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Physical activity, motor competence and movement and gait quality: A principal component analysis

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ABSTRACT

Objective: While novel analytical methods have been used to examine movement behaviours, to date, no studies have examined whether a frequency-based measure, such a spectral purity, is useful in explaining key facets of human movement. The aim of this study was to investigate movement and gait quality, physical activity and motor competence using principal component analysis.
Methods: Sixty-five children (38 boys, 4.3 ± 0.7y, 1.04 ± 0.05 m, 17.8 ± 3.2 kg, BMI; 16.2 ± 1.9 kg·m^2) took part in this study. Measures included accelerometer-derived physical activity and movement quality (spectral purity), motor competence (Movement Assessment Battery for Children 2nd edition; MABC2), height, weight and waist circumference. All data were subjected to a principal component analysis, and the internal consistency of resultant components were assessed using Cronbach's alpha.
Results: Two principal components, with excellent internal consistency (Cronbach $\alpha > 0.9$) were found; the 1st principal component, termed "*movement component*", contained spectral purity, traffic light MABC2 score, fine motor% and gross motor% ($\alpha = 0.93$); the 2nd principal component, termed "*anthropometric component*", contained weight, BMI, BMI% and body fat% ($\alpha = 0.91$).
Conclusion: The results of the present study demonstrate that accelerometric analyses can be used to assess motor competence in an automated manner, and that spectral purity is a meaningful, indicative, metric related to children's movement quality.

1. Introduction

Global physical activity guidelines advocate that pre-school aged children (3–5 years) engage in at least 180 min of physical activity every day (Tremblay et al., 2012), with variables such as demographic, biological, sociocultural, and motor competence, defined as a child's ability to perform a wide range of motor skills in a proficient manner (Haga, 2008), all influencing physical activity levels (Bingham et al., 2016; Lubans, Morgan, Cliff, Barnett, & Okely, 2010). Recent studies have established that

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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, Baghurst, & Mwavita, 2014), improve academic performance (Jaakkola, Hillman, Kalaja, & Liukkonen, 2015), and are protective against obesity (Rodrigues, Stodden, & Lopes, 2015). Concerningly, studies have reported low levels of motor competence among primary school aged children (Bryant, Duncan, & Birch, 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 skills development (Gallahue & Donnelly, 2003) and a facilitator for lifelong physically active lifestyles; moreover, children's perceptions of their competency is asserted to influence this development (LeGear et al., 2012).

Motor competence in the early years is traditionally assessed using subjectively scored observation tools in a controlled setting, most commonly, the movement assessment battery for children (MABC2 (Henderson, Sugden, & Barnett, 2007)) or the test of gross motor development (TGMD (Ulrich, 2000)). Although empirical and conceptual evidence exists to support the reciprocal relationship between motor competence and PA (Stodden et al., 2008), there is a limited evident base of motor competence related to PA measurement in pre-school children, largely due to the complexity in examining such constructs in this age group (Adamo et al., 2016; Goldfield, Harvey, Grattan, & Adamo, 2012). When studies have investigated PA and motor competence they tend to examine this as a relationship, where large variability in not only motor competence, but also PA, is reported, which can conceivably mask, or indeed create spurious, responses or relationships (Adamo et al., 2016; Clark et al., 2018).

Recently there have been developments in technological and analytical capability, permitting the quantification of complex human movement behaviours (Clark et al., 2016) which have as yet untapped potential to be applied to the assessment of motor competence. Pervasive technologies, such as accelerometers, inertial measurement units and magnetometers have been used, albeit in only a small number of studies, with reasonable success to automatically assess and score motor competence (Barnes, Clark, Rees, Stratton, & Summers, 2018; Bisi, Panebianco, Polman, & Stagni, 2017). For example, Barnes et al. (2018) demonstrated good agreement between observer and magnetometry derived motor competency scores, where raw tri-axial magnetometer traces underwent pattern recognition and were systematically compared against human-assessed scores, with correlation coefficients of the overall score in the range of 0.62–0.71 for different cohorts. Whilst Bisi et al. (2017), with the application of inertial measurement units, which consisted of an in-built, tri-axial, magnetometer, gyroscope and accelerometer, showed that automatic assessment, compared to observer assessment, yielded an agreement of 87% on average across an entire cohort for each skill. Recently, a novel metric, spectral purity, has been proposed as a viable measure of movement and gait quality, where the purity of the fundamental frequency spectra (signal) during movement, specifically relating to gait, is quantified (Clark, 2017). Interestingly, in Clark et al. (2017), it was suggested that spectral purity may be a viable proxy for motor competence, assessed using MABC2, and movement quality in pre-school children. Concomitantly, in slightly older children, the same metric, spectral purity, was shown to be hierarchically clustered with cardiovascular fitness (Clark, Barnes, Holton, Summers, & Stratton, 2016a).

