Profiling movement behaviours in pre-school children: A self-organised map approach

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Title page

Title: Profiling Movement Behaviours in Pre-School Children: A Self-Organized Map Approach

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Abstract

Application of machine learning techniques has the potential to yield unseen insights into movement and permits visualisation of complex behaviours and tangible profiles. The aim of this study was to identify profiles of relative motor competence (MC) and movement behaviours in pre-school children using novel analytics. One-hundred and twenty-five children (4.3±0.5y, 1.04±0.05m, 17.8±3.2kg, BMI: 16.2±1.9 $kg{\cdot}m^2$) took part in this study. Measures included accelerometer-derived 24-h activity, MC (Movement Assessment Battery for Children 2nd edition), height, weight and waist circumference, from which zBMI was derived. Self-Organized Map (SOM) analysis was used to classify participants' profiles and a *k-means* cluster analysis was used to classify the neurons into larger groups according to the input variables. These clusters were used to describe the individuals' characteristics according to their MC and PA compositions. The SOM analysis indicated five profiles according to MC and PA. One cluster was identified as having both the lowest MC and MVPA (profile 2), whilst profiles 4 and 5 show moderate-high values of PA and MC. We present a novel pathway to profiling complex tenets of human movement and behaviour, which has never previously been implemented in pre-school children, highlighting that the focus should change from obesity monitoring, to 'moving well'.

Keywords:

Motor Competence; Machine Learning; Unsupervised; Cluster Analysis; Physical Activity

Introduction

Recently, numerous prospective studies have established that development of motor competence (MC) has numerous tangible health and developmental benefits. For example, higher levels of MC are shown to positively predict cardiorespiratory fitness [1], improved academic performance [2], and are protective against the accrual of excess weight and obesity [3]. Concerningly, international investigations have reported low levels of MC among primary school aged children [4-6]; whilst some empirical data exists, suggesting that motor incompetence may already be manifest in the pre-school period. The period encompassing the pre-school ages (3-5y) is considered to be a critical phase for fundamental movement skill development [7]; putatively mediated by attaining adequate levels of physical activity (PA). However, epidemiological evidence suggests that the majority of pre-school children do not accrue adequate levels of PA [8], where global guidelines and advocacy groups recommend engagement in at least 180 minutes of PA every day [9-11].

Although empirical and conceptual evidence exists to support the reciprocal relationship between MC and PA [12, 13], there is a limited evident base of MC related to PA measurement in pre-school children, largely due to the difficulty in examining such constructs in this age group [14, 15]. For example, young children tend to have inflated perceptions of their own MC [16], as they do not possess the cognitive ability to distinguish between actual competence and effort [17, 18], whilst LeGear et al [5] suggest that certain skills or movements in MC assessments are more tangible or feasible than others for children, and thus, may not accurately reflect MC. Furthermore, when studies have investigated PA and MC they tend to examine this as a relationship, where large variability in MC, but also PA, is reported [14, 19]; it is therefore conceivable that small associations observed could be due to an insensitive statistical approach, i.e. over-simplification of complex movement behaviours and their variable, interrelationships.

Recent advances in methods of assessment has yielded success, for example, person-centred approaches, which combines actual and perceived MC variables through cluster analysis into MC-based profiles that allow distinguishing between (low or highly proficient) realists, whose perception of MC is aligned with their actual competence, and over- or under-estimators, who perceive their own MC better or worse than it actually is, respectively [20]. Moreover, advances in sophisticated data analytics has also provided a platform for novel insights into movement behaviours [21-25]. Recently, a machine-learning approach, specifically, self-organized maps (SOM), has gained popularity [26, 27]. This analytical technique can be used to classify participants, visualise input variables, and provide hitherto unseen profiles according to their similarities in terms of input variables [28]. To date, no study has applied SOM profiling in pre-school; however, information yielded from such an approach is key in the development of the area and knowledge base because it will permit visualisation of complex movement behaviours and tangible profiles. Therefore, the aim of this study was to identify profiles of relative MC and movement behaviours in pre-school children using novel analytics.

