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Pia Skovdahl

pia.skovdahl@gu.se

University of Gothenburg

Mats Börjesson

Sahlgrenska Academy, University of Gothenburg

Eivind Aadland

Western Norway University of Applied Sciences

Gisela Nyberg

Swedish School of Sport and Health Sciences

Karin Kjellenberg

Swedish School of Sport and Health Sciences

Anna Karin Lindroos

Uppsala University

Jessica Petrelius Sipinen

Swedish Food Agency

Peter Friberg

Sahlgrenska Academy, University of Gothenburg

Yun Chen

Sahlgrenska Academy, University of Gothenburg

Daniel Arvidsson

University of Gothenburg

Jonatan Fridolfsson

Sahlgrenska Academy, University of Gothenburg

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Authors:

Pia Skovdahl[1], Mats Börjesson[2,3], Eivind Aadland[4], Gisela Nyberg[5,6], Karin Kjellenberg[5], Anna Karin Lindroos[7], Jessica Petrelius Sipinen[8], Peter Friberg[9], Yun Chen[9], Daniel Arvidsson[1,3], Jonatan Fridolfsson[2,3]

Affiliations:

[1]Department of Food and Nutrition, and Sport Science, University of Gothenburg, Gothenburg, Sweden

[2]Department of Molecular and Clinical Medicine, Institute of Medicine, Sahlgrenska Academy, University of Gothenburg, Gothenburg, Sweden

[3]Center for Lifestyle Interventions, Department of Medicine, Geriatrics and Emergency Medicine, Sahlgrenska University Hospital, Region Västra Götaland, Gothenburg, Sweden

[4]Faculty of Education, Arts and Sports, Western Norway University of Applied Sciences, Sogndal, Norway

[5]Department of Health Sciences, The Swedish School of Sport and Health Sciences, Stockholm, Sweden

[6]Department of Global Public Health, Karolinska Institutet, Stockholm, Sweden

[7]Department of Food Studies, Nutrition and Dietetics, Uppsala University, Uppsala, Sweden

[8]Division for Risk and Benefit Assessment, Swedish Food Agency, Uppsala, Sweden

[9]School of Public Health and Community Medicine, Institute of Medicine, Sahlgrenska Academy, University of Gothenburg, Gothenburg, Sweden

Abstract

Background:

Accurate assessment of physical activity (PA) using hip-worn accelerometers depends heavily on data processing decisions, yet implications of these choices for health-related outcomes remain insufficiently understood in children and adolescents.

Aim:

This study examined how different data-processing settings (frequency filter, epoch length, and axis selection) influence estimates of PA intensity and their associations with health measures in youth.

Methods:

Data were drawn from four Norwegian and Swedish cohorts comprising 1842 children and 3019 adolescents, including hip-worn accelerometer measurements (GT3X and GT3X+) alongside measures of physical and psychological health. Laboratory data were used to calibrate accelerometers and to derive comparable estimates of PA intensity and time across intensity categories. Associations were analysed using partial least squares and ordinary least squares regression.

Results:

Overall, the level of PA was consistently associated with the three physical health measures (Body Mass Index, High density Lipoprotein Cholesterol and Cardiorespiratory Fitness) and with the four psychological measures (Stress, Cognition, Psychosomatic Symptoms and Health Realted Quality of Life), across all processing methods.

Accelerometer processing choices substantially influence estimated PA distributions as well as the magnitude and pattern of associations between PA and investigated health outcomes. In general, processing approaches combining 4 Hz frequency filtering, shorter epoch lengths, and triaxial data produced stronger and more consistent associations with health measures in both children and adolescents, confirming the higher predictive validity of this combination of processing settings.

Conclusions:

Findings highlight the importance of carefully selecting processing settings when analysing accelerometer data in children and adolescents. This study provides a fundament for a processing standard of hip accelerometer data for more accurate characterization of PA patterns relevant to health.

Corresponding Author:

Pia Skovdahl

Email: pia.skovdahl@gu.se

Abbreviations

1.63V60	1.63Hz filter, vertical axis, 60 sec epochs
1.63VM1	1.63Hz filter, VM, 1 sec epochs
4VM1	4 Hz filter, VM, 1 sec epochs
ASK	Active Smarter Kids
BMI	Body mass index
CRF	Cardiorespiratory Fitness
ENMO	Euclidean Norm Minus One
ENMO1	ENMO, VM, 1 sec epochs

HDL	High-density lipoprotein cholesterol
HP	High Pass
HRQoL	Health Related Quality of Life
ICAD	International Children's Accelerometry Database
PA	Physical activity
LPA	Light physical activity
MET	Metabolic Equivalent of Task
MPA	Moderate physical activity
MVPA	Moderate-to-vigorous physical activity
OLS	Ordinary least squares regression
PLS	Partial least squares regression
PSP	Psychosomatic symptoms
ROA	"Re-examination of physical activity measurement with accelerometers"
SED	Sedentary behaviour
SR	Selectivity ratios
STARS	Study of Adolescence Resilience and Stress
VM	Vector magnitude
VO_2	Oxygen uptake
VPA	Vigorous physical activity
VVPA	Very vigorous physical activity

Background

Physical activity (PA) is fundamental for healthy development in children and adolescents, playing a key role in preventing cardiometabolic disease (1–3), supporting cardiorespiratory fitness (CRF) (4), and maintaining a healthy body weight (3,4). Beyond physical health, PA is

97 closely linked to psychological wellbeing, with evidence showing improvements in mood,
98 self-esteem, and reductions in symptoms of anxiety, stress and depression (2,3). Because
99 childhood and adolescence are critical stages of development, they offer a unique window for
100 shaping lifelong habits (5).
101
102 The evidence of the importance of PA for physical and psychological health is dependent on
103 accurate and precise assessment of PA. Accelerometry has revolutionized the assessment of
104 PA in free-living conditions and are today widely used in large population-based studies
105 worldwide (6). Although accelerometers provide highly objective and detailed data, the use of
106 such data depend on several data processing decisions required to convert acquired raw
107 signals into the measure of interest, including frequency filtration, utility of acceleration axes,
108 epoch length, and selection of wear-time criteria. These decisions are not simply technical
109 details but key methodological choices that can affect/severely influence research outcome by
110 introducing various degree of measurement error (7,8).
111
112 Today, substantial inconsistencies exist in accelerometry-based research. Studies in both
113 children and adults have shown that differences in accelerometer data processing such as the
114 number of axes analysed, (9–11), the frequency filter applied (11–16), and the selected epoch
115 length (17–19) can substantially influence the PA measures. Still, the consequences of these
116 adjustments on the associations with physical and psychological health indicators remain
117 largely unexplored. As far as we are aware, only one study has assessed the effects of
118 different accelerometer processing on the relationship between PA intensity and physical
119 health indicators in middle-aged adults (11). The results show that the explained variance (R^2)
120 in health outcomes varied substantially across combinations of accelerometer processing
121 settings, including frequency filtering, epoch length, number of axes, wear-time criteria,

recalibration, and time-composition metrics. It ranged from 12.1% to 20.8% for aerobic fitness and from 5.8% to 14.0% for BMI, with frequency filtering and epoch length having the greatest influence. Moreover, the PA intensity ranges contributing most to the explained variance differed across processing combinations, indicating that processing choices influence not only the overall strength of association, but also which part of the PA intensity spectrum most strongly associated with health outcomes.

