Preventive Medicine 145 (2021) 106437

Contents lists available at ScienceDirect

Preventive Medicine

journal homepage: www.elsevier.com/locate/ypmed

The multivariate physical activity signature associated with body mass index in young children

Eivind Aadland *, Oddbjørn Kvalheim Holmøy, Ada Kristine Ofrim Nilsen

Western Norway University of Applied Sciences, Faculty of Education, Arts and Sports, Department of Sport, Food and Natural Sciences, Campus Sogndal, Sogndal, Norway

ARTICLE INFO

Keywords:
Children
Preschoolers
Accelerometer
Adiposity
Multivariate pattern analysis

ABSTRACT

The evidence regarding associations between intensity-specific physical activity and adiposity in young children is conflicting. Moreover, the evidence is limited by analytical approaches that cannot handle the multicollinearity among multiple variables across the entire intensity spectrum. We aimed to determine the multivariate physical activity intensity signature associated with body mass index in a large sample of preschool children aged 3–6 years. 1182 Norwegian preschool children (mean age 4.7 years, 51% boys) provided data on physical activity (ActiGraph GT3X+) and body mass index during 2015–2016. Multivariate pattern analysis was used to determine associations between the entire triaxial intensity spectra (time spent in intensities from 0-99 to $\geq$ 15000 counts per minute) and body mass index in the total sample and in subgroups split by sex and age (median split). The association patterns were comparable across the three axes. For the vertical axis, associations were negative for time spent sedentary (0–99 counts per minute), positive for time spent in lower intensities (100–2999 counts per minute), and negative for time spent in vigorous intensities (4000–12,999 counts per minute). Associations were stronger in older than in younger children and no associations were observed for vigorous intensities among younger children. Association patterns were comparable for boys and girls. In conclusion, we found clear associations with body mass index across the physical activity intensity spectrum in preschool children. However, the age-specific association patterns suggest negative (unfavorable) associations with vigorous physical activity intensities develop around 5–6 years of age.

1. Introduction

Overweight and obesity are major health concerns globally (The Global Burden of Disease 2015 Obesity Collaborators, 2017) and develop in many cases from an early age (Monteiro and Victora, 2005). While there is convincing evidence of a negative association for physical activity (PA) with adiposity and metabolic health in school-aged children and youth (Poitras et al., 2016; Ekelund et al., 2012; Aadland et al., 2018a; Jimenez-Pavon et al., 2010; Cooper et al., 2015), the evidence for such an association in younger children is weaker and mixed (Carson et al., 2017; Bingham et al., 2016; Wiersma et al., 2020). These findings suggest the association between PA and adiposity develops over time, but it is uncertain when this relationship starts to emerge.

The conflicting evidence regarding the association between PA and adiposity in preschool-aged children probably results from several limitations of the prevailing literature. First, sample sizes of existing studies are small to moderate ($n \leq 540$ among the 56 studies included in the most recent systematic review and meta-analysis by Wiersma et al (2020)). Given the weak associations sought uncovered, such sample sizes will inherently lead to instable association estimates and heterogeneity among study conclusions.

Second, while Wiersma et al. (Wiersma et al., 2020), in line with other systematic reviews (Carson et al., 2017; Bingham et al., 2016), generally found no association between PA and body mass index (BMI), significant associations were observed for percentage body fat and weight status (normal weight versus overweight or obese). The stronger association with weight status (a dichotomous variable) than with BMI (a continuous variable) is unexpected given the loss of information resulting from categorization, an approach which is generally not recommended (Altman and Royston, 2006; Dawson and Weiss, 2012). Similarly, many studies apply a dichotomized PA variable of whether children achieve the guideline amount of PA or not. Thus, application of

* Corresponding author at: Western Norway University of Applied Sciences, Faculty of Education, Arts and Sports, Department of Sport, Food and Natural Sciences, Campus Sogndal, Box 133, 6851 Sogndal, Norway.

E-mail addresses: eivind.aadland@hvl.no (E. Aadland), oddbjorn.kvalheim.holmoy@hvl.no (O.K. Holmøy), ada.kristine.ofrim.nilsen@hvl.no (A.K.O. Nilsen).

https://doi.org/10.1016/j.ypmed.2021.106437
Received 28 June 2020; Received in revised form 27 November 2020; Accepted 17 January 2021
Available online 23 January 2021

different, and potentially suboptimal, operationalization of exposure and outcome variables may confuse findings across studies.

Third, associations with adiposity appear to be intensity-specific, but many studies include only few intensities in their analyses, limiting the knowledge regarding associations across the intensity spectrum (Carson et al., 2017; Wiersma et al., 2020). Sedentary time (SED) and moderate-to-vigorous PA (MVPA) are the most studied intensities, whereas light PA (LPA), moderate PA (MPA), and vigorous PA (VPA) are less studied. Moreover, Wiersma et al. (Wiersma et al., 2020) observed some counterintuitive findings; while associations with BMI were *negative* for SED, they tended to be *positive* for other intensities. Such associations might reflect the limitations of BMI in capturing fat mass, though they could also result from the great inconsistencies in accelerometer data reduction methods across studies (Wiersma et al., 2020; Cain et al., 2013; Aadland et al., 2019a). Thus, to obtain a broader and more detailed picture of how PA associates with adiposity, studies should include the entire PA intensity spectrum in their analysis (Poitras et al., 2016; Wiersma et al., 2020; van der Ploeg and Hillsdon, 2017; Pedisic, 2014), derived from a harmonized data reduction approach.

Fourth, statistical analyses including the entire PA intensity spectrum have historically been restricted by the use of linear regression that cannot handle multicollinearity among explanatory variables. However, multiple approaches have been suggested recently to solve the multicollinearity challenge, including isotemporal substitution modelling, compositional analyses, and multivariate pattern analysis (see Aadland et al. (Aadland et al., 2019b) for a brief review). Aadland et al. (Aadland et al., 2018a; Aadland et al., 2019a) introduced multivariate pattern analysis to analyze associations between PA and metabolic health in 10-year-old children. Multivariate pattern analysis is widely applied in other fields of research (Rajalahti and Kvalheim, 2011; Rajalahti et al., 2010; Madsen et al., 2010) and can handle completely multicollinear explanatory variables using latent variable modelling (Wold et al., 1984; Kvalheim and Karstang, 1989). Thus, it allows for inclusion of the entire (triaxial) intensity spectrum in analysis of associations, which have previously been shown to substantially improve associations with metabolic health compared to using traditional blunt descriptions of data (i.e., reducing the intensity spectrum to a few summary measures) or uniaxial accelerometry (Aadland et al., 2018a; Aadland et al., 2019c).