Materials and Methods

Participants and Settings

A final sample of one-hundred and twenty-five pre-school children (80 boys, 4.3±0.5y, 1.04±0.05m, 17.8±3.2kg, body mass index; 16.2±1.9 $kg{\cdot}m^2$) volunteered to take part in this cross-sectional study (77% South Asian, 12% White British, 11% Other/Mixed), and were recruited by way of convenience sampling. Prior to research commencing, informed parental consent and child assent was attained. One-hundred and thirty-three participants from three pre-schools were invited to participate; however, eight children declined to participate before study commencement. This research was conducted following approval of the institutional ethics committee and all protocols conformed to the Declaration of Helsinki.

Instruments and Procedures

Anthropometrics

Stature (measured to the nearest 0.01m) and body mass (to the nearest 0.1kg) were measured according to standard procedures using a stadiometer and digital scales (SECA, Hamburg, Germany), respectively [29]. All participants were classified based on body-mass index percentiles as either; underweight (≤5^{th} percentile), normal weight (5^{th} to 85^{th} percentile), overweight (>85^{th} to <95^{th} percentile) or obese (≥ 95th percentile) [30]. Waist circumference was measured in line with the naval and measurements were subsequently used to estimate body fat percentage using standard techniques [31, 32].

Motor competence

All children completed the movement assessment battery for children, second edition, using standardised procedures (MABC2) as detailed in Henderson [33]. Briefly, the tasks of the MABC2 are separated into three age bands that include specific task and scoring variations: age-band 1 (3–6 years old), age-band 2 (7–10 years old), and age-band

3 (11–16 years old). Thus, for the present study, tasks of age-band 1 were used. The MABC2 is separated into three subscales: manual dexterity (three tasks; posting coins, threading beads, drawing) (henceforth: *fine motor control*), and aiming and catching (two tasks; tossing and catching a beanbag), and total balance (three tasks; one-leg balance, walking heels raised, jumping) (henceforth: *gross motor control*). Scoring on the MABC2 is quantitative and each task yields a product-oriented score. For the tasks of posting coins and threading beads, children complete the task as quickly as possible. The time required to complete each task is recorded. The drawing task is not timed; however, children are instructed to draw a line as quickly as possible, but to stay within specific boundaries. An error is scored each time the line crosses the boundary [33]. The number of errors is recorded based on manual guidelines. Children complete 10 attempts of the aiming and catching tasks. A child is given a score of 1 or 0, if an attempt was successful or not, respectively. One-leg balance is scored based on the amount of time a child balances on each leg. The walking-with-heels-raised task is scored based on the number of successful steps (up to 15) taken in a straight line. The number of consecutive jumps (up to 5) within specific boundaries is recorded for the jumping task. Children completed practice and formal trials for each task. The number of practice and formal trials varied for each task and was based on the test instructions. The MABC2 was scored by a trained, experienced assessor and raw scores were described as an overall percentile score (0-100%) and traffic light classification system including a red zone (1: $<5^{th}$ percentile indicating significant movement difficulty), amber zone (2: between the 5^{th} and 15^{th} percentiles indicating at risk of movement difficulty), and green zone (3: $>15^{th}$ percentile indicating no movement difficulty detected), following standard procedures [33].

Physical activity

Study participants wore an ActiGraph GT3X+ accelerometer (Actigraph, Pensacola, FL, USA) for seven consecutive days [34, 35]. Participants were instructed to wear the accelerometer constantly except when bathing or swimming. The accelerometer measures 4.6 cm × 3.3 cm × 1.5 cm, and weighs 19 g. Its sampling frequency was set to 100 Hz, and the sampling interval (epoch) in the present study was set to be 1-s [36, 37]. Participants wore their accelerometer on the waist, above the right hip, affixed using an elastic belt [38]. Accelerometer data were analysed to measure the following parameters: daily duration of sedentary behaviour, light PA, moderate PA, vigorous PA, and MVPA [39].

Analytical methods

ActiGraph acceleration data were analysed using a commercially available analysis tool (KineSoft version 3.3.67, KineSoft; www.kinesoft.org). Non-wear periods were defined as any sequence of >20 consecutive minutes of zero activity counts [40]. While cut points discerned by Sirard et al were used to define sedentary, light, moderate and vigorous PA, respectively [41-43].

