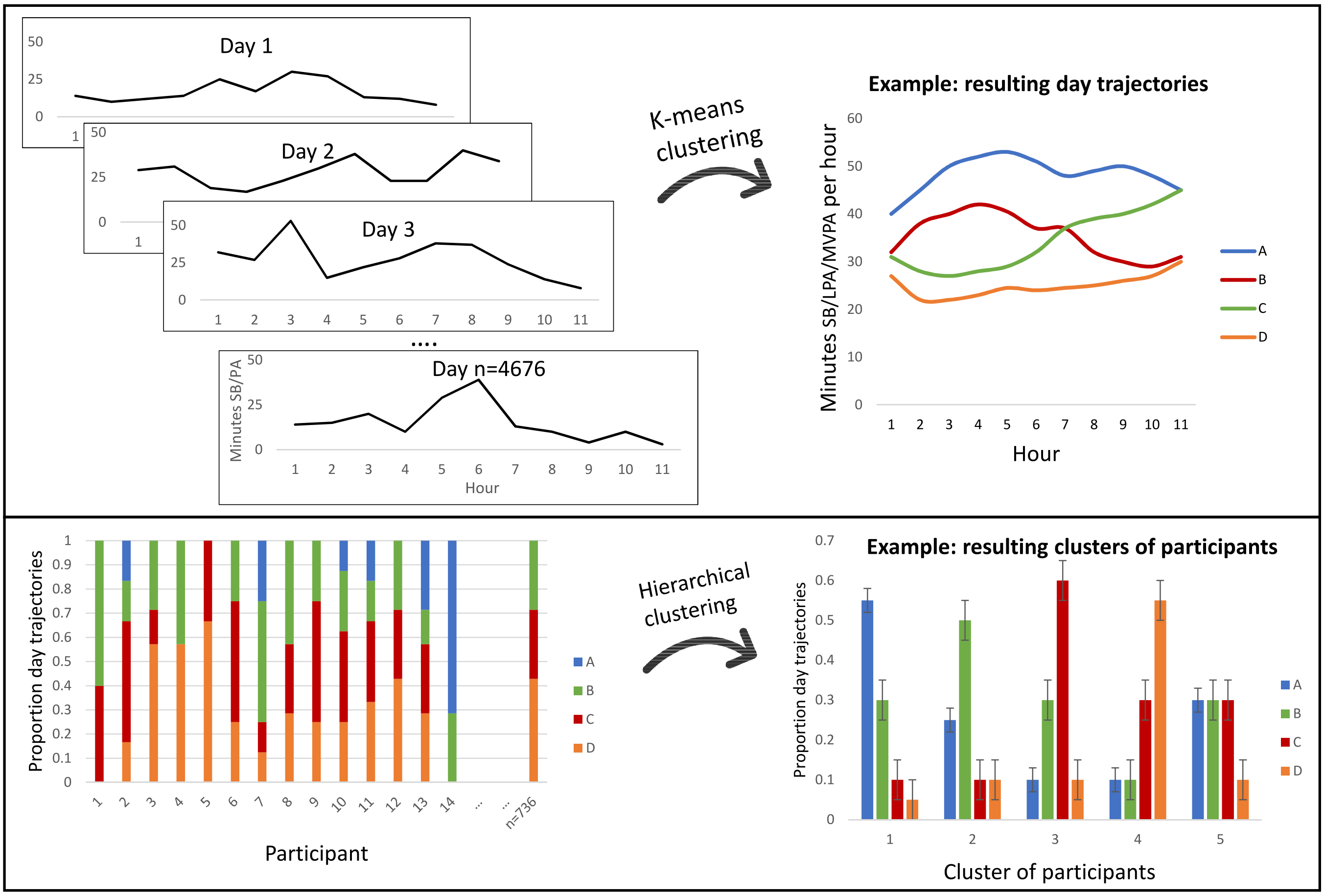


**Fig. 1.** "Steps and example of the two-phase clustering of participants based on SB, LPA or MVPA across the day". The upper panel shows phase 1, in which days are clustered based on similarities in within-day timing, i.e., the trajectories. The lower panel shows phase 2, in which participants are clustered based on the proportion of the phase 1 day trajectories in their data. In this example, the clustering results in four different day trajectories in phase 1 with a different amount and timing of SB/LPA/MVPA. Note that the best fitting number of clusters can also be only 2 day trajectories or any other number of trajectories. In this example, phase 2 clustering results in five clusters of participants with different proportions and mixture of A, B, C or D days. Note that the best fitting number of clusters can be any number of clusters of participants.

between 1 and 12. A bout of at least 30 min in SB, i.e., the lowest intensity, is classified as 1, 10–29.9 min SB is classified as 2, less than 10 min SB as 3. The states of PA behaviours start with 4, indicating less than 10 min of LPA, up to 12, i.e., the state with the highest intensity (VPA) and longest duration (bout of at least 10 min) (see Supplementary Table S2 for the rest of the states).