The main aim of the present study was to determine the multivariate PA intensity signature associated with BMI in a large sample of preschool children aged 3–6 years. Secondary objectives were to compare association patterns across sex and age groups, and to compare the performance of BMI and weight status as outcomes.

2. Methods

2.1. Participants

The present study is based on data from the Sogn og Fjordane Preschool Physical Activity Study (PRESPAS) (Nilsen et al., 2019). PRESPAS is a population-based cross-sectional study of PA and related correlates conducted in Sogn og Fjordane, a rural area in western Norway, between September 2015 and June 2016. Sogn og Fjordane is characterized by fjords and mountains, and a scattered population with an education level marginally below the average of Norway (28.9 vs 34.7% having higher education). A total of 1308 preschool children aged 2.8–6.5 years (born in 2010–2012) from 68 preschools (response rate of preschools: 92%; response rate of children: 68%) participated in the study (Nilsen et al., 2019).

Parents of all participating children received oral and written information about the study and provided written consent prior to testing. Preschools received information and agreed to participate in the study. We explained the procedures according to the children's level of understanding. The Norwegian Centre for Research Data (NSD) approved the study (reference number 39061).

2.2. Procedures

2.2.1. Physical activity measurement

PA was measured using the ActiGraph GT3X+ accelerometer (ActiGraph, LLC, Pensacola, Florida, USA) (John and Freedson, 2012). Children wore an elastic belt with the accelerometer on the right hip and were instructed to wear the monitor at all times for 14 consecutive days, except during water-based activities and while sleeping (at night). Units were initialized at a sampling rate of 30 Hz and files were analyzed restricted to hours 06:00 to 23:59 using the KineSoft analytical software version 3.3.80 (KineSoft, Loughborough, UK). Time use is based on summation of 1-s epochs to avoid misclassification of PA intensities, in particular to capture low and high intensity PA correctly (Aadland et al., 2019a). Yet, counts in 1-s epochs were scaled to counts per minute (cpm) for classification and interpretation of intensities (e.g., 100 counts in a 1-s epoch equals 6000 cpm). Periods of ≥20 min of zero counts were defined as non-wear time (Esliger et al., 2005). We applied wear time requirements of ≥8 h/day and ≥ 4 days/week to constitute a valid measurement (Aadland et al., 2020; Aadland and Johannessen, 2015).

For determination of association patterns with BMI, we created 17 variables of time spent in narrow intensity intervals (from 0-99, 100–999, 1000–1999, 2000–2999, … 14,000–14,999, to ≥15,000 cpm) (Nilsen et al., 2020) from each of the three axes, to capture movement across the triaxial intensity spectra. The first bin is consistent with the most used cut point for SED, whereas the rest of the intensity spectrum is defined by 1000 cpm bins. In previous publications, we have primarily used 500 cpm bins (Aadland et al., 2018a; Aadland et al., 2019a; Nilsen et al., 2020). However, since 500 and 1000 cpm bins provide similar results (Aadland et al., 2020), we prefer the simpler descriptor (i.e., resulting in fewer variables). For descriptive purposes, we reported total PA (average cpm), and minutes per day spent SED (≤ 100 cpm), in LPA (101–2295 cpm), MPA (2296–4011 cpm), VPA (≥ 4012 cpm), and in MVPA (min/day) (≥ 2296 cpm) using the cut points suggested by Evenson et al. (Evenson et al., 2008) applied to the vertical axis. These cut points were also used to guide our interpretation of the vertical axis intensity spectrum. Due to the limited knowledge of which activities and intensities that are captured on the anteroposterior and mediolateral axes, we have focused our interpretation on the vertical axis.

2.2.2. Anthropometrics and demographics

Body mass was measured to the nearest 0.1 kg using an electronic scale (Seca 899, SECA GmbH, Hamburg, Germany), and height was measured to the nearest 0.1 cm with a portable stadiometer (Seca 217, SECA GmbH, Hamburg, Germany). BMI (kg/m^2) was calculated and children were classified as thin, normal weight, overweight, or obese based on criteria proposed by Cole et al. (Cole et al., 2000; Cole et al., 2007). We used BMI as a continuous variable as the primary outcome, whereas we performed a sensitivity analysis using weight status where children were dichotomized as normal weight versus overweight or obese. Parental socioeconomic status (based on the highest education level of mother or father) was assessed using a questionnaire completed by each child's mother and/or father at baseline.

2.2.3. Statistical analysis

Children's characteristics and PA were reported as frequencies, means, and standard deviations (SD). The multivariate PA intensity signature associated with BMI (and weight status) was determined using multivariate pattern analysis applied to the triaxial intensity spectra, equivalent to its previous application to accelerometer data (Aadland et al., 2018a; Nilsen et al., 2020). Partial least squares (PLS) regression analyses (Wold et al., 1984) were used to determine the association pattern between BMI (outcome variable) and the full triaxial intensity spectra (all 51 variables included as explanatory variables in one joint model). Briefly, PLS regression decomposes the explanatory variables into orthogonal linear combinations (PLS components), while simultaneously maximizing the covariance with the outcome variable. Thus, PLS regression is able to handle completely collinear variables through the use of latent variable modelling (Wold et al., 1984). Models were validated using Monte Carlo resampling (Kvalheim et al., 2018) with 1000 repetitions by repeatedly and randomly keeping 50% of the subjects as an external validation set. For each model, we used target projection (Rajalahti and Kvalheim, 2011; Kvalheim and Karstang, 1989) followed by reporting of multivariate correlation coefficients with 95% confidence intervals (CIs) to show the importance of each PA intensity variable in the multivariate space (Rajalahti et al., 2009a; Rajalahti et al., 2009b; Aadland et al., 2019d). To adjust for sources of variation and confounding, we obtaining residuals from linear regression models using BMI (adjusted for sex and age) and PA variables (adjusted for sex, age, wear time, and season) as outcomes, prior to performing the multivariate pattern analysis. We compared the association patterns related to BMI between boys and girls and between younger and older children (defined by median split) by performing the analyses separately for these subgroups. The multivariate PA signatures were compared among groups by correlating association patterns using Pearson's r. *P*-values ≤0.05 was considered statistically significant. Multivariate pattern analyses were performed using the commercial software Sirius version 11.0 (Pattern Recognition Systems AS, Bergen, Norway).

3. Results

3.1. Children's characteristics

Of the 1308 children that participated in the study, 1182 (90%) children provided valid data on both PA and BMI and were included in the present analysis. The children's characteristics are shown in Table 1. Time use across all PA intensities and axes are shown in Supplemental Table 1. The age range of the younger and older children were 2.8–4.8 and 4.8–6.5 years, respectively.

Table 1
Children's characteristics. Values are means (SDs) if not otherwise stated.