Motor competence, sedentary, light PA and MVPA were used as the input variables for the SOM analysis. The SOM was computed using the Matlab R2018a program (Mathworks Inc., Natick, USA) and the SOM toolbox (version 2.0 beta) for Matlab [44]. The SOM analysis was used to classify the participants' profiles by their similarities in the input variables. To obtain the SOM, a three-step procedure was implemented [28]: 1) the construction of a neuron network; a lattice size was selected for the sample size of the study (i.e. 9 x 6 neurons) to create a neural network. 2) The initialization by assigning a value or weight to each neuron for each input variable by two different ways (i.e. randomized and linear initialization). 3) The training by modifying the values or weights of the initially assigned neurons (i.e. sequential and batch training algorithms were used) [45]. During step 3 (training), several factors influence the modification of the neuronal weights in each iteration [26]. First, an input vector (i.e., a case or subject of the study) is presented to the network. Second, the neurons in the lattice "*compete*" to win the input vectors (i.e., compare the Euclidian distance of their weight vector and the input vector values) by achieving the smallest Euclidean distance between its weight vector and the input vector. Third, the weight vector of the winning neuron has the closest values to the cases in the neuron. Forth, all the neurons in the lattice then adapt their weight values closer to the values of the input vector [27].

The magnitude of the adaptation is dependent on the learning ratio and the neighbour function. The learning ratio has a high value during the beginning of the training process and is gradually reduced as the training process progresses and the neighbour function maximises the adaptation of the "*winning*" neuron. The size of the adaptation magnitude is negatively associated with the distance between the neuron and the "*winner*". This process is repeated until the training process ends [26, 28].

As the final analysis depends on the random procedure (e.g. initialization and entry order of the input vector), the aforementioned process described above was repeated 100 times to enhance the odds of finding the best solution. As a result, 1600 SOM were obtained from the two different training methods, four neighbourhood functions and two initialization methods (i.e. 100 x 2 x 4 x 2). After multiplying the quantization and topographical errors, the map with the minimum error was then chosen [27, 28].

After the SOM analysis, a *k-means* method was then used to classify the neurons into larger groups according to the input variables. The number of clusters was established to range between 2 and 10 to avoid an excessive number of profiles [26]. The final number of clusters was the one with the lowest Davies-Bouldin index [46]. These clusters were used to describe the individuals' characteristics according to their MC, sedentary behaviour and intensity of PA compositions. The repertoire of profiles found was termed according to the relative value (i.e., low, medium, high) of the input variable in the sample under study [26].

Statistical analysis

To examine how cluster profiles' relate to BMI, waist circumference, MC and PA compositions, statistical analyses were conducted using SPSS 23.0 (SPSS Inc., Chicago, IL). Parametric tests were used, as the Kolmogorov-Smirnov test verified that all variables met with the normality assumption. The mean and standard deviation were obtained by standard statistical methods. A 2-way multivariate model of analysis of the variance (MANOVA) [cluster (5) x sex (2)] was conducted to determine the influence of cluster and children's sex on the variables under study (fine, gross and overall MC, sedentary time, light PA and MVPA). The follow up of the multivariate analysis was performed by means of univariate contrast. Pairwise comparisons with Bonferroni correction were requested when significant univariate contrasts were found. Partial eta-squared (η_p^2) values below .01, .01–.06, .06–.14, and above .14 were considered to have trivial, small, medium, and large effect sizes, respectively [47]. In addition, two Pearson Chi-Square (χ^2) tests were applied to determine the existence of an association within a particular cluster between the frequency of being boy/girl and being red/amber/green for MC. The strength of the associations was measured by Cramer's *V* with values between .1-.35, .36-.49 and above .5, considered to have small, moderate, and large associations, respectively [48]. A *p*-value of 0.05 was accepted as the level of significance in all the statistical analyses.

Results

The SOM analysis indicated five different profiles according to MC and PA (Figure 1). In Table 1, the categorization according to the relative value in every input variable for every profile is displayed. Profile 1 (*Aligned– Low*) demonstrated low values in MC, high in sedentary, low in light and MVPA. Profile 2 (*Aligned partially – Low*) demonstrated low values in MC and MVPA, and medium light PA and sedentary. Profile 3 (*Non-aligned – Medium-Low*) was characterised by medium MC, high light PA, low sedentary and MVPA. Profile 4 (*Aligned partially – Medium-High*) demonstrated medium values in MC, low sedentary, high light and MVPA. Profile 5 (*Aligned partially – Medium*) was characterised by high MC, medium sedentary, light and MVPA.

