A comparison of analytical approaches to investigate associations for accelerometry-derived physical activity spectra with health and developmental outcomes in children

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Abstract

The use of high-resolution physical activity intensity spectra obtained from accelerometry can improve knowledge of associations with health and development beyond the use of traditional summary measures of intensity. The aim of the present study was to compare three different approaches for determining associations for spectrum descriptors of physical activity (the intensity gradient, principal component analysis, and multivariate pattern analysis) with relevant outcomes in children. We used two datasets including physical activity spectrum data (ActiGraph GT3X+) and 1) a cardiometabolic health outcome in 841 schoolchildren and 2) a motor skill outcome in 1081 preschool children. We compared variance explained (R^2) and associations with the outcomes for the intensity gradient (slope) across the physical activity spectra, a two-component principal component model describing the physical activity variables, and multivariate pattern analysis using the intensity spectra as the explanatory data matrices. Results were broadly similar for all analytical approaches. Multivariate pattern analysis explained the most variance in both datasets, likely resulting from use of more of the information available from the intensity spectra. Yet, volume and intensity dimensions of physical activity are not easily disentangled and their relative importance may be interpreted differently using different methodology.

Keywords Multivariate pattern analysis; Intensity gradient; Cardiometabolic health; Motor skills; Children; Accelerometer

Background

Accelerometers capture movement across an intensity spectrum, from which summary measures of time spent in different physical activity (PA) intensities, typically sedentary time (SED), light PA (LPA), moderate PA (MPA), vigorous PA (VPA), and/or moderate-to-vigorous PA (MVPA), is commonly derived. Although this approach is intuitively appropriate and results regarding PA levels and associations with health and developmental outcomes apparently may be easily interpreted, it holds important limitations. First, it requires the application of a priori defined intensity cut points, which due to the lack of consistency in their application hamper comparison across studies [1]. Second, limiting the description of the intensity spectrum to a few variables leads to a loss of information from accelerometry [2], in particular when using linear regression analysis that cannot handle the multicollinearity among the variables [3, 2].

Recently, two different cut point-free approaches that incorporate more detailed descriptions of the PA intensity spectrum have been applied to handle these challenges in association analysis: multivariate pattern analysis [4] and the intensity gradient [5]. However, the manner in which these methods handle the PA intensity spectrum differs to a great extent. Aadland et al. [4] introduced *multivariate pattern analysis* to analyze associations between the multicollinear explanatory PA variables and cardiometabolic health in children. Multivariate pattern analysis is widely applied in other fields of research with the objective of revealing patterns of important biomarkers among hundreds or thousands of highly interrelated variables [6-8], and can handle completely collinear explanatory variables using latent variable modelling [9, 10]. Thus, Aadland et al. [2, 4] were able to determine association patterns for multiple intensity variables across the spectrum, which led to improved association models compared to the use of traditional summary measures of intensity. In contrast to the inclusion of multiple intensity variables in the association analysis, Rowlands et al. [5] used the spectrum intensity distribution to construct the *intensity gradient,* which is a simple metric that reduces an individual's intensity profile to a single variable. The intensity gradient is the slope describing the curvilinear relation between time spent in lower and higher PA intensity regions (i.e., the log-log of the time-intensity curve). The intensity gradient is always negative, but is higher (i.e., the curve is flatter) the more time individuals spend in higher intensity regions [5]. The intensity gradient has been shown to perform better than traditional summary measures of PA intensity (e.g., MVPA) with regard to revealing associations with health outcomes [5, 11, 12]. Thus, this approach is promising given its simplicity and applicability using common statistical approaches. Description of the intensity profile with a single metric also has potential for use in population comparisons and/or generation of norms.

In addition to describing the intensity distribution in a single metric, Rowlands [5] aimed to develop an intensity metric that is less dependent on the overall volume of PA. Associations between the intensity gradient and overall PA level (mean acceleration) have been shown to be moderate (r = 0.36–0.56), which suggest the intensity gradient is more reflective of the intensity *per se* than summary measures of PA intensity [5, 11, 12]. Yet, the intensity gradient and the overall PA level are not independent measures of intensity and volume, respectively. Thus, research should attempt to better disentangle these constructs. Principal component analysis is a well-known approach for dimension-reduction of data [10], but have to the best of our knowledge not been applied to describe the dimensions of intensity spectrum descriptions of PA.