	Total	Boys	Girls	Younger	Older
n	1182	606	576	593	589
Age (years)	4.7 (0.9)	4.8 (0.8)	4.7 (0.9)	4.0 (0.5)	5.5 (0.4)
Body mass (kg)	19.3 (3.2)	19.5 (3.2)	19.1 (3.3)	17.6 (2.3)	21.1 (3.1)
Height (cm)	109 (7)	110 (7)	108 (7)	104 (5)	114 (5)
BMI (kg/m^2)	16.2 (1.4)	16.2 (1.3)	16.2 (1.5)	16.3 (1.3)	16.1 (1.5)
Weight status (%)[1]					
Thin	4.8	5.0	4.7	4.7	4.9
Normal weight	76.9	79.6	73.9	77.9	75.9
Overweight	15.8	13.9	17.9	15.5	16.1
Obese	2.5	1.5	3.5	1.9	3.1
Parental education level (%)					
Upper secondary school	22.0	22.5	21.5	21.7	22.4
University <4 years	25.9	25.5	26.4	25.5	26.3
University ≥4 years	52.0	52.0	52.1	52.8	51.3
Physical activity[2]					
Wear time (min/day)	699 (51)	703 (51)	695 (50)	688 (49)	711 (50)
Overall activity (cpm)	723 (199)	757 (203)	688 (190)	690 (187)	757 (206)
SED (min/day)	483 (43)	478 (43)	489 (42)	476 (42)	490 (42)
LPA (min/day)	142 (20)	147 (20)	136 (18)	142 (20)	141 (19)
MPA (min/day)	35 (7)	38 (8)	33 (6)	34 (7)	37 (7)
VPA (min/day)	35 (11)	37 (11)	33 (11)	32 (10)	38 (11)
MVPA (min/day)	71 (17)	75 (18)	66 (16)	66 (16)	75 (17)

BMI = body mass index; SED = sedentary time; LPA = light physical activity; MPA = moderate physical activity; VPA = vigorous physical activity; MVPA = moderate-to-vigorous physical activity. [1]Defined by the Cole et al. (Cole et al., 2000; Cole et al., 2007) criteria. [2]Defined by the Evenson et al. cut points (Evenson et al., 2008) applied to the vertical axis.

3.2. Association patterns between physical activity and body mass index

The multivariate triaxial PA signature associated with BMI in the total sample of children is shown in Fig. 1 (explained variance = 11.1%, 6 PLS components). The association patterns were comparable across the three axes (*r* = 0.62–0.78). For the vertical axis, associations with BMI were negative for time spent in 0–99 cpm, positive for time spent in 100–2999 cpm, and negative for time spent in 4000–12,999 cpm. The strongest negative associations were found for time spent in 6000–8999 cpm. No associations were significant for the anteroposterior axis. Associations for the mediolateral axis differed from the associations for the vertical axis for intensities ≤4000 cpm, but were similar for higher intensities. The use of triaxial spectra improved model fit compared to the use of the specter obtained from the vertical axis only (explained variances = 11.1 versus 6.2%), but association patterns for the vertical axis were similar in both models (*r* = 0.99). The use of weight status (dichotomized) instead of BMI (continuous) as the outcome variable led to poorer model fit (explained variances = 6.5 versus 11.1%), but association patterns were similar in both models (*r* = 0.90, Supplemental Fig.1).

The association patterns were comparable (*r* = 0.72) for boys (explained variance = 11.4%, 5 PLS components) and girls (explained variance = 14.6%, 6 PLS components), although associations for intensities ≥4000 cpm derived from the vertical and anteroposterior axes were stronger and negative for girls as compared to boys (Fig. 2). The association between PA and BMI was stronger for older (explained variance = 16.6%, 6 PLS components) than for younger children (explained variance = 8.0%, 4 PLS components), reflected by the negative associations for all axes (≥ 4000 cpm) in the older children. Association patterns also differed between the age groups (*r* = 0.46) (Fig. 3). With regard to the vertical axis, we observed a negative association for 0–99 cpm, positive associations for lower intensities (100–3999 cpm), and non-significant associations with higher intensities (≥ 4000 cpm) in younger children. In contrast, no association was found for 0–99 cpm, whereas significant negative associations were observed for higher intensities (4000–12,999 cpm) in older children; the strongest associations were observed for 6000–8999 cpm. These differences in association patterns were also reflected by the other axes.

4. Discussion

In the present paper, we determined associations for the entire PA intensity spectrum with BMI and weight status in preschoolers. Our findings show that associations between PA and BMI is evident already at a young age. However, associations for vigorous intensities were clearly stronger in older (4.8–6.5-year-old) than in younger (2.8–4.8-year-old) children. Associations were comparable for boys and girls, although marginally stronger in girls. Associations for BMI were stronger than for weight status. These findings suggest the inverse relationship between PA and BMI develops during the early years and is established already at the age of 5–6 years.

Previous systematic reviews and a meta-analysis have generally concluded that there are no association between PA and BMI in children aged ≤6 years (Carson et al., 2017; Bingham et al., 2016; Wiersma et al., 2020). However, there are great heterogeneity among study findings. Given that many studies are small, have targeted different PA intensities and different adiposity outcomes, and have relied on many different data reduction approaches, mixed findings in the literature would be expected. Additionally, since we show the associations differ by age (and partly by sex), our findings suggest summation of findings among all children under the age of 6 (and between boys and girls) may add