****Table 1 about here****

*****Figure 1 about here*****

Multivariate analysis showed a main effect of cluster (Wilks $\Lambda_{(8,32)} = 5.70$; $p < .001$; $\eta_p^2 = .31$) and an interaction effect of cluster*sex (Wilks $\Lambda_{(8,32)} = 2.03$; $p = .001$; $\eta_p^2 = .14$) but not a main effect of sex (Wilks $\Lambda_{(8,32)} = .58$; $p = .789$; $\eta_p^2 = .04$). The follow up of univariate contrast showed the main effect of the cluster on fine MC ($F_{(4,108)} = 1.22$; $p = .031$; $\eta_p^2 = .04$), gross MC ($F_{(4,108)} = 3.59$; $p < .009$; $\eta_p^2 = .12$), zBMI ($F_{(4, 108)} = 2.91$; $p = .025$; $\eta_p^2 = .10$), sedentary ($F_{(4, 108)} = 21.30$; $p < .001$; $\eta_p^2 = .44$), light PA ($F_{(4, 108)} = 7.90$; $p = .001$; $\eta_p^2 = .23$), moderate PA ($F_{(4, 108)} = 3.87$; $p = .006$; $\eta_p^2 = .13$), vigorous PA ($F_{(4, 108)} = 3.49$; $p = .010$; $\eta_p^2 = .12$), and MVPA ($F_{(4, 108)} = 4.75$; $p = .001$; $\eta_p^2 = .15$). No effect of cluster was found on overall MC or waist circumference. Pairwise comparisons and absolute values of PA and MC are presented in Table 2. In addition, regarding the interaction effect of cluster*sex, the follow up of univariate contrast revealed no significant effects.

****Table 2 about here****

Pearson Chi-Square tests showed, firstly, a significant association between cluster and the frequency of boys and girls (χ^2_4 = 11.55; *p* = .021). Moreover, profile 4 presented a higher frequency of boys than girls (*V* = .31). On the contrary, a similar distribution of boys and girls was found in clusters 1, 2, 3 and 5. Secondly, a significant association was found between children in cluster 2 and the traffic light classification of the MABC2 (i.e. red, amber, green) (χ^2_4 = 17.67; *p* = .024; Cramer *V* = .274). Of those in cluster 2, the proportion of children in the red category for overall MC (60%) was higher than those in the green category (15.2%).

Discussion

Robust, unsupervised machine learning of human activity behaviours permits a visual, discretized representation of complex data [26, 27]. Such analytical techniques can be used to classify, visualise, and provide hitherto unseen profiles according to their similarities in terms of input variables [28]. Whilst more traditional statistical analysis of complex data persists, it has been asserted, by Clark and colleagues [21], that novel analytical approaches will facilitate novel insights into quantitative assessments of human activity. Although the assessment of children's PA and MC has become commonplace, there is a paucity of evidence to confirm that MC is strongly related to PA measurement in pre-school children, largely due to the complexity in examining such constructs in this age group, and indeed complexity of movement patterns; where children can be both highly sedentary, and also active, so looking at these independently is not representative of their true patterns [14, 15]. It is conceivable, however, that novel and robust analytics, such as SOM machine learning may facilitate the assessment of PA and MC in pre-school children, providing robust profiles of movement behaviours. The present study is the first to apply SOM machine learning approaches to identify profiles of MC and movement behaviours in pre-school children. In accord with the aim of this study, the key findings of this study were, first, that one cluster was identified as having both the lowest MC and MVPA (profile 2). Second, profiles 4 and 5 show positive values in terms of PA and MC, and present aligned partially medium or medium-high with no cluster member presenting low levels of MC; although, interestingly, minimal differences in zBMI, and no differences in waist circumference, were found between any of the profiles.