Associations for the PA intensity spectrum with health and developmental outcomes using the intensity gradient, principal component analysis, and multivariate pattern analysis have not been compared. Thus, the aim of the present study was to compare associations for these three approaches using two large datasets (in preschool- and schoolchildren) and two different outcomes (cardiometabolic health and motor skills).

Methods

We have previously published the PA signature associated with cardiometabolic health in the *Active Smarter Kids (ASK)* study [4, 13, 2] and the PA signature associated with motor skills in *The Sogn og Fjordane Preschool Physical Activity Study (PRESPAS)* [14]. The aim of the present study is limited to *compare* associations using multivariate pattern analysis, the intensity gradient, and principal component analysis within these datasets. We refer readers to previously published descriptions of sampling and children's characteristics, study protocols, instruments, and procedures of the ASK study [4, 13, 2, 15] and the PRESPAS study [16, 14] for detailed study information. Thus, we provide below only a brief overview of the most relevant information to provide sufficient context to support the study aim of comparing associations between these approaches.

Participants

The ASK study was conducted in western Norway during 2014–2015 and included 841 10-year old schoolchildren providing relevant explanatory (PA) and outcome (cardiometabolic health) data [4, 13, 2, 15]. The PRESPAS study was conducted in western Norway during 2015–2016 and included 1081 3-6-year old preschool children providing relevant explanatory (PA) and outcome (locomotor skills) data [16]. Procedures and methods in both studies conform to ethical guidelines defined by the World Medical Association's Declaration of Helsinki and its subsequent revisions. The Norwegian South-East Regional Committee for Medical Research Ethics and the Norwegian Centre for Research Data approved the study protocols. We obtained written informed consent from each child's parents or legal guardians and from the responsible preschool and school authorities prior to all testing.

Procedures

Physical activity

PA was measured using the ActiGraph GT3X+ accelerometer (Pensacola, FL, USA) [17] worn at the waist over seven (ASK) and 14 (PRESPAS) consecutive days, except during water activities (swimming, showering) or while sleeping. Units were initialized at a sampling rate of 30 Hz and files were analyzed restricted to hours 06:00 to 23:59 using 1-second epochs to capture low and high intensity PA [18] using the KineSoft analytical software version 3.3.80 (KineSoft, Loughborough, UK). Consecutive periods of ≥ 20 min (PRESPAS) and 60 min (ASK) of zero counts were defined as non-wear time. We applied wear time requirements of ≥ 8 hours/day and ≥ 4 days/week to constitute a valid measurement [19, 20].

We determined time (min/day) spent in PA intensities obtained from the vertical axis using descriptions of 12 variables (from 0–99, 100–999, 1000–1999, … 9000–9999, to ≥ 10000 cpm) in the ASK dataset [2] and 17 variables (from 0–99, 100–999, 1000–1999, … 14000–14999, to ≥ 15000 cpm) in the PRESPAS dataset [14], to capture movement in narrow intensity intervals across the intensity spectrum. These models using spectra of reduced resolutions performed similarly to previously published models [2, 14] using spectra with higher resolution [21]. In the multivariate pattern analysis, these spectra were included as the explanatory data matrix. We used the natural log (ln) of time to ensure comparability with the intensity gradient.

The concept of the intensity gradient was developed using raw acceleration data [5]. We applied the theoretical premise outlined by Rowlands et al. [5] to ActiGraph count data and determined the intensity gradient across the intensity spectra outlined above by calculating the slope between the ln of the intensity and ln of the time distribution. However, while Rowlands et al. used 24-hour raw acceleration data, we did not have 24-hour data and used therefore only waking time count data for the analysis. Wear time was not normalized among individuals as the distribution of time (i.e., the slope) is independent of the total wear time. We excluded the most extreme intensity category from the calculation, since accumulated time in this larger bin caused violation of linearity of the ln time-intensity distribution. Yet, results were similar whether this bin was included or excluded. In addition to the intensity gradient as a proposed measure of intensity, we included overall PA (average cpm) as a measure of PA volume.