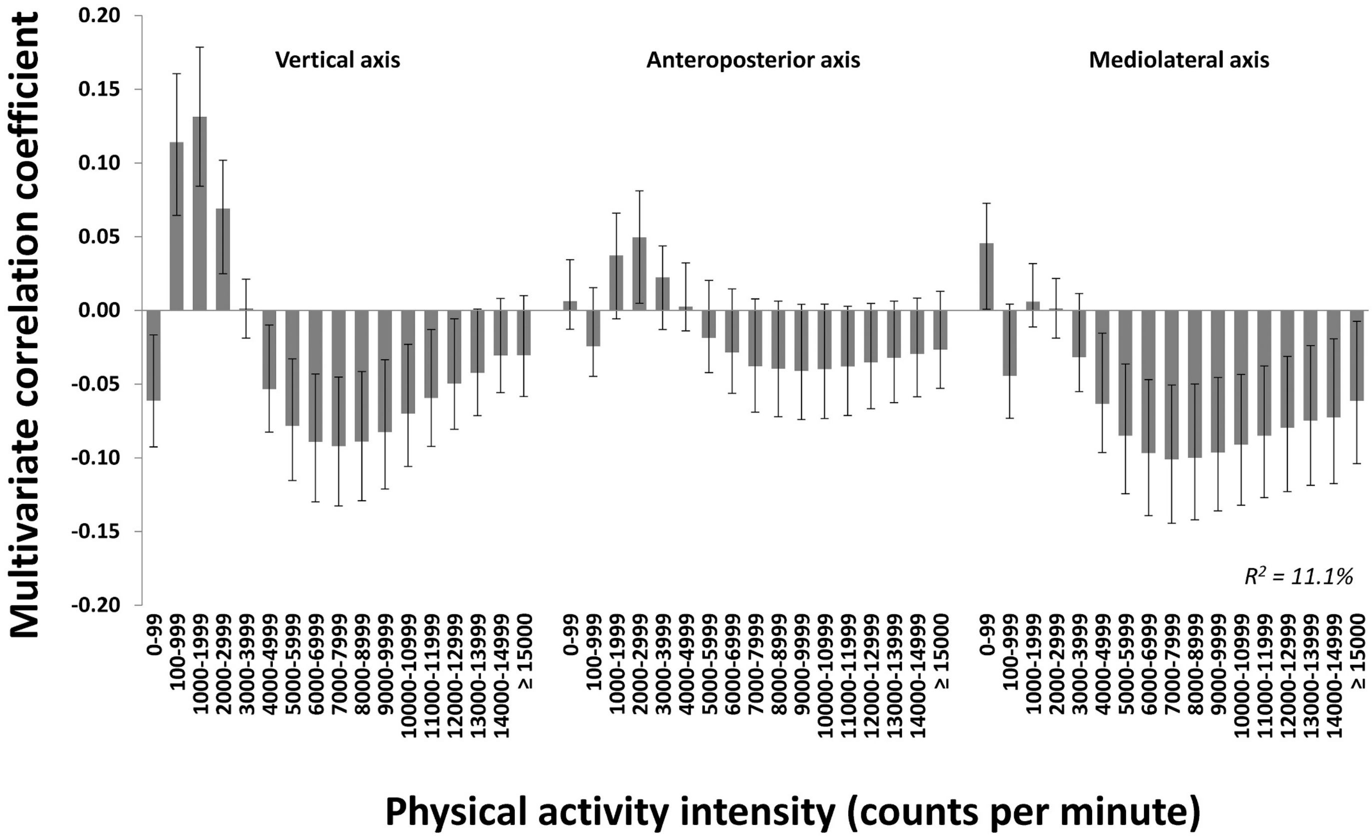

Fig. 1. The multivariate physical activity signature associated with body mass index in preschoolers. Results are reported as multivariate correlation coefficients from a joint model including all 51 physical activity intensities from the triaxial accelerometry (explained variance 11.1%, 6 PLS components). Correlations coefficients can be interpreted equivalent to bivariate correlations, though they are derived from the full multivariate model.

additional confusion.

In the total group of children, we found a negative association for time spent in SED (0–99 cpm), positive associations for time spent in LPA and partly MPA (100–2999 cpm), and negative associations for time spent in VPA (4000–12,999 cpm) with BMI. In other words, *less* time spent sedentary and *more* time spent in low to moderate intensities were associated with higher BMI. With respect to the associations in the lower end of the intensity spectrum, this finding was contrary to belief. Using similar methodology, we have shown an expected unfavorable association for SED and then gradually stronger favorable associations for higher intensities, particularly VPA, with motor skills in preschoolers (Nilsen et al., 2020) and metabolic health indices in schoolchildren (Aadland et al., 2018a; Aadland et al., 2019a; Aadland et al., 2019c). However, consistent with our finding herein, Wiersma et al. (Wiersma et al., 2020) also observed a negative association between SED and BMI in a meta-analysis of seven previous studies in young children. Unfortunately, few studies were available to determine associations for LPA, MPA, and VPA with BMI, but a tendency of a positive association was evident for LPA with weight status across six studies (Wiersma et al., 2020). Together, these findings suggest young children having a higher BMI spend less time sedentary and move more. Consistent with the view of Wiersma et al. (Wiersma et al., 2020), we suggest the cause of these findings may be ascribed to the inability of BMI to capture adiposity. Thus, a higher BMI among preschoolers might reflect early growth and development to a larger extent than adiposity, which is consistent with an increased PA level in children from 2 to 6 years (Nilsen et al., 2019; Schmutz et al., 2018). However, our findings suggest this association changes during the early years: In the youngest children ($\leq$ 4.8 years), the association was negative for SED, whereas we found no association for VPA; in the oldest children ($\geq$ 4.8 years), we found no association for SED, whereas we found a negative association for VPA. Although this age-related association pattern probably change gradually, our results suggest the negative associations with higher PA intensities originate at approximately 5 years of age. However, the positive (unfavorable) associations for LPA (100–1999 cpm) remained in the older children, which could reflect that the hypothesized influence of growth and development on movement accrued at lower intensities remains at 5–6 years of age. Alternatively, it might simply indicate that children spending less time at higher intensities necessarily spend more time at lower intensities. A similar pattern has been observed for longer bouts of LPA in schoolchildren, though no association was found for total LPA (Aadland et al., 2018b). Nevertheless, future studies and reviews should investigate age-specific association patterns in preschoolers to further clarify the relationship with age and possibly verify our findings. Such investigations should be extended to study the influence of accumulation patterns (i.e., bouts and breaks) of PA, given the inconclusive evidence regarding the importance of accumulation patterns in relation to adiposity and metabolic health in older children (Aadland et al., 2018b; Tarp et al., 2018; Mark, 2009; Willis et al., 2015).

We found comparable association patterns for boys and girls, though associations were marginally stronger in girls for the vertical and anteroposterior axes. The weaker (though significant) negative associations for VPA in boys than in girls are partly consistent with the positive associations with MVPA for boys found by Wiersma (Wiersma et al., 2020), though associations are still in opposite directions. It is well known that boys are more active than girls already at a young age (Nilsen et al., 2019; Hnatiuk et al., 2012). Thus, we speculate that the higher drive towards more vigorous and rough physically active play in boys than in girls, possibly irrespective of body size, may restrict and delay the unfavorable association between VPA and adiposity from developing. This hypothesis could be in line with weaker tracking of PA from 5 to 15 years in boys than in girls (Francis et al., 2013).