The proportion of boys-to-girls was comparable in every profile, except in profile 4 (*Aligned partially – Medium-High)*, wherein the proportion of boys was higher, which could support the tendency of boys displaying higher values of MC and PA than girls [49]. In profile 4, the MVPA was higher than in profiles with a proportionate gender-split. Although this could be seen as an evidence of the different profiles between boys and girls in the infancy or early childhood, it must be noted that on one hand, the strength of the association in profile 4 was small, and on the other hand there is a similar distribution of boys and girls in profile 5 that is positive in terms of girls also presenting relative high values of MC and PA. Although the promotion of PA in girls with relative medium and low values in MC is suggestible, the existing evidence regarding sex-mediated differences in pre-school children is not clear. Thus, further examination of the association of sex and MC in preschool children is needed. Although the principal aim of this study focussed on relative differences, with respect to absolute levels of PA and SB and alignment with global PA guidelines, all profiles achieved the recommended 180 mins/day PA (considering light PA and MVPA [9-11]); however, only profiles 1, 4 and 5 achieved 60 minutes of MVPA per day, on average. This suggests that, even in a homogenous sample, we are able to discern low and high MVPA, both in terms of absolute and relative values. However, in order to explicate the more nuanced differences in the whole PA composition, and their alignment to global guidelines, larger and more heterogenous samples will be required.

Recently, Figueroa et al [50] comprehensively reviewed MC and PA in pre-school children, and asserted that an association is consistently documented between MC and PA. However, the authors suggested that future research is needed to explicate the underlying causal link, examine potential sources of heterogeneity, and determine the role of environment in the relationship between MC and PA among pre-schoolers, respectively. In Silva-Santos et al [51], it was highlighted that pre-schoolers who had high levels of MC accrued greater time spent in MVPA than those that had low level of MC, and Hall et al [52] reported that good motor competence is an important correlate of children accruing adequate PA. The results of the present study were somewhat correspondent with the aforementioned reports, where children in profile 5 consisted of children all situated in the green traffic light classification, whilst maintaining among the highest levels of MVPA with large effect sizes found. Moreover, this is congruent with evidence in the literature that having high fundamental movement skill level may increase options for participation in PA, being an important correlate of preschool children meeting PA guidelines for health [53], as well as increased participation leading to further development of motor skills [54, 55]. Furthermore, in the systematic review of Figueroa et al [50], an overarching conclusion was that the nature and strength of the relationship between MC and PA in pre-school children tends to differ by sex, PA intensity, motor skill type, and day of the week (weekdays versus weekends). However, with the development of robust analytics, such as SOM, numerous variables could conceivably be built into any analyses, and permit greater insight into how clusters are composed.

We found that children in profiles 2 and 3, where at least 50% of the cluster members were categorised as having low or medium levels of MC, had higher zBMI scores than those in profile 5, who had the highest, relative, MC scores. Interestingly, children in profile 1 had lower zBMI than those in profile 3, despite having higher levels of sedentarism, which is conceivably attributable to children in profile 1 accruing greater time spent engaging in MVPA. There is antecedence in the literature to suggest that PA can counteract high sedentary time; Bakrania et al [56] report, albeit in adults, that in comparison to individuals who are physically inactive with high sedentary time, those who are physically active have a more desirable health profile across multiple cardiometabolic markers even when combined with high sedentary time. Whilst Ekelund et al [57], in a systematic review and meta-analysis, report that high levels of moderate intensity PA may eliminate the detrimental effects associated with high sitting time. Although in children, Lopes et al [58] asserted that PA levels, *per se*, may not overcome the negative influence of high levels of sedentary behaviour on MC; indicating that in order to establish healthy lifestyles, actions aiming to address inactivity should attempt to increase PA levels and decrease sedentary behaviour concurrently [59]. Moreover, the necessity for public health recommendations targeting sedentary behaviour has already been advocated to include transportation, sitting time, and time spent indoors [60]. These guidelines suggest that for conferment of health benefits, children should minimize the time they spend being sedentary each day by limiting recreational screen time to no more than 2 hours per day, in addition to limiting sedentary transportation, prolonged sitting time, and time spent indoors throughout the day [61, 62]. However, recommendations regarding limits on total time per day spent in sedentary activities are still lacking; where minimal studies have addressed links between total sedentary behaviour and health outcomes in children and adolescents [63]; thus, highlighting the need for enhanced monitoring and robust profiling of movement behaviours.

The reciprocal relationship between MC and PA is very important, especially in pre-school children, where PA appears to be positively correlated with object control and locomotor skill competence, and negatively correlated with sedentary behaviour [64, 65], however, relatively few studies have examined the association between MVPA and MC in pre-school children [64]. Considering that MC is essential for children to maintain a sufficient PA level throughout the life-course, it is important for key stakeholders to understand the associations between PA and MC to target the most effective ways to enhance pre-schoolers' MC and PA.

Of particular interest was the finding of one cluster (profile 2; Figure 1) who displayed the lowest values for gross and fine motor control, and lowest accrual of MVPA in the entire cohort. However, through SOM profiling it was evident that although profile 2 children exhibited low scoring movement behaviours, with only a small association, this had not yet conferred any negative consequences to zBMI or waist circumference. Moreover, there was no differences noted for waist circumference, and limited differences in zBMI, between all five profiles, demonstrating that whilst discrepancies in movement behaviours may already be evident, adiposity is relatively unaffected. Sedentary behaviour is also believed to have an inverse relationship with motor coordination in pre-school children in the literature [58, 66], where an important determinant of childhood PA and sedentary behaviour may be that of motor development in infancy and childhood [66]. Insufficient MVPA levels and high amounts of sedentary time are associated with poor motor skills, longitudinally [64]. Given that we have highlighted a profile that, although inactive and less motor competent, has no adverse effect on adiposity, it is recommended that routine screening of young children go beyond just basic anthropometric assessment, as children who are inactive and less motor competent could be at risk in later childhood, adolescence and beyond [64].

Finally, although we are the first to demonstrate the use of SOM profiling in pre-school children; there is some previous work that has utilised SOM analyses in children in relation to motor skill competence [26], and postural control [67]. In Estevan et al, [26] the authors reported 4 clusters, where children with high motor ability and perception exhibited higher PA participation and were more likely to be of normal-weight compared to those with low motor ability and/or perception. Whilst in Garcia-Masso [67], six clusters were discerned, and the authors highlighted that boys were more frequently classified as having high postural control. Furthermore, some work has examined active commuting to school in adolescents [27], and eight specific clusters were discerned, which yielded insight into the impact of residential density and proximity and connectivity within neighbourhoods. Importantly, in all three previous examples [26, 27, 67], the input variables for the SOM were also included in the models for further comparisons, highlighting antecedence for, and robustness in, the procedure we followed.

Limitations

Taking into account that, according to the model of motor development [12], it is desirable to find alignment in the input variables of the SOM i.e. high levels of MC and PA (with low in the case of sedentary) in preschool children, However, conceivably due to the limited cognitive and motor development in pre-school aged children, alignment between MC and PA levels is unclear. The only cluster in which clear alignment was found is profile 1 with low values. Furthermore, whilst informative and successful in this cohort, given the known discrepancies between activity behaviours in children of varying ethnic origins and country of residence, it is pertinent to investigate whether comparable SOM profiles emerge across varying populations. Finally, accelerometer position was restricted to the waist, and whilst accepted to elicit an accurate representation of human activity, the position an accelerometer is placed, e.g. hip, wrist, ankle, will impact subsequent outputs and my result in changes between PA classification [22, 68], and thus, should be further explored. Moreover, tracking movement behaviours in a longitudinal fashion would provide greater insight into the stability and development of profiles, as well as factors that may influence or mediate change. Although monitoring compliance was absolute (100%) the homogenous nature of the sample may suggest that the generalisability of the findings may be limited, and further work must be undertaken to ascertain the veracity of incumbent profiles. Furthermore, because the sample was homogenous, in terms of geographical area, we were unable to cluster based on location; thus, systematically collecting and combining various regional, national and international datasets should be undertaken to better elucidate the manifestation of specific profiles.

Conclusions

The implementation of PA into children's everyday life, as early as the pre-school period, is of paramount importance given higher levels of PA during childhood are associated with fundamental movement skill proficiency and health [64, 69]. We present a novel pathway to profiling complex tenets of human movement and behaviour, which has never previously been implemented in pre-school children, and have shown that whilst differences in movement behaviours are already manifest in young children, resultant changes in adiposity are not clear, highlighting that basic anthropometric screening is insensitive, inadequate, and the authors of the present study assert that the focus should change from obesity monitoring, to one of 'moving well'. Given the importance of this stage of life for future health, activity engagement and MC, it is of critical importance accurate profiles, particularly of relative low competence children, be ascertained, so that nuanced, early, interventions may be implemented.