Analytically, feature extraction and principal component analysis have been used to highlight the key components in any given set of variables to reveal hidden or '*unseen*' patterns (Clark, Barnes, Stratton, et al., 2016). The feature extraction approach revolves around the idea that data representations can be constructed in subspaces with reduced dimensions, while concurrently retaining, and conceivably increasing, the discriminative capability of the new set of feature variables (Jain, Duin, & Mao, 2000; Mannini & Sabatini, 2010); thereby reducing complex and cumbersome data into more manageable or revealing components.

Given the complexity inherent within human movement, its' assessment, and the inception of novel variables, exploring and understanding such complexity is of paramount importance for eventual, and successful, interventions. While novel analytical methods are starting to be used to examine PA and motor competence, to date, no studies have examined whether a measure, such as spectral purity, is useful in explaining key facets of human movement in pre-school children. Such an examination is a needed first step for enhancing our knowledge base and to provide previously unreported insights in to movement behaviours. Thus, the aim of this study was to investigate movement and gait quality, physical activity and motor competence using principal component analysis.

2. Methods

2.1. Participants and settings

Sixty-five children (38 boys, 4.3 ± 0.7y, 1.04 ± 0.05 m, 17.8 ± 3.2 kg, body mass index; 16.2 ± 1.9 kg·m^2 (underweight, N = 3; normal weight, N = 40; overweight, N = 13; obese, N = 9)) volunteered to take part in this study. Prior to research commencing, informed parental consent and child assent was attained. In order to be included in this study, each participant had to be free from any physical or neurological impairment that may hinder normal movement. This research was conducted following approval of the institutional research ethics committee and conformed to the Declaration of Helsinki.

2.2. Instruments and procedures

Children participated in free-play (100 ± 3 min per day), which in the context of this work is synonymous with outdoor recess, where children had access to an enclosed playground, whilst wearing a custom-built Micro Electro-Mechanical System (MEMS) based device, which incorporated a tri-axial accelerometer with a ± 16 g dynamic range, 3.9 mg point resolution and a 13-bit resolution (with a z-axis amplitude coefficient of variation of 0.004 at 40 Hz (Clark, Barnes, Holton, Summers, & Stratton, 2016b); 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, which has been validated in previous studies (Barnes, Clark, Holton, Stratton, & Summers, 2016; Clark, Barnes, Holton, et al., 2016a), and does not violate the Nyquist-Shannon sampling theorem, which specifies that the sample must contain all the available frequency information from the signal to result in a faithful reproduction of the analogue waveform signal (Farrow, Shaw, Kim, Juhas, & Billinge, 2011). Further, put simply, if the highest frequency component, in Hz, for a given analogue signal is fmax, according to the Nyquist-Shannon sampling theorem, the sampling rate must be at least 2fmax, or twice the highest analogue frequency component. Mannini, Intille, Rosenberger, Sabatini, and Haskell (2013) highlighted that for movement characteristics related to ambulation, an ankle-mounted monitor may be most suitable, whilst Barnes et al. (2016) systematically demonstrated that ankle affixed accelerometers can be used to accurately compute locomotion. Data were stored locally on the device, with no incidences of data loss.

Physical activity was concurrently recorded using an ActiGraph GT3X+ device (ActiGraph, Pensacola, FL, USA). 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 (Østbye et al., 2013; Pate, Almeida, McIver, Pfeiffer, & Dowda, 2006). Participants wore their accelerometer on the waist, above the right hip, affixed using an elastic belt (Hesketh et al., 2014), in accordance with manufacturer guidelines (Migueles et al., 2017). All children also completed the MABC2, using standardised procedures as described below Henderson et al. (2007).