We included descriptive characteristics and associations with the outcomes for traditional summary measures of PA intensity as supplemental material using the Evenson et al. [22, 23] intensity cut points of 0–99, 100–2295, 2296–4011, and ≥ 4012 cpm to determine intensities across the spectrum as SED, LPA, MPA, and VPA, respectively.

Anthropometry

In both studies, body mass was measured using an electronic scale (Seca 899, SECA GmbH, Hamburg, Germany) with children wearing light clothing. Height was measured using a portable Seca 217 (SECA GmbH, Hamburg, Germany). Body mass index ($kg \cdot m^{-2}$) was calculated and children were classified as normal weight, overweight, or obese using the Cole et al. criteria [24].

Metabolic health – outcome in the ASK study

Aerobic fitness was measured with the Andersen intermittent running test [25]. Waist circumference was measured with a Seca 201 (SECA GmbH, Hamburg, Germany) ergonomic circumference measuring tape two cm over the level of the umbilicus. We calculated the waist:height ratio. Systolic blood pressure were measured using the Omron HBP-1300 automated blood pressure monitor (Omron Healthcare, Inc, Vernon Hills, IL, US). Serum blood samples were collected in the morning after an overnight fast and analyzed for total cholesterol, triglyceride, high-density lipoprotein (HDL) cholesterol, glucose, and insulin at the accredited Endocrine Laboratory of the VU Medical Center (VUmc; Amsterdam, the Netherlands). We calculated the total:HDL cholesterol ratio and HOMA of insulin resistance [26].

We calculated a composite score as the mean of six variables (systolic blood pressure, triglyceride, total:HDL cholesterol ratio, HOMA of insulin resistance, waist:height ratio, and the inverse Andersen test) by averaging standardized scores after adjustment for sex and age using residuals from linear regression. A higher score indicates poorer cardiometabolic health. A similar approach have been used previously [27].

Motor skills – outcome in the PRESPAS study

Motor skills was a sum score of three locomotor movement tasks (run, horizontal jump, hop) guided by the Test of Gross Motor Development 3 test battery [28, 29]. A higher score indicates better locomotor skills. Children were scored quantitatively based on whether they did or did not demonstrate specific criteria for each skill based on the original scoring procedures. The criteria scores were averaged for each task and the total locomotor score (minimum 0, maximum 2). The score was standardized after adjustment for sex, age, body mass index, and assessor of motor skills using residuals from linear regression prior to analysis.

Statistical analyses

Principal component analysis. We extracted two interpretable principal components (PCs) describing the main association patterns within the explanatory data matrix including all PA variables. The first component (PC 1) maximally explains the mutual variation among the variables, whereas the next component (PC 2) maximally explains the most of the remaining mutual variation (etc.), with the constraint that these components are mutually orthogonal (i.e., not correlated). Thus, this analysis reveals the underlying association patterns of the PA variables by creating latent variables maximizing explained variance among the explanatory variables. Variable loadings on each PC was reported to illustrate the structure of data. On this basis, the first component was indicative of volume of PA (i.e., a higher score indicates that an individual spend more time in PA and less time in SED; PC_{Volume}) and the second component was indicative of intensity of PA (i.e., a higher score indicates that an individual spend more time in lower intensities of PA and less time in higher intensities of PA; $PC_{Intensity}$). Each individual's scores on these components, indicating to what degree an individual scored high or low on these patterns, were used for analysis.

Linear regression. Associations between overall PA, the intensity gradient, PC_{Volume}, and $PC_{Intensity}$, as well as associations for these explanatory variables with the outcomes (cardiometabolic health (ASK dataset) and locomotor skills (PRESPAS dataset)), were determined using linear regression. For the principal component analysis approach, PC_{Volume} and $PC_{Intensity}$ were included in one joint model (since variables were orthogonal). For the intensity gradient approach, overall PA and the intensity gradient were analyzed using separate models due to collinearity of these variables. We determined associations as standardized regression coefficients and reported the explained variance (R^2) of the models for comparison of model performance.