List of Abbreviations

MC: Motor competence; PA: Physical activity; MVPA: Moderate-to-vigorous physical activity; SOM: Self-organized map; BMI: Body mass index; MABC2: Movement assessment battery for children 2nd edition; MANOVA: Multiple analysis of variance

Declarations

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Availability of data and material

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Ethics approval and consent to participate

Ethical approval was granted by the institutional research ethics committee. Informed parental/carer consent and informed child assent was obtained from all participants.

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Table 1. Categorised relative value of the input variables in the SOM analyses.

	Profile 1 *Aligned– Low*	**Profile 2** *Aligned partially: Low*	**Profile 3** *Non-aligned: Medium-Low*	**Profile 4** *Aligned partially: Medium-High*	**Profile 5** *Aligned partially: Medium*
Sedentary	High	Medium	Low	Low	Medium
Light	Low	Medium	High	High	Medium
MVPA	Low	Low	Low	High	Medium
Gross MC	Low	Low	Medium	Medium	High
MABC2 split (%)	20/12.5/19.6	60/25/15.2	20/37.5/26.1	0/25/19.6	0/0/19.6
Sex (M/F)	17.9/20	23.1/15.0	20.5/40	25.6/5	12.8/20

Note. MVPA: moderate vigorous physical activity, MC: motor competence. MABC2 split refers to the profile composition of children scoring ‘red’, ‘amber’ and ‘green’ expressed as percentage of total red/amber/green. Sex refers to the proportion of boys and girls in every cluster expressed as a percentage of the whole sample.

Table 2. Descriptive values according to the profile.

	Profile 1 *Aligned– Low* (*n*=22)		**Profile 2** *Aligned partially – Low* (*n*=24)		**Profile 3** *Non-aligned – Medium-Low* (*n*=32)		**Profile 4** *Aligned partially – Medium-High* (*n*=22)		**Profile 5** *Aligned partially – Medium* (*n*=18)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Fine MC (%)	39.82	28.58	27.33	19.84	35.31	18.53	43.00	30.41	54.56	25.15
Gross MC (%)	15.18	18.85 [5]	9.54	7.92 [5]	22.94	14.25 [5]	28.18	30.93 [5]	48.11	16.89
Overall MC (%)	27.50	17.81	18.44	12.59	29.13	13.83	35.59	20.89	51.33	19.08
zBMI	-0.43	2.02 [3]	0.44	0.76 [5]	0.81	1.26 [5]	0.38	1.48	-0.31	1.00
WC (cm)	49.65	4.10	50.09	3.29	52.08	5.79	51.96	7.43	50.03	2.77
Sedentary (mins/day)	626.47	42.95 [2,3,4,5]	521.99	22.04 [3,4]	460.94	28.81 [5]	453.19	31.98 [5]	530.93	20.21
Light (mins/day)	234.49	36.35 [2,5]	307.37	30.15 [3,4]	365.39	18.39 [5]	347.11	36.13	316.59	32.21
Moderate (mins/day)	44.94	4.38 [2,3]	41.45	3.07 [4]	41.96	3.42 [4]	48.35	3.78	44.01	2.70
Vigorous (mins/day)	18.05	8.32 [2,4]	9.90	3.53 [3,4,5]	15.30	5.93 [4]	38.61	7.70 [5]	16.37	7.87
MVPA (mins/day)	62.99	11.04 [2,4]	51.35	6.19 [3,4,5]	57.26	6.54 [4]	86.97	7.92 [5]	60.37	7.69

Note. MC: motor competence, zBMI: body mass index expressed as a z-value, WC: waist circumference, MVPA: moderate to vigorous physical activity. The number at the right of the SD denotes significant difference (P<0.05) with this specific profile.

Figure 1.