Children's movement patterns differ from those of adults due to their unique biomechanical, metabolic, and developmental characteristics (15,20–25). These differences emphasize the importance of investigating how accelerometer processing combinations influence the association to health in children and adolescents. To our knowledge, no comparable research investigating the effect on processing combination has been done in younger populations.

Our primary aim was to examine how multiple data processing methods (frequency filtering, epoch lengths and axes) for hip accelerometer data affect estimates of PA and their associations with physical and psychological health measures in representative samples of Swedish and Norwegian children and adolescents. With this aim we seek to propose a methodological standard for processing hip-worn accelerometer data in children and adolescents.

Method

Study overview

The study consists of two phases:

1) A calibration part conducted in a laboratory setting, to enable comparisons across processing combinations.
2) A free-living part with two age groups, children (10-11 years) and adolescents (13-14 years), to evaluate the effect of processing combinations on the PA intensity distribution, and the strength and shape of the association with measures of physical and psychological health, (predictive validity).

Samples and data collection

Laboratory Study

We used data from the "Re-examination of physical activity measurement with accelerometers" (ROA) study aiming to improve accelerometry methodology and enhance calibration of accelerometer-derived measures (12,14,15). In this study, oxygen consumption data (VO_2) and accelerometer data were collected at rest and during treadmill walking and running in 20 participants across 2 age groups: children (10 years) and adolescents (15 years). Participants were recruited through personal contacts, such as local sports clubs, and institutional staff and students. Inclusion criteria required participants to be healthy, physically capable of completing the test protocol, and free from chronic disease, physical disability, or conditions affecting PA or metabolism, as determined by self-reported medical history. The study was approved by the Regional Ethics Committee in Gothenburg (Ref No. 1026-17) and the Swedish Ethical Review Authority (Ref No. 2023-02192-02). Written informed consent was obtained from all participants and from caregivers.

Participants were instructed to avoid strenuous PA the day before and fast for 3 hours prior to the laboratory visit (26). Each participant completed a single continuous protocol beginning

with measurements of body weight and height, followed by 20 minutes of seated rest, 4 minutes of standing (excluded from analyses), and multiple 4-minute walking and running stages on a treadmill. Participants wore a safety harness during treadmill activities. All participants completed walking at 3 and 6 km/h and running at 8 and 10 km/h, with 15-year-olds additionally running at 12 km/h. One 10-year-old was unable to complete the highest speed and was supplemented by an additional participant to maintain group size. Triaxial acceleration was recorded at 100 Hz using an Axivity AX3 accelerometer (Axivity Ltd., Newcastle upon Tyne, UK) worn on the right hip. VO_2 was measured continuously, breath by breath, using the Oxycon Pro system (Jaeger, BD Corporation, Franklin Lakes, NJ, USA). Resting VO_2 was defined as the lowest 2-minute average during the final 10 minutes of seated rest, and activity VO_2 values were calculated from the final minute of each stage.

Measured Metabolic Equivalent of Task (MET = VO_{2total}/VO_{2rest}) from the last minute of each activity was used to calibrate accelerometer outputs for absolute intensity. Recent advances in research promote the use of an intensity spectra rather than using crude PA intensity levels, permitting more detailed information of the assessed PA (13,27). Accordingly, calibration cut-points on the accelerometer scale corresponding to a spectrum of 30 absolute intensity categories (0.5 MET increments up to 15 METs and above) were derived from linear regression of accelerometer output on MET values from the laboratory protocol. In addition, visualisation of broader categories was based on traditional crude cut-points: sedentary behaviour (SED) (<1.5 METs), light PA (LPA) (1.5–<3.0 METs), moderate PA (MPA) (3.0–<6.0 METs), vigorous PA (VPA) (6.0–<9.0 METs), and very vigorous PA (VVPA) (≥9.0 METs). Through this calibration, raw accelerometer values were converted to a standardized MET-based physiological scale, enabling consistent comparison of PA intensity distribution and health-association patterns across processing combinations. Simple linear algorithms have

been shown to estimate energy expenditure from hip acceleration data with accuracy comparable to more complex algorithms (28).

Free-living Studies

Raw accelerometer baseline data and different measures of physical and psychological health were obtained from four separate cohorts: the Active Smarter Kids (ASK) (29,30); Study of Adolescence Resilience and Stress (STARS) (31); Physical Activity for Healthy Brain Functions in School Youth ("Brain Health in School") (32,33) and Riksmaten Adolescents 2016–2017 (34). Participants from the four cohorts were grouped into two age-based categories, children (10-11 years) and adolescents (13-14 years), to account for developmental differences in physiology, behaviour, and responses to PA. These age groups represent distinct stages of growth and maturation, with evidence indicating that associations between PA and health outcomes vary across childhood and adolescence (35). In all four cohorts, the participants wore a triaxial accelerometer (GT3X or GT3X+, ActiGraph, Pensacola, FL, USA) on the right hip for seven continuous days, waking hours only. Devices recorded movement at 30 Hz with a ±6 g dynamic range.

Accelerometer Data Processing

Across all cohorts, analyses were restricted to participants with valid accelerometer recordings for ≥ 4 days of measurement including ≥ 1 weekend day, with valid days identified based on wear time (10 h/day). Non-wear periods were defined as 60 min of consecutive zeros, with allowance of <2 min of acceleration value corresponding to 1.5 METs (36).