Multivariate pattern analysis. Partial least squares (PLS) regression analysis [9] was used to determine the multivariate association patterns for PA intensities (explanatory variables) with the outcomes. 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 [9]. The procedure differs from that of principal component analysis by creating components that maximize the covariation with the outcome, not internally among the explanatory variables. Prior to PLS regression, all variables were centered and standardized to unit variance. Models were cross-validated using Monte Carlo resampling with 1000 repetitions by repeatedly and randomly keeping 50% of the subjects as an external validation set when estimating the models to validate the number of PLS components to be included in the model [30]. Validation is an integrated part of the procedure to avoid overfitting due to inclusion of minor PLS components representing noise. For each validated PLS regression model, a single predictive component was subsequently calculated by means of target projection [10, 6] to express all the predictive variance in the PA intensity spectrum related to cardiometabolic health in a single intensity vector. Selectivity ratios (SRs) with 95% CIs were obtained as the ratio of this explained predictive variance to the total variance for each PA intensity variable [31-33]. The procedure for obtaining the multivariate patterns is completely data-driven, with no assumptions on variable distributions or degree of collinearity among variables.

The principal component analysis and linear regression was performed using IBM SPSS v. 24 (IBM Corporation, Software Group, Somers, NY). The multivariate pattern analysis was performed using Sirius version 11.0 (Pattern Recognition Systems AS, Bergen, Norway).

Results

We included 841 schoolchildren (mean (SD) 10.2 (0.3) years old, 50% boys) and 1081 preschool children (4.7 (0.9) years old, 52% boys) who provided valid data on all relevant variables (Table 1). Children's intensity-specific PA levels are shown in Supplemental Table 1.

Table 1. Children's characteristics.

	ASK (n = 841)	PRESPAS (n = 1081)
Anthropometry		
Body mass (kg)	37.0 (8.1)	19.4 (3.3)
Height (cm)	142.9 (6.7)	109.1 (7.5)
Body mas index (kg/m^2)	18.0 (3.0)	16.2 (1.4)
Overweight and obese (%)	20.8	18.2
Waist circumference (cm)	61.9 (7.5)	-
Waist:height (ratio)	0.43 (0.05)	-
Indices of metabolic health		
Andersen test (m)	898 (103)	-
Systolic blood pressure (mmHg)	105.2 (8.4)	-
Total cholesterol (mmol/l)	4.46 (0.69)	-
HDL-cholesterol (mmol/l)	1.59 (0.35)	-
Total:HDL-cholesterol (ratio)	2.91 (0.71)	-

Triglyceride (mmol/l)	0.78 (0.38)	-
Glucose (mmol/l)	4.98 (0.32)	-
Insulin (pmol/l)	55.0 (29.8)	-
HOMA of insulin resistance (index)	1.71 (0.98)	-
Motor skills		
Locomotor skills (score)		1.3 (0.4)
Physical activity (vertical axis)		
Wear time (min/day)	795 (56)	702 (50)
Overall physical activity (cpm)	708 (272)	722 (197)
Intensity gradient		
Explained variance (%)	90 (3)	86 (3)
Constant	11.0 (0.5)	12.4 (0.7)
Slope	-1.07 (0.10)	-1.30 (0.12)

HDL = high-density lipoprotein; HOMA = homeostasis model assessment. All values are means (SDs) if not otherwise stated.

Figure 1 shows the two extracted PCs in the two datasets. The first PCs (PC_{Volume}) in both datasets explained 62.8–69.0% of the total variation among the variables and indicate that spending more time in PA of any intensity is related to less time spent in SED. The second PCs ($PC_{Intensity}$) explained 14.4–14.8% of the remaining variation among the variables and indicate that more time spent in light and moderate intensity PA is related to less time spent in vigorous PA. The total explained variances of the two PCs were 77.3 and 83.8% in the ASK and PRESPAS datasets, respectively.

While the two PCs were orthogonal, the overall PA (cpm) and the intensity gradient were strongly positively associated (r = 0.73–0.86) in both datasets (Table 2). Both overall PA and the intensity gradient were strongly positively associated with PC_{Volume} in both datasets (r = 0.77–0.91), whereas the intensity gradient was moderately negatively associated with $PC_{Intensity}$ (r = -0.41–-0.40).

Table 2. Bivariate correlation matrix for the explanatory variables used in the linear regression in the PRESPAS dataset (upper right) and the ASK dataset (lower left and shaded).

