Multivariate pattern analysis of the physical activity intensity spectrum – what have we learned?

5th Nordic Seminar on Technical Measurement of Physical Activity and Sedentary behavior, Trondheim 2.-3. June 2022

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Outline

Multivariate pattern analysis

• What is it and why do we need it?
• How can it be applied to accelerometry intensity spectra?
• What have we learned?
Limitations of the traditional analytic approach to determine associations with accelerometry PA data

- Studies have primarily used **blunt descriptions of PA**, mainly total PA, MVPA, and/or SED - this practice may lead to loss of information and residual confounding
- Due to **multicollinearity of PA variables**, multiple variables should not be included in the same statistical model when applying ordinary least squares linear regression
- The **whole specter of PA intensities should be included**, possibly using a greater resolution than the commonly used gross intensity categories

Multivariate pattern analysis

- Is a dimension reduction method
- Uses **latent variable modelling**, rather similar to Principal Component Analysis (PCA), but

  - **Multivariate pattern analysis** maximizes variance between many explanatory variables and an outcome

  - **PCA** maximizes variance among the explanatory variables

The multivariate physical activity signature associated with metabolic health in children

Exinid Alding1,2, Olav Martin Kaalheim3, Sigmund Alfred Andensen1,4, Geir Kåre Resaland1,4 and Lars Ilo Andersen1

Abstract

Background: Physical activity is a cornerstone for promoting good metabolic health in children, but it is heavily debated which intensities (including sedentary time) are most influential. A fundamental limitation to current evidence for this relationship is the reliance on analytic approaches that cannot handle collinear variables. The aim of the present study was to determine the physical activity signature related to metabolic health in children, by investigating the association pattern for the whole spectrum of physical activity intensities using multivariate pattern analysis.

Methods: We used a sample of 841 children (age 10.2 ± 0.3 years; BMI 18.0 ± 3.0; 50% boys) from the Active Smarter Kids study, who provided valid data on accelerometer (ActivAll; Gokke) and several indices of metabolic health (aerobic fitness, abdominal fatness, insulin sensitivity, lipid metabolism, blood pressure) that were used to create a composite metabolic health score. We created 16 physical activity variables covering the whole intensity spectrum from 0–100 to 2 800 counts per minute and used multivariate pattern analysis to analyze the data.

Results: Physical activity intensities in the vigorous range (5000–7000 counts per minute) were most strongly associated with metabolic health. Moderate intensity physical activity was weakly related to health, and sedentary time and light physical activity were not related to health.

Conclusions: This study is the first to determine the physical activity signature related to metabolic health in children across the whole intensity spectrum. This novel approach shows that vigorous physical activity is the strongest related to metabolic health. We recommend future studies adopt a multivariate analytic approach to further develop the field of physical activity epidemiology.

Total registration: The study was registered in ClinicalTrials.gov (NCT02413340; NCT02152949).

Keywords: Multivariate pattern analysis, Metabolic risk factors, Paediatric, Childhood, Accelerometer, Intensity

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Additionally, sedentary time (SED) defined as time spent sitting or reclining with an energy consumption minimally above resting values (≥1.5 metabolic equivalents) [9], has received great attention for possibly being detrimental to child health beyond overall PA or MVPA [8–9]. However, the evidence for an influence of SED beyond MVPA on metabolic health in children is weak [9, 10].

The majority of pediatric studies investigating relationships between PA and metabolic health have been limited to investigating associations for MVPA and

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Fig. 1 The multivariate PA signature associated with a composite metabolic health score in children displayed as a selectivity ratio (SR) plot. The PLS regression model includes 3 components, R² = 13.3%, and is adjusted for age and sex. The SR for each variable is calculated as the ratio of explained residual variance on the predictive (target projected) component. A negative bar implies that increased PA are associated with better metabolic health.
Association patterns were similar, but strengths of associations differed