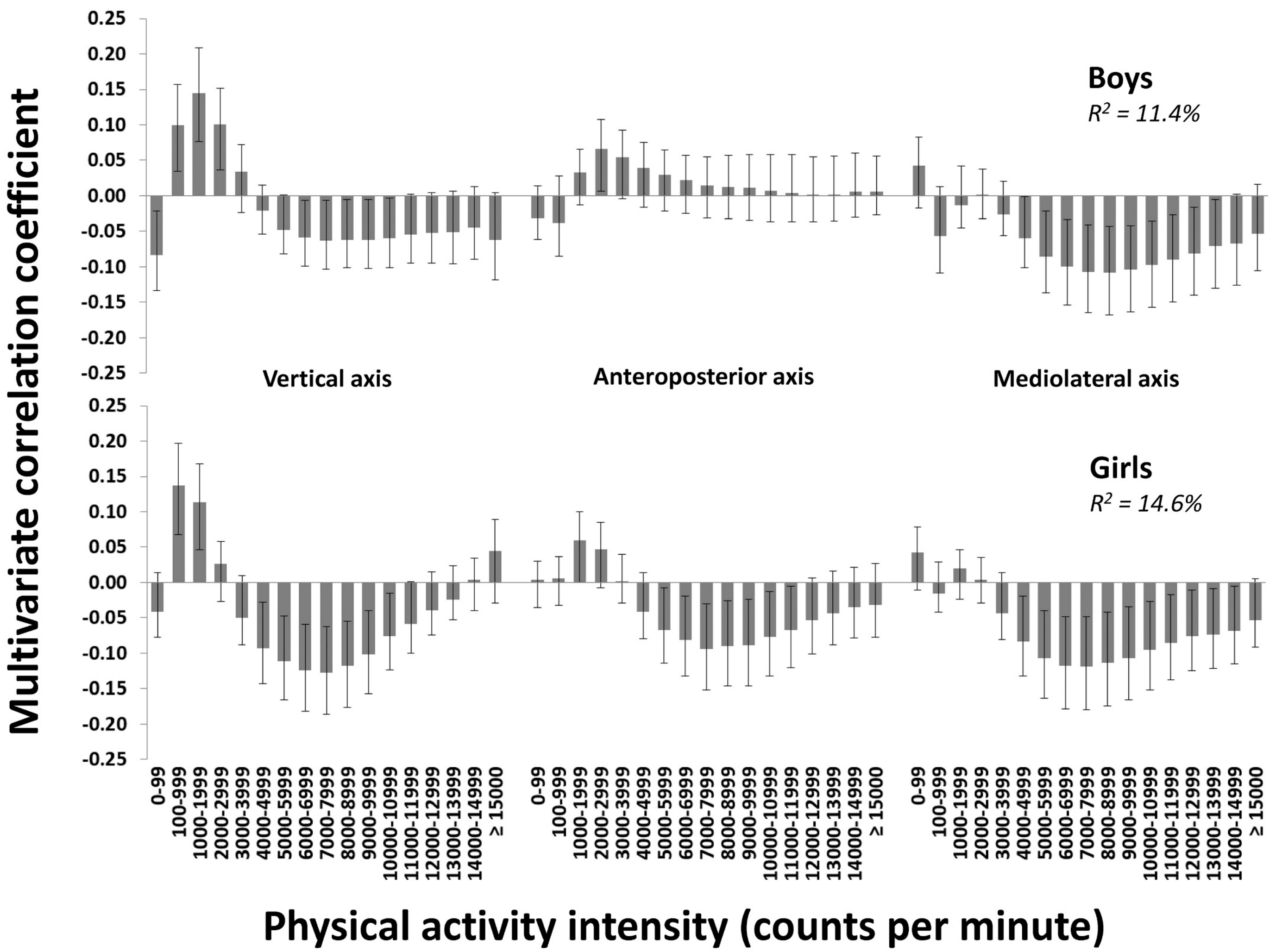

Fig. 2. The multivariate physical activity signatures associated with body mass index in boys and girls. Results are reported as multivariate correlation coefficients from joint models including all 51 physical activity intensities from the triaxial accelerometry (boys: explained variance 11.4%, 5 PLS components; girls: explained variance 14.6%, 6 PLS components). Correlations coefficients can be interpreted equivalent to bivariate correlations, though they are derived from the full multivariate model.

Interestingly, associations for girls showed similarity with those for older children, whereas associations for boys were more similar to those for younger children. This finding is consistent with the earlier maturation of girls than boys (Lloyd et al., 2014), which is shown to affect PA trajectories (Francis et al., 2013), although the influence of such maturational differences below the age of 6 years are less clear. We did unfortunately not have a sufficient sample size to obtain good association models across both age and sex; such subgroups could have provided additional information with regard to possible differential effects of age or maturation in boys and girls.

Consistent with the loss of information resulting from dichotomizing BMI into weight statuses (normal weight versus overweight or obese), we observed a poorer model fit for weight status than for BMI (6.5 versus 11.1% explained variance). Thus, to avoid attenuation of associations and increased probability of making type II errors, our findings support recommendations to avoid categorization of continuous variables in statistical analyses (Altman and Royston, 2006; Dawson and Weiss, 2012). However, our finding contrasts the findings of Wiersma et al. (Wiersma et al., 2020), who observed significant associations for weight status but not for BMI. A larger sample size included for weight status than for BMI, or possible inconsistencies in handling of accelerometry data across studies, could be possible explanations for their finding. With respect to PA, we have previously shown how we can use the entire intensity spectra from triaxial accelerometry data to significantly improve information about children's movement behavior and strengthen associations with metabolic health compared to the use of traditional summary measures of PA intensities (Aadland et al., 2019c). A similar substantial improvement was observed in the present study: while time spent in MVPA (mean of coefficients ≥2000 cpm for the vertical axis) and in 7000–7999 cpm (the intensity strongest associated with BMI from the vertical axis) resulted in explained variances of 0.3 and 0.8%, respectively, the entire intensity spectrum from the vertical axis and the entire triaxial intensity spectra resulted in explained variances of 6.2 and 11.1%, respectively. These findings strongly support the use of multivariate pattern analysis and the entire triaxial intensity spectrum to determine associations for PA with health and developmental outcomes.

4.1. Strengths and limitations

Given the weak associations that may be anticipated in this area of research, the inclusion of a large sample of preschoolers is an important strength of the present study. This sample allowed for investigating age- and sex-specific associations, although an even larger sample would allow for further exploration of these potential moderators and their interactions. Moreover, we applied multivariate pattern analysis to

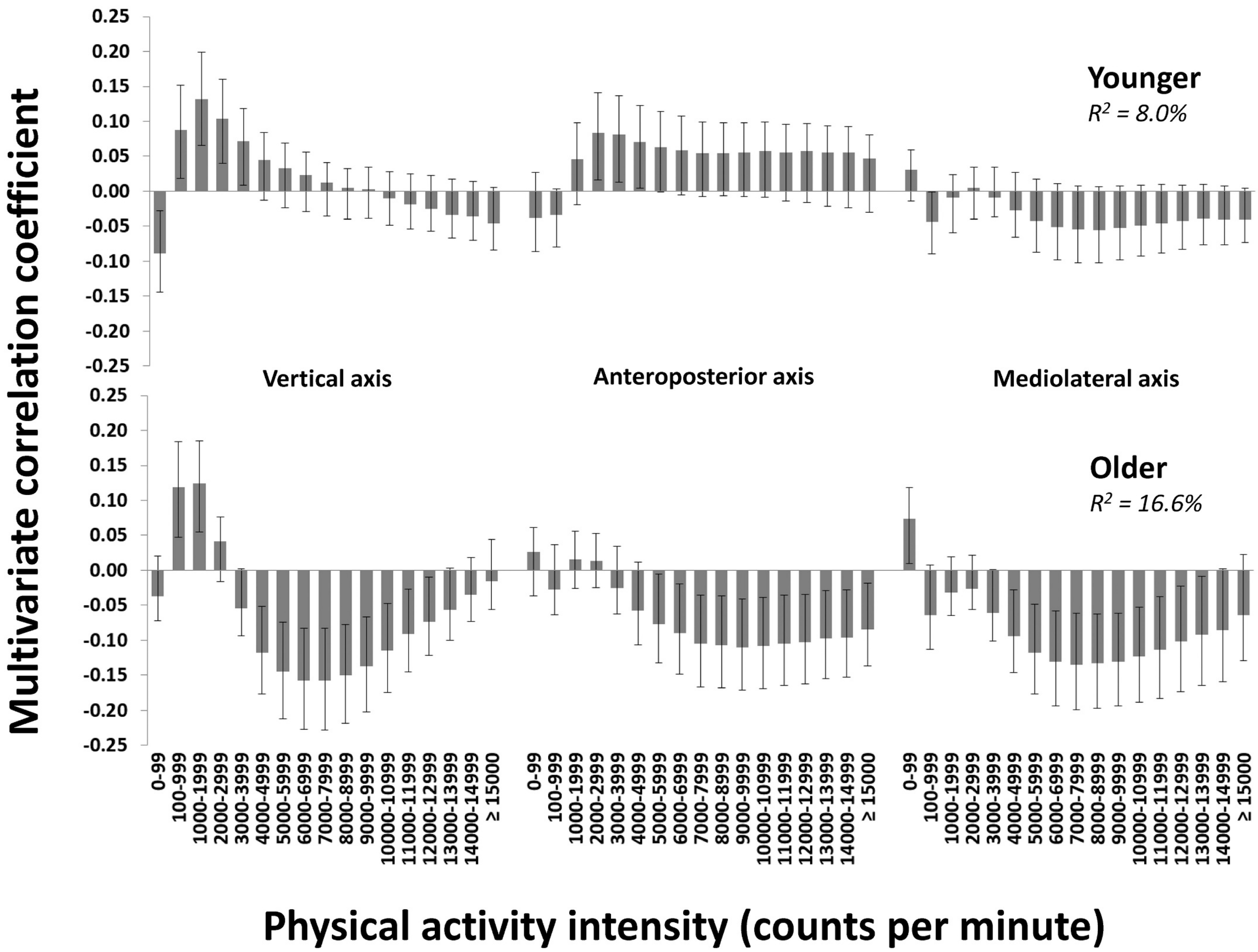

Fig. 3. The multivariate physical activity signatures associated with body mass index in younger (2.8–4.8-year-old) and older (4.8–6.5-year-old) children. Results are reported as multivariate correlation coefficients from joint models including all 51 physical activity intensities from the triaxial accelerometry (younger children: explained variance 8.0%, 4 PLS components; older children: explained variance 16.6%, 6 PLS components). Correlations coefficients can be interpreted equivalent to bivariate correlations, though they are derived from the full multivariate model.

determine association patterns with adiposity for the entire PA intensity spectra from triaxial accelerometry. Since this analytic approach can handle completely multicollinear explanatory variables (Wold et al., 1984), it allows for exploiting the information captured by accelerometers beyond what traditional summary measure of PA and ordinary linear regression allows. Thus, we obtained a detailed picture of how the entire triaxial PA intensity spectra associates with BMI, which promotes an improved interpretation and understanding of these relationships in young children. Importantly, this approach circumvent the well-known “cut point conundrum”, as it does not require pre-determined intensity cut points. Although we have interpreted intensities according to the cut points suggested by Evenson et al. (Evenson et al., 2008), the reporting of association patterns across the entire range of intensities allows for alternative interpretations post hoc. Because there is limited knowledge of which activities and intensities that are captured across the anteroposterior and the mediolateral axes, we have focused our interpretation on the vertical axis only. Future validation studies are needed to reveal what information these axes capture.

The cross-sectional design of the present study restricts conclusions regarding causality of the observed associations. While there is no doubt PA can induce weight loss, observational evidence in children suggest adiposity may be a stronger determinant of future PA than vice versa (Metcalf et al., 2011; Hjorth et al., 2014). Thus, despite we show PA is a marker of BMI in young children, longitudinal studies are needed to investigate the temporality of this association during the early years. Moreover, we adjusted the analyses for sex, age, wear time, and season. Further adjustment for preschool did not change any findings (results not shown). Nevertheless, residual confounding by, for example, diet cannot be excluded. Furthermore, as discussed previously, BMI have limited sensitivity with respect to capturing children’s levels of adiposity. Indeed, while Wiersma et al. (Wiersma et al., 2020) observed significant negative associations for PA with percent body fat, fat mass, and skinfold thickness, no associations were revealed with BMI. Yet, due to its simplicity and acceptability, BMI is the most commonly used measure of adiposity in young healthy children. Thus, we argue our findings significantly improve clarity and understanding in this field of research.

5. Conclusion

We determined the multivariate association pattern between PA and BMI in a large sample of preschool children. Our findings showed that the association with PA strengthened and association patterns for PA intensities changed from children were aged 3 to 6 years. In the youngest children, the association was negative for SED, whereas we found no association for VPA; in the oldest children, we found no association for

SED, whereas we found a negative association for VPA. Our findings suggest public health initiatives should be initiated during children's first years of life to have optimal conditions of succeeding in prevention of unhealthy weight gain and in promotion of optimal PA trajectories during childhood.

Declaration of Competing Interest

The authors declare that they have no competing interests.

Acknowledgments

We thank all children, parents and staff at the participating preschools for their participation in the study and their excellent cooperation during the data collection. We also thank colleagues and students at the *Western Norway University of Applied Sciences* (formerly *Sogn og Fjordane University College*) for their contribution to the study. The study was funded by the Sogn og Fjordane County Municipality and Sogn og Fjordane University College.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ypmed.2021.106437.

References

Aadland, E., Johannessen, K., 2015. Agreement of objectively measured physical activity and sedentary time in preschool children. Prev. Med. Rep. 2, 635–639.

Aadland, E., Kvalheim, O.M., Anderssen, S.A., Resaland, G.K., Andersen, L.B., 2018a. The multivariate physical activity signature associated with metabolic health in children. Int. J. Behav. Nutr. Phys. Act. 15 (77) https://doi.org/10.1186/s12966-018-0707-z.

Aadland, E., Andersen, L.B., Anderssen, S.A., Resaland, G.K., Kvalheim, O.M., 2018b. Associations of volumes and patterns of physical activity with metabolic health in children: a multivariate pattern analysis approach. Prev. Med. 115, 12–18. https://doi.org/10.1016/j.ypmed.2018.08.001.

Aadland, E., Andersen, L.B., Anderssen, S.A., Resaland, G.K., Kvalheim, O.M., 2019a. Accelerometer epoch setting is decisive for associations between physical activity and metabolic health in children. J. Sports Sci. 1–8. https://doi.org/10.1080/02640414.2019.1693320.

Aadland, E., Kvalheim, O.M., Anderssen, S.A., Resaland, G.K., Andersen, L.B., 2019b. Multicollinear physical activity accelerometry data and associations to cardiometalbolic health: Challenges, pitfalls, and potential solutions. Int. J. Behav. Nutr. Phys. Act. 16 (74) https://doi.org/10.1186/s12966-019-0836-z.

Aadland, E., Kvalheim, O.M., Anderssen, S.A., Resaland, G.K., Andersen, L.B., 2019c. The triaxial physical activity signature associated with metabolic health in children. Med. Sci. Sports Exerc. 51 (10), 2173–2179. https://doi.org/10.1249/mss.0000000000002021.

Aadland, E., Andersen, L.B., Resaland, G.K., Kvalheim, O.M., 2019d. Interpretation of multivariate association patterns between multicollinear physical activity Accelerometry data and Cardiometabolic health in children—a tutorial. Metabolites. 9 (7), 129.

Aadland, E., Nilsen, A.D.O., Ylvisåker, E., Johannessen, K., Anderssen, S.A., 2020. Reproducibility of objectively measured physical activity: reconsideration needed. J. Sports Sci. https://doi.org/10.1080/02640414.2020.1743054.

Aadland, E., Andersen, L.B., Migueles, J.H., Ortega, F.B., Kvalheim, O.M., 2020. Interpretation of associations between the accelerometry physical activity spectrum and cardiometabolic health and locomotor skills in two cohorts of children using raw, normalized, log-transformed, or compositional data. J. Sports Sci. https://doi.org/10.1080/02640414.2020.1796462.

Altman, D.G., Royston, P., 2006. Statistics notes - The cost of dichotomising continuous variables. BMJ 332 (7549), 1080. https://doi.org/10.1136/bmj.332.7549.1080.

Bingham, D.D., Costa, S., Hinkley, T., Shire, K.A., Clemes, S.A., Barber, S.E., 2016. Physical activity during the early years a systematic review of correlates and determinants. Am. J. Prev. Med. 51 (3), 384–402. https://doi.org/10.1016/j.amepre.2016.04.022.

Cain, K.L., Sallis, J.F., Conway, T.L., Van Dyck, D., Calhoon, L., 2013. Using accelerometers in youth physical activity studies: a review of methods. J. Phys. Act. Health 10 (3), 437–450.

Carson, V., Lee, E.Y., Hewitt, L., Jennings, C., Hunter, S., Kuzik, N., et al., 2017. Systematic review of the relationships between physical activity and health indicators in the early years (0-4 years). BMC Public Health 17, 31. https://doi.org/10.1186/s12889-017-4860-0.

Cole, T.J., Bellizzi, M.C., Flegal, K.M., Dietz, W.H., 2000. Establishing a standard definition for child overweight and obesity worldwide: international survey. BMJ. 320 (7244), 1240–1243.

Cole, T., Flegal, K.M., Nicholls, D., Jackson, A.A., 2007. Body mass index cut offs to define thinness in children and adolescents: international survey. BMJ 335 (194). https://doi.org/10.1136/bmj.39238.399444.55.

Cooper, A.R., Goodman, A., Page, A.S., Sherar, L.B., Esliger, D.W., van Sluijs, E.M.F., et al., 2015. Objectively measured physical activity and sedentary time in youth: the international children's accelerometry database (ICAD). Int. J. Behav. Nutr. Phys. Act. 12 https://doi.org/10.1186/s12966-015-0274-5.

Dawson, N.V., Weiss, R., 2012. Dichotomizing continuous variables in statistical analysis: a practice to avoid. Med. Decis. Mak. 32 (2), 225–226. https://doi.org/10.1177/0272989x12437605.

Ekelund, U., Luan, J.A., Sherar, L.B., Esliger, D.W., Griew, P., Cooper, A., et al., 2012. Moderate to vigorous physical activity and sedentary time and cardiometabolic risk factors in children and adolescents. JAMA. 307 (7), 704–712. https://doi.org/10.1001/jama.2012.156.

Esliger, D.W., Copeland, J.L., Barnes, J.D., Tremblay, M.S., 2005. Standardizing and optimizing the use of accelerometer data for free-living physical activity monitoring. J. Phys. Act. Health 2 (3), 366.

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. J. Sports Sci. 26 (14), 1557–1565.

Francis, S.L., Morrissey, J.L., Letuchy, E.M., Levy, S.M., Janz, K.F., 2013. Ten-year objective physical activity tracking: Iowa bone development study. Med. Sci. Sports Exerc. 45 (8), 1508–1514. https://doi.org/10.1249/MSS.0b013e31828b2f3a.

Hjorth, M.F., Chaput, J.P., Ritz, C., Dalskov, S.M., Andersen, R., Astrup, A., et al., 2014. Fatness predicts decreased physical activity and increased sedentary time, but not vice versa: support from a longitudinal study in 8-to 11-year-old children. Int. J. Obes. 38 (7), 959–965. https://doi.org/10.1038/ijo.2013.229.

Hnatiuk, J., Ridgers, N.D., Salmon, J., Campbell, K., McCallum, Z., Hesketh, K., 2012. Physical activity levels and patterns of 19-month-old children. Med. Sci. Sports Exerc. 44 (9), 1715–1720. https://doi.org/10.1249/MSS.0b013e31825825c4.

Jimenez-Pavon, D., Kelly, J., Reilly, J.J., 2010. Associations between objectively measured habitual physical activity and adiposity in children and adolescents: systematic review. Int. J. Pediatr. Obes. 5 (1), 3–18. https://doi.org/10.3109/17477160903067601.

John, D., Freedson, P., 2012. ActiGraph and Actical physical activity monitors: a peek under the hood. Med. Sci. Sports Exerc. 44 (1 Suppl 1), S86–S89. https://doi.org/10.1249/MSS.0b013e3182399f5e.