Stature (measured to the nearest 0.01 m) and body mass (to the nearest 0.1 kg) were measured using standard procedures using a stadiometer and digital scales (SECA, Hamburg, Germany), respectively (Lohmann, Roche, & Martorell, 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, Heelan, & Welk, 2004; Slaughter et al., 1988). Intra- and inter-observer technical error of measurement (TEM) for waist circumference, triceps and subscapular skinfolds were evaluated and relative TEMs were acceptable and indicative of 'skilful' anthropometrists (Perini, de Oliveira, Ornelia, & de Oliveira, 2005).

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

2.3.1. Spectral purity (Movement quality)

Raw acceleration data from the MEMS device were uploaded into MatLab (MATLAB version R2016a), where spectral purity was derived (Barnes et al., 2016; Clark, Barnes, Holton, et al., 2016a; Clark, Barnes, Summers, Mackintosh, & Stratton, 2018). 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 (Barnes et al., 2016; Clark, Barnes, Holton, et al., 2016a). Acceleration data were converted from the time into the frequency domain. To convert the data into the frequency domain, a Fast Fourier transform (FFT) was applied to the data. The FFT computes the discrete Fourier transform (DFT) of a sequence.

Let x_0, …,x_(N-1) be a sequence of N complex numbers. The Fast Fourier transform computes the Discrete Fourier transform.

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

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 Hz up to N-1 Hz), 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.

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., 2016a).

2.3.2. Actigraphy

ActiGraph acceleration data were analysed using commercially available analytics (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, Catellier, Gill, Ondrak, & McMurray, 2008; Trost, Loprinzi, Moore, & Pfeiffer, 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 (Migueles et al., 2017).

2.3.3. Motor competence

The MABC2 measures both fine and gross motor skill performance for children in three age bands (3–6 years, 7–10 years, and 11–16 years). It contains eight tasks for each of the three age bands in three different constructs: manual dexterity, ball skills, and static and dynamic balance, and was scored by a trained, experienced assessor. Each participant received a standardised familiarisation of the test battery, in line with the MABC2 manual (Henderson et al., 2007). Each task's raw score can be converted to a standard score, and a total test score can be calculated by summing the eight task standard scores. Using the total test score, a percentile score can be found from the norm tables published in the *MABC2 manual* to determine a child's motor delays. The test percentile scores were described as a traffic light scoring system including a *red zone (1)*, *amber zone (2)*, and *green zone (3)*. A percentile score ≤ 5th is classified in the *red zone* indicating a significant movement difficulty, a percentile score between the 5th and 15th is classified in the *amber zone* indicating at risk of movement difficulty, and a percentile score > 15th is classified in the *green zone* indicating no movement difficulty detected. Fine (i.e., manual dexterity) and gross (i.e., ball skills, static and dynamic balance) motor skill raw scores were converted to percentile scores for each child using the MABC2 conversion tables (Henderson et al., 2007). The percentile scores were generated for each area (i.e., manual dexterity, ball skills, static and dynamic balance) and their overall percentile scores (combination of all eight tasks) (Henderson et al., 2007). All tests were video recorded using a high-resolution (350 fps) video camera (Bonita 480 m, Biometrics, France) positioned medio-laterally to the participant, and assessed post-hoc, and 5 participants were classified as "*red*", 10 participants classified as "*amber*", and 50 participants classified as "*green*".

2.3.4. Statistical analysis

All data were subjected to a principal component analysis using '*one*' as the prior communality estimate (Kline, 2000; Pearson, 1901). Varimax orthogonal transformation was used to convert the set of physical and anthropometric variables into a set of linearly uncorrelated variables, termed principal components. The number of distinct principal components was equal to either, the number of original variables or the number of observations minus one (whichever is smallest). This transformation was defined in such a way that the first principal component had the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors were an uncorrelated orthogonal basis set. Principal components with Eigen values greater than one were retained (Kline, 2000; Nunnally & Bernstein, 1994). The internal consistency of components were assