Profiling Movement and Gait Quality Characteristics in Pre-School Children

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Title;

Profiling movement and gait quality characteristics in early-years children (3-5y) - *Original Research Article*

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Abstract

There is a dearth of suitable metrics capable of objectively quantifying motor competence. Further, objective movement quality characteristics during free-play have not been investigated in early years' children. The aims of this study were to characterise children's free-play physical activity and to investigate how gait quality characteristics cluster with free-play in children (3-5y). Sixty-one children (39 boys, 4.3±0.7y, 1.04±0.05m, 17.8±3.2kg) completed the movement assessment battery for children and took part in free-play whilst wearing an ankle- and hip-mounted accelerometer. Characteristics of movement quality were profiled using a clustering algorithm. Spearman's rho and the Mann-Whitney U tests were used to assess relationships between movement quality characteristics and motor competence classification differences in integrated acceleration and spectral purity, respectively. Significant differences were found between motor competency classifications for spectral purity and integrated acceleration ($P<0.001$). Spectral purity was hierarchically clustered with motor competence and integrated acceleration. Significant positive correlations were found between spectral purity, integrated acceleration and motor competence ($P<0.001$). This is the first study to report spectral purity in early years' children and our results suggest that the underlying frequency component of movement is clustered with motor competence.

Key words: Clustergram; Accelerometer; Spectral purity; Motor competence;

Running head: Early years' children movement characteristics

Introduction

Global physical activity guidelines recommend that early years' children (3-5 years) engage in at least 180 minutes of physical activity every day (Department of Health, 2011; Tremblay et al., 2011). Demographic, biological, sociocultural, and motor competence can all impact upon physical activity levels (Barnett et al., 2016; Bingham et al., 2016; Hesketh et al., 2014; Lubans et al., 2010). Specifically, Stodden et al. (2008) highlighted inter-relations between motor competence, perceived motor competence, cardiorespiratory fitness and physical activity levels. Further, recent prospective studies have established that development of motor competence has numerous tangible health and developmental benefits. For example, higher levels of motor competence are shown to positively predict cardiorespiratory fitness (Vlahov et al., 2014), improved academic performance (Jaakkola et al., 2015), and are protective against overweight and obesity (Rodrigues et al., 2015). Concerningly, studies have reported low levels of competence among primary school aged children (Bryant et al., 2013; LeGear et al., 2012). These findings highlight the need to examine motor competence during early years (3-5 years), which is considered a critical phase for fundamental movement skill development (Gallahue & Donnelly, 2003). During this period, neuromuscular maturation and rapid cognitive development affect motor skill acquisition and development (Malina et al., 2004). Motor development during the early years is considered a facilitator for lifelong physically active lifestyles, and children's perceptions of their competency is asserted to influence this development (LeGear et al., 2012). For example, older children who perceive themselves as having poor motor competence may fall into a negative spiral of disengagement, further limiting motor development, physical activity and cardiorespiratory fitness (Stodden et al., 2008). Several studies have documented low levels of motor competence among early years' children (Barnett et al., 2014; Cliff et al., 2009; Goodway et al., 2010; Hardy et al., 2010; Robinson, 2011; Ulrich, 2000). Motor competence in the early years is traditionally assessed

using observation tools in a controlled setting, such as the movement assessment battery for children (MABC2 (Henderson et al., 2007)) or the test of gross motor development (TGMD (Ulrich, 1985, 2000)). To our knowledge there have been no objective measurements of motor competence and movement quality during habitual child activity (Clark, Barnes, Stratton, et al., 2016), and this dearth of literature has resulted in limited insight into children's motor development. We postulate that objective measures and novel analytics will provide insight into the quality and quantity of movement in parallel (Clark, Barnes, Stratton, et al., 2016).

Developments in the field of objectively measured physical activity are moving with expediency (Clark, Barnes, Stratton, et al., 2016). For example, accelerometers can be used to characterise gait patterns and determine safety, control, balance, variability and rhythmicity during ambulation (Aziz et al., 2014; Aziz & Robinovitch, 2011; Bellanca et al., 2013; Brach et al., 2011; Kangas et al., 2015). In addition, movement quality characteristics are retrievable using Fourier analysis and the harmonic content of an accelerometer signal, by analysing the symmetry within a movement, exploiting the periodicity of the signal (Gage, 1964; Smidt et al., 1971). The resulting spectral purity and integrated accelerations of each movement can be analyzed to assess, and profile, movement quality in children (Bellanca et al., 2013; Clark, Barnes, Holton, et al., 2016b; Clark et al., 2015). This type of analysis is highly suggestive of the fundamental neural control of movement (Stergiou & Decker, 2011) and shown to be representative of movement quality in standardised settings (Clark, Barnes, Holton, et al., 2016b). However, this has not been investigated in early years' children.

Statistically, the use of traditional measures to study physical activity in humans assumes that variations are random and independent of past and future repetitions (Lomax, 2007), contrastingly however, it has been shown that such variations are distinguishable from noise and warrant further investigation (Delignieres & Torre, 2009; Dingwell & Cusumano, 2000; Dingwell & Kang, 2007; Stergiou et al., 2004; Stergiou & Decker, 2011). Moreover, frequency

spectrum characteristics derived from an accelerometer signal are significantly related to movement quality, cardiorespiratory fitness, running strategy and body mass index in primary school children (Barnes et al., 2016; Clark, Barnes, Holton, et al., 2016b).

Although some recent work has examined the relationship between motor skills and physical activity, in a standardised setting (incorporating accelerometry) (Laukkanen, Finni, et al., 2013; Laukkanen, Pesola, et al., 2013), there has been no attempt in the literature to use clustering algorithms to profile and compare derivatives of a raw acceleration trace (spectral purity, integrated acceleration) during free-play in early years' children. There is clearly potential to derive more information from the signal output of accelerometers (Clark, Barnes, Stratton, et al., 2016). Therefore, the aims of this study were two-fold; to characterise children's free-play physical activity and investigate how movement quality characteristics of gait cluster in children (3-5y).

2.0 Method

2.1. Participants and Settings

Sixty-one children (39 boys, 4.3±0.7y, 1.04±0.05m, 17.8±3.2kg, body mass index; 16.2±1.9 kg·m^2) volunteered to take part in this study from two primary schools in Northern England, United Kingdom (U.K) (77% South Asian, 12% White British, 11% Other/Mixed). Prior to research commencing, informed parental consent and child assent was attained. This research was conducted in agreement with the guidelines and policies of the institutional ethics committee.

2.2. Instruments and Procedures

Children took part in a free-play period, which for the purpose of this study is synonymous with recess, (104 ± 12 minutes per day) while their physical activity was recorded using a custom-built Micro Electro-Mechanical System (MEMS) based device, which incorporated a

tri-axial accelerometer with a +/- 16g dynamic range, 3.9mg point resolution and a 13-bit resolution (with a z-axis amplitude coefficient of variation of 0.004 at 40 Hz (Clark, Barnes, Holton, et al., 2016c);ADXL345 sensor, Analog Devices). The MEMS device was housed in a small plastic case and affixed via a Velcro strap to the lateral malleolar prominence of the fibula of the right leg and set to record at 40 Hz (Barnes et al., 2016; Clark, Barnes, Holton, et al., 2016b). Mannini et al. (2013) highlighted that for movement quality characteristics related to ambulation, an ankle-mounted monitor may be most suitable, and Barnes et al. (2016) systematically demonstrated that ankle affixed accelerometers can be used to accurately compute leg lift angle. Data were stored locally on the device and there were no incidences of data loss. Moderate-to-vigorous physical activity was also measured using an additional ActiGraph GT3X+ device (ActiGraph, Pensacola, FL, USA) mounted on the right hip and set to record at 100 Hz, in accordance with manufacturer guidelines. All children also completed the movement assessment battery for children, second edition, using standardised procedures (MABC2; as detailed in: Henderson et al. (2007)).

2.2.1. Anthropometrics

Stature (measured to the nearest 0.01m) and body mass (to the nearest 0.1kg) were measured using standard procedures using a stadiometer and digital scales (SECA, Hamburg, Germany), respectively (Lohmann et al., 1988). Skinfold measurements of the left triceps and subscapular were made by trained researchers using calibrated skinfold callipers (Harpenden, Baty International, U.K.), waist circumference was measured at the level of the naval and measurements were subsequently used to estimate body fat percentage (Eisenmann et al., 2004; Slaughter et al., 1988). Reliability metrics indicated good intra- and inter-observer technical error for measurements (Collings et al., 2017). Further, children were classified based on body-mass index percentiles as either; underweight (≤5th percentile), normal weight (5th to 85th

percentile), overweight (>85th to <95th percentile) or obese (≥ 95th percentile) (Cole & Lobstein, 2012).

2.3. Data Analysis

Raw acceleration data from the MEMS device were uploaded into MatLab (MATLAB version R2016a), where integrated acceleration and spectral purity were derived (Barnes et al., 2016; Clark, Barnes, Holton, et al., 2016b). The characteristics used for analysis were derived from acceleration in the axis along the lower leg towards the origin of motion, termed the radial axis. The integrated acceleration was determined using an integration of the rectified raw acceleration signal (van Hees et al., 2010).

Acceleration data were converted from the time into the frequency domain. In order to convert the data into the frequency domain the Fast Fourier transform was applied to the data. The Fast Fourier Transform computes the discrete Fourier transform (DFT) of a sequence.

Let $x\_0,\ldots,x\_(N-1)$ be a sequence of N complex numbers. The Fast Fourier transform computes the Discrete Fourier transform

$$X_k = \sum_{n=0}^{N-1} x_n . e^{-i2\pi kn/N} , k \in Z$$

Equation 1. Fast Fourier Transform

Where, N = number of time samples, n = current sample under consideration (0 .. N-1), x_n = value of the signal at time n, k = current frequency under consideration (0 Hertz up to N-1 Hertz), X_k = amount of frequency k in the signal (amplitude and phase, a complex number), n/N is the percent of the time gone through, 2 * pi (π) * k is the speed in radians·sec^{-1}, e^-ix is the backwards-moving circular path.

In order to determine the quality of a child's movement - 'Spectral purity' was calculated from the cumulative distribution function (CDF) of the frequency spectrum. The CDF plot is used to generate a value for spectral purity. The empirical CDF *F(x)* is defined as the proportion of X values less than or equal to some value *x*. In this case, it is the number of values less than or equal to some frequency in a spectrum being considered. A measure for spectral purity is therefore considered to be the frequency at which the midway point of the CDF (0.5) occurs. As a result, spectra that is 'clean', i.e. consisting of a tall narrow peak at the fundamental frequency and only low amount of noise and small harmonics will have a different value to spectra where there is lots of noise, a shorter wider peak, and higher peaks at the harmonics.

Spectral purity measures how tightly the frequency components of the raw accelerations are distributed using fundamental frequency to harmonics and the frequency spectrum analysis is directly related to the ambulation of a participant (Barnes et al., 2016; Clark, Barnes, Holton, et al., 2016b). A participant could have high spectral purity and low overall activity, which indicates that cyclical, high periodicity movement has occurred. However, in combination with low integrated acceleration this equates to the participant remaining static, for example, sat down in one location for prolonged periods.

ActiGraph acceleration data were analyzed 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 (Tudor-Locke et al., 2015). Sedentary behaviour was defined as <100 counts per minute, while 100, 2296 and 4012 counts per minute were thresholds to define light, moderate and vigorous physical activity, respectively (Evenson et al., 2008; Trost et al., 2011). Mean counts per minute during valid wear time and percentage of total time spent in moderate-to-vigorous physical activity (MVPA) were used to define physical activity.

The MABC2 was scored by a trained, experienced assessor and scores were described in a traffic light classification system including a red zone (1: <5th percentile indicating significant movement difficulty), amber zone (2: between the 5th and 15th percentiles indicating at risk of movement difficulty), and green zone (3: >15th percentile indicating no movement difficulty detected), following standard procedures (Henderson et al., 2007).

2.3.1 Cluster analysis

Hierarchical clustering is an analytic procedure that reduces multi-factorial data into smaller subsets, where numerous and complex characteristics of movement and lifestyle in adults and children (9-11y) can be reliably analysed (Clark, Barnes, Holton, et al., 2016b; Schonlau, 2002; Tonkin et al., 2012). Clustering yields groupings that are based on the similarity of whole cases, as opposed to the individual variables that comprise those cases (Leonard & Droege, 2008).

Cluster analysis has been used to profile and classify systems or taxonomies (Leonard & Droege, 2008; Sokal & Rohlf, 1962), and whilst it has consistently been applied in other disciplines, such as nanotechnology and cell biology (Armstrong et al., 1996; Johnson, 1997; Schweitzer & Renehan, 1997; Semmar et al., 2005; Winterstein et al., 2004), it has only recently been used successfully to investigate human movement characteristics (Clark, Barnes, Holton, et al., 2016b).

The derived characteristics (integrated acceleration, spectral purity, overall activity counts, MVPA percentage, BMI percentile, MABC2 classification, body fat percentage) were normalised so that they could be compared and input into an in-built clustering algorithm (MATLAB version R2016a). This algorithm goes through multiple iterative processes in order to cluster the data along the columns of the dataset. The similarity or dissimilarity between metrics was determined by calculating the pairwise Euclidean distances between the values of the different metrics.

$$d_{2st} = (x_s - x_t)(x_s - x_t)'$$

Equation 2. Euclidean distance

Where, *d* is the Euclidean distance; x_s and x_t represent the data values being compared.

Once the distances between the characteristics (integrated acceleration, spectral purity, overall activity counts, MVPA percentage, BMI percentile, MABC2 classification, body fat percentage) for each child were derived, a linkage function was applied, to determine the proximity of the metrics to each other. These were paired into binary clusters, which were subsequently grouped into larger clusters until a hierarchical tree was formed. The resulting clustergram was displayed in terms of a heat map and dendrogram. The height of the link at which two observations on the dendrogram were joined was analysed using cophenetic distance (Equation 3), to demonstrate the similarity between two clusters (Saracli et al., 2013; Schonlau,

2002; Sokal & Rohlf, 1962). The values for the dendrogram linkages were subsequently normalised. The cophenetic distance ratio for the overall clustergram was also measured to demonstrate how successfully the dendrogram preserved the pairwise distances between the original unmodeled data points (where 1 is maximum).

$$c = \frac{\sum_{i<j}(Y_{ij} - y)(Z_{ij} - z)}{\sqrt{\sum_{i<j}(Y_{ij} - y)^2 \sum_{i<j}(Z_{ij} - z)^2}}$$

Equation 3. Cophenetic distance equation

Where Y_{ij} is the distance between objects i and j in Y. Z_{ij} is the cophenetic distance between objects i and j, from Z. y and z are the average of Y and Z, respectively.

A Shapiro-Wilk test determined that data were not normally distributed ($P<0.001$) and therefore non-parametric inferential methods were used for analysis. Descriptive data were presented as mean, median and upper and lower quartiles (Clark, Barnes, Holton, et al., 2016b). The Kruskall-Wallis test was used to determine differences between motor competence traffic light groups and post-hoc Mann-Whitney U tests, with continuity correction and tie adjustment (Gibbons & Chakraborti, 2011), to determine specific differences between groups. Spearman's rho was used to calculate correlation coefficients between each characteristic. All inferential statistics were performed using MatLab (MATLAB version R2016a). Statistical significance was accepted at $P\leq0.05$.

3.0 Results

Significant differences were found between MABC2 classification groups for spectral purity and integrated acceleration. Post-hoc testing found significant differences between green, amber and red MABC2 classifications for spectral purity and integrated acceleration ($P<0.001$). Descriptive data for movement and physical activity characteristics are detailed in Table 1. Significant ($P\leq0.05$) relationships were found between MABC2 classification and percentage of time spent in moderate-to-vigorous physical activity ($r=0.29$), integrated acceleration ($r=0.66$) and spectral purity ($r=0.7$). Significant correlations were also found between spectral purity and integrated acceleration ($r=0.57$), and body fat percentage and BMI percentile ($r=0.75$). Figure 1 illustrates that integrated acceleration and spectral purity (cophenetic distance (CD): 0.19), integrated acceleration and MABC2 classification (CD: 0.19), spectral purity and MABC2 classification (CD: 0.06), were clustered together (Figure 1), with a cophenetic distance ratio for the overall clustergram of 0.95.

Discussion

The aims of this study were to characterise children's free-play physical activity, and investigate how movement quality characteristics of gait cluster in children (3-5y).

Clustergram overview

In order for a clustergram to be considered statistically accurate, a cophenetic distance ratio of 0.75 is required (Bradley & Stentiford, 2003). The clustergram in this study had a cophenetic distance ratio of 0.95, indicating confidence in the veracity of clusters identified. The clustering algorithm hierarchically linked each characteristic (integrated acceleration, spectral purity, overall activity counts, MVPA percentage, BMI percentile, MABC2 classification, body fat percentage), accordingly. The proximity of two or more characteristics within the clustergram indicated how closely the movement quality characteristics were linked to each other

(Schonlau, 2002; Sokal & Rohlf, 1962), for example, MABC2 classification and spectral purity: 0.06, integrated acceleration and spectral purity: 0.19. The cophenetic distance ratio reported in the present study indicates that movement characteristics were successfully, and reliably, clustered. Hierarchically clustering movement characteristics has previously been shown to be successful in pre-adolescent children and close cophenetic distances between spectral purity and aerobic performance were highlighted (Clark, Barnes, Holton, et al., 2016b). However, this is the first study to utilise and report the hierarchical clustering of movement characteristics in early-years children.

Integrated acceleration, spectral purity and motor competence

The frequency and harmonic content of movement is reflective of movement characteristics such as gait pattern and overall physical activity, in addition to cardiorespiratory fitness (Clark, Barnes, Holton, Mackintosh, et al., 2016; Clark, Barnes, Holton, et al., 2016b). In this study, spectral purity and motor competence (MABC2 classification) were more closely cophenetically linked (0.06) than integrated acceleration (0.19), which was previously unreported. Furthermore, traditional correlation analyses found spectral purity (r=0.7) and integrated acceleration (0.66) were significantly correlated with motor competence. These findings suggest that spectral purity and integrated acceleration may be movement quality indicators in early years' children, congruent with previous findings where spectral purity was demonstrated to be indicative of fundamental aspects of movement in pre-adolescent children (9-11y) (Clark, Barnes, Holton, et al., 2016b). Furthermore, in a population of geriatric and Parkinsonian sufferers', accelerometer signals in the frequency domain reveal deteriorating gait characteristics and predict fall potential, respectively (Howcroft et al., 2013; Sejdic et al., 2014). To the authors' knowledge, the present study is the first to demonstrate that spectral purity and motor competence are related in early years' children (Figure 1).

Integrated acceleration, a proxy measure for overall physical activity (Clark, Barnes, Holton, et al., 2016b; van Hees et al., 2012), was positively related to motor competence in the present study and this is supported widely in the literature (Barnett et al., 2016; Barnett et al., 2014, 2015; Robinson et al., 2015). Although some studies have relied upon self-report proxies of physical activity (Erwin & Castelli, 2008; Graf et al., 2004), a recent review found a positive relationship between motor competence and health-related benefits (Barnett et al., 2016). Further, Holfelder and Schott (2014) and Lubans et al. (2010) also reported positive associations in respective systematic reviews, and Cohen et al. (2014) demonstrated that overall physical activity was positively correlated with locomotor and object control competency. Congruent with previous work (Cohen et al., 2014; Holfelder & Schott, 2014; Lubans et al., 2010), integrated acceleration was significantly different by MABC2 classification ($P<0.001$). However, spectral purity was also found to significantly different by MABC2 classification ($P<0.001$). In preceding work, empirical evidence suggested that spectral purity was a viable proxy measure of the fundamental aspects of movement and that it clustered with motor competence (see: Clark, Barnes, Holton, et al. (2016b) and Barnes et al. (2016)). Further, given that the present study has demonstrated that spectral purity is clustered with motor competence and significantly different between motor competency classification, suggests underlying frequency components of movement should be further investigated for the measurement of movement quality in children (Clark, Barnes, Holton, et al., 2016b). Moreover, whilst it has been demonstrated that a proxy for overall physical activity was positively correlated with motor competence (Cohen et al., 2014; Holfelder & Schott, 2014; Lubans et al., 2010), spectral purity (r=0.7) was found to have a stronger relationship to motor competence than overall activity (0.66) in the present study, thereby highlighting the need for future research to examine and further establish this relationship.

Anthropometrics. age and actigraphy

Congruent with previous research, the present study found that BMI and body fat percentage were closely cophenetically clustered and significantly positively correlated (Cui et al., 2013; Lindsay et al., 2001). Whilst previous research has highlighted that motor competence and physical activity are inversely correlated with weight status in children (Cairney et al., 2005; Lopes et al., 2011; Lopes et al., 2012; Rivilis et al., 2011), we found that anthropometric characteristics were not clustered, nor correlated to any other measure (Figure 1). This is reflected in the literature, as Ekelund et al. (2012) and Vorwerg et al. (2013) reported no differences in physical activity levels in early years' children according to BMI and that physical activity levels did not significantly differ between overweight/obese children and normal-weight peers, respectively. Further, Williams et al. (2008) reported that there was no significant association between BMI and motor skill performance concluding that whilst weight status of early years' children was considerably influenced by socioeconomic status, physical activity levels were not, potentially due to the highly transitory and frequent movement during nursery/preschool.

Traditional hip-mounted accelerometer data did not cluster with any movement characteristic, whilst concurrent ankle-mounted raw accelerometry yielded significant results. One explanation is that traditional hip-mounted accelerometers have inadequate band-pass filtering, where high frequency movement and noise information can escape the filter adding unexplained variation in activity counts (Brond & Arvidson, 2015). Further, Wundersitz et al. (2015) identified that filters with at least an 8 or 10 Hz cut-off frequency were most suitable to process accelerations in ambulatory tasks, and thus adopted in the present study, whereas the actigraphy device utilised filters out frequencies higher than 2.5 Hz (Brond & Arvidson, 2015; Wundersitz et al., 2015). This finding highlights the insensitivity of traditional, hip-worn

actigraphy units to measure contextualised physical activity. Physical activity is a multi-directional, complex construct and summative activity counts are a measure of centrality that are missing vital information (Bussmann & van den Berg-Emons, 2013; Stergiou & Decker, 2011). This study highlighted that integrated acceleration and spectral purity are hierarchically clustered and significantly correlated with motor competency, whereas traditional, hip mounted, physical activity measures do not.

Limitations

The clustering algorithm utilised within this study was structured using hierarchical methods, thereby pairing characteristics according to proximity. This means inverse relationships may be difficult to ascertain. However, this can be mitigated with careful interpretation of the clustergram, in addition to incorporating other correlation analyses (i.e. Spearman's rho). Although this study employed novel signal analytics of accelerometer data, it only assessed spectral purity and integrated acceleration, and therefore further analytics could be employed and should be the focus of future research.

Conclusion

The aims of this study were to characterise children's free-play physical activity and to investigate how movement characteristics of gait cluster in children (3-5y). Overall, integrated acceleration and spectral purity were significantly different between motor competence classifications. Further, that overall physical activity and spectral purity cluster during uncontrolled free-play physical activity, whilst spectral purity was more closely linked to motor competence than integrated acceleration. Anthropometric and actigraphy characteristics were not correlated to, or clustered meaningfully with, any other measure.

This study has built upon previous research (Barnes et al., 2016; Clark, Barnes, Holton, et al., 2016a, 2016b) highlighting cophenetic clustering of spectral purity with integrated physical

activity and motor competence. The analysis of frequency and harmonic content of movement and overall physical activity concomitantly is demonstrably sensitive and informative and may be able to distinguish between motor competency in early childhood. We recommend that future research seeks to better quantify and qualify physical activity in contextualised settings to enhance our understanding of specific movement and gait patterns. Furthermore, the link between spectral purity and motor competence highlighted in this study necessitates detailed further investigation.

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Conflict of Interest

The authors declare that there are no conflict of interests or sources of financial assistance regarding the publication of this paper and that the results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation.

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Table 1. Descriptive data for; overall activity counts, percentage of time spent in MVPA, integrated acceleration and spectral purity.

	Counts	MVPA%	IA	SP
Mean	1613	25.0	21.7	3.9
Med	1678	26.1	22.2	4.2
LQ	1193	18.7	17.2	3.2
UQ	1923	30.6	27.1	4.7

Counts: overall activity counts, MVPA%: percentage of time spent in moderate-to-vigorous physical activity, IA: mean Integrated acceleration, SP: mean Spectral purity, Med: Median, UQ: Upper quartile, LQ: Lower quartile.
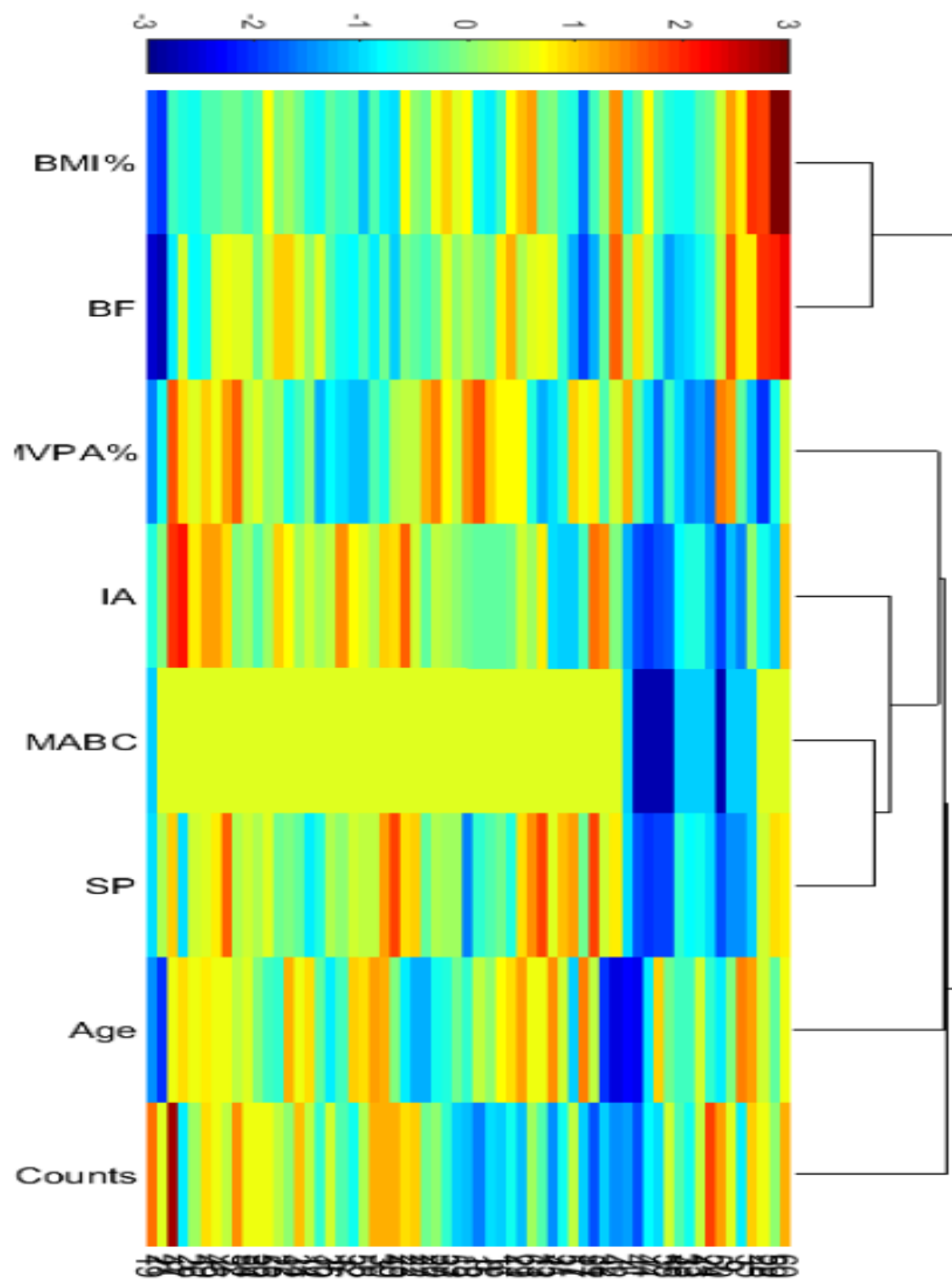
Figure 1 caption

Figure 1. Clustergram and Dendrogram

Colours represent z-scores in the Clustergram. The Dendrogram highlights linkage between two or more characteristics. BMI%: body-mass index percentile, BF: body fat percentage estimation, MVPA%: percentage of time spent in moderate-to-vigorous physical activity, IA: integrated acceleration, MABC: movement ABC classification, SP: spectral purity, Counts: accelerometer counts.