Next, dynamic time warping (DTW: Rpackage *dtw* (Giorgino, 2009)) and hierarchical cluster analysis (function *hclust*) were applied to identify clusters of participants with similar behavioral sequence maps. DTW tries to find the underlying similarities in temporal sequences, and these sequences can vary in length. The silhouette index was used to determine the optimal number of clusters. We compared the well-being scores

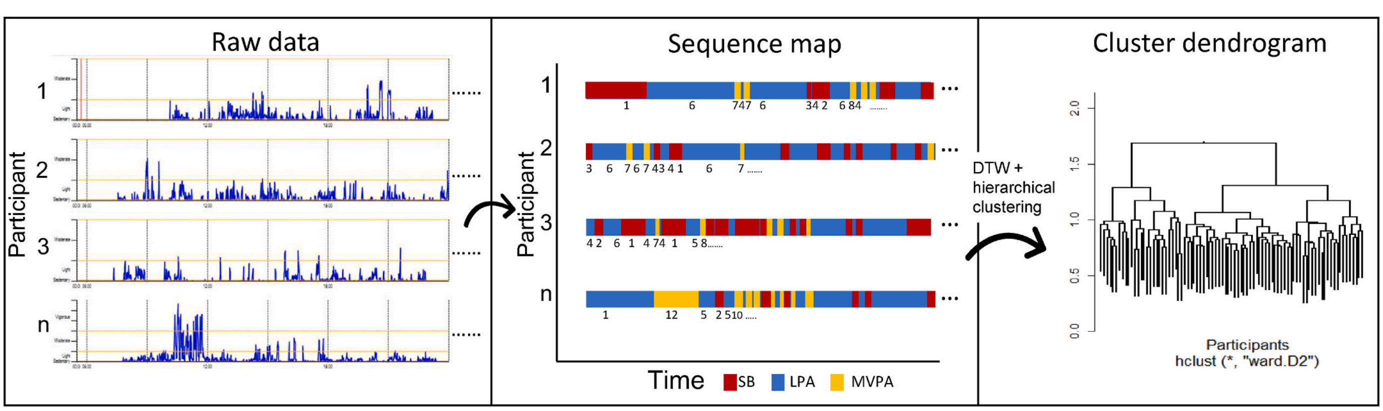


**Fig. 2.** "Visualization of the sequence mapping and clustering". First, the raw data is converted in a sequence of states, i.e., numbers between 1 and 12 reflecting the intensity and duration of activity (middle panel, see Supplementary Table S2 for the states linked to the numbers). Using dynamic time warping (DTW) and hierarchical clustering, participants with similar sequence maps are then clustered in groups. In this example, two clusters of participants are found based on the sequence maps (right panel).

of the participants in the different clusters to investigate the relation between well-being and the joint accumulation of SB and PA (see Fig. 2 for a visualization of the analysis).

**Workdays vs non-workdays.** We created the sequence maps separately for non-work days and work days and repeated the clustering analyses.

## 3. Results

### 3.1. Descriptives

The sample included 660 participants, with a mean age of 30.4 (*SD* = 8.1), range 18–65 years, 74.5% female. See Table 2 for more descriptive statistics.

### 3.2. Part 1. Summary measures

The left panel of Fig. 3 presents the results of the GEE analyses relating the different metrics of SB, LPA and MVPA to well-being. Controlling for the covariates, i.e., sex, age, BMI and educational attainment, none of the summary measures of SB, LPA and MVPA were associated with well-being.

**Occupational time vs non-occupational time.** During occupational time, the associations between SB/LPA/MVPA and well-being did not reach significance (see Supplementary Table S3 for all estimates).

During non-occupational time, time spent in SB (bouts) ($\beta = -0.12$, 95%CI = −0.21 to −0.04 and $\beta = -0.12$, 95%CI = −0.20 to −0.04, $p <$ .001) and time spent in LPA (bouts) ($\beta = 0.13$, 95%CI = 0.07–0.21 and $\beta$ = 0.16, 95%CI = 0.09–0.23, $p <$ .001) was significantly associated with respectively lower and higher levels of well-being (see Fig. 3, right panel). This standardized effect indicates that a standard deviation increase in SB or LPA is associated with 0.12 SD decrease and 0.13 SD increase in well-being respectively. The associations between MVPA and well-being were not significant (see Supplementary Table S4 for all estimates).

**Compositional data analysis.** The exploratory compositional data analysis showed that when total wear time and occupational time were analysed, none of the compositional predictors were associated with well-being (see Supplementary Table S5 for the results). In non-occupational time, replacing LPA or MVPA with SB will lead to a decrease in well-being (ilr$_1$: $\beta$ = -0.56, *SE* = 0.16, $p$ = .001). Indicating that the association with well-being is strongest for the ratio of SB over LPA instead of the ratio of SB over MVPA, the separate substitutions indicated that replacing SB with LPA in non-occupational accelerometer time is associated with an increase in well-being (ilr$_2$: $\beta$ = 0.67, *SE* = 0.19, $p = 4.4\text{x}10^{-4}$), whereas replacing SB with MVPA has no significant effect (ilr$_2$: $\beta$ = 0.30, *SE* = 0.10, $p$ = .004).