After resampling the accelerometer data to 30 Hz, the raw accelerometer data were processed through three main steps: raw data filtration, axis selection and epoch length. Raw accelerometer data was first filtered using five different data reduction approaches: low-pass filters at 1.63 Hz (original ActiGraph setting (AG)) (37), 4 Hz and 10 Hz (12), without upper cut-point (High pass (HP)) and Euclidean Norm Minus One (ENMO) (38) to remove gravity and noise. A shared high-pass filter at 0.29 Hz excluded gravity and low frequency noise, while low-pass filters at 1.63 Hz, 4 Hz, and 10 Hz defining the range of measurable movement frequency (12), or without upper cut-point (HP). ENMO does not use frequency filtering; instead, the vector magnitude (VM) is calculated from the raw triaxial data, subtracting gravitational acceleration (1 g) and truncating negative values to zero (15,39). PA intensity was then derived from either vertical acceleration or VM, calculated as $\sqrt{x^2 + y^2 + z^2}$, and finally averaged into 1-, 3-, 5-, 10-, 15- and 60 second epochs. Shorter epochs preserve rapid fluctuations in movement, capturing intensity variation more effectively than longer epochs (17). As ENMO rely on triaxial data (38), vertical-axis data were not included in the ENMO metric. Consequently, any uniaxial ENMO settings were excluded, reducing the total number of processing combinations to 54.

Physical and psychological health

All health outcomes available across the contributing cohorts were screened in the initial analysis. Outcomes that were significant across all the 54 PA processing combinations were retained for further analysis. Among physical health measures, body mass index (BMI), cardiorespiratory fitness (CRF) and high-density lipoprotein cholesterol (HDL) were statistical significant across all 54 combinations; among psychological health measures (adolescents only), perceived stress, psychosomatic symptoms, cognition and Health Related Quality of Life (HRQoL) reached statistical significance across all 54 combinations.

Physical health measures

All four cohorts contained BMI, resulting in a final analytic sample of 1819 children and 3014 adolescents. BMI was calculated separately for the child and adolescent groups, as weight in kilograms divided by height in meters squared (kg/m^2).

For the children's group, cardiorespiratory fitness ($ml \cdot kg^{-1} \cdot min^{-1}$) was available for the ASK cohort (n = 926), and for the adolescent group of the Brain Health cohort (n = 957). Children's fitness was assessed using the intermittent field-based Andersen test (40), a practical running test shown to be reliable and valid for this age group (41). Adolescent fitness was assessed using the Ekblom-Bak test, a submaximal cycle ergometer protocol (42), showing good validity in adolescents (43).

HDL was measured through serum samples (mmol/L) and were available for both cohorts included in the children group (n = 1176) as well as for the Riksmaten cohort in the adolescent group (n = 331).

Psychological health measures

Among the psychological health measures, stress (n = 1278), psychosomatic symptoms (n = 1277), HRQoL (n = 953) and cognition (n = 980), were statistically significant across all 54 processing combinations in the model for the adolescent group. No psychological measures were significant in the children's group.

The 10-item Perceived Stress Scale (PSS-10) was used to assess adolescents' perceived stress (44,45). The scale measures the extent to which individuals perceive their lives as unpredictable, uncontrollable, and overloaded. Responses were given on a 5-point scale from 0 (never) to 4 (very often), with up to one missing item allowed and imputed using the participant's mean score. Total scores ranged from 0 to 40, with higher scores indicating greater perceived stress. Psychosomatic symptoms (PSP), including concentration and sleep difficulties, headaches, stomach-aches, poor appetite, tension, low mood, and dizziness, were measured using the psychosomatic problem scale (44). Responses were given on a 0 (never) to 4 (always) scale, with up to one missing item imputed using the participant's mean. Total scores ranged from 0 to 32, with higher values reflecting greater symptom burden.

Kidscreen-10 was used to assess HRQoL in individuals aged 8–18 and is validated for both healthy and clinical populations (46). Participants rated the frequency of various emotional and physical well-being experiences over the past week on a five-point scale. Scores are summed (with two items reverse scored) to a total ranging from 10 to 50, where higher scores indicate better well-being (46).

Cognition was represented as a latent variable using structural equation modelling techniques (32). A battery of six computer-based tasks was used to evaluate two areas of cognition: working memory (letter updating, numerical 3-back, spatial updating) and episodic memory (word recall, number-word recall, object-position recall), with a composite cognitive performance score was calculated and used as the outcome variable for cognitive performance (47).

Statistics

This study presents results of three different analyses of accelerometer data processing: 1) time distribution across the range of PA intensities; 2) strength of associations between PA intensities and the physical and psychological health measures (R^2); and 3) association patterns between PA intensities and the physical and psychological health measures. The physical and psychological health measures were analysed separately and pooled. The outcome of four historically relevant processing combinations is visualized in the present study: 1) 1.63Hz filter, vertical axis, 60 sec epochs (1.63V60); 2) 1.63Hz filter, VM, 1 sec epochs (1.63VM1); 3) 4 Hz filter, VM, 1 sec epochs (4VM1); and 4) ENMO, VM, 1 sec epochs (ENMO1).

Partial least squares (PLS) regression was used to determine the association strength and the association pattern across the PA intensity spectrum, as the intensity categories are collinear (up to 14% $r > 0.9$, depending on processing combination) (48). The 31 predictors were the 30 absolute intensity categories and the non-wear time, expressed as average minutes per 24 h and standardised. The PLS reduces the spectrum into a smaller number of latent variables that best explain variation in the health outcomes. The number of latent variables was determined separately for each model through Monte Carlo cross-validation with 1000 repetitions (50/50 train/test split), adding a latent variable only when it lowered the cross-validation error in a sufficient proportion of the repetitions (threshold 0.5 standard deviations) (49). Statistical significance of each PLS model was assessed using permutation testing with 10 000 repetitions. Before PLS modelling, each health outcome was regressed on sex and age using ordinary least squares regression, and the standardized residuals were used as the dependent variable in the PLS analysis; this adjusts for sex and age, but not for cohort. Selectivity ratio plots were used to visualize the contribution of each predictor, signed by the corresponding

regression coefficient so that intensities contributing to opposite directions can be distinguished. To ease interpretation, colour-formatted in-text labels are used, matching the abbreviated processing combinations to the colours shown in the figures.

Two complementary levels of analysis were performed: single-outcome analysis and pooled-outcome analysis. Single-outcome analyses, presented in the supplementary material (Supplement 1 for physical and Supplement 2 for psychological outcomes), provide one PLS model per health variable so that outcome-specific association strengths and patterns remain visible. The pooled-outcome analysis, presented in the main text, is built from these same per-outcome models, aggregated across outcomes in two steps: first association strength, then association pattern. The following two paragraphs describe the additional steps for the pooled-outcome analysis.