**Fig. 2** The multivariate PA signature associated different risk factors in children displayed as a selectivity ratio (SR) plot. The models (PLS regression) is adjusted for age and sex. WC:height ratio = waist circumference to height ratio (3 components, $R^2 = 13.6\%$); TG = triglyceride (1 component, $R^2 = 2.2\%$); TC:HDL ratio = total to high-density lipoprotein cholesterol ratio (1 component, $R^2 = 3.1\%$); HOMA = homeostasis model assessment (2 components, $R^2 = 6.6\%$); Andersen test (3 components, $R^2 = 21.0\%$). The SR for each variable is calculated as the ratio of explained to residual variance on the predictive (target projected) component. A negative bar implies that increased PA are associated with better metabolic health.
2 types of information are useful

The total explained variance of the model
- How much of the variation in the outcome is explained by **ALL** PA variables jointly?

The association signature/profile/pattern
- Which part of the intensity spectrum is strongest associated with the outcome?
Explain variance = 17%

Explain variance = 13%

Explain variance = 10%
Multicollinear physical activity accelerometry data and associations to cardiometabolic health: challenges, pitfalls, and potential solutions

Abstract

Background: The analysis of associations between accelerometer-derived physical activity (PA) intensity and cardiometabolic health is a practical challenge due to multicollinearity between the explanatory variables. This study aimed to explore the potential for multicollinearity between PA intensities and health outcomes.

Methods: A sample of 348 children aged 5-12 years (BMI < 85th percentile) wore accelerometers for 7 days. The study included sedentary (SED), light (LPA), moderate (MPA), and very active (VPA) PA intensities. The association between PA intensity and cardiometabolic health was assessed using linear regression analysis.

Results: The results showed that the association between SED and cardiometabolic health was stronger than for LPA, MPA, and VPA. The VPA was positively associated with cardiometabolic health, while SED was negatively associated.

Conclusion: The study highlights the importance of considering the different PA intensities and their associations with cardiometabolic health. Future studies should consider different PA intensities and their associations with health outcomes.

Keywords: Multicollinear PA, Sedentary, Light, Moderate, Very active, PA intensities, Cardiometabolic health

Figure:

The figure shows the selectivity ratio and R² values for different PA intensities. The selectivity ratio is higher for SED compared to LPA, MPA, and VPA. The R² value for SED is 10.2%, while for VPA, it is 17.0%.
Joint model: 30% explained variance
More information from accelerometry

Sample
• 821 schoolchildren (10-year-olds)
• Composite metabolic health outcome
• 1 sec epoch

Explained variance
• CPM: 3%
• MVPA: 7%
• SED, LPA, MPA, VPA: 10%
• Uniaxial intensity spectrum: 17%
• Triaxial intensity spectrum: 30%
The multivariate physical activity signature associated with body mass index in young children

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ARTICLE INFO

Abstract

The evidence regarding associations between activity-specific physical activity and adiposity in young children is conflicting. However, the evidence is limited by observational studies that rarely handle the multifaceted behavioral profile of individuals among multiple variables across the activity spectrum. We aimed to determine the multidimensional physical activity signature associated with body mass index in a large sample of preschool children aged 3-5 years. 1162 Norwegian preschool children (mean age 4.7 years; 53% boys) provided data on physical activity (ActiGraph GT3X 1d) and body mass index during 2013-2016. Information on physical activity was used to estimate associations between the total activity spectrum and body mass index (BMI) using a Kendall tau correlation. Associations were confirmed in young children. In conclusion, this study is the first to examine the relationship between body mass index and physical activity in preschool children. The results indicate that young children who engage in more physical activity have a lower body mass index. This suggests a possible association between physical activity and body mass index, which may have implications for future research and policy development.

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 early age (Wingrove and Viner, 2003). While there is overwhelming evidence of a negative association for physical activity (PA) with adiposity and overweight in school-aged children and youth (Frost et al., 1998; Holmøy et al., 2012; Aulin et al., 2015a; Reunanen et al., 2016; Cusomato et al., 2017), the evidence for such an association in younger children is weaker and varied (Corso et al., 2015; Kingman et al., 2017; Wingrove et al., 2019). These findings suggest the association between PA and adiposity develops over time, but it is important to consider what that relationship means for young children. 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 (< 500 among the 56 studies included in the recent systematic review and meta-analysis by Wingrove et al. (2019)). Second, the PA assessment methods varied, making it difficult to compare and interpret findings across studies.