	Overall PA	**Intensity gradient**	**PC_{Volume}**	**$PC_{Intensity}$**
Overall PA	-	0.86	0.86	-0.10
Intensity gradient	0.73	-	0.91	-0.40
PC_{Volume}	0.77	0.90	-	0.00

$PC_{Intensity}$	-0.13	-0.41	0.00	-

Table 3 shows the associations between the PA intensity spectrum and cardiometabolic health (ASK dataset) and locomotor skills (PRESPAS dataset) using the intensity gradient and principal component analysis as determined using linear regression. Associations for traditional summary measures of PA intensity are shown in Supplemental Table 2. Due to the strong associations between overall PA and the intensity gradient, we analyzed these variables in separate models. Among all variables, the intensity gradient was the single variable that was most strongly associated with the outcomes in both datasets (R^2 = 14.0 and 6.1% in the ASK and PRESPAS datasets, respectively). In the ASK dataset (i.e., for cardiometabolic health), the association for the intensity gradient was considerably stronger than for overall PA, whereas the associations for these variables were rather similar in the PRESPAS dataset (i.e., for motor skills). However, in comparison with the intensity gradient, the two orthogonal PCs led to an improved model fit in both datasets (R^2 = 17.4 and 6.5% in the ASK and PRESPAS datasets, respectively). In the ASK dataset, both a higher volume and a higher intensity were associated with better cardiometabolic health. In contrast, only volume was significantly associated with locomotor skills in the PRESPAS dataset.

Table 3. Associations for the intensity gradient and principal components indicative of physical activity volume and intensity with cardiometabolic health and motor skills.

Analytic approach	**Cardiometabolic health (ASK)**		**Motor competence (PRESPAS)**	
	Coeff. (p-value)	Model R^2	Coeff. (p-value)	Model R^2
Intensity gradient				
Overall PA (cpm)	-0.18 (< .001)	3.1	0.21 (< .001)	4.4
Intensity gradient (slope)	-0.38 (< .001)	14.0	0.25 (< .001)	6.1
Principal component analysis				
PC_{Volume} (score)	-0.27 (< .001)		0.25 (< .001)	
$PC_{Intensity}$ (score)	0.31 (< .001)	17.4	-0.05 (.083)	6.5

Figure 2 shows the multivariate association patterns between PA and cardiometabolic health (ASK dataset) and between PA and locomotor skills (PRESPAS dataset). In the ASK dataset, the strongest association with cardiometabolic health was found for 7000–7999 cpm. In the PRESPAS dataset, the strongest association with motor skills was found for 10000–10999 cpm. Explained variances for the multivariate pattern models were 20.5% (6 PLS components) and 7.4% (2 PLS components) in the ASK and PRESPAS datasets, respectively. Finally, associations for all three approaches (principal component analysis, the intensity gradient, and multivariate pattern analysis) were stronger than for the traditional summary measures of PA intensity, though differences were minor for motor skills.

Discussion

In the present study we used two large datasets in children to explore associations between two different outcomes (cardiometabolic health and motor skills) and spectrum descriptions of PA using three different approaches to handle the intensity spectrum. While the intensity gradient and principal component analysis reduce the dimensions of the intensity spectrum to simpler metrics prior to conducting association analysis, multivariate pattern analysis retains the full intensity spectrum for analysis and interpretation. Thus, the approaches differ with regard to how much of the information captured by the descriptor of the accelerometry data that is subsequently retained for analysis of associations with outcomes. Consistent with these different features of the analytical approaches, multivariate pattern analysis led to the best model fit, indicating that this approach retains relevant information from the accelerometry data that is lost when applying the other approaches. However, results were broadly consistent between all three approaches. Thus, a key question, is how results from these different approaches can be interpreted in practical terms.

Aadland et al. have previously shown that the use of multivariate pattern analysis and the inclusion of multiple variables across the intensity spectrum can increase the variance explained by PA in relation to health outcomes significantly [4, 18, 13, 2]. These findings result from the high-resolution descriptor capturing more of the available information from the accelerometers in combination with the use of an analytical approach that allows for appropriate modelling of this information [2]. Since the PA variables across the intensity spectrum are highly correlated, approaches other than multiple linear regression may be needed to handle such data. However, such data have certain distributional and structural features which allow for reducing the complexity of the data to simpler metrics, like the intensity gradient or orthogonal PCs. If such dimension reduction methods can be demonstrated to retain sufficient information in the data and provide (comparable) interpretable findings, it may provide simple solutions to handle the multicollinearity of the PA intensity spectrum in association analysis, which may be particularly attractive for researchers with less advanced statistical expertise. Consistent with previous studies [12, 11, 5], our findings showed that the intensity gradient explained more variance in outcomes compared to the traditional summary measures of PA, in particular in relation to cardiometabolic outcomes. Still, association models improved further when using principal component analysis, though both these approaches explained less variance than the use of multivariate pattern analysis. These findings suggest dimension reduction methods to construct simpler metrics of the PA intensity distribution or data structure lead to a loss of information retained for association analysis compared to the use of the high-resolution intensity spectrum in multivariate pattern analysis.

Beyond overall model performance, a crucial point that deserves attention is to which extent the three models lead to similar interpretations, or whether they may lead to new knowledge of associations between PA and health and developmental outcomes. Specifically, our results may provide new perspectives on the relative importance of the volume and intensity dimensions of PA, and thus be of importance for future PA research and guideline development. Rowlands et al. [5] aimed to develop the intensity gradient as a metric that compared to traditional summary measures of PA intensity was less dependent on the overall PA level. It has been shown in several studies that associations between overall PA level and the intensity gradient are considerably weaker ($r = 0.36$–0.56) than between overall PA level and MVPA ($r = 0.93$–0.96), which suggest the intensity gradient is more reflective of the intensity *per se* than summary measures of PA intensity [5, 11, 12]. However, we found much stronger associations between overall PA and the intensity gradient in both our datasets (r = 0.73–0.86) than found in previous studies. The use of raw acceleration data in previous studies versus count data used herein likely explains the findings. The frequency dependent filtering used in the generation of ActiGraph counts attenuates capture of high intensity activity reducing associations between the intensity spectrum and cardiometabolic health [34]. This has direct implications for the intensity gradient, which is sensitive to even very small amounts of high intensity activity [35]. Consequently, we observed that the intensity gradient was strongly associated with PC_{Volume} (r = 0.90–0.91), but weakly associated with $PC_{Intensity}$ (r = -0.41–-0.40), which indicates the intensity gradient was not primarily a measure of intensity in the present study. Notably, the collinearity of the intensity gradient and overall PA restricted us from including these variables in joint multiple linear regression models, which may have resulted in poorer model performance than for the principal components analysis for which both volume and intensity components were included.

We are not aware of previous studies that have used principal component analysis for investigating the structure of the PA intensity spectrum. The structure of the two datasets included in the present analysis was similar: For PC 1, a higher score indicate a child exhibit more PA and less SED (i.e., indicative of PA volume), while for PC 2, a higher score means a child have relatively more light intensity PA and relatively less high intensity PA (i.e., indicative of PA intensity). Thus, our findings suggest both higher volume and higher intensity are favourably associated with cardiometabolic health in the ASK dataset, whereas only higher volume was favourably associated with motor skills in the PRESPAS dataset. The latter finding might be counterintuitive given that the strongest association with motor skills were found for 10000–10999 cpm, which could be interpreted as spending time at very high intensities, as opposed to lower intensities, would be favourable to develop motor skills. Notably, it can be observed that high intensities (5000–7999 and 8000–10999 cpm in the ASK and PRESPAS datasets, respectively) have the highest loadings for PC_{Volume} in both datasets, which means these variables contribute most to the overall volume of PA. Although not immediately intuitive, this finding may be reasonable given that time spent at higher intensities will lead to accumulation of much more counts than time spent at lower intensities (e.g., 1 minute spent at 10000 cpm will accumulate as many counts as 100 minutes spent at 100 cpm). Thus, time spent in higher intensities will inherently contribute largely to the volume of PA, as determined by average counts per minute or average acceleration, which is consistent with our findings from the principal component analysis. Thus, despite we extracted two apparently interpretable PCs, the volume and intensity dimensions of PA might still be difficult to separate and apply. This point may also be illustrated by the finding that PC_{Volume} explained 62.8–69.0% of the total variation among the PA variables, whereas $PC_{Intensity}$ only explained 14.4–14.8% of this variation. This finding shows that the relative intensity distribution only constitute a minor part of the overall PA data structure.

While the association pattern derived from the multivariate pattern analysis shown for cardiometabolic health in the ASK dataset was similar to the pattern shown previously (using 1-second epoch data) [18], we observed the strongest associations for motor skills in the PRESPAS dataset for 10000–10999 cpm herein compared to 6000–6999 cpm observed previously [14]. Since the intensity gradient is constructed using log-transformed data [5] and since log-transformed (and log-centred) data has been shown to improve model fit compared to raw data [2], all analyses in the present study were based on log-transformed raw data. The variable distributions are typically positively skewed for the highest PA intensities. Skewed data may lead to a problem for modelling since validation and optimization of model selection (i.e., the number of PLS components included) is based on repeated Monte-Carlo resampling. The procedure use half of the sample for modelling and half of the sample for prediction, randomly partitioned for each repetition. Skewed distributions at the higher end of the PA intensity spectrum means that several PLS components that are weakly associated with the predicted outcome are needed to accommodate this variation between participants. The use of log-transformed data makes the distributions for these higher PA intensities less skewed, and thus more stable to resampling, which ultimately leads to simpler and more robust descriptions of data. This effect has probably led to stronger associations for the highest intensities in the PRESPAS dataset, for which we included the most detailed description of the highest intensities (up to ≥ 15000 cpm). This finding could indicate that very high intensity or impact activities, possibly accrued through early sport participation, are the strongest markers of young children's motor development.

Strengths and limitations

The main strength of the present study is the direct comparison of different analytic approaches to analyze associations between PA intensity spectra and two different outcomes in two large datasets. The use of these two datasets allowed for robust comparisons of the statistical approaches, and provided a nuanced picture of the findings beyond what would be possible with only one dataset. Importantly, the structure of the datasets with respect to inter-relationships between variables and extraction of PCs were similar, which illustrates stability and consistency of the findings.

The cross-sectional designs limit our ability to draw conclusions about causality. It should also be kept in mind that use of other cohorts, for example spanning other age groups, and the use of other outcomes, could lead to other findings due to different correlation structures among the explanatory PA variables and/or different association patterns between PA intensities and outcomes. The use of waking time count data herein compared to the use of 24-hour raw acceleration data in previous studies [5, 11, 12] could possibly influence the performance of the intensity gradient. Yet, this is the first time the intensity gradient is calculated using waking time count data, which improves our understanding of its features as applied to various types of data. Further studies are warranted to explore these analytic issues and extend our findings.

Conclusion

Our results demonstrate broadly consistent findings are evident across all three analytical approaches. The use of high-resolution PA intensity spectra for determination of associations with outcomes may circumvent limitations imposed by the use of a priori defined intensity cut points and improve the information obtained from accelerometry beyond that of traditional summary measures of intensity. We compared multivariate pattern analysis, which can handle the multicollinearity among variables and thus retain all the information in the data, with dimension reduction methods that can be used to reduce the intensity spectrum to simpler metrics, for determining associations with health and development outcomes in children. Our findings suggest that multivariate pattern analysis explains the most variance in outcomes since it is able to retain information from the data that is lost in other approaches. Yet, the intensity gradient provided the best descriptor of the data using one single metric. Thus, both multivariate pattern analysis and the intensity gradient are preferred over the traditional summary measure approach, depending on the application. Finally, our results suggest volume and intensity dimensions of PA are inherently related and thus not easily disentangled. Principal component analysis might therefore have limited application in association analysis of spectrum PA descriptions.

Data availability

The datasets used in the current study are available from the corresponding author on reasonable request.

Disclosure of interests

The authors declare that they have no competing interests.

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Authors' contributions

EAA developed the idea of the study. EAA and AKON collected the data. EAA and OMK designed the study and analyzed the data. EAA wrote the manuscript draft. All authors discussed the interpretation of the results, and read and approved the final manuscript.

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Figure Legends

Figure 1. Factor loadings for physical activity intensity variables on the two principal components extracted from the principal component analysis. The total explained variances of the two principal components were 77.3 and 83.8% in the ASK and PRESPAS datasets, respectively.

Figure 2. Association patterns between physical activity intensities and a composite cardiometabolic health score (ASK dataset) and locomotor skills (PRESPAS dataset). Models included 6 and 2 PLS components, respectively. Selectivity ratios are calculated as explained to total variance on the predictive (target projected) component.