Kvalheim, O.M., Karstang, T.V., 1989. Interpretation of latent-variable regression-models. Chemom. Intell. Lab. Syst. 7 (1–2), 39–51. https://doi.org/10.1016/0169-7439(89)80110-8.

Kvalheim, O.M., Arneberg, R., Grung, B., Rajalahti, T., 2018. Determination of optimum number of components in partial least squares regression from distributions of the root-mean-squared error obtained by Monte Carlo resampling. J. Chemom. https://doi.org/10.1002/cem.2993.

Lloyd, R.S., Oliver, J.L., Faigenbaum, A.D., Myer, G.D., De Ste Croix, M.B.A., 2014. Chronological age vs. biological maturation: implications for exercise programming in youth. J. Strength Cond. Res. 28 (5), 1454–1464. https://doi.org/10.1519/jsc.0000000000000391.

Madsen, R., Lundstedt, T., Trygg, J., 2010. Chemometrics in metabolomics-a review in human disease diagnosis. Anal. Chim. Acta 659 (1–2), 23–33. https://doi.org/10.1016/j.aca.2009.11.042.

Mark, A.E., Janssen, I., 2009. Influence of bouts of physical activity on overweight in youth. Am. J. Prev. Med. 36 (5), 416–421. https://doi.org/10.1016/j.amepre.2009.01.127.

Metcalf, B.S., Hosking, J., Jeffery, A.N., Voss, L.D., Henley, W., Wilkin, T.J., 2011. Fatness leads to inactivity, but inactivity does not lead to fatness: a longitudinal study in children (EarlyBird 45). Arch. Dis. Child. 96 (10), 942–U7. https://doi.org/10.1136/adc.2009.175927.

Monteiro, P.O.A., Victora, C.G., 2005. Rapid growth in infancy and childhood and obesity in later life - a systematic review. Obes. Rev. 6 (2), 143–154. https://doi.org/10.1111/j.1467-789X.2005.00183.x.

Nilsen, A.K.O., Anderssen, S.A., Ylvisåker, E., Johannessen, K., Aadland, E., 2019. Moderate-to-vigorous physical activity among Norwegian preschoolers varies by sex, age, and season. Scand. J. Med. Sci. Sports 29, 862–873. https://doi.org/10.1111/sms.13405.

Nilsen, A.K.O., Anderssen, S.A., Loftesnes, J.M., Johannessen, K., Ylvisaaker, E., Aadland, E., 2020. The multivariate physical activity signature associated with fundamental motor skills in preschoolers. J. Sports Sci. 38 (3), 264–272. https://doi.org/10.1080/02640414.2019.1694128.

Pedisic, Z., 2014. Measurement issues and poor adjustments for physical activity and sleep undermine sedentary behaviour research - the focus should shift to the balance between sleep, sedentary behaviour, standing and activity. Kinesiology. 46 (1), 135–146.

Poitras, V.J., Gray, C.E., Borghese, M.M., Carson, V., Chaput, J.P., Janssen, I., et al., 2016. Systematic review of the relationships between objectively measured physical activity and health indicators in school-aged children and youth. Appl. Physiol. Nutr. Metab. 41 (6), S197–S239. https://doi.org/10.1139/apnm-2015-0663.

Rajalahti, T., Kvalheim, O.M., 2011. Multivariate data analysis in pharmaceutics: a tutorial review. Int. J. Pharm. 417 (1–2), 280–290. https://doi.org/10.1016/j.ijpharm.2011.02.019.

Rajalahti, T., Arneberg, R., Berven, F.S., Myhr, K.M., Ulvik, R.J., Kvalheim, O.M., 2009a. Biomarker discovery in mass spectral profiles by means of selectivity ratio plot. Chemom. Intell. Lab. Syst. 95 (1), 35–48. https://doi.org/10.1016/j.chemolab.2008.08.004.

Rajalahti, T., Arneberg, R., Kroksveen, A.C., Berle, M., Myhr, K.M., Kvalheim, O.M., 2009b. Discriminating variable test and selectivity ratio plot: quantitative tools for

interpretation and variable (biomarker) selection in complex spectral or chromatographic profiles. Anal. Chem. 81 (7), 2581–2590. https://doi.org/10.1021/ac802514y.
Rajalahti, T., Kroksveen, A.C., Arneberg, R., Berven, F.S., Vedeler, C.A., Myhr, K.-M., et al., 2010. A multivariate approach to reveal biomarker signatures for disease classification: application to mass spectral profiles of cerebrospinal fluid from patients with multiple sclerosis. J. Proteome Res. 9 (7), 3608–3620. https://doi.org/10.1021/pr100142m.
Schmutz, E.A., Haile, S.R., Leeger-Aschmann, C.S., Kakebeeke, T.H., Zysset, A.E., Messerli-Burgy, N., et al., 2018. Physical activity and sedentary behavior in preschoolers: a longitudinal assessment of trajectories and determinants. Int. J. Behav. Nutr. Phys. Act. 15, 12. https://doi.org/10.1186/s12966-018-0670-8.
Tarp, J., Child, A., White, T., et al., 2018. Physical activity intensity, bout-duration, and cardiometabolic risk markers in children and adolescents. Int. J. Obes. 42 (9), 1639–1650. https://doi.org/10.1038/s41366-018-0152-8.
The Global Burden of Disease 2015 Obesity Collaborators, 2017. Health effects of overweight and obesity in 195 countries over 25 years. NEJM. https://doi.org/10.1056/NEJMoa1614362.
van der Ploeg, H.P., Hillsdon, M., 2017. Is sedentary behaviour just physical inactivity by another name? Int. J. Behav. Nutr. Phys. Act. 14, 8. https://doi.org/10.1186/s12966-017-0601-0.
Wiersma, R., Haverkamp, B.F., van Beek, J.H., Riemersma, A.M.J., Boezen, H.M., Smidt, N., et al., 2020. Unravelling the association between accelerometer-derived physical activity and adiposity among preschool children: a systematic review and meta-analyses. Obes. Rev. 21 (2), 15. https://doi.org/10.1111/obr.12936.
Willis, E.A., Ptomey, L.T., Szabo-Reed, A.N., Honas, J.J., Lee, J., Washburn, R.A., Donelly, J.E., 2015. Length of moderate-to-vigorous physical activity bouts and cardio-metabolic risk factors in elementary school children. Prev. Med. 73, 76–80. https://doi.org/10.1016/j.ypmed.2015.01.022.
Wold, S., Ruhe, A., Wold, H., Dunn, W.J., 1984. The collinearity problem in linear-regression - the partial least-squares (PLS) approach to generalized inverses. SIAM J. Sci. Comput. 5 (3), 735–743. https://doi.org/10.1137/0905052.