For association strength, the R^2 values from the per-outcome PLS models, one for each processing combination and outcome, were stacked and modelled as the dependent variable in ordinary least squares (OLS) regression, using the three processing components treated as categorical variables converted to dummies and excluding the reference setting of each, with outcome included as an additional dummy. The reference settings, 1 s epoch, low pass filter at 1.63 Hz (AG), and vertical axis data, were chosen based on prior studies (7,11). The resulting coefficients display the direction and magnitude of the change in explained variance when switching from the reference configuration to an alternative one. As ENMO is defined only for the vector magnitude, its coefficient is not fully separable from the axis term.

For association pattern, the per-outcome selectivity ratio spectra were combined as an R^2-weighted average across outcomes, so that outcomes with stronger associations contributed

proportionally more to the pooled intensity spectrum. Because the selectivity ratio is signed, outcomes for which a higher value indicates poorer health (BMI, perceived stress and psychosomatic symptoms) were multiplied by −1 before averaging, so that all outcomes were expressed in the same health direction. The single-outcome panels are not reversed.

Together, explained variance and selectivity ratio plots reflect predictive validity. Because non-wear detection depends on the processing applied, inclusion was determined once from the reference combination (4 Hz filter, VM, 1 sec epochs), and that sample was analysed in all 54 combinations. All processing and analyses were conducted in MATLAB R2026a (plsregress, Statistics and Machine Learning Toolbox) and in Python (actigraph/agcounts package).

Result

The children group included 1842 (51% female) participants from the ASK and the Riksmaten cohorts, while the adolescent group included 3019 (57% female) participants from the Riksmaten, the Brain Health and the STARS cohorts (Table 1). Description of the individual cohorts can be found in Supplement 3.

Table 1: Participant characteristics.

Variable	Children	Adolescents
ASK (n)	993	-
Riksmaten children (n)	849	-
Riksmaten adolescents (n)	-	758
Brain Health (n)	-	982

STARS (n)	-	1279
N (after inclusion)	1842 (51% female)	3019 (57% female)
Age (years)	10.8 (0.7) [n=1842]	13.7 (0.5) [n=3019]
Height (cm)	146.7 (8.2) [n=1820]	163.9 (7.9) [n=3019]
Weight (kg)	40.2 (9.8) [n=1819]	54.2 (11.0) [n=3014]
BMI (kg/m2)	18.5 (3.2) [n=1819]	20.1 (3.3) [n=3014]
HDL (mmol/L)	1.6 (0.3) [n=1176]	1.5 (0.3) [n=331]
VO_{2max} ($ml \cdot kg^{-1} \cdot min^{-1}$)	55.9 (6.9) [n=926]	51.3 (11.9) [n=957]
Psychosomatic problems, PSP (scale)	-	11.4 (5.4) [n=1277]
Stress (scale)	-	15.2 (6.1) [n=1278]
Cognition (score)	-	0.0 (0.8) [n=980]
HRQOL (Kidscreen score)	-	39.7 (5.3) [n=953]

Effect of processing setting on physical activity intensity distribution

Figure 1. Free-living physical activity time distribution across four processing combinations in children and adolescents.

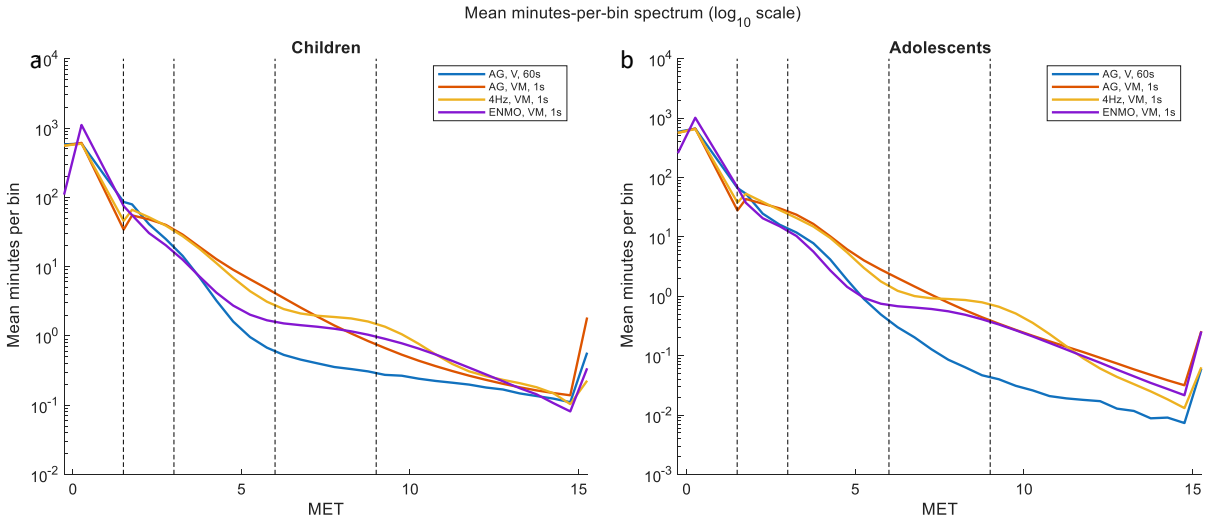


Figure 1. Time distribution (log_{10}scale) of free-living PA data for the four processing combinations in children and adolescents.
Values are log-transformed (log_{10}) to facilitate visualization. Time distribution of MET calibrated free-living PA data for the four processing combinations in a) children, b) adolescents. Values are log-transformed (log_{10}) to facilitate visualization.

The choice of processing combination clearly influenced the time distribution across MET-calibrated free-living PA, with a similar pattern observed in both children (Figure 1a) and adolescents (Figure 1b, Supplement 4). The 1.63V60 processing combination showed the greatest deviation to the other combinations, shifting the time distribution to lower PA intensities, generating a total of approximately 33 min moderate-to-vigorous PA (MVPA)/day in the children group and 28 min MVPA/day in the adolescent group (Supplement 4). By applying shorter epoch length and VM (1.63VM1), a large part of this deviation disappeared, showing similar distribution as 4VM1. Still, there is a remaining difference between 1.63VM1 and 4VM1, where 4VM1 shifts time towards even higher intensities, which is an effect of the wider frequency filter. Using the 1.63VM1 participants accumulated approximately 98 min MVPA/day in the children group and 72 min MVPA/day in the adolescent group, with the 4VM1, showing a total of 89 min MVPA/day in the children group and 64 min MVPA in the adolescent group. Applying the ENMO1 combination, participants accumulated approximately 43 min MVPA/day in the children group and 27 min MVPA/day in the

adolescent group. Further, the ENMO1 lead to higher estimates of SED relative to the other processing combinations and thereafter follows the 1.63V60 time distribution across LPA and MPA, finally approaching 1.63VM1 and 4VM1 from VPA and higher intensities.