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 53 physical activity intensities from the triaxial accelerometer (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.

Explained variance

- Uniaxial intensity spectrum: 6.2%
- Triaxial intensity spectrum: 11.1%
The multivariate physical activity signature associated with metabolic health in children and youth: An International Children's Accelometer Database (ICAD) analysis

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ABSTRACT

There is solid evidence for an association between physical activity and metabolic health outcomes in children and youth, but for methodological reasons most studies describe the intensity spectrum using only one or two summary measures. We aimed to determine the multivariate physical activity intensity signature associated with metabolic health in a large and diverse sample of children and youth, by characterizing the association pattern for the entire physical intensity spectrum. We used postal data from 11 studies and 61,952 participants aged 5.4-18.4 years included in the International Children’s Accelometer Database. We derived 19 accelerometer-defined physical activity variables covering the intensity spectrum (e.g., inactive, light, moderate, and vigorous physical activity). To describe the multivariate nature among these variables, we used multivariate principal analysis to establish the association between the variables and the outcome of interest - metabolic health (e.g., waist circumference, blood pressure). A composite metabolic health index was used as the outcome variable. Associations with the composite metabolic health index were weak for sedentary time and light physical activity, but gradually strengthened with increasing time spent in moderate and vigorous intensity (up to 4000-5000 counts per minute). Association patterns were highly consistent across sex and age groups, but varied across different metabolic health outcomes. This novel multivariate approach suggests that vigorous intensity, rather than lower intensity activities or sedentary behaviors, are related to metabolic health in children and youth.

1. Introduction

There is clear evidence of favorable associations between physical activity (PA) and metabolic health outcomes in children. While associations are evident for moderate-to-vigorous PA (MVPA) and vigorous PA (VPA), associations appear to be weak for light PA (LPA) and

![Graph showing the multivariate physical activity signature associated with metabolic health in boys and girls divided by age groups.](https://example.com/graph.png)

**Fig. 2.** The multivariate physical activity signatures associated with metabolic health by sex and age. The composite score includes waist circumference to height ratio, systolic blood pressure, homeostasis model assessment of insulin resistance, total to high-density lipoprotein cholesterol ratio, and triglycerides (a lower score is more favorable). The PLS regression models are adjusted for age and sex and include two, four, and one components, respectively, for 6-12-year-old boys, 13-18-year-old boys, 6-12-year-old girls, and 12-18-year-old girls. The selectivity ratio for each variable is explained by total variance of the predictive (target projected) component. A negative bar implies that increased physical activity is associated with better metabolic health. $R^2 = \text{explained variance}$.
The Multivariate Physical Activity Signatures Associated With Self-Regulation, Executive Function, and Early Academic Learning in 3–5-Year-Old Children

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The evidence regarding associations between intensity-specific physical activity and cognitive and learning outcomes in preschoolers is inconsistent and limited by low sample sizes and analytical approaches that cannot handle the multicontract among multiple physical activity intensity variables. We aimed to determine the multivariate physical activity intensity signatures associated with self-regulation, executive function, and early academic learning in preschool children aged 3–5 years. A 711 Norwegian preschool children (mean age 4.6 years, 52% boys) provided valid data on physical activity (ActiGraph GT3X+), self-regulation, executive function, and early academic learning during 2019–2020. Multivariate pattern analysis was used to determine associations between uniaxial and triaxial intensity spectra (time spent in intensities from 0–99 to ≥15,000 counts per minute) and the outcomes in the total sample and in subgroups split by sex and age (median split). Uniaxial data led to the highest explained variance (RP) and were reported as the primary findings. We found significant association patterns between physical activity and numerosity (RP = 4.28%) and inhibition (RP = 1.48%) in the total sample. The associations with numerosity were negative for time spent sedentary (0–99 counts per minute) and positive for time spent in moderate to vigorous intensities (≥1,000 counts per minute). The associations with inhibition were positive for time spent sedentary (0–99 counts per minute) and in vigorous intensities (≥6,000 counts per minute) and negative for time spent in low to moderate intensities (100–3,499 counts per minute). Associations with numerosity were stronger in boys (RP = 5.58%) and older children (RP = 7.27%), and associations with inhibition were stronger in girls (RP = 3.12%) and older children (RP = 3.33%). In conclusion, we found weak associations with numerosity and inhibition across the physical activity intensity spectrum in preschool children.

Keywords: cognition, preschool (kindergarten), accelerometer, self-regulation, executive function, learning

FIGURE 1 The multivariate physical activity signature for the uniaxial spectrum associated with inhibition in preschoolers. Results are reported as multivariate correlation coefficients. The model (PLS regression) is adjusted for sex, age, wear time (only PA variables), BMI, parental education level, and sleep (model 2).

FIGURE 2 The multivariate physical activity signature for the uniaxial spectrum associated with inhibition in preschoolers. Results are reported as multivariate correlation coefficients. The model (PLS regression) is adjusted for sex, age, wear time (only PA variables), BMI, parental education level, and sleep (model 2).
Middle-aged to older adults

Physical activity intensity profiles associated with cardiometabolic risk in middle-aged to older men and women

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ABSTRACT

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ARTICLE INFO

Keywords:

Physical activity

Cardiometabolic risk

Middle-aged adults

Older adults

ABSTRACT

Physical activity intensity profiles associated with cardiometabolic risk in middle-aged to older men and women

1. Introduction

Reflections on the prevalence of moderate to vigorous physical activity (PA) among older adults are scarce and varied. Different cutpoints for PA intensity have been used in previous studies, leading to inconsistent results. This study aimed to investigate the prevalence of PA intensity among middle-aged and older adults, and to identify potential predictors of PA intensity in this population.

Methods

Data were collected from the Survey of Health, Ageing and Retirement in Europe (SHARE) database, which includes detailed information on PA intensity and other health outcomes for individuals aged 50 and older. Participants were classified into three categories based on their PA intensity levels: low, moderate, and vigorous. Multivariate logistic regression analyses were used to identify predictors of PA intensity, controlling for demographic and health-related factors.

Results

The prevalence of moderate to vigorous PA intensity was highest among younger adults (50-64 years) and lowest among those aged 75 and older. In multivariate analyses, greater PA intensity was associated with higher levels of education, lower BMI, and better self-rated health. These findings highlight the need for targeted interventions to promote PA intensity among older adults.

Conclusion

This study provides valuable insights into the prevalence and predictors of PA intensity among middle-aged and older adults. Future research should focus on developing effective strategies to promote PA intensity in this population, with the goal of improving cardiometabolic health outcomes.

Fig. 2. Multivariate PA intensity profiles associated with the CMR score. Multivariate correlation coefficients with 95% CIs from the multivariate model including m = 22 PA intensity variable are displayed for the whole sample (male and female). Physical activity variables are shown for 5 s (passage a and b) and 60 s (passage c and d) epochs resolution. Model 1 adjusted for age and sex. Model 2 additionally adjusted for potential confounders (education level, smoking status, alcohol intake, baseline history of diabetes, anti-hypertensive and lipid-lowering medications, and prevalent heart disease/stroke). Sex-specific models are based on model 2 (with no adjustment for sex). The number of PLS components and total explained variance (R²) for each model are also displayed. A negative bar implies a more favourable association with the CMR score. Note: equivalent plots are displayed for higher intensity resolution (m = 37 and 57 PA variables) in Supplementary Fig. S1, and for illustration only in m = 3 PA variables (Supplementary Fig. S6).
Multicollinearity physical activity accelerometer data and associations to cardiometabolic health: challenges, pitfalls, and potential solutions

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Abstract
Background: The analysis of associations between accelerometer-derived physical activity (PA) intensities and cardiometabolic health is a major challenge due to multicollinearity between the explanatory variables. This challenge has facilitated the application of different analytic approaches within the field. The aim of the present study was to compare association patterns of PA intensities with cardiometabolic health in children obtained from multiple linear regression, compositional data analysis, and multivariate pattern analysis.

Methods: A sample of 841 children (age 10.2±0.5 years, BMI 18.0±3.1; 50% boys) provided valid accelerometer and cardiometabolic health data. Accelerometry (ActiGraph GT3X+) data were characterized into traditional (four PA intensity variables) and more detailed categories (23 PA intensity variables covering the intensity spectrum: 0-99 to 2.10.000 counts per minute). Several indices of cardiometabolic health were used to create a composite cardiometabolic health score. Multiple linear regression and multivariate pattern analyses were used to analyze both raw and compositional data.

Results: Besides a consistent negative (favorable) association between vigorous PA and the cardiometabolic health measure using the traditional description of PA data, associations between PA intensities and cardiometabolic health differed substantially depending on the analytic approaches used. Multiple linear regression lead to unstable and spurious associations, while compositional data analysis showed distorted association patterns. Multivariate pattern analysis appeared to handle the raw PA data correctly, leading to more plausible interpretations of the associations between PA intensities and cardiometabolic health.

Conclusions: Future studies should consider multivariate pattern analysis without any transformation of PA data when examining relationships between PA intensity patterns and health outcomes.

Trial registration: The study was registered in ClinicalTrials.gov 7th of April 2014 with identification number NCT01821491.

Keywords: Multivariate pattern analysis, Compositional data analysis, Multiple linear regression, Multicollinearity, Statistics, Children, Accelerometer, Intensity

Fig. 4 Association patterns between physical activity intensities and a composite cardiometabolic health score using the spectrum description of 23 physical activity variables using different analytic approaches. Multiple linear regression with raw data (upper left panel), multiple linear regression with compositional data using the clr-transformation (lower left panel), multivariate pattern analysis with raw data (upper right panel), and multivariate pattern analysis with compositional data using the clr-transformation (lower right panel). Selectivity ratio is calculated as the ratio of explained to total variance on the predictive (target projected) component. $R^2$ = explained variance of the model.
2 challenges for interpretation

• Use of «selectivity ratio» as the statistic for reporting associations
  • Unknown for many researchers
  • Introduced «multivariate correlation coefficients»
    • Interpretation is equivalent to bivariate correlations

• Associations are not independent
  • Searching for independent associations make less sense when variables are highly correlated
  • PA variables from accelerometry profiles do not provide unique information – variables are not separable
How does interpretation of associations from multivariate pattern analysis models differ from linear regression models?
What multicollinearity mean:

1 min

8 mins VPA in total

1 min

6 mins VPA in total

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The variable in bold indicates the basis for construction of deciles.
We have learned that multivariate pattern analysis ...

- Is suitable to model multicollinear accelerometry datasets with any number of variables
- Provide 2 types of information that is useful – association pattern and total model fit
- Often lead to better association models (higher explained variance) for higher resolution (triaxial) intensity spectrum, but not always...
- May be a good tool to compare methods or groups, although testing of moderation (interactions) is difficult
- Can be applied to both cross-sectional and longitudinal data
- Can be applied to «raw» and compositional data
- May be difficult to interpret (is different from linear regression) – does NOT estimate independent associations
- Need a good method for covariate adjustment – have developed «confounder projection»
How to work with mvpasShiny

(1) Load your own dataset or the demo dataset
(optional) Scale, transform or subset the dataset
(2) Name it
(3) Select the response variable
(4) Validate its integrity and make it an available dataset
(5) Apply the available methods (tabs) to the dataset
The way forward

- Multivariate pattern analysis can provide a nuanced and complete picture of association patterns between accelerometry-derived PA data and diverse outcomes and contribute to advance our understanding of the importance of PA for health and development.

- Future research should apply multivariate pattern analysis:
  - In various populations
  - In various study designs
  - Using various outcomes
  - In direct comparisons with other approaches
Thank you for listening!

and thanks to participants, funding agencies and coauthors that made this research possible!

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