**Table 2**
Descriptives of the sample.

| Demographics (n = 660) | Mean (SD) or % | Range |
|---|---|---|
| Age | 30.4 (8.2) | 18–65 |
| Sex (% female) | 74.5% | |
| BMI | 23.2 (3.4) kg/m$^2$ | 16.8–45.4 |
| Well-being | 27.3 (5.0) | 7–35 |
| Educational attainment (%) | | |
| *Lower* | 3% | |
| *Intermediate* | 21% | |
| *Higher* | 59% | |
| *Unknown* | 17% | |
| **Accelerometer metrics (n=660)** | **Mean (SD)** | **Range** |
| Valid days | 7.3 (0.9) | 4–8 |
| Total wear time (minutes/day) | 870 (58) | 686–1135 |
| % SB | 66% (8%) | 34%–86% |
| % LPA | 31% (8%) | 14%–62% |
| % MVPA | 3.3% (2.0%) | 0%–16% |
| Average length SB bout | 24.8 min (3.5) | 17–41.6 |
| Average length LPA bout | 15.3 min (2.5) | 10.3–51.5 |
| Average length MVPA bout | 9.7 min (4.9) | 0.0–42.6 |
| Fragmentation SB | 0.03 (0.00) | 0.02–0.04 |
| Fragmentation LPA | 0.02 (0.01) | 0.00–0.04 |
| Fragmentation MVPA | 0.05 (0.02) | 0.00–0.12 |
| % in SB bouts | 53% (11%) | 13%–81% |
| % in LPA bouts | 12% (7%) | 1%–54% |
| % in MVPA bouts | 1.8% (1.6%) | 0%–13% |

### 3.3. Part 2. Time of the day

Allowing the association of PA/SB with well-being to vary over the day, the multilevel models of total wear time resulted in no main effects of well-being for the time spent in SB, LPA and MVPA and no interaction between well-being and time of the day (see Fig. 4, left panel). The analyses of time spent in SB/LPA/MVPA bouts resulted in similar results (see Supplementary Table S6).

#### 3.3.1. Workdays and non-workdays

When only including workdays, there was no main effect of well-being and no significant interaction effects between well-being and time of the day. However, the direction of the interaction effect between well-being and SB during the evening ($\beta = -0.12$, 95%CI = −0.20 to −0.03, $p$ = .009) and LPA ($\beta$ = 0.12, 95%CI = 0.03-0.20, $p$ = .011) suggests that higher well-being could be associated with less SB and more LPA during the evening (see Fig. 4, middle panel and Supplementary Table S7).

When only including non-working days, there was no interaction effect between well-being and the time of the day and no significant main effects of well-being. However, the direction of the main effect of well-being suggest that less time in SB ($\beta = -0.08$, 95%CI = −0.14 to −0.02, $p$ = .062) and more time in LPA ($\beta$ = 0.10, 95%CI = 0.02- 0.17, $p$ = .009) could be associated with higher well-being (see Fig. 4 right panel and Supplementary Table S7).

### 3.4. Part 3: Clustering based on SB, LPA or MVPA

**SB.** In phase 1, the clustering of days based on the timing and level of SB resulted in two trajectories. Days with trajectory A were characterized by higher SB levels across the day, whereas days with trajectory B were characterized by lower SB levels across the day (see Fig. 5, top left panel). In phase 2, based on the proportion of A and B trajectories in the data of the participants, participants were clustered in 2 clusters. Participants in cluster 1 (n = 411) had on average more high sedentary days (77%) compared to participants in cluster 2 (n = 249; 21%) (see Fig. 5, top panels). The well-being of participants in the different clusters did not differ (see Table 3).

**LPA.** In phase 1, the clustering based on LPA resulted in two trajectories. Days with trajectory A were characterized by a lower level of LPA across the day, whereas days with trajectory B were characterized by more LPA throughout the day (see Fig. 5, middle left panel). In phase 2, participants were grouped in 2 clusters. Participants in cluster 1 (n = 411) had on average more LPA days (79%) compared to participants in cluster 2 (n = 249; 21%). The well-being of participants in the different clusters did not differ (see Table 3).

**MVPA.** In phase 1, the clustering based on MVPA resulted in three trajectories of MVPA across the day. Days with trajectory A were characterized by a low level of MVPA across the day, whereas days with trajectory B were characterized by a higher level of MVPA in the afternoon, i.e., "MVPA afternoon days" and days with trajectory C by a higher level of MVPA in the morning, i.e., "MVPA morning days" (see Fig. 5, bottom left panel). In phase 2, participants were grouped in 3 clusters. Most participants (cluster 1: n = 614) had generally low MVPA across all days. Participants in cluster 2 (n = 18) had mostly "MVPA afternoon days" and some low MVPA days. Finally, a small group of participants in cluster 3 (n = 28) had a mixture of low MVPA days and "MVPA morning days" (see Fig. 5, bottom right panel). The well-being of

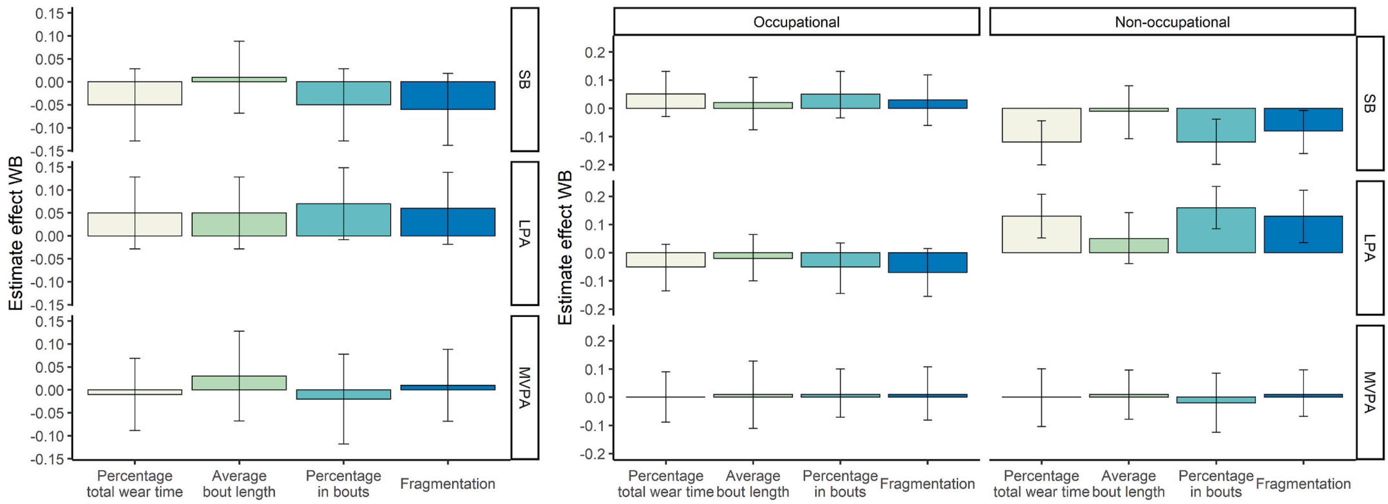


**Fig. 3.** "The association between the summary measures of SB, LPA and MVPA and well-being". Left panel: analyses based on total wear time. Right panel: wear time split by occupational vs non-occupational time. The error bars reflect the 99% confidence intervals.

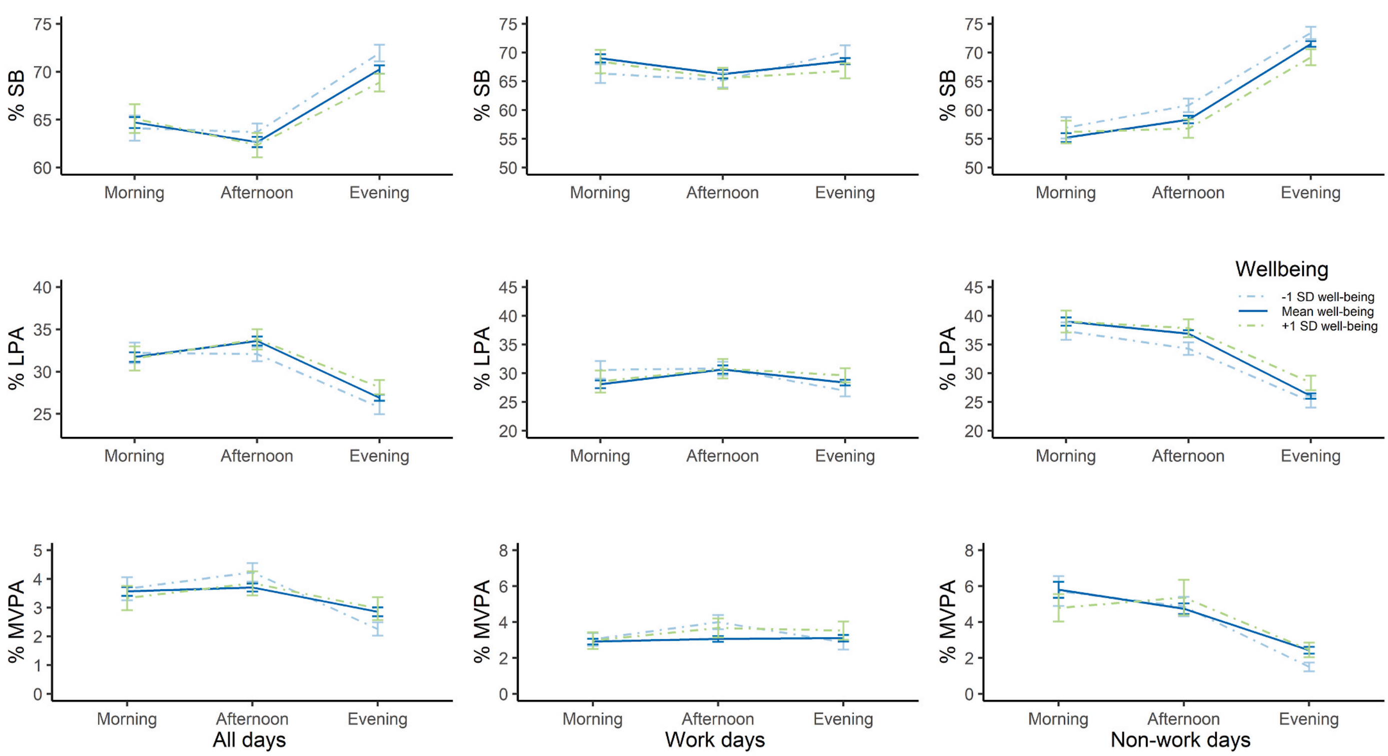


**Fig. 4.** "The association between well-being and the time spent in SB, LPA and MVPA across the day for all days (left panel), workdays (middle panel) and non-work days (right panel)". The error bars reflect the 99% confidence intervals. The solid lines indicate the trajectory of SB/LPA/MVPA for average well-being and the dotted lines indicate the trajectory for well-being 1 SD below (blue) and 1 SD above the mean (green). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

participants in the clusters did not differ (see Table 3).

*3.4.1. Workdays*

The subsample to cluster participants on workdays included 436 participants and 2044 days. For both SB, LPA and MVPA, the clustering resulted in two clusters, a high sedentary or low activity cluster and a low sedentary or high active cluster. There was no difference in well-being between the two SB/LPA/MVPA clusters of participants (see Table 3).

*3.4.2. Non-work days*

The subsample for clustering participants based on non-work days included 504 participants and 1008 days. The cluster analyses for SB resulted in two clusters of participants. Participants in cluster 1 ($n = 298$) were characterized by less SB minutes per hour (i.e., low sedentary) than participants in cluster 2 ($n = 206$), but did not differ on well-being (see Table 3).

Similarly, the cluster analyses for LPA resulted in two clusters. Participants in cluster 1 ($n = 207$) were characterized by more LPA minutes per hour than participants in cluster 2 ($n = 297$). Although participants in the high LPA ($M = 28.2$, $SD = 4.6$) cluster had a higher well-being

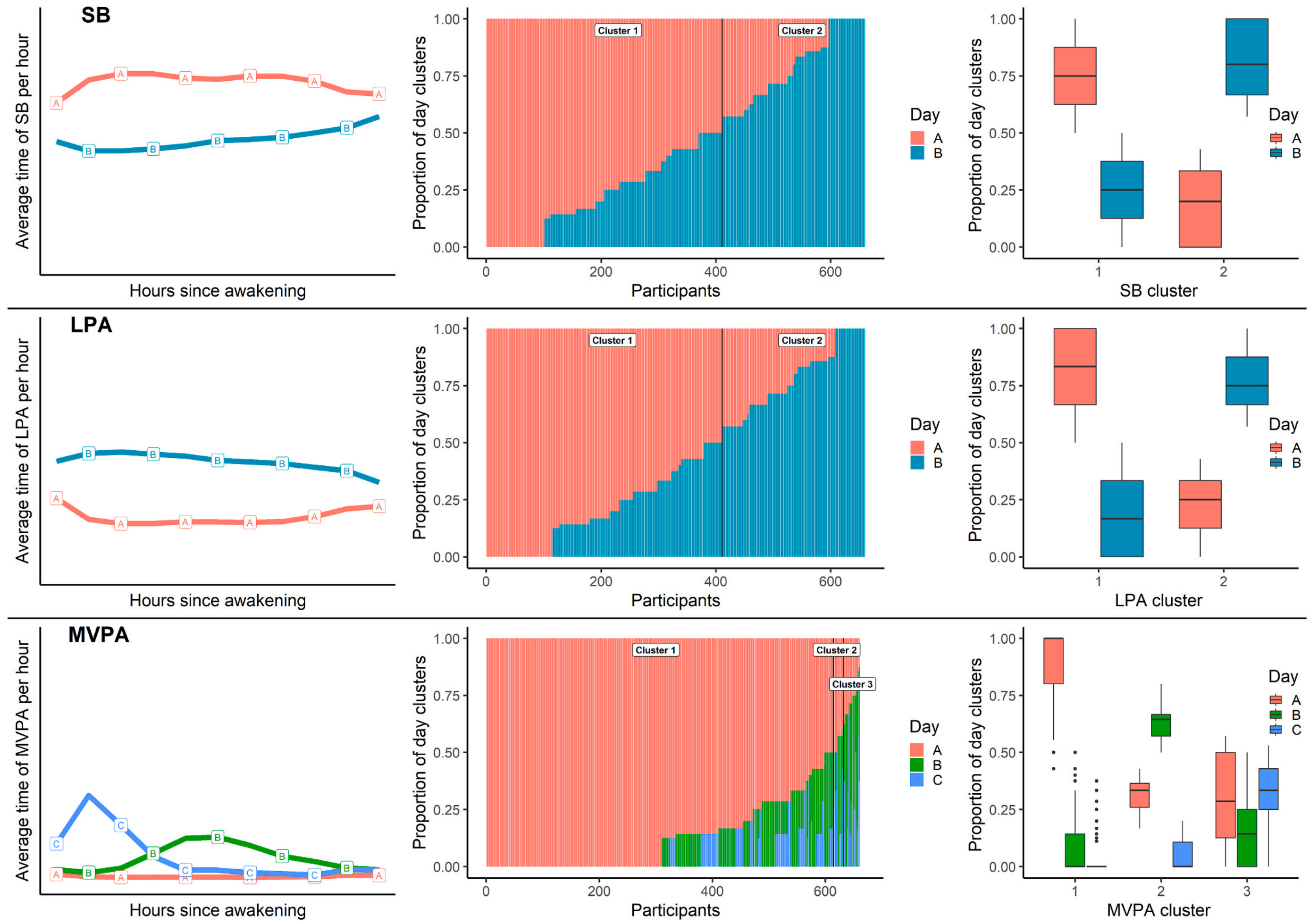


**Fig. 5.** "The clustering of days and participants based on minutes per hour spent in SB, LPA and MVPA". The left panel shows the clustering of days based on timing and duration of SB, LPA or MVPA across the day (phase 1). The middle panel shows the clustering of people based on the proportion of day trajectories (phase 2). The right panel shows the distribution of proportion of day trajectories per participant cluster.

**Table 3**
The average well-being score (*SD*) for each cluster of participants and the p-value of the comparison between the clusters of participants, based on all days, work days and non-work days.

| | Total | | | Workdays | | | Non-work days | | |
|---|---|---|---|---|---|---|---|---|---|
| | SB | LPA | MVPA | SB | LPA | MVPA | SB | LPA | MVPA |
| Cluster 1 | 27.3 (4.9) | 27.4 (4.8) | 27.3 (4.9) | 27.7 (4.8) | 27.2 (4.6) | 27.3 (4.9) | 27.1 (5.0) | 28.2 (4.6) | 27.0 (5.3) |
| | n = 411 | n = 411 | n = 614 | n = 237 | n = 171 | n = 276 | n = 298 | n = 207 | n = 100 |
| Cluster 2 | 27.2 (4.9) | 27.1 (5.0) | 28.5 (3.4) | 27.2 (4.7) | 27.7 (4.9) | 27.9 (4.5) | 27.9 (4.8) | 26.9 (5.0) | 27.3 (4.8) |
| | n = 249 | n = 249 | n = 18 | n = 199 | n = 265 | n = 160 | n = 206 | n = 297 | n = 132 |
| Cluster 3 | | | 27.1 (5.6) | | | | | | 27.7 (4.8) |
| | | | n = 28 | | | | | | n = 258 |
| Cluster 4 | | | | | | | | | 27.4 (5.6) |
| | | | | | | | | | n = 14 |
| *p*-value | .823 | .483 | .872 | .328 | .332 | .200 | .061 | ***.003*** | .226 |

compared to the lower LPA cluster ($M = 26.9$, $SD = 5.0$), this effect did not reach significance ($p = .003$) (see Table 3).

Finally, the cluster analyses for MVPA resulted in four clusters. Participants in cluster 1 (n = 100) were on average active as participants in cluster 2 (n = 132), but participants in cluster 1 have longer bouts of MVPA when they are active. Participants in the largest cluster 3 (n = 258) were on average the least active with the most SB and least MVPA. A small group of participants in cluster 4 (n = 14) were most active and had more MVPA than the other clusters. The participants in the different MVPA clusters did not differ on well-being (see Table 3).

### *3.5. Part 4: Clustering based on sequence maps of SB and PA*

Based on the sequence maps of SB and PA, the analysis resulted in two participant clusters. Participants in cluster 1 (n = 338) engaged in more SB (bouts) and less LPA (bouts) and MVPA (bouts) than participants in cluster 2 (n = 120) (see Fig. 6 and Supplementary Table S8 for the estimates). The clusters did not differ on well-being ($M_1 = 27.3$, $SD_1 = 4.9$, vs $M_2 = 27.3$, $SD_2 = 4.5$).

#### *3.5.1. Workdays versus non-workdays*

When only including workdays, participants were clustered in two

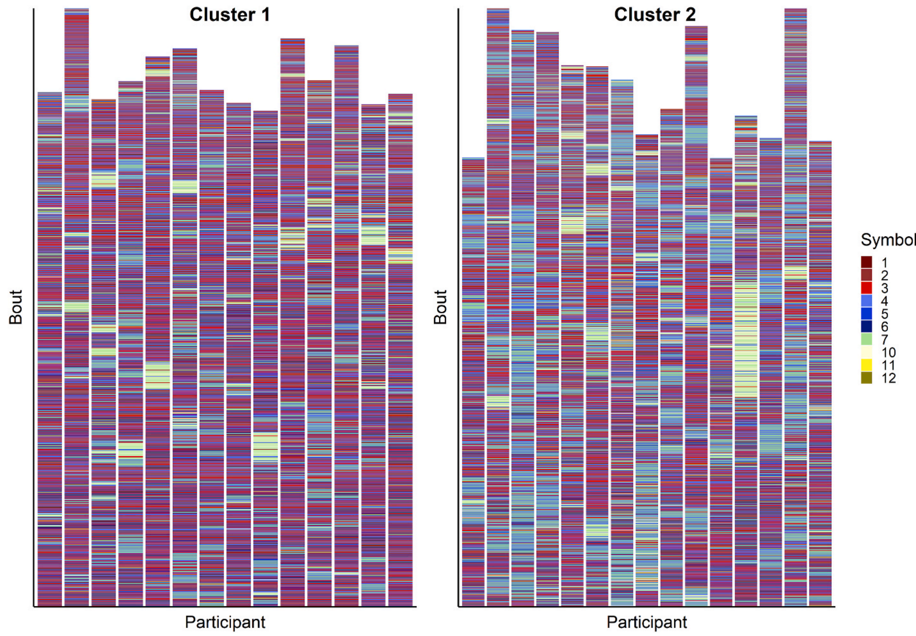


**Fig. 6.** Sequence maps of a random subsample of participants in the two clusters (n = 15). Red = sedentary behavior, blue = LPA, green = MPA, yellow = VPA. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

clusters. Participants in cluster 1 (n = 277) were characterized by less PA and more SB compared to participants in cluster 2 (n = 146) (see Supplementary Table S8). The participants in the clusters did not differ on well-being (cluster 1: $M = 27.4$, $SD = 4.8$, cluster 2: $M = 27.5$, $SD = 5.0$), $p = .929$.

When only including non-work days, participants were clustered in three clusters. Participants in cluster 1 (n = 283) were characterized by more LPA and MVPA and less SB compared to participants in cluster 2 (n = 290) (see Supplementary Table S8). The participants in the clusters did not differ on well-being (cluster 1: $M = 27.6$, $SD = 4.9$, cluster 2: $M = 27.2$, $SD = 4.9$, cluster 3: $M = 27.5$, $SD = 4.9$), $p = .337$.

## 4. Discussion

Using a large variation of accelerometer assessed SB, LPA and MVPA measures, we found no association between well-being and SB/LPA and MVPA in total accelerometer wear time. Clustering the participants based on their timing and level of SB and/or LPA/MVPA during the day resulted mostly in two clusters, i.e., one more sedentary/less active cluster and one less sedentary/more active cluster. Participants in the different clusters did not differ on their well-being levels.

When dividing the data in occupational and non-occupational time, significant associations between the total time spent in SB and LPA (bouts) and well-being emerged during non-occupational time, but not during occupational time. Compositional data analysis indicated that the combined effect of relatively less SB and relatively more LPA is associated with higher well-being. Similarly, clustering participants based on non-working days, the less sedentary or more LPA cluster of participants reported slightly higher well-being levels compared to the more sedentary or less LPA cluster of participants. The timing or patterns of PA/SB accumulation had no added value in explaining the association between PA or SB and well-being (see Table 1 for an overview).

### *4.1. Occupational versus non-occupational SB, LPA and MVPA*

The association between total PA and well-being during non-occupational time was only found for LPA and not for MVPA. Compared to LPA, MVPA occurs less often (mean of 31% versus 3.3% in this sample). The lower power may explain the lack of an association for MVPA. However, conflicting results on the differential associations between LPA and MVPA and well-being have been reported before. For example, self-reported leisure LPA has been associated with high well-being, whereas MPA was associated with the lowest well-being (Downward & Dawson, 2016). Other studies reported a positive association between accelerometer assessed LPA and MPA and well-being, and a non-significant or negative association between VPA and well-being (Panza et al., 2019; Wicker & Frick, 2015). Therefore, the combination in one MVPA category could explain the non-significant associations with well-being. We were unable to investigate MPA and VPA separately because of the low base rates.

A potential explanation for the positive association between LPA and well-being is that LPA is often accumulated in activities that have a social, recreational or fun purpose (Downward & Dawson, 2016). When having the freedom to choose one's activities, i.e., during leisure time, more PA cam be associated with higher well-being. As leisure time is part of non-occupational time, our findings of associations between LPA and well-being during non-occupational time but not occupational time supports this notion, but further research is needed to confirm this.

Besides leisure time PA, a large part of non-occupational LPA includes household activities, such as cleaning, gardening, and doing laundry (Van Der Ploeg et al., 2013). People who do not work or work part-time often perform a larger part of these household activities. The positive association between non-occupational LPA and well-being could therefore be confounded by work status, i.e., if people with a part-time job have a higher well-being than people with a full-time job.

In general, more research on the specific PA types and contexts that are associated with well-being in both occupational and non-occupational time is needed. Furthermore, it is important to know what the main activity is of people, both during work (i.e., physical demanding work vs white collar workers) and outside work. The amount of non-occupational time varies greatly depending on whether you work fulltime, part-time or not at all, since non-occupational LPA is strongly associated with what part of the household chores you do. We need more context about the participants and their exercise behavior when studying the associations with well-being, information which the accelerometer and the current diary method did not provide.

For SB, we found an association between lower SB and higher well-being during non-occupational time but no association during occupational time. In contrast, when investigating mental health symptoms, in a recent study, objectively assessed SB during the week, i.e., mostly working time, was associated with increased symptoms of anxiety and depression, but there was no association between weekend SB and these measures of mental health (Gibson et al., 2017). Similar to the recommendations for PA, more research on the contexts and types of SB during occupational and non-occupational time and their association with well-being is needed.

To account for the compositional nature of the accelerometer-assessed SB and PA data, we applied an exploratory compositional data analysis. Although compositional data analyses can lead to different results compared to "standard" analysis (Gupta et al., 2018), the results of this analysis replicated the opposite associations of SB and LPA with well-being in non-occupational time when both were included in an integrated analysis. In line with Giurgiu et al. (2022) findings on mood, the combined effect of SB and PA indicates that more SB relative to less PA was related to lower well-being. In the current study, the strongest association was with LPA, indicating that replacing SB by LPA in non-occupational time might lead to higher well-being.

### 4.2. Timing and accumulation patterns of SB and PA

The timing of SB, LPA and/or MVPA over the day was not associated with well-being. In the cluster analyses, we based the number of best-fitting clusters on the silhouette index and most analyses resulted in two clusters, i.e., an less sedentary/LPA/MVPA and a more sedentary/LPA/MVPA cluster. Based on the results of previous studies, we expected to be able to distinguish between multiple clusters of participants with a different timing of SB and PA. For example, Reuter et al. (2020) reported four different clusters of older women (mean age = 79) with a different timing of SB, and this SB timing was associated with health measures. Chinapaw et al. (2019) clustered children on their sequence maps of SB/PA and reported seven different clusters of participants with different sequences.

An explanation for the higher number of clusters and more variability in PA/SB in these previous studies could be the difference in sample characteristics, i.e. children (Chinapaw et al., 2019) and elderly (Reuter et al., 2020) versus adults (current sample). Children and elderly might have less structured life's and more free time and choices in their SB/PA compared to (employed) adults. Although dependent on the job, during working hours adults might not have much of a choice in their SB or PA, resulting in more uniform patterns among adults. Furthermore, our sample is relatively homogenous in other characteristics, with an overrepresentation of women and younger, higher educated people. Therefore, the sample could be too small or homogenous to detect (smaller) differences in SB/PA patterns.

Since these more detailed measures of SB and PA require more complex and multiple processing steps, each of which may add some measurement error, we recommend future studies applying cluster analyses to patterns of SB/PA accumulation to use larger and more diverse samples.

### 4.3. Direction of association

In the current study, we can only report on the association between PA or SB and well-being and not on its underlying source or direction of the association. Often, studies on PA/SB and well-being focus on a presumed causal effect of PA/SB on well-being. For example, using an ecological momentary assessment (EMA) approach, a direct influence of daily PA and SB on life satisfaction was reported (Maher et al., 2014). In a longitudinal study, changes in self-reported leisure time PA were associated with changes in well-being, suggesting a possible causal effect of PA on well-being (Blomstrand et al., 2009). However, experimental or intervention studies are needed to confirm this causality.

Alternatively, the association between PA/SB and well-being could arise from reverse causality. Higher levels of well-being can cause more PA or less SB. For example, happier people might have the adequate levels of self-control to be active and do exercise whereas the characteristic of low well-being, lack of energy, anhedonia, and social withdrawal, all exert a negative influence on PA (Dishman, 1990; Goodwin, 2003). A recent longitudinal study indeed reported a *bi*directional association between self-reported leisure time PA and well-being (Kim et al., 2021), indicating that well-being might lead to more PA and vice versa.

However, based on the results of twin studies, the association between PA and well-being seems, at least in part, to be due to non-causal mechanisms, including overlapping genetic factors underlying both PA and well-being (Bartels et al., 2012; Stubbe et al., 2007). The association reported in the current study between non-occupational time SB/LPA and well-being could therefore also be (partly) caused by genetic factors having an effect both on well-being and non-occupational time SB/LPA. This would be in keeping with the triangulation across the results from different designs for causal inference (randomized control trials, prospective studies) that supported the existence of causal effects of regular exercise on mental health and residual confounding by genetic factors (de Geus, 2021).

### 4.4. Limitations

A limitation of this study is the different timing of collection of the accelerometer and well-being data. Although measures of well-being are quite stable over time (Fujita & Diener, 2005; Lucas & Donnellan, 2007) and the sensitivity analysis found no influence of the time between the measures, the results should be interpreted in light of this limitation. More research should combine accelerometer data with ecological momentary assessment (EMA) to assess well-being multiple times throughout the participant's day (e.g., Giurgiu et al., 2022).

A further limitation is the representativeness of our sample for the Dutch population. Fifty-eight percent of the sample indicated to have attended higher vocational school or university, significantly higher than the 38% of adults (25-64 year-olds) in the Dutch population (OECD, 2019). As we distinguish between non-occupational and occupational PA/SB this could be important, since higher educated people more often have sedentary jobs than lower educated people. A strength of the study was the use of accelerometer date in a relatively large study sample, which allowed us to study timing and patterns. On the other hand, the accelerometer data provided no data on the type and context of the behaviours, which would have been useful to better understand the association with well-being beyond the (non-)occupational diary data.

### 4.5. Conclusion

We found no associations between various measures of sedentary behaviour or physical activity and well-being in total accelerometer wear time. We did find a positive and negative association of non-occupational LPA and SB respectively with well-being, both in an absolute and relative sense. The more detailed measures including the timing or accumulation of PA/SB had no added value in explaining the association with well-being.

## Ethics approval and consent to participate

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration. The data collection was approved and declared to be of low risk by the METc of the Vrije Universiteit Medical Center Amsterdam. Informed consent was obtained from all individual participants included in the study.

## Availability of data and materials

The data from the Netherlands Twin Register can be accessed through the Netherlands Twin Register (ntr.fgb@vu.nl) upon approval of the data access committee.


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## Credit author statement

**Lianne de Vries**: Conceptualization, Formal analysis, Methodology, Project administration, Visualization, Writing - original draft. **Dirk Pelt**: Conceptualization, Writing - review & editing. **Hidde van der Ploeg**: Investigation, Funding acquisition, Writing - review & editing. **Mai Chinapaw**: Methodology, Writing - review & editing. **Eco de Geus**: Investigation, Funding acquisition, Writing - review & editing. **Meike Bartels**: Conceptualization, Investigation, Funding acquisition, Supervision, Writing - review & editing.

## Declaration of competing interest

Given their role as an Editorial Board member de Geus E.J.C. had no involvement in the peer-review of this article and had no access to information regarding its peer-review. All other authors declare that there were no competing interest with respect to the authorship or the publication of this article.


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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.mhpa.2022.100446.

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