Effect of processing setting on strength and pattern of association with physical health

Figure 2. Strength and pattern of association with pooled physical health.

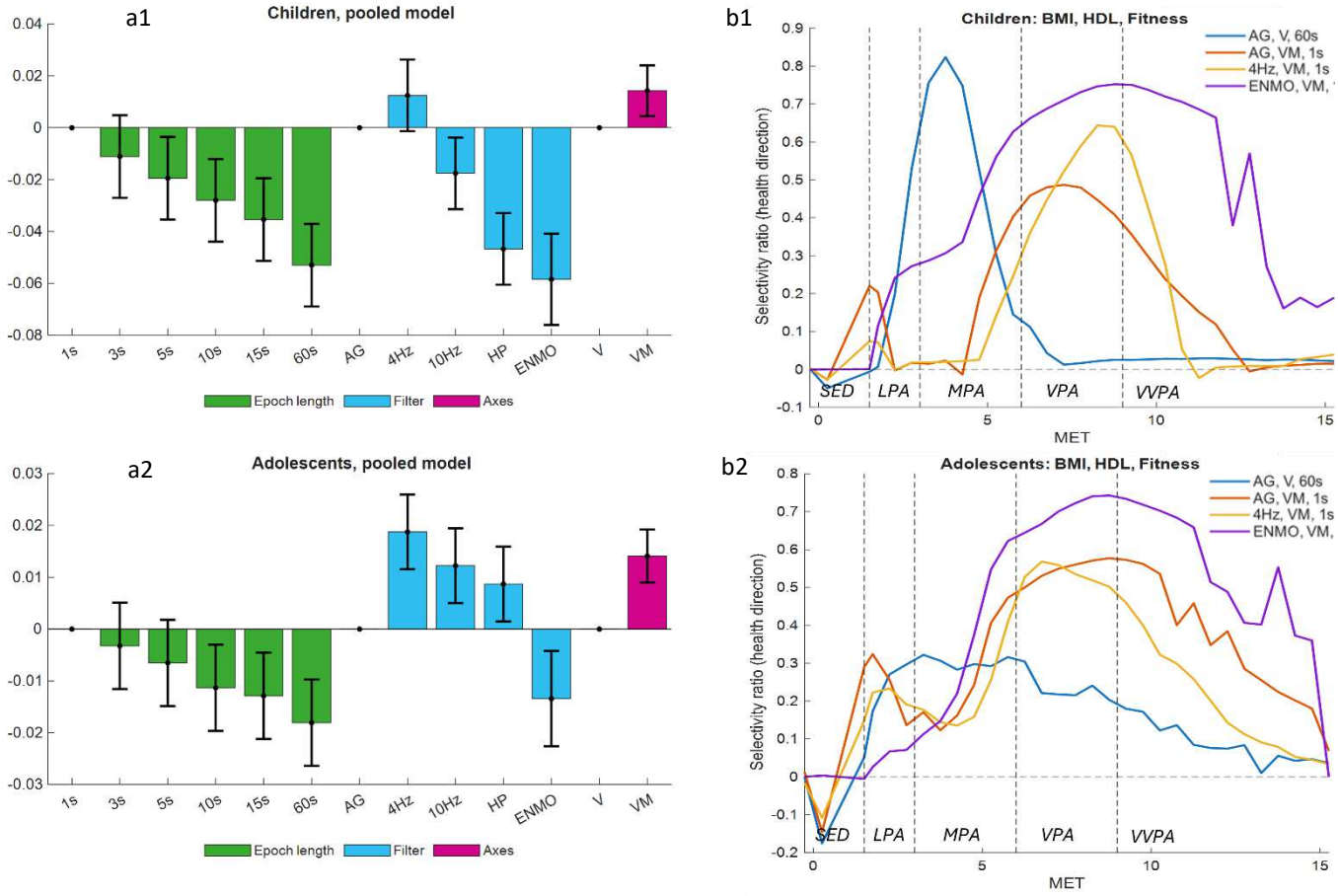


Figure 2a1+2) Strength of association with pooled physical health (BMI, CRF, HDL). Multiple regression analyses to evaluate the effect on explained variance (R^2, increase or decrease) of pooled physical health by changing from the reference configuration (1-second epochs, 1.63Hz filter, vertical axis) to alternative setting in (a1) children and (a2) adolescents. Bars with confidence intervals that do not cross zero represent statistically significant effects; intervals that overlap zero indicate non-significant estimate.
2b1+2) Pattern of association between MET-calibrated PA and pooled physical health (BMI, CRF, HDL). The strength of association across the intensity spectrum is presented as Selectivity ratio (health direction) in b1) children and b2) adolescents. BMI, Body Mass Index; CRF, Cardiorespiratory Fitness; HDL, High Density Lipoprotein.

The analysis of the pooled physical health data revealed similar results in both children and adolescent (Figure 2a1 and 2a2). In children (Figure 2a1), moving from 1-second to >5-

second epochs showed a significant decrease in the strength of association with physical health (explained variance (R^2) decreased 2.0% - 5.3%), whereas moving from 1-second to 3-second epochs resulted in non-significant change in associations. The 1.63 Hz filter and 4 Hz filter demonstrated similar strength, with non-significant yet positive effects observed for the 4 Hz configuration. In contrast, the 10 Hz, HP, and ENMO processing components all contributed to significantly decreased strength of association (explained variance (R^2) decreased 1.8% - 5.9%). Using VM data generally showed significant positive effects on explained variance (increased explained variance 1.4%).

In adolescents (Figure 2a2), moving from 1-second epochs to 10-second-, 15-second- and 60-second epochs significantly decreased the strength of association with physical health (decreased explained variance between 1.1% and 1.8%), whereas 1-second epochs to 3-second- and 5 second epochs showed no significant change in the associations. Broadening the filter to 4 Hz showed the largest significant increase in explained variance, while both the 10Hz and high-pass (HP) filters were associated with significant increases. In contrast, ENMO was associated with a significant decrease in explained variance of 1.3% for physical health outcomes. VM data generally showed significant positive effects on explained variance (explained variance (R^2) increased 1.4%).