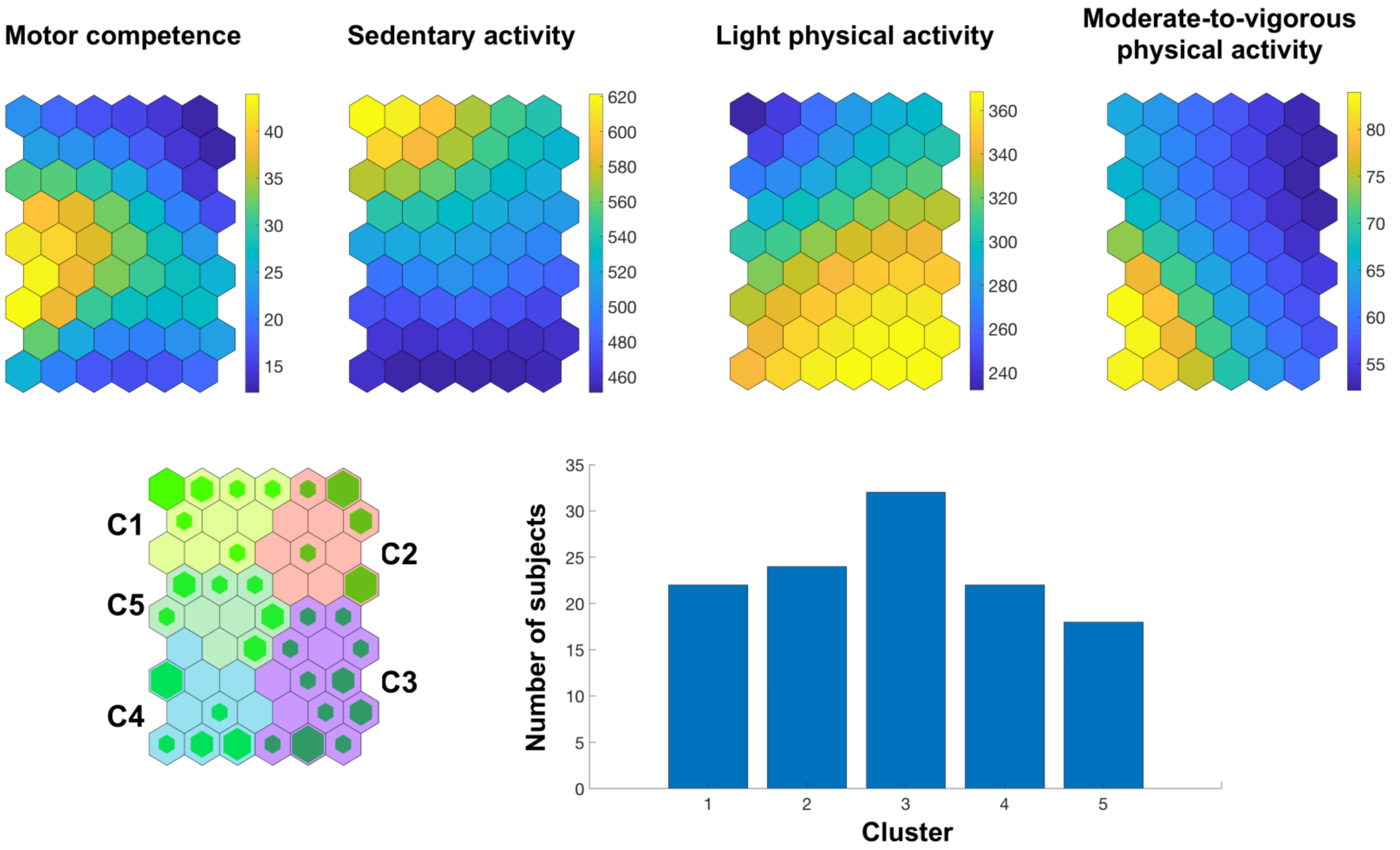
Motor competence
Sedentary activity
Light physical activity
Moderate-to-vigorous physical activity
C1
C2
C3
C4
C5
Number of subjects
Cluster

Figure caption

Figure 1. SOM activity behaviour profiles.

Note. For each hexagonal heat map, the accompanying colour-bar represents high (yellow) to low (blue) values for each respective variable. C1-5 denotes cluster 1, cluster 2, cluster 3, cluster 4 and cluster 5; in every neuron, the bigger the green shadow the higher the number of children included. On the bottom, right side, sample distribution in every cluster.