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ORIGINAL RESEARCH

Sequential Activity Patterns and Outcome-Specific, Real-Time, and Target Group-Specific Feedback: The SPORT Algorithm

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Purpose: Physical activity (PA) is crucial for health, but there is insufficient evidence about PA patterns and their operationalization. The authors developed two algorithms ($SPORT_{constant}$ and $SPORT_{linear}$) to quantify PA patterns and check whether pattern information yields additional explained variance (compared with a compositional data approach [CoDA]). ***Methods:*** To measure PA, 397 (218 females) adolescents with a mean age of 12.4 ($SD = 0.6$) years wore an ActiGraph on their lower back for 1 week. The SPORT algorithms are based on a running value, each day starting with 0 and minutely adapting depending on the behavior being performed. The authors used linear regression models with a behavior-dependent constant ($SPORT_{constant}$) and a function of time-in-bout ($SPORT_{linear}$) as predictors and body mass index *z* scores (BMI_z) and fat mass percentages (%FM) as exemplary outcomes. For generalizability, the models were validated using five-fold cross-validation where data were split up in five groups, and each of them was a test data set in one of five iterations. ***Results:*** The CoDA and the $SPORT_{constant}$ models explained low variance in BMI_z (2% and 1%) and low to moderate variance in %FM (both 5%). The variance being explained by the $SPORT_{linear}$ models was 6% (BMI_z) and 9% (%FM), which was significantly more than the CoDA models ($p < .001$) according to likelihood ratio tests. ***Conclusion:*** Among this group of adolescents, $SPORT_{linear}$ explained more variance of BMI_z and %FM than CoDA. These results suggest a way to enable research about PA patterns. Future research should apply the $SPORT_{linear}$ algorithm in other target groups and with other health outcomes.

Keywords: obesity, physical activity, real-time feedback, sedentary behavior, sitting pattern

Physical inactivity during adolescence has been associated with obesity (Rauner, Mess, & Woll, 2013; Ten Hoor et al., 2018), and children and adolescents aged 5–17 years are recommended to achieve a daily minimum of 60 min of moderate to vigorous physical activity (MVPA) (World Health Organization, 2010). Yet, 60 min of MVPA fill only 5–10% of the waking day, while the remainder is composed of sedentary behavior (SB) and light physical activity (LIPA). For example, European adolescents spend on average 9 hr of their day in SBs (Ruiz et al., 2011). However, independently of an individual's MVPA, certain types, such as television viewing time, of SB were found to be associated with multiple harmful health indicators, such as unfavorable body composition and higher cardiometabolic risk (Carson et al., 2016).

The findings regarding the causal association between SB and obesity are inconsistent (Biddle, Bengoechea, & Wiesner, 2017; Ekelund et al., 2012; Kuzik et al., 2017). One of the reasons might be the different ways of operationalizing SB (Kang & Rowe, 2015). Some stressed that SB is not merely the sitting time, but the pattern in which SB bouts are collected: it should include rather many short periods than a few longer SB periods (Bailey, Charman, Ploetz, Savory, & Kerr, 2017; Werneck et al., 2019). Parameters that have been used to represent SB patterns are, for instance, the average duration of sitting bouts (Carson et al., 2016), the number of sitting interruptions (Bailey et al., 2017; Werneck et al., 2019), and the average duration of these interruptions (Chinapaw et al., 2014). Still, it is questionable whether a single SB pattern parameter suffices to explain enough variance of obesity or other health parameters. When decreasing SB, other behaviors need to increase, since all physical behaviors add up to 100% of the day (Chastin, Palarea-Albaladejo, Dontje, & Skelton, 2015). Similarly, the compositional nature of physical behaviors have been respected by creating simulation scenarios, in which SB is substituted by different activity types before being regressed onto mortality (Rowe, Tremblay, & Manuel, 2012). Therefore, considering all physical behaviors and their patterns provides more information and might reduce the inconsistency of the findings regarding the association of obesity with physical behaviors.

Next to considering all physical behaviors and information about the bouts, it might be necessary to consider their daily sequential orders. Due to a short-term elevation of the resting metabolic rate in response to physical activity (PA), behaviors being performed after physically active sessions show a more beneficial energy balance (Speakman & Selman, 2003). Therefore, a SB bout might have a different impact on health when following another SB bout than when following a PA bout. Figure 1 shows identical bouts yet altered daily sequential orders. In Day A, a SB bout S_2 follows a short MVPA bout M_1, while in Day B, the SB bout succeeds an hour of activity. Despite same numbers and lengths of physical behavior bouts, Day A might have worse impact on obesity, since the SB bouts are collected almost directly one after another. Incorporating the sequential patterns of all physical behaviors in a quantifiable way is needed, because additional information about sequential patterns of physical

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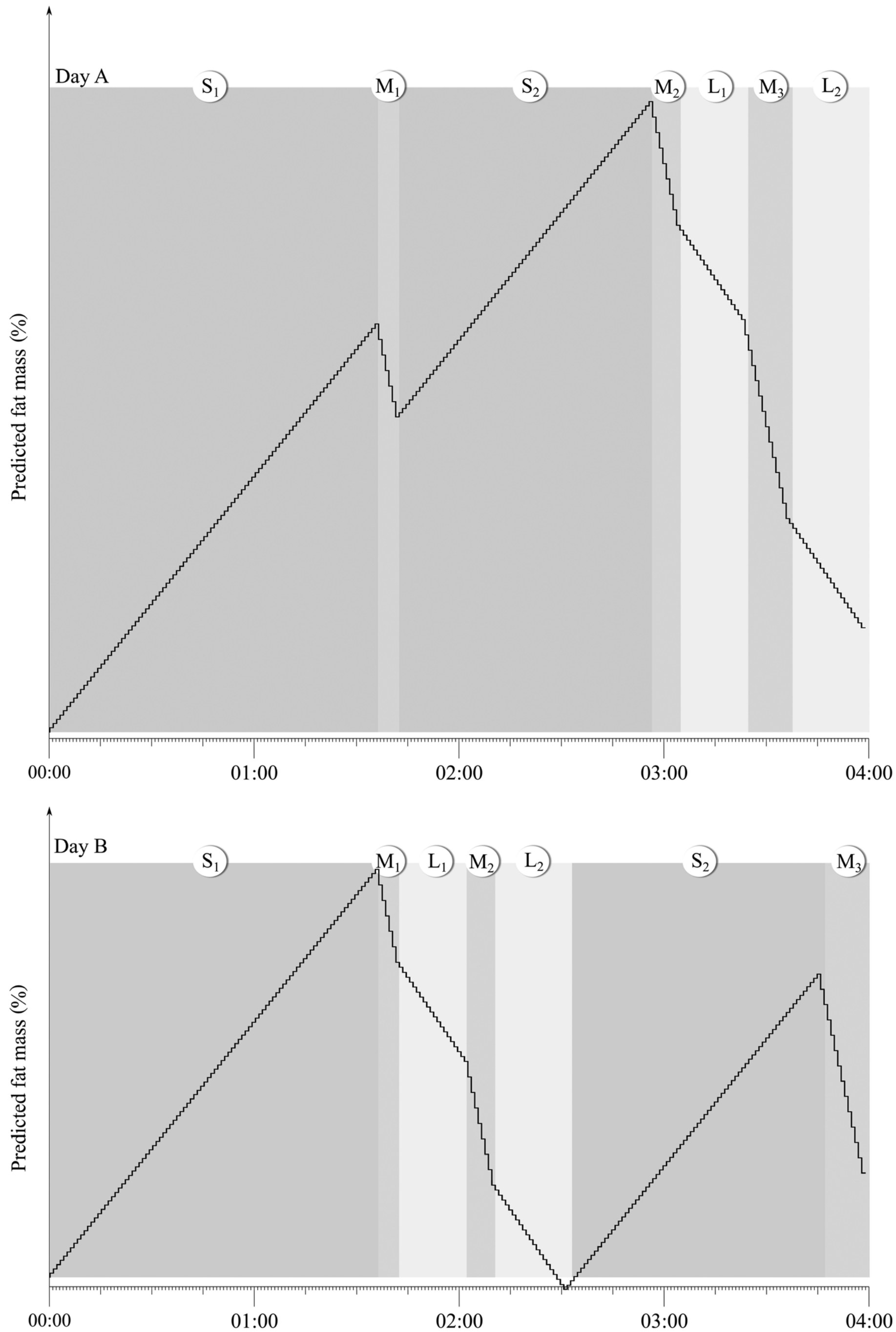

Figure 1 — The SPORT algorithm illustrated with segments of 2 days with identical number and durations of physical behavior bouts but different sequential orders. At the beginning of the day, the running value X_0 is 0, and with each additional minute i (or another time unit), the running value X_i adapts. S = sedentary behavior bout; L = light physical activity bout; M = moderate to vigorous physical activity bout; SPORT = Sequence, Pattern, Outcome-specific, Real-time, Target group-specific.

behaviors might explain additional variance in health outcomes, and it might, eventually, facilitate real-time and individualized feedback.

Previously, PA patterns and their sequence have been represented using multistate sequences. Each of the states is characterized by the following three variables: (a) type (e.g., SB, walking); (b) intensity (e.g., low, moderate) and (c) duration. Structural complexity metrics were used to quantify how complex the PA patterns (i.e., the switches between all the fine-grained states) are and used as parameters to predict health (Paraschiv-Ionescu et al., 2016). Others represented time series physical behavior patterns in visual items using colored time bars, where colors represent physical behavior categories, and at first glance, healthy patterns can be distinguished from unhealthy patterns (Loudon & Granat, 2015).

In this paper, we introduce two algorithms labeled with the acronym SPORT (Sequence, Pattern, Outcome-specific, Real-time, Target group-specific). Both SPORT algorithms calculate scores representing sequential PA patterns. The SPORT$_{constant}$ algorithm includes a behavior-dependent constant, and the SPORT$_{linear}$ algorithm additionally includes a behavior-dependent function of the time that is spent within a physical behavior bout. To incorporate the sequence of behaviors, each value should include a memory of the behaviors being performed before. Therefore, the SPORT algorithms are based on a running value, which accumulatively changes each minute (i.e., Real-time; see Figure 1). The amount and direction of change will depend on the behavior being performed in this particular minute (e.g., when walking, the running value recovers by *a* points per minute). The recommended length of a sitting bout will then depend on the average of all running values collected on that day. Resulting values of the SPORT algorithms can be used to represent sequential physical behavior patterns in such a way that they can easily be inserted into regression models to explain variance in specific health outcomes. The results will then depend on the health outcome to be predicted. In other words, the regression coefficients might be different if body fat is the dependent variable compared with back pain as dependent variable (Outcome-specific), which is again different for populations of 20-year-old individuals and populations of 50-year-old individuals (Target group-specific). The SPORT algorithms distinguish days being started with a walk from days being started with SB (Sequence), as well as days with a different number and lengths of physical behavior bouts (Pattern).

We demonstrate the development of two SPORT algorithms that quantify sequential physical behavior patterns. We use a Dutch adolescent population and their body mass index *z* scores (BMI$_z$) (with objectively measured height and weight, and adjusted for gender and age based on national reference values; Fredriks, van Buuren, Wit, & Verloove-Vanhorick, 2000) as well as fat mass percentages (%FM; using the valid and objective deuterium dilution procedure; Westerterp, Wouters, & van Marken Lichtenbelt, 1995) as illustrative adiposity markers to test the SPORT algorithms and to compare the explanatory power with a compositional data (CoDA) approach (Chastin, Palarea-Albaladejo, et al., 2015). Since the CoDA approach also incorporates all physical behaviors in one single model when explaining the variance of health outcomes, this was the most adequate comparator for the SPORT algorithm. We hypothesize that the SPORT algorithms are able to explain more variance of both BMI$_z$ and %FM compared with the CoDA approach because SPORT contains additional information on the daily sequence of the behaviors.

Methods

All materials and supporting documents are available at the Open Science Framework repository at https://osf.io/k8nrq/?view_only=9a7a6dfc2be94d118b8f06edfd96786c.

Design

The data in the current study are from a cohort of Dutch adolescents (11–15 years) from the Focus on Strength randomized controlled trial (2014–2016), which examined the effects of strength exercises and motivational sessions on PA and body composition (Ten Hoor et al., 2016). Participants wore the ActiGraph (GT3X; ActiGraph, Pensacola, FL) accelerometer for 1 week at baseline and after 12 months follow-up (Ten Hoor et al., 2016, 2018). Since too few adolescents had data at both time slots, we only considered the baseline data but conducted sensitivity analyzes with the post-test data.

Data Collection

Nine Dutch Schools were recruited via the school management. Of the 808 students, 113 declined. Among the 695, 435 participants had accelerometer data for at least 4 days of at least 7 hr (see "Measurements and Procedure" section for details), and 397 participants remained after the exclusion of outliers. Written informed consents were obtained by the schools. Participants and their parents were informed about the study and were allowed to withdraw from the study at any time. The study was approved by the ethics review committee of the Faculty of Psychology and Neuroscience, Maastricht University, The Netherlands (ERCPN-05-09-2012A1).

Measurements and Procedure

The student administrations of the schools provided the adolescents' gender and date of birth. Standard procedures to measure anthropometrics were used (Centers for Disease Control and Prevention, 2016). Height (SECA 213 stadiometer; seca GmbH, Hamburg, Germany) and weight (SECA 877 scale; seca GmbH) were measured to the nearest 1 mm and 0.1 kg, respectively. Participants took off shoes and heavy clothes during measurements. We calculated BMI as weight/height squared (in kilogram per meter squared) and BMI$_z$ from age- and sex-specific reference values (Fredriks et al., 2000). Body composition was assessed by deuterium dilution (Schoeller et al., 1986; Westerterp et al., 1995), and fat-free mass was calculated using age-specific hydration fractions (Lohman, 1989). Compared with underwater weighing, deuterium dilution validly measures body composition (van der Kooy et al., 1992; Westerterp et al., 1991).

To assess physical behaviors, students wore the ActiGraph GT3X on their lower back for 5 days (including school days and at least one weekend day) except during water activities (Plasqui, 2017; Plasqui, Bonomi, & Westerterp, 2013; Yngve, Nilsson, Sjostrom, & Ekelund, 2003). The accelerometer was attached by an elastic belt. Accelerations were read with a rate of 30 Hz and reintegrated with an output data rate of 15-s epochs (Banda et al., 2016; Evenson, Catellier, Gill, Ondrak, & McMurray, 2008). We used ActiLife (version 6.13.3; https://www.actigraphcorp.com/actilife/) to scan the raw data and to determine wear times by using the vertical axis counts (counts per minute [CPM]) and a minimum nonwear time window of 90 min (Choi, Ward, Schnelle, & Buchowski, 2012). When making decisions on wear-time cutoff values, there is a trade off between reliability and sample retention (Toftager et al., 2013). Therefore, an analysis was performed to determine a high wear time cut off while keeping a maximum of analyzable data points. We created data sets with all possible cut offs and tested for differences of participant characteristics (i.e., age, sex, BMI$_z$) of those data sets compared with characteristics of the original sample using Wilcoxon signed-rank tests (see Open Science Framework repository). This resulted in establishing 7 hr per day for a minimum of 4 days cut off. We classified SB (≤100 CPM); LIPA (101–2,295 CPM); and MVPA (≥2,296 CPM) (Evenson et al., 2008; Trost, Loprinzi, Senso, & Pfeiffer, 2009).

The SPORT algorithms are based on the assumption that the impact of behaviors of a waking day depends on the sequential patterns of all previous behaviors on that waking day. Hence, before aggregating the raw data by dates and user identifiers, we subtracted 4 hr from the timestamps. Thereby, we ensured that behaviors being performed after midnight but before sleeping time would still be analyzed with the waking day before participants went to bed. We were able to simply reduce these 4 hr, since none of the participants went to bed after 4:00 in the morning or woke up before 4:00 in the morning. However, in other samples, the data need to be inspected previous to such a deduction.

Compositional Analyses

Waking days are composed of three behaviors: SB, LIPA, and MVPA, of which the proportions will always add up to 100% of the wearing time. Increasing the amount of one of these behaviors necessarily yields a decline in the two other behaviors. Hence, each behavior is always seen in relation to the proportion spent in the other two behaviors. CoDA regression models are based on isometric log-ratio data transformations to adjust for time spent in other behaviors (Chastin, Palarea-Albaladejo, et al., 2015). Thereby, the daily proportions spent in SB, LIPA, and MVPA are each transformed into isometric log ratios by adjusting them for the proportions spent in the other two behaviors. Three regression models each incorporating one of the three physical behaviors as the first part of the composition (e.g., $z1_{\mathrm{SB}} = \sqrt{\frac{2}{3}}\ln\left(\frac{\mathrm{SB\%}}{\sqrt{\mathrm{LIPA\%} \times \mathrm{MVPA\%}}}\right)$), and another physical behavior as the second part (e.g., $z2_{\mathrm{LIPA}} = \sqrt{\frac{1}{2}}\ln\left(\frac{\mathrm{LIPA\%}}{\sqrt[1]{\mathrm{MVPA\%}}}\right)$) constitute the basis of the CoDA approach, whereby all of the three behaviors are once the first and once the second part of the composition. We used the log-ratio expectation–maximization algorithm to impute the zeros in the 115 days (5.48% of all days) that adolescents had not collected any MVPA (Palarea-Albaladejo & Martín-Fernández, 2008, 2015). This allowed to calculate log ratios, while preserving the log ratios between the other behaviors. Although sleep is a health behavior that is of importance in the first version of the SPORT algorithms, we focused on PA and SB.

SPORT Algorithms

The SPORT algorithms are based on a running value X_i. Each day starts with $X_0 = 0$. Depending on the physical behavior being performed, X_i is increased or decreased. In the example pattern in Figure 2, X_i might decrease when being active in periods M_1 and L_1 and might worsen when sitting in S_2. In each minute (or another time unit) i, X_i is a result of a cumulative adaption: $X_{i-1} + a_{i-1}$, where a_{i-1} represents the amount of change (approximately size of the step).

SPORT$_{\mathrm{constant}}$

The average of the running values X_i of all waking minutes (i.e., time units) n will be the independent variable when predicting health outcomes.

$$\mathrm{BMI}_z = \beta_0 + \frac{\sum_0^n x_i}{n}. \quad (1)$$

With each minute, X_i adapts by an activity-dependent amount of change a_i.

$$\mathrm{BMI}_z = \beta_0 + \frac{x_0 + (x_0 + a_0) + (x_0 + a_0 + a_1) + \cdots + (x_0 + \sum_0^{n-1} a_i)}{n}. \quad (2)$$

In Equation (2), X_0 is 0, since each day starts with a running value of 0. In addition, n is known as an individual's amount of collected minutes. Therefore, the behavior dependent amounts of change (a_i) and the intercept (β_0) are the only unknown variables. The amount of the change a_{i-1} affecting X_i depends on the physical behavior performed in minute $i - 1$. We assume that SB is detrimental and should have a worsening effect. Therefore, when predicting BMI_z (higher ~ less healthy), a_{SB} should be a positive number. Accordingly, a_{LIPA} and a_{MVPA} should be negative. Therefore, a_i is determined by the function:

$$a_i = f(\mathrm{Activity\_Category}) = \begin{cases} a_{\mathrm{SB}}, & i \text{ is spent in SB} \\ a_{\mathrm{LIPA}}, & i \text{ is spent in LIPA} \\ a_{\mathrm{MVPA}}, & i \text{ is spent in MVPA} \end{cases} \quad (3)$$

By the help of matrix calculations, a_{SB}, a_{LIPA}, and a_{MVPA} can be isolated in such a way that simple linear regression analyses can help to get these a-values (see Supplementary Material [available online]).

$$\mathrm{BMI}_z = \beta_0 + a_{\mathrm{SB}}\frac{U_{\mathrm{SB}}}{n} + a_{\mathrm{LIPA}}\frac{U_{\mathrm{LIPA}}}{n} + a_{\mathrm{MVPA}}\frac{U_{\mathrm{MVPA}}}{n}. \quad (4)$$

U_{SB}, U_{LIPA}, and U_{MVPA} from Equation (4) can be retrieved by multiplying three matrixes (see Equation 5): (a) an all ones matrix with 1 row and n columns, (b) a binary lower triangular matrix (n rows and n columns) with all values above the diagonal being 0 and all values below and including the diagonal being 1, and (c) a binary matrix with n rows and 1 column with Boolean values for SB, LIPA, or MVPA. In the last matrix, the first row is always 0, and the last row represents the second to last minute of a day. For example, for calculating U_{SB}, if the $i - 1$st (e.g., first) minute of a day was spent sitting; the ith (e.g., second) row is 1; and 0 if it was spent in LIPA or in MVPA. U_{LIPA} and U_{MVPA} are calculated accordingly.

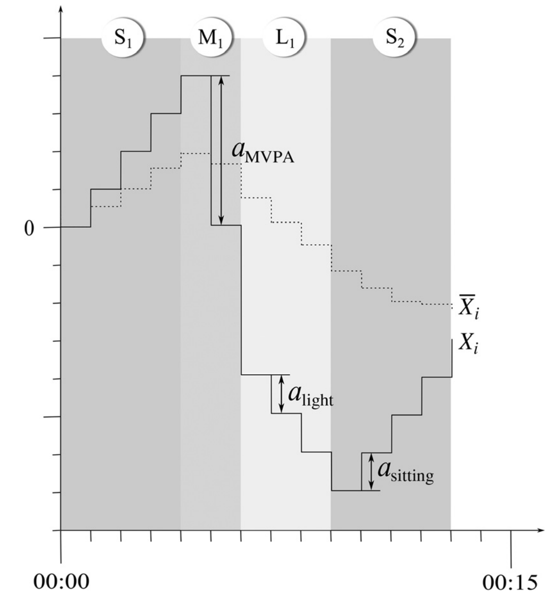

Figure 2 — Intensity-dependent accumulation of the running value. When predicting BMI_z and when being active, the running value X_i (solid line) is assumed to decrease ($a_{\mathrm{LIPA}} < 0$ and $a_{\mathrm{MVPA}} < 0$). When being sedentary, the running value is assumed to increase ($a_{\mathrm{SB}} > 0$). With each additional running value X_i, the average running value $\overline{X}_i$ adapts (dotted line). S = sedentary behavior bout; L = light physical activity bout; M = moderate to vigorous physical activity bout; BMI_z = BMI z scores; SB = sedentary behavior; MVPA = moderate to vigorous physical activity; LIPA = light physical activity.

$$U_{\mathrm{SB}} = [1 \ \cdots \ 1]_{1,n} \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 1 & 1 & \cdots & 1 \end{bmatrix}_{n,n} \begin{bmatrix} 0 \\ S_0 \\ \vdots \\ S_{n-1} \end{bmatrix}_{n-1}. \quad (5)$$

If participants have multiple days of data, they have multiple U_{SB}s, U_{LIPA}s, and U_{MVPA}s. These are each added up, and the three results are divided by the total amount of collected minutes on all days.

Amount of Change as Behavior-Dependent Function of Time in Bout

The amount of change a_i affecting the running value X_i might also depend on the time having spent in a certain bout. We assume for SB that the running value is increasing and that this amount of increase is steeper the longer the person has been sitting. Accordingly, we assume $A_{\mathrm{SB}}(t_i)$, $A_{\mathrm{LIPA}}(t_i)$, and $A_{\mathrm{MVPA}}(t_i)$ to be linear functions of the time spent in the concerning bout $A_{\mathrm{SB}}(t_i) = \gamma_0 + \gamma_1 t_1$, $A_{\mathrm{LIPA}}(t_i) = \delta_0 + \delta_1 t_1$, and $A_{\mathrm{MVPA}}(t_i) = \epsilon_0 + \epsilon_1 t_i$. Assumingly, the intercept γ_0 will be positive (X_i rises when sitting), and δ_0 and ϵ_0 will be negative. We assume that the slope γ_1 in function $A_{\mathrm{SB}}(t_i)$ will be positive. (The rise of X_i is bigger the longer a person is sitting in a row.) Furthermore, we assume that the size of the benefit of spending time in PA decreases or stays the same by the time spending in the bouts (Quinn, Klooster, & Kenefick, 2006; Tarp et al., 2018). Thus, we assume the slopes δ_1 and ϵ_1 to be either positive or zero. Figure 3 visualizes the difference between the SPORT$_{\mathrm{constant}}$ and the SPORT$_{\mathrm{linear}}$ algorithm. In summary, a_i is determined by the function:

$$a_i = f(t_i) = \begin{cases} A_{\mathrm{SB}}(t_i) = \gamma_0 + \gamma_1 t_i \, , i \text{ is spent in SB} \\ A_{\mathrm{LIPA}}(t_i) = \delta_0 + \delta_1 t_i \, , i \text{ is spent in LIPA} \\ A_{\mathrm{MVPA}}(t_i) = \epsilon_0 + \epsilon_1 t_i \, , i \text{ is spent in MVPA} \end{cases}. \quad (6)$$

The process to isolate the six unknown variables (γ_0, γ_1, δ_0, $\delta 1$, ϵ_0, ε_1) is described in the additional materials. The resulting regression formula is:

$$\mathrm{BMI}_z = \beta_0 + \gamma_0 \frac{V_{\mathrm{SB}}}{n} + \gamma_1 \frac{W_{\mathrm{SB}}}{n} + \delta_0 \frac{V_{\mathrm{LIPA}}}{n} + \delta_1 \frac{W_{\mathrm{LIPA}}}{n} + \epsilon_0 \frac{W_{\mathrm{MVPA}}}{n} + \epsilon_1 \frac{W_{\mathrm{MVPA}}}{n}. \quad (7)$$

V_{SB}, V_{LIPA}, and V_{MVPA} are known and can be calculated like it is done to get U_{SB}, U_{LIPA}, and U_{MVPA} (see Equation 5). W_{SB}, W_{LIPA}, and W_{MVPA} are calculated similarly, but the last factor includes information about the time t_i that was spent in the concerning bout until minute i:

$$W_{\mathrm{SB}} = \begin{bmatrix} 1 & \cdots & 1 \end{bmatrix}_{1,n} \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 1 & 1 & \cdots & 1 \end{bmatrix}_{n,n} \begin{bmatrix} 0 \\ S_0 t_0 \\ \vdots \\ S_{n-1} t_{n-1} \end{bmatrix}_{n,1}. \quad (8)$$

Statistical Analyses

We computed descriptive univariate statistics and assessed the distributions of the variables using histograms and Q–Q plots. Nonnormally distributed variables were reported as medians and interquartile ranges, normally distributed variables as means and *SD*s. Physical behaviors were reported as compositional geometric means and log-ratio variances (i.e., "the variances of the logarithms of all pair-wise ratios between parts") (Chastin, Palarea-Albaladejo, et al., 2015). These values consider the codependence between the three physical behaviors all being compositional parts of the waking day (Aitchison, 1982; Chastin, Palarea-Albaladejo, et al., 2015).

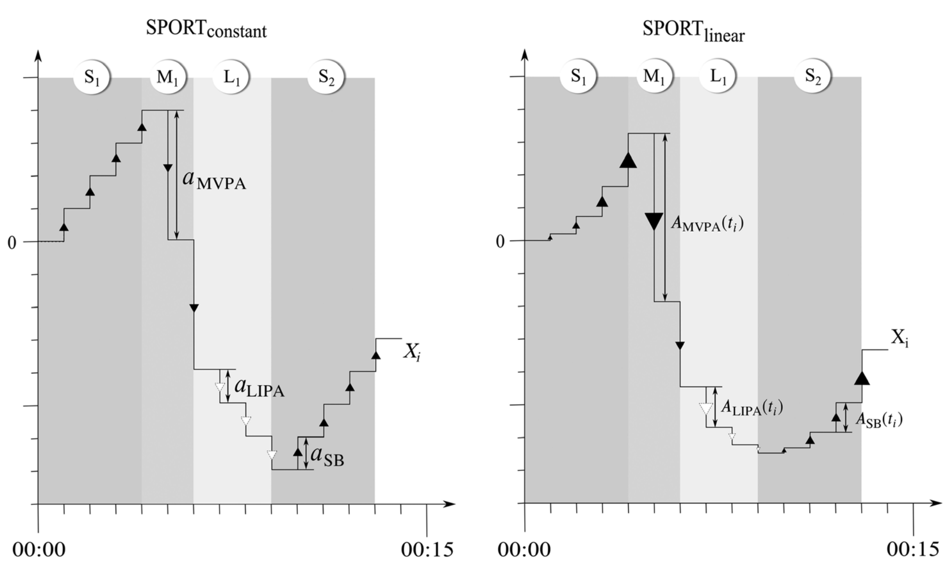

Figure 3 — Representation of the difference between the SPORT$_{\mathrm{constant}}$ and the SPORT$_{\mathrm{linear}}$ algorithm. When predicting BMI$_z$ with the SPORT$_{\mathrm{constant}}$ algorithm, the running value X_i is assumed to change by a constant a_{SB}, a_{LIPA}, or a_{MVPA} depending on the behavior being performed. When predicting BMI$_z$ with the SPORT$_{\mathrm{linear}}$ algorithm, the running value X_i is assumed to change by a linear function of time in bout $A_{\mathrm{SB}}(t_i)$, $A_{\mathrm{LIPA}}(t_i)$, or $A_{\mathrm{MVPA}}(t_i)$ depending on the behavior being performed and on the time having spent in the concerning SB, LIPA, or MVPA bout. S = sedentary behavior bout; L = light physical activity bout; M = moderate to vigorous physical activity bout; BMI$_z$ = BMI z scores; SB = sedentary behavior; MVPA = moderate to vigorous physical activity; LIPA = light physical activity; SPORT$_{\mathrm{constant}}$ = behavior-dependent constant; SPORT$_{\mathrm{linear}}$ = function of time in bout.

In order to analyze the performance of the SPORT algorithm, we used linear regression models with either CoDA, the $SPORT_{constant}$ or the $SPORT_{linear}$ variables as predictors. Normalized BMI (i.e., BMI z scores) and %FM constituted the outcome variables. We then assessed the explanatory power of the SPORT and the CoDA models by reporting the explained variances (adjusted R^2) and by testing the differences of the explanatory power by means of likelihood ratio tests.

We checked for covariations using backward elimination starting with age and gender as covariates and retained them as a predictor if the p value was <.20. Consequently, we controlled for age and gender (locked in the models) when predicting BMI_z scores and for gender when predicting %FM. Outliers that were detected with the Mahalanobis distance in either of the variables from the models (CoDA, $SPORT_{constant}$, or $SPORT_{linear}$) were excluded from all models (Mahalanobis, 1936). All tests for statistical significances were two-sided, with a Type I error at $p < .05$, and effect sizes were calculated using 95% confidence intervals (CIs). Data cleaning and inferential analyses were performed using R (version 3.4.1). The outcomes of the models were evaluated using five-fold cross-validation, where data sets are divided into five groups of nearly equal number of data points. Each group was taken as test data set in one of the five iterations. The remaining groups constituted the training set on which the models were fit before being evaluated on the test set (Kuncheva, 2014). For readability, we only report the results of the cross-validation; the results of the regression models without cross-validation can be retrieved from the additional material.

Results

The descriptive statistics are displayed in Table 1. Of all 695 participants, 595 wore the accelerometer, and 397 provided 7 hr of accelerometer data each for at least 4 days. BMI_z was available in all of the 397 (218 females and 179 males) adolescents, and 260 (153 females and 107 males) adolescents provided urine samples to have their %FM measured. The variability of the compositional PA data is displayed with pairwise log-ratio variances. A log-ratio variance close to zero refers to a high proportional relationship of the two behaviors: SB and LIPA were highly codependent; the time spent in MVPA was relatively independent of the time spent in SB.

Regression Results of the CoDA Approach

Table 2 presents the results of the CoDA models. After cross-validation, the amount of variance being explained by the CoDA models was low when predicting BMI_z ($R^2_{adjusted} = .02$) and when predicting %FM ($R^2_{adjusted} = .05$) (Cohen, 1988). None of the parts each in relation to the other parts (i.e., isometric log ratios) was significantly associated with the outcomes.

Regression Results of the SPORT Algorithm

Amount of change as behavior-dependent constant. Table 3 presents the results of the linear regressions using the $SPORT_{constant}$ algorithm. When cross-validating, the amount of variance being explained by the $SPORT_{constant}$ models was low when predicting BMI_z ($R^2_{adjusted} = .01$), and low to moderate when predicting %FM

Table 1 Descriptive Characteristics of Participants

Variable	Female $n = 218$	Male $n = 179$	Total $N = 397$
Age (years), *M* (*SD*)	12.4 (0.5)	12.5 (0.6)	12.4 (0.6)
PA			
Wear time, median (IQR)	735.5 (251)	720.2 (263.8)	726.5 (257.8)
SB (min/day) median (IQR)	531 (184.5)	510.5 (183.2)	521 (184.8)
SB compositional GM (%) (log-ratio variances LIPA, MVPA)	77.8 (0.1, 0.4)	77.6 (0.1, 0.4)	77.7 (0.1, 0.4)
LIPA (min/day) median (IQR)	160.5 (85.4)	160 (91.4)	160 (87.8)
LIPA compositional GM (%) (log-ratio variances SB, MVPA)	22.2 (0.1, 0.2)	22.4 (0.1, 0.2)	22.3 (0.1, 0.2)
MVPA (min/day) median (IQR)	24.2 (24.6)	28.4 (31.6)	25.8 (27.2)
MVPA compositional GM (%) (log-ratio variances SB, LIPA)	0 (0.4, 0.2)	0 (0.4, 0.2)	0 (0.4, 0.2)
Meeting guidelines (no. of days per individual)[a]	0.4 (0.8)	0.8 (1.1)	0.6 (1)
Anthropometrics			
Height (cm) *M* (*SD*)	159.5 (7.2)	160.2 (9.6)	159.8 (8.4)
Weight (kg) *M* (*SD*)	50.9 (10.7)	48.7 (11.6)	49.9 (11.2)
BMI (kg/m^2), median (IQR)	19.9 (3.5)	18.8 (3.2)	19.4 (3.4)
BMI_z, median (IQR)	0.3 (1.1)	0.1 (1.2)	0.2 (1.2)
%FM, median (IQR)	26.8 (7.6)	22.6 (7.9)	25.1 (8)
Underweight, *n* (%)	24 (11)	33 (18.4)	57 (14.4)
Normal weight, *n* (%)	129 (59.2)	109 (60.9)	238 (59.9)
Overweight, *n* (%)	49 (22.5)	22 (12.3)	71 (17.9)
Obese, *n* (%)	16 (7.3)	15 (8.4)	31 (7.8)

Note. IQR = interquartile range; GM = geometric mean; BMI = body mass index; BMI_z = BMI z scores; %FM = fat mass percentage; SB = sedentary behavior; PA = physical activity; LIPA = light PA; MVPA = moderate to vigorous PA.

[a]Meeting guidelines is defined as the average number of days that participants accumulated at least 60 min of MVPA.

Table 2 Compositional (CoDA) Behavior Models for BMI_z (Controlled for Age and Gender) and %FM (Controlled for Gender)

	BMI_z, $N = 397$				%FM, $n = 260$			
PA	β	*SE*	*p*	95% CI	β	*SE*	*p*	95% CI
CoDA analysis								
$z1_{SB}$	0.20	0.26	.44	[−0.31, 0.71]	1.02	2.17	.59	[−3.26, 5.31]
$z1_{LIPA}$	0.07	0.34	.70	[−0.59, 0.74]	−3.16	2.82	.31	[−8.73, 2.40]
$z1_{MVPA}$	−0.28	0.17	.14	[−0. 62, 0.06]	2.14	1.43	.19	[−0.69, 4.97]
Intercept	−3.31	1.48	.04	[−6.21, −0.41]	29.12	2.94	<.001	[23.32, 34.91]

Note. BMI_z = body mass index *z* score; %FM = fat mass percentage; CI = confidence interval; SB = sedentary behavior; CoDA = compositional data approach; PA = physical activity; LIPA = light PA; MVPA = moderate to vigorous PA.

$$z1_{SB} = \sqrt{\frac{2}{3}}\ln\left(\frac{SB\%}{\sqrt{LIPA\% \times MVPA\%}}\right).$$

$$z1_{LIPA} = \sqrt{\frac{2}{3}}\ln\left(\frac{LIPA\%}{\sqrt{SB\% \times MVPA\%}}\right).$$

$$z1_{MVPA} = \sqrt{\frac{2}{3}}\ln\left(\frac{MVPA\%}{\sqrt{LIPA\% \times SB\%}}\right).$$

Table 3 $SPORT_{constant}$ Models for BMI_z (Controlled for Age and Gender) and %FM (Controlled for Gender)

	BMI_z, $N = 397$				%FM, $n = 260$			
PA[a]	β[a]	*SE*[a]	*p*	95% CI[a]	β[a]	*SE*[a]	*p*	95% CI[a]
SPORT (constant type)								
SB	0.02	0.04	.62	[−0.07, 0.10]	0.02	0.36	.78	[−0.69, 0.74]
LIPA	0.05	0.09	.58	[−0.12, 0.22]	0.30	0.75	.65	[−1.18, 1.78]
MVPA	−0.56	0.25	.05	[−1.06, −0.06]	−2.88	2.31	.24	[−7.43, 1.67]
Intercept	−280.06	150.36	.09	[−575.90, 15.78]	2,726.63	420.94	<.001	[1,896.66, 3,556.61]

Note. BMI_z = body mass index *z* score; %FM = fat mass percentage; CI = confidence interval; SB = sedentary behavior; PA = physical activity; LIPA = light PA; MVPA = moderate to vigorous PA; SPORT = Sequence, Pattern, Outcome-specific, Real-time, Target group-specific; $SPORT_{constant}$ = behavior-dependent constant.
[a]Since these values are very small, considering the predictors each being 15 s of an entire day, these values are presented as $x \times 10^2$, to read 0.23, instead of 0.00 after rounding.

($R^2_{adjusted}$ = .05) (Cohen, 1988). Likelihood ratio tests showed no significant improvement for the $SPORT_{constant}$ models compared with the CoDA models when predicting BMI_z ($p = .10$) and when predicting %FM ($p = .43$). When considering the specific behaviors, minutes of MVPA were negatively associated with BMI_z (β = −0.56; *SE* = 0.25; $p = .05$; 95% CI [−1.06, −0.06]), while sedentary minutes and light PA minutes did not show significant associations with BMI_z. None of the physical behaviors was associated with %FM.

Amount of change as behavior-dependent function of time in bout. Table 4 presents the results of the linear regressions using the $SPORT_{linear}$ algorithm. When cross-validating, the amount of variance being explained by the $SPORT_{linear}$ models was low to moderate when predicting BMI_z ($R^2_{adjusted}$ = .06) and moderate when predicting %FM ($R^2_{adjusted}$ = .09) (Cohen, 1988). Likelihood ratio tests showed significant improvements of the $SPORT_{linear}$ model compared with the CoDA models when predicting both BMI_z and %FM ($p < .001$). Minutes of LIPA were negatively associated with BMI_z (β = −0.55; *SE* = 0.22; $p = .03$; 95% CI [−0.98, −0.11]). The time in bout dependent association of LIPA minutes with BMI_z was positive (β = 0.16; *SE* = 0.04; $p < .001$; 95% CI [0.08, 0.24]). None of the other physical behaviors or time in bouts were associated with BMI_z. When predicting %FM, the time in bout dependent association of LIPA minutes with %FM was positive (β = 1.20; *SE* = 0.33; $p < .01$; 95% CI [0.56, 1.85]). None of the other physical behaviors was associated with %FM.

Discussion

The SPORT models provide a way to quantify sequential physical behavior patterns that they can be inserted in regression models to predict health. The $SPORT_{linear}$ models showed more explanatory power compared with the CoDA models, because they contained additional information about sequential patterns of the physical behaviors. In this study, most of the models explained low to low-to-moderate amounts of variance when predicting BMI_z. Previous studies that applied the CoDA approach with similar target groups showed similar results when predicting BMI_z (Carson, Tremblay, Chaput, McGregor, & Chastin, 2019; Talarico & Janssen, 2018). Yet, when using waist circumference as proxy for %FM, other studies found 4–29% of explained variances when using the CoDA approach (Carson et al., 2019; Talarico & Janssen, 2018). The reasons for the negligible amounts of explained variance for %FM in the current study might root in considerably fewer participants when predicting %FM or in the fact that, in this study, sleep was not

Table 4 SPORT$_{linear}$ Models for BMI$_z$ (Controlled for Age and Gender) and %FM (Controlled for Gender)

	BMI$_z$, $N = 395$				%FM, $n = 260$			
PA	β[a]	*SE*[a]	*p*	95% CI[a]	β[a]	*SE*[a]	*p*	95% CI[a]
SPORT (linear type)								
SB	0.06	0.06	.31	[–0.05, 0.18]	0.38	0.50	.46	[–0.60, 1.36]
SB (time in bout)	0.00	0.00	.65	[0.00, 0.00]	0.00	0.01	.75	[–0.02, 0.01]
LIPA	–0.55	0.22	.03	[–0.98, –0.11]	–3.84	1.87	.06	[–7.53, –0.16]
LIPA (time in bout)	0.16	0.04	<.001	[0.08, 0.24]	1.20	0.33	<.01	[0.56, 1.85]
MVPA	0.04	0.42	.72	[–0.78, 0.86]	–4.99	3.51	.19	[–11.92, 1.94]
MVPA (time in bout)	–0.05	0.05	.34	[–0.16, 0.05]	0.77	0.42	.09	[–0.05, 1.59]
Intercept	–326.79	146.31	.04	[–614.69, –38.89]	2,547.18	433.62	<.001	[1,692.12, 3,402.24]

Note. BMI$_z$ = body mass index *z* score; %FM = fat mass percentage; CI = confidence interval; SB = sedentary behavior; PA = physical activity; LIPA = light PA; MVPA = moderate to vigorous PA; SPORT$_{linear}$ = function of time-in-bout.
[a]Since these values are very small, considering the predictors each being 15 s of an entire day, these values are presented as $x \times 10^2$, to read 0.23, instead of 0.00 after rounding.

included as predictor as opposed to other studies. The findings show that it might be very important to consider daily sequential patterns when giving PA guidelines or when considering associations with health.

When examining the associations of the single physical behaviors (SB, LIPA, and MVPA) with the outcomes in the SPORT models, most of the associations between the physical behaviors and the outcomes were as expected. In the SPORT$_{constant}$ models, minutes in MVPA showed a negative association with BMI$_z$. In the SPORT$_{linear}$ models, minutes in LIPA were negatively associated with both outcomes. However, the longer LIPA bouts were, the less this impact was. Therefore, for BMI$_z$ and %FM, LIPA minutes might be most beneficial when collected in short bouts, assuming a causal association with the outcomes. Indeed, some researchers found that regular interruptions of SB with LIPA or standing is at least equally effective compared with accumulating MVPA with equal energy expenditure within one bout (Duvivier et al., 2013, 2017). Interestingly, we found adverse, yet not significant, estimates for MVPA in the SPORT$_{linear}$ models. The longer MVPA bouts were, the more negatively the time spent in MVPA was associated with BMI$_z$. Adversely, minutes in MVPA were negatively associated with %FM, but this association decreased by the time spent within MVPA bouts. Therefore, concerning %FM, MVPA seems to be more beneficial when collected in many short bouts as opposed to one long bout, while concerning BMI$_z$, MVPA seems to be more beneficial when collected in longer bouts, again assuming causality. These results are in line with previous research stressing the crucial role of replacing SB with LIPA and MVPA (Aadland, Kvalheim, Anderssen, Resaland, & Andersen, 2018; Fairclough et al., 2017). However, it remains unclear whether MVPA should be collected in many shorter bouts or in fewer longer bouts.

Recommendations and How to Give Real-Time Feedback

The SPORT algorithm is an adequate method to represent sequential physical behavior patterns on a minute by minute basis and might therefore be helpful when giving real-time feedback (e.g., in SB interventions). Recommendations should consider a balance between value, context, and focus: although presumably sitting will need to be reduced to a minimum, this will hardly be realizable in all contexts. For example, in a school environment (context), the maximum allowable average running value (i.e., X_i in the SPORT algorithm) will then be higher not to result in potentially disturbing getting up reminders (focus on prevention). In contrast, when having interventions with a target group from a rehabilitation institution (context), it is not only about maintaining health but about recovering from a disease. Therefore, the average allowed running value should be lower (focus on cure). The application of the SPORT algorithm in real-time interventions should be investigated in future studies. The current paper describes an approach that can be applied in various contexts with different focuses. An example to incorporate the SPORT algorithm would be an intervention being based on a wearable device, which allows for real-time synchronization with a back-end server. Thereby, the server would process the data and calculate the status quo of the running value. The results can be used to provide the user with visual or auditive feedback that is tailored to the characteristics of the target person, to the health outcome of interest, and to the sequential order of the physical behaviors of that day.

Strengths and Limitations

Both approaches, the CoDA and the SPORT algorithms, that were applied in the current paper respect the collinearities that come with PA data. Although BMI$_z$ might not fully represent the healthiness of body compositions (Bogin & Varela-Silva, 2012), the measurements allowed for a recruitment of a representative sample from a relatively difficult setting (high schools). Furthermore, the measurements of the independent as well as the dependent variables where objectively measured by using accurate and valid tools. Finally, we considered not only the complex and sequential nature of physical behavior patterns, but we also considered the lengths of the specific bouts (SPORT$_{linear}$ models) that might be of relevance (e.g., light PA or standing might be very healthy in the beginning but the effects diminish, the longer it is performed). The focus of this paper is on presenting a way to represent physical behavior patterns in a way that they can be inserted in standard regression models and therefore explored further in research. However, when coming up with PA pattern recommendations, longitudinal data should be used to allow potentially higher explained variances and casual inferences. Since there is first evidence that standing breaks in addition to PA breaks can have a beneficial impact on health

(Chastin, Egerton, Leask, & Stamatakis, 2015), measurement tools should be applied that are able to distinguish between postures, such as VitaBit, activPAL, or the ActiGraph being worn on the thigh (Atkin et al., 2012; Berninger, Ten Hoor, & Plasqui, 2018). Since we aimed for a simplified and interpretable way to represent physical behavior patterns, we did not include sleeping time, and we merged all intensity levels above moderate activity into one category (MVPA). However, previously contradictory associations between different intensities within the MVPA spectrum and cardiometabolic health were found and the importance of considering sleep was addressed (Aadland, Kvalheim, Anderssen, Resaland, & Andersen, 2019; Carson et al., 2019; Chastin, Palarea-Albaladejo, et al., 2015; Howard et al., 2015). The SPORT algorithm is very flexible, and it can be applied to more or less fine-grained data using 10- or 60-s epochs using more intensity levels of PA and including sleep as additional component.

Conclusion

The SPORT algorithms might be a suitable method for representing complex PA patterns and their sequential order in a way that they can be used in standard regression models. If other PA researchers succeed in representing their data in a long format data frame (several rows per individual, each row representing 1 min of the day), it is easy to use a single function to transform their data into SPORT variables (e.g., with R, Excel [Microsoft Excel, Microsoft Corporation, Redmond, WA], or SPSS [IBM SPSS Statistics, Armonk, NY]) that can be inserted into regression models. Compared with an approach also considering all physical behaviors of the waking day, additionally considering the sequential nature of SB, LIPA, and MVPA yielded in higher, yet small, amounts of explained variances when predicting BMI_z and %FM among a cohort of Dutch adolescents. The results from this study further support the hypothesis that it might be rather the sequential order and the patterns than the intensity of PA that matters when interrupting sitting. To satisfy the "T" (target group-specific) and the "O" (outcome-specific) in the SPORT acronym, future studies are needed that apply the SPORT algorithm to other target groups predicting other and more specific (i.e., more sensitive or minutely measurable) biomarkers.

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References

Aadland, E., Kvalheim, O.M., Anderssen, S.A., Resaland, G.K., & Andersen, L.B. (2018). The multivariate physical activity signature associated with metabolic health in children. *International Journal of Behavioral Nutrition and Physical Activity, 15*(1), 77. doi:10.1186/s12966-018-0707-z

Aadland, E., Kvalheim, O.M., Anderssen, S.A., Resaland, G.K., & Andersen, L.B. (2019). Multicollinear physical activity accelerometry data and associations to cardiometabolic health: Challenges, pitfalls, and potential solutions. *International Journal of Behavioral Nutrition and Physical Activity, 16*(1), 74. doi:10.1186/s12966-019-0836-z

Aitchison, J. (1982). The statistical analysis of compositional data. *Journal of the Royal Statistical Society: Series B (Methodological), 44*(2), 139–160.

Atkin, A.J., Gorely, T., Clemes, S.A., Yates, T., Edwardson, C., Brage, S., . . . Biddle, S.J. (2012). Methods of measurement in epidemiology: Sedentary behaviour. *International Journal of Epidemiology, 41*(5), 1460–1471. PubMed ID: 23045206 doi:10.1093/ije/dys118

Bailey, D.P., Charman, S.J., Ploetz, T., Savory, L.A., & Kerr, C.J. (2017). Associations between prolonged sedentary time and breaks in sedentary time with cardiometabolic risk in 10–14-year-old children: The HAPPY study. *Journal of Sports Sciences, 35*(22), 2164–2171. PubMed ID: 27892780 doi:10.1080/02640414.2016.1260150

Banda, J.A., Haydel, K.F., Davila, T., Desai, M., Bryson, S., Haskell, W.L., . . . Robinson, T.N. (2016). Effects of varying epoch lengths, wear time algorithms, and activity cut-points on estimates of child sedentary behavior and physical activity from accelerometer data. *PLoS One, 11*(3), e0150534. PubMed ID: 26938240 doi:10.1371/journal.pone.0150534

Berninger, N.M., Ten Hoor, G.A., & Plasqui, G. (2018). Validation of the vitabit sit–stand tracker: Detecting sitting, standing, and activity patterns. *Sensors, 18*(3), 877. doi:10.3390/s18030877

Biddle, S.J., Bengoechea, E.G., & Wiesner, G. (2017). Sedentary behaviour and adiposity in youth: A systematic review of reviews and analysis of causality. *International Journal of Behavioral Nutrition and Physical Activity, 14*(1), 43. doi:10.1186/s12966-017-0497-8

Bogin, B., & Varela-Silva, M. (2012). The body mass index: The good, the bad, and the horrid. *Bulletin de la societe Suisse d'Anthropologie, 18*(2), 5–11.

Carson, V., Hunter, S., Kuzik, N., Gray, C.E., Poitras, V.J., Chaput, J.-P., . . . Tremblay, M.S. (2016). Systematic review of sedentary behaviour and health indicators in school-aged children and youth: An update. *Applied Physiology, Nutrition, and Metabolism, 41*(6), S240–S265. doi:10.1139/apnm-2015-0630

Carson, V., Tremblay, M.S., Chaput, J.-P., McGregor, D., & Chastin, S. (2019). Compositional analyses of the associations between sedentary time, different intensities of physical activity, and cardiometabolic biomarkers among children and youth from the United States. *PLoS One, 14*(7), e0220009. PubMed ID: 31329609 doi:10.1371/journal.pone.0220009

Centers for Disease Control and Prevention (CDC), N.C.f.H.S.N., and US Department of Health and Human Services. (2006). *NHANES: Body composition procedures manual*. Retrieved from http://www.cdc.gov/nchs/data/nhanes/nhanes_05_06/BC.pdf

Chastin, S.F., Egerton, T., Leask, C., & Stamatakis, E. (2015). Meta-analysis of the relationship between breaks in sedentary behavior and cardiometabolic health. *Obesity, 23*(9), 1800–1810. PubMed ID: 26308477 doi:10.1002/oby.21180

Chastin, S.F., Palarea-Albaladejo, J., Dontje, M.L., & Skelton, D.A. (2015). Combined effects of time spent in physical activity, sedentary behaviors and sleep on obesity and cardio-metabolic health markers: A novel compositional data analysis approach. *PLoS One, 10*(10), e0139984. PubMed ID: 26461112 doi:10.1371/journal.pone.0139984

Chinapaw, M.J.M., de Niet, M., Verloigne, M., De Bourdeaudhuij, I., Brug, J., & Altenburg, T.M. (2014). From sedentary time to sedentary patterns: Accelerometer data reduction decisions in youth. *PLoS One, 9*(11), e111205. PubMed ID: 25369021 doi:10.1371/journal.pone.0111205

Choi, L., Ward, S.C., Schnelle, J.F., & Buchowski, M.S. (2012). Assessment of wear/nonwear time classification algorithms for triaxial accelerometer. *Medicine & Science in Sports & Exercise, 44*(10), 2009. PubMed ID: 22525772 doi:10.1249/MSS.0b013e318258cb36

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Duvivier, B.M.F.M., Schaper, N.C., Bremers, M.A., Van Crombrugge, G., Menheere, P.P.C.A., Kars, M., & Savelberg, H.H.C.M. (2013). Minimal intensity physical activity (standing and walking) of longer duration improves insulin action and plasma lipids more than shorter periods of moderate to vigorous exercise (cycling) in sedentary subjects when energy expenditure is comparable. *PLoS One, 8*(2), e55542. PubMed ID: 23418444 doi:10.1371/journal.pone.0055542

Duvivier, B.M.F.M., Schaper, N.C., Hesselink, M.K.C., van Kan, L., Stienen, N., Winkens, B., … Savelberg, H.H.C.M. (2017). Breaking sitting with light activities vs structured exercise: A randomised crossover study demonstrating benefits for glycaemic control and insulin sensitivity in type 2 diabetes. *Diabetologia, 60*(3), 490–498. PubMed ID: 27904925 doi:10.1007/s00125-016-4161-7

Ekelund, U., Luan, J.a., Sherar, L.B., Esliger, D.W., Griew, P., Cooper, A., & International Children's Accelerometry Database Collaborators. (2012). Moderate to vigorous physical activity and sedentary time and cardiometabolic risk factors in children and adolescents. *JAMA, 307*(7), 704–712. PubMed ID: 22337681 doi:10.1001/jama.2012.156

Evenson, K.R., Catellier, D.J., Gill, K., Ondrak, K.S., & McMurray, R.G. (2008). Calibration of two objective measures of physical activity for children. *Journal of Sports Sciences, 26*(14), 1557–1565. PubMed ID: 18949660 doi:10.1080/02640410802334196

Fairclough, S.J., Dumuid, D., Taylor, S., Curry, W., McGrane, B., Stratton, G., … Olds, T. (2017). Fitness, fatness and the reallocation of time between children’s daily movement behaviours: An analysis of compositional data. *International Journal of Behavioral Nutrition and Physical Activity, 14*(1), 64. doi:10.1186/s12966-017-0521-z

Fredriks, A.M., van Buuren, S., Wit, J.M., & Verloove-Vanhorick, S. (2000). Body index measurements in 1996–7 compared with 1980. *Archives of Disease in Childhood, 82*(2), 107–112. PubMed ID: 10648362 doi:10.1136/adc.82.2.107

Howard, B., Winkler, E.A., Sethi, P., Carson, V., Ridgers, N.D., Salmon, J., … Dunstan, D.W. (2015). Associations of low- and high-intensity light activity with cardiometabolic biomarkers. *Medicine & Science in Sports & Exercise, 47*(10), 2093–2101. PubMed ID: 25668400 doi:10.1249/MSS.0000000000000631

Kang, M., & Rowe, D.A. (2015). Issues and challenges in sedentary behavior measurement. *Measurement in Physical Education and Exercise Science, 19*(3), 105–115. doi:10.1080/1091367X.2015.1055566

Kuncheva, L.I. (2014). *Combining pattern classifiers: Methods and algorithms*. Hoboken, New Jersey: John Wiley & Sons.

Kuzik, N., Carson, V., Andersen, L.B., Sardinha, L.B., Grøntved, A., Hansen, B.H., … Ekelund, U. (2017). Physical activity and sedentary time associations with metabolic health across weight statuses in children and adolescents. *Obesity, 25*(10), 1762–1769. PubMed ID: 28782888 doi:10.1002/oby.21952

Lohman, T.G. (1989). Assessment of body composition in children. *Pediatric Exercise Science, 1*(1), 19–30. doi:10.1123/pes.1.1.19

Loudon, D., & Granat, M.H. (2015). Visualization of sedentary behavior using an event-based approach. *Measurement in Physical Education and Exercise Science, 19*(3), 148–157. doi:10.1080/1091367X.2015.1048342

Mahalanobis, P.C. (1936). *On the generalized distance in statistics*. Proceedings of the National Institute of Science of India, 2, 49–55

Palarea-Albaladejo, J., & Martín-Fernández, J. (2008). A modified EM alralgorithm for replacing rounded zeros in compositional data sets. *Computers & Geosciences, 34*(8), 902–917. doi:10.1016/j.cageo.2007.09.015

Palarea-Albaladejo, J., & Martín-Fernández, J.A. (2015). zCompositions—R package for multivariate imputation of left-censored data under a compositional approach. *Chemometrics and Intelligent Laboratory Systems, 143,* 85–96. doi:10.1016/j.chemolab.2015.02.019

Paraschiv-Ionescu, A., Mellone, S., Colpo, M., Bourke, A., Ihlen, E.A.F., Achkar, C.M.e., … Aminian, K. (2016). Patterns of human activity behavior: From data to information and clinical knowledge. Paper presented at the Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct, Heidelberg, Germany. doi:10.1145/2968219.2968283

Plasqui, G. (2017). Smart approaches for assessing free-living energy expenditure following identification of types of physical activity. *Obesity Reviews, 18,* 50–55. PubMed ID: 28164455 doi:10.1111/obr.12506

Plasqui, G., Bonomi, A., & Westerterp, K. (2013). Daily physical activity assessment with accelerometers: New insights and validation studies. *Obesity Reviews, 14*(6), 451–462. PubMed ID: 23398786 doi:10.1111/obr.12021

Quinn, T.J., Klooster, J.R., & Kenefick, R.W. (2006). Two short, daily activity bouts vs. one long bout: Are health and fitness improvements similar over twelve and twenty-four weeks? *Journal of Strength & Conditioning Research, 20*(1), 130–135. PubMed ID: 16506860 doi:10.1519/R-16394.1

Rauner, A., Mess, F., & Woll, A. (2013). The relationship between physical activity, physical fitness and overweight in adolescents: A systematic review of studies published in or after 2000. *BMC Pediatrics, 13*(1), 19. doi:10.1186/1471-2431-13-19

Rowe, G., Tremblay, M.S., & Manuel, D.G. (2012). Can we make time for physical activity? Simulating effects of daily physical activity on mortality. *Epidemiology Research International, 2012,* 304937. doi:10.1155/2012/304937

Ruiz, J.R., Ortega, F.B., Martínez-Gómez, D., Labayen, I., Moreno, L.A., De Bourdeaudhuij, I., … Molnar, D. (2011). Objectively measured physical activity and sedentary time in European adolescents: The HELENA study. *American Journal of Epidemiology, 174*(2), 173–184. PubMed ID: 21467152 doi:10.1093/aje/kwr068

Schoeller, D.A., Ravussin, E., Schutz, Y., Acheson, K.J., Baertschi, P., & Jequier, E. (1986). Energy expenditure by doubly labeled water: Validation in humans and proposed calculation. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology, 250*(5), R823–R830. doi:10.1152/ajpregu.1986.250.5.R823

Speakman, J.R., & Selman, C. (2003). Physical activity and resting metabolic rate. *Proceedings of the Nutrition Society, 62*(3), 621–634. doi:10.1079/PNS2003282

Talarico, R., & Janssen, I. (2018). Compositional associations of time spent in sleep, sedentary behavior and physical activity with obesity measures in children. *International Journal of Obesity, 42*(8), 1508–1514. PubMed ID: 29568110 doi:10.1038/s41366-018-0053-x

Tarp, J., Child, A., White, T., Westgate, K., Bugge, A., Grøntved, A., … Davey, R. (2018). Physical activity intensity, bout-duration, and cardiometabolic risk markers in children and adolescents. *International Journal of Obesity, 42*(9), 1639–1650. PubMed ID: 30006582 doi:10.1038/s41366-018-0152-8

Ten Hoor, G.A., Kok, G., Rutten, G.M., Ruiter, R.A.C., Kremers, S.P.J., Schols, A.M.J.W., & Plasqui, G. (2016). The Dutch ‘Focus on Strength’ intervention study protocol: Programme design and production, implementation and evaluation plan. *BMC Public Health, 16*(1), 496. doi:10.1186/s12889-016-3150-6

Ten Hoor, G.A., Rutten, G.M., Van Breukelen, G.J.P., Kok, G., Ruiter, R.A.C., Meijer, K., … Schols, A.M.J.W. (2018). Strength exercises during physical education classes in secondary schools improve body composition: A cluster randomized controlled trial. *International Journal of Behavioral Nutrition and Physical Activity, 15*(1), 92. doi:10.1186/s12966-018-0727-8

Toftager, M., Kristensen, P.L., Oliver, M., Duncan, S., Christiansen, L.B., Boyle, E., … Troelsen, J. (2013). Accelerometer data reduction in adolescents: Effects on sample retention and bias. *International*

Journal of Behavioral Nutrition and Physical Activity, 10(1), 140. doi:10.1186/1479-5868-10-140

Trost, S.G., Loprinzi, P.D., Senso, M., & Pfeiffer, K.A. (2009). Comparison of accelerometer cut-points for predicting physical activity intensity in youth. *Medicine & Science in Sports & Exercise, 41*(5), 173. doi:10.1249/MSS.0b013e318206476e

van der Kooy, K., Leenen, R., Deurenberg, P., Seidell, J.C., Westerterp, K.R., & Hautvast, J. (1992). Changes in fat-free mass in obese subjects after weight loss: A comparison of body composition measures. *International Journal of Obesity and Related Metabolic Disorders, 16*(9), 675–683. PubMed ID: 1328092

Werneck, A.O., Silva, E.C., Bueno, M.R., Vignadelli, L.Z., Oyeyemi, A.L., Romanzini, C.L., … Romanzini, M. (2019). Association(s) between objectively measured sedentary behavior patterns and obesity among Brazilian adolescents. *Pediatric Exercise Science, 31*(1), 37–41. PubMed ID: 30500315 doi:10.1123/pes.2018-0120

Westerterp, K.R., Meijer, G.A., Saris, W., Soeters, P.B., Winants, Y., & ten Hoor, F. (1991). Physical activity and sleeping metabolic rate. *Medicine & Science in Sports & Exercise, 23*(2), 166–170. PubMed ID: 2017012

Westerterp, K.R., Wouters, L., & van Marken Lichtenbelt, W.D. (1995). The Maastricht protocol for the measurement of body composition and energy expenditure with labeled water. *Obesity Research, 3,* 49–57. PubMed ID: 7736290 doi:10.1002/j.1550-8528.1995.tb00007.x

World Health Organization. (2010). *Global recommendations on physical activity for health*. Retrieved from https://www.who.int/dietphysicalactivity/global-PA-recs-2010.pdf

Yngve, A., Nilsson, A., Sjostrom, M., & Ekelund, U. (2003). Effect of monitor placement and of activity setting on the MTI accelerometer output. *Medicine & Science in Sports & Exercise, 35*(2), 320–326. PubMed ID: 12569223 doi:10.1249/01.MSS.0000048829.75758.A0