The same overall association pattern with pooled physical health appears for both children and adolescents (Figure 2b1 and 2b2), as shown by Selectivity Ratios (SR). SR indicates the relative contribution of each PA intensity to the association with the outcome. The pattern of SR values across the intensity spectrum illustrates which PA intensities contribute most strongly to the association. The 1.63V60 combination appears limited in detecting associations at higher intensities, shifting the associations towards lower intensities (LPA–MPA). The 1.63VM1 and 4VM1 combinations place the association more toward VPA-

VVPA, especially 4VM1, which is particularly evident in children (Figure 2b1). In children, ENMO1 deviates from the other combination by finding associations across the intensity spectra, whereas in adolescents it is more similar to the 1.63VM1 and 4VM1 combinations.

Table 2: Explained variance R^2 of separate physical and psychological health parameters.

	1.63Hz, 60s, V	1.63Hz, 1s, VM	4Hz, 1s, VM	ENMO, 1s, VM
Children				
BMI	0.0712	0.1803	**0.1869**	0.0904
HDL	0.0181	0.0222	**0.0223**	0.0184
CRF	0.1489	0.2215	**0.2833**	0.1203
Adolescents				
BMI	0.0178	0.0901	**0.1087**	0.0544
HDL	**0.0315**	0.0155	0.0271	0.0187
CRF	0.0852	0.1209	**0.1393**	0.1122
PSP	0.0187	0.0132	**0.0234**	0.0190
Stress	0.0161	0.0124	**0.0227**	0.0210
Cog	**0.0670**	0.0190	0.0354	0.0371
Kidscreen	0.0301	0.0361	**0.0394**	0.0320

Explained variance R^2 of the outcome of the four processing combinations for separate physical and psychological health parameters. Bold format indicates the highest explained variance among the settings.

The 4VM1 has the highest explained variance for the physical health measures in children (range: 2.23–28.33%) and adolescent (range: 2.71-13.93%), but the order for the other combinations is less clear (Table 2). The 1.63V60 showed the lowest explained variance for physical health in both children (range: 1.81–14.89%) and adolescent (range: 1.78–8.52%), followed by ENMO1 in children (range: 1.84–12.03%) and adolescents (range: 1.87–11.22%).

Effect of processing setting on strength and pattern of association with psychological health

Figure 3. Strength and pattern of association with pooled psychological health.

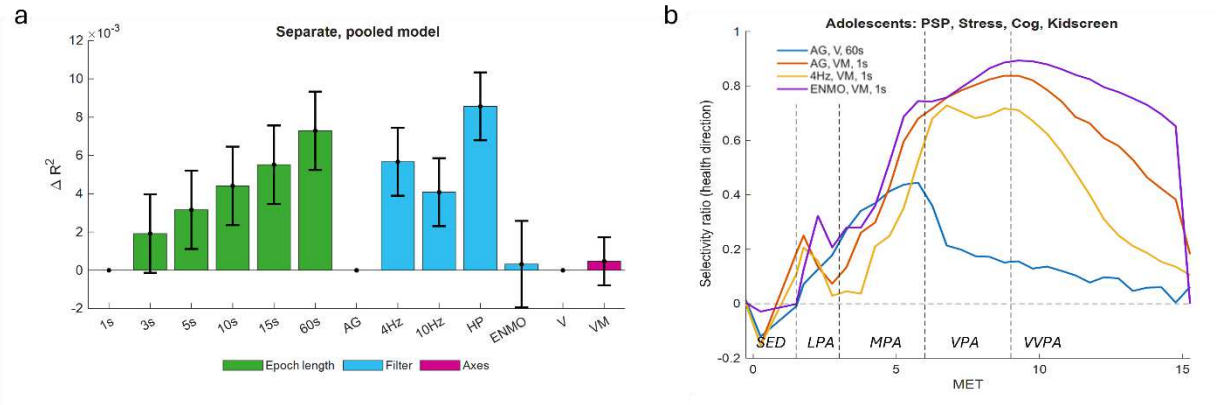


Figure 3a) Strength of association with pooled psychological health (Psychosomatic problems, stress, cognition, HRQoL), adolescents
Multiple regression analyses to evaluate the effect on explained variance (R^2, increase or decrease) of pooled psychological health by changing from the reference configuration (1-second epochs, 1.63Hz filter, vertical axis) to alternative setting in adolescents. Bars with confidence intervals that do not cross zero represent statistically significant effects; intervals that overlap zero indicate non-significant estimate.
Figure 3b) Pattern of association between MET-calibrated PA and pooled psychological health (psychosomatic problems, stress, cognition HRQoL). The strength of association across the intensity spectrum is presented as Selectivity ratio (health direction) **in** adolescents.
Cog, cognition; HRQoL, Health-Related Quality of Life; MET, Metabolic Equivalent of Task; PSP, Psychosomatic Problem; V, Vertical, VM, Vector Magnitude.

In contrast to the pooled physical measures, the pooled psychological parameters in the adolescent group showed an increased explained variance with longer epochs, with epochs of 5 seconds and longer reaching statistical significance (Figure 3a). Expanding the frequency filter from the reference setting of 0.29–1.63 Hz to >4Hz had positive effect on the explained variance, with the greatest effect applying the high pass filter (increased explained variance 0.86%). The association pattern of the psychological parameters revealed similar effects of the processing combinations as in the physical models. The 1.63V60 combination shifts the association towards the lower intensity ranges (LPA-MPA), whereas the other processing combinations reveal the highest association in the upper part of the intensity spectra (>mid

MPA). The 1.63VM1 and ENMO1 follow a similar pattern, finding the strongest associations from mid MPA and higher intensities, whereas the 4VM1 is shifted slightly to even higher intensities. For the individual psychological health measures, the 1.63V60 showed the highest explained variance for *cognition*, whereas the 4VM1 outperformed the other combinations for the remaining three psychological measures (Table 2).

Discussion

The main finding of the present study is that processing choices for hip-worn accelerometer substantially alter both the distribution of PA intensity, and the strength and pattern of association with physical and psychological health in children and adolescents. The 4VM1 processing combination showed consistently the strongest association with the health measures, achieving the highest predictive validity.

The commonly used processing combination 1.63V60 appears systematically limited sensitivity in detecting higher intensities, resulting in observed associations being concentrated at lower intensity ranges (LPA–MPA). This pattern is consistent with previously documented measurement limitations of this processing approach (12,15). Previous analyses of free-living accelerometer data have shown that PA-related acceleration signals extend beyond the 1.63 Hz frequency range (50). A similar pattern was observed in the signal frequency distributions of the cohorts included in the present study (Supplement 5). By restricting the frequency range to 0.29–1.63 Hz, a substantial portion of these higher-frequency components is lost, and the filter compromises the ability to differentiate between activity intensities (12,15,50,51), resulting in misclassification of MET-calibrated data, leading to a less accurate assessment of association between PA intensity and health.

Epoch length fundamentally alters how intensity is represented and linked to health measures (17,52). By smoothing out short, intense bursts across a long window of time, long epochs reduce their apparent intensity and shift them into the moderate range. Thus, first, high-frequency (vigorous) signals are attenuated and misclassified by the narrow 1.63 Hz filter, then the remaining signal is averaged over a 60-second timespan, reducing the acceleration peaks even further. With shorter epochs and triaxial data, 1.63VM1 improves the detection of higher-intensity movement compared to the standard approach, shifting the distribution of activity to higher intensities and increasing the R^2 in the pooled physical health in the children group and the adolescent group compared to the 1.63V60. However, it still appears limited in fully capturing the highest intensities.

ENMO1 shows a somewhat divergent pattern in children, with consistently elevated SR values across the entire PA intensity spectrum, indicating that a broad range of PA intensities contributed to the explained variance, despite an overall underestimation of the associations with health measures. In adolescents, the ENMO1 aligns more closely with 1.63VM1 and 4VM1, indicating that the performance of the signal structure may depend on age-related differences in activity patterns, possibly due to truncation of data in the processing of ENMO data. Here, all negative acceleration values are set to zero after gravity removal (38), eliminating negative acceleration between 0 and −1 g (15). Removing a constant amount of amplitude may attenuate a substantial portion of high-intensity acceleration as parts of the signal are removed. This can systematically distort the recorded movement and obscure the true activity pattern. It may also amplify variation in the PA spectrum that is unrelated to the health outcome, suggesting the presence of measurement artefacts rather than meaningful signal.

The 4VM1 combination shows a strong shift toward the highest intensities, especially in children. A plausible explanation is that the broader filter in combination with short epochs captures more high-frequency movement signals. Together with using data from all three axis, the sensitivity to capture more intermittent and high-intensity PA is heightened. The lower explanatory information at low intensities increases around 4 METs and remains high at higher intensities, indicate that activity above mid-MPA contributes most to explaining health variation. This pattern aligns with expected physiology (53), as CRF contributes heavily to the pooled outcome, making higher intensities more strongly represented in the pooled data.

Although vertical acceleration has been seen to dominate the signal during ambulatory activities in adults (11), the horizontal acceleration constitutes a major component of total acceleration in running (50,54). Conversely, in children, each of the three axes is seen to provide distinct and valuable information about their intermittent and sporadic way of moving (10,55) and the relationship between these specific PA patterns and health outcomes (10,56). Relying on the vertical axis alone primarily reflects upright ambulatory activity, while overlooking movements contributing to the signal in the horizontal or lateral planes (50,54). Our results are consistent with this. The similar trend observed in both children and adolescents suggests that the influence of processing choices on associations between PA and physical health outcomes are relatively stable across the age groups.

For the pooled psychological health outcomes, shifting away from the reference settings produced a different relationship in the strength of associations compared with the physical health parameter. Here, longer epochs (>5 seconds) perform better than shorter epochs. The longer epochs may work as a minor bout-setting of the performed activity, with the longer epochs capturing key distinguishing features of sustained PA patterns which in turn

512 strengthens the associations detected in the analyses. A broad basis of reviews and meta-
513 analyses suggests that PA benefits cognition and psychological health through several,
514 interconnected molecular/cellular, structural, functional, and psychosocial pathways (57–59).
515 Together, these mechanisms support executive functions, attention, and learning, with
516 psychosocial factors such as better mood, reduced stress and increased self-efficacy, further
517 contribute to the cognitive and psychological benefits observed, likely through molecular and
518 structural brain changes (58,60,61). Therefore, psychological health parameters may benefit
519 from a wider range of intensities where the volume, sustainability and the length of activity
520 might be more influential than shorter burst of PA. Longer PA interventions have generally
521 been shown to produce larger and more consistent effects, where the optimal range appears to
522 be approximately 40–60 minutes of exercise per session, performed 3–5 times per week and
523 sustained for at least 12 weeks (59). Exploring bout duration and frequency could therefore
524 help identify whether sustained PA has distinct associations with health and developmental
525 outcomes compared with the intermittent activity patterns typically observed in children.
526
527 The finding of the 1.63V60 intensity misclassification has important implications. It can
528 distort both how active participants appear to be, but also where the associations with health
529 outcomes are located in the intensity spectrum, the very interpretation of dose–response
530 relationships. For example, if using the 1.63V60 combination the children reached
531 approximately 33 min/day of MVPA, when they accumulated 89 min/day applying the 4VM1
532 combination (Supplement 4), leading to different conclusions of the PA level in the
533 population. Because research on PA and health forms the basis for policy documents and
534 public health recommendations, it is essential that data processing is carried out in an accurate
535 and well-justified manner. One of the largest databases for children's accelerometer data, the
536 International Children's Accelerometry Database (ICAD), harmonizes raw accelerometer data

from various cohorts worldwide by applying consistent processing methods. Typically, raw or study-specific epoch data are re-aggregated to a common epoch length, 60 seconds in ICAD 1.0, and shorter epochs (around 10–15 seconds) in later versions, together with the narrow frequency filtering and other original device-specific processing (62). Specifically, benchmark work using the ICAD, examined how objectively measured PA and SED relate to cardiometabolic health in over 20 000 children and adolescents (63). The results showed that MVPA was strongly and consistently associated with a healthier cardiometabolic profile. However, our findings suggest that traditional accelerometer processing approaches may attenuate the observed associations between PA and health outcomes. Processing criteria commonly applied in studies using traditional ActiGraph processing can truncate the acceleration signal, underestimate acceleration amplitude, and consequently misclassify high-intensity activity as lower-intensity PA. The additional use of 60-second epochs may further smooth short bursts of high-intensity activity. Some activity that would otherwise be classified as MVPA may be assigned to lower intensity categories, potentially weakening the observed associations between MVPA and health outcomes. Consequently, there is an increased risk of incorrect conclusions, including underestimating the importance of MVPA, overestimating the role of light activity, and flattening dose-response relationships. Extending the findings of Aadland et al. (17), who demonstrated stronger associations between higher PA intensities and cardiometabolic health when using shorter epoch lengths in children, our findings, together with previous evidence in adults (11), suggest that the strongest associations with health outcomes may occur at relatively higher absolute PA intensities than indicated by traditional accelerometer processing approaches.

Based on the findings of this study, we propose a modified processing standard for hip-worn accelerometer data, aiming to improve data quality and increase comparability across studies

(Figure 4). The consistent strength of association with health measures (predictive validity) was the criteria for selecting the 4VM1 combination as the standard. This proposal closely aligns with suggested standard for middle-aged adults (11). The processing standard brings us closer to the association we assume exists between PA and health, and thereby also the true PA pattern in the investigated populations - bridging the gap from movement to meaning.

Figure 4. Proposed processing standard for hip accelerometer data in children and adolescents.

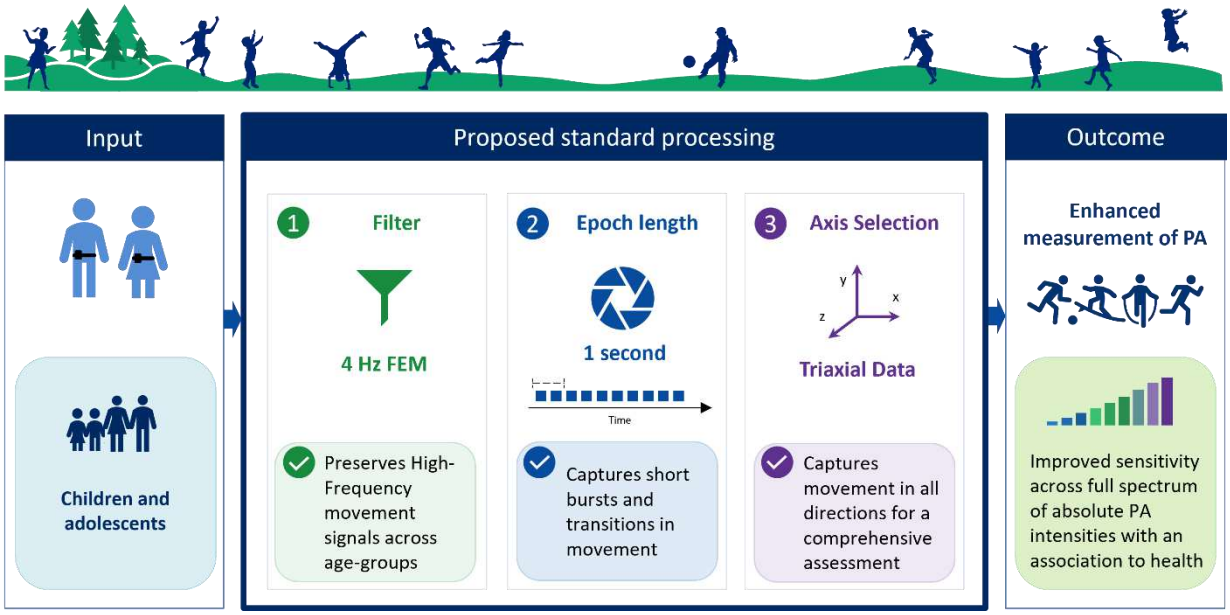


Figure 4. Proposed processing standard for hip accelerometer data.
Proposed processing standard for hip accelerometer data collected during daytime in children and adolescents with an association to physical and psychological health.

Strengths and limitations

Using data from four cohorts of children and adolescents, this study is, to our knowledge, the first to evaluate how multiple hip-worn accelerometer data-processing combinations influence estimates of physical activity and their associations with physical and psychological health outcomes. The dataset captures a wide variety of relevant physical and psychological health measures to enable robust analyses associations with health outcomes to determine the

predictive validity of various approaches. By only including health parameters that met predefined criterion of showing a significant association across all 54 processing combinations, the analysis focused on indicators that were consistently associated with the outcomes of interest. This ensures that the analysis is based on health parameters that show reliable associations, supporting clearer evaluation of the link to health. Consequently, the results are specific to hip-derived accelerometer data and the health measures included in the analysis. Thus, depending on the specific health or developmental outcome being investigated, the optimal accelerometer processing approach may vary.

Future studies could evaluate whether similar patterns are observed using additional health indicators across larger cohorts and within broader age groups, and also across different accelerometer positions. Other metrics used in research, such as MAD, Activity Index, and MIMS, could also be considered for comparative analyses. In addition, the results may not be directly generalizable to accelerometer brands beyond the ActiGraph accelerometer, as previous research has shown that different accelerometer brands can produce slightly different outputs even when the same processing methods are applied (37).

The ASK cohort showed a consistently higher power across the signal frequency distribution of the included cohorts of study (Supplement 5), indicating a larger volume of PA. Given the comparable measurement, and identical processing protocols across the cohorts, systematic bias is unlikely, suggesting that the difference reflects genuine physiological or behavioural variation, such as higher total PA volume, movement intensity or frequency among the children.

Conclusions

Our findings emphasize the importance of carefully selecting the processing settings when analysing accelerometer data in children and adolescents. The study provides a foundation for the standardization of hip-worn accelerometer data processing (as proposed in Figure 4), in order to capture the PA pattern relevant to health in the pediatric population.

Declarations

Ethics approval and consent to participate

The study was conducted in accordance with the ethical principles of the Declaration of Helsinki. Ethics approval have been achieved for all data included, and written informed consents for participation have been obtained from all participants and from caregivers: Regional Ethics Committee in Gothenburg (Ref No. 1026-17) and the Swedish Ethical Review Authority (Ref No. 2023-02192-02) (Re-examination of physical activity measurement with accelerometers" (ROA) study); South-East Regional Committee for Medical Research Ethics (reference 2013/1893), registered at ClinicalTrials.gov (ID nr: NCT02132494. Date of registration, 6th of May, 2014) (Active Smarter Kids (ASK), Only baseline data were employed); Ethics Committee at the Sahlgrenska Academy at the University of Gothenburg (reference 578-15) (Study of Adolescence Resilience and Stress (STARS)); Ethical Review Agency in Stockholm, Sweden (Dnr: 2019-03579) (Physical Activity for Healthy Brain Functions in School Youth (Brain Health) Cohort; Regional Ethical Review Board in Uppsala (No. 2015/190) (Riksmaten Youth Cohort). All study procedures were performed in accordance with relevant ethical guidelines and regulations.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author (in communication with coauthors) on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Author contributions

DA and JF conceptualized the study. Processing of data was performed by JF, with PS and JF performed the analysis and visualization. PS, EA, GN, KK, AKL, JPS, PF, YC, DA and JF were responsible for data collection. The manuscript was drafted by PS, DA and JF, with MB, EA, GN, KK, AKL, JPS, PF and YC providing substantial input during the revision process. All authors approved the final manuscript and accepted responsibility for their contributions and the quality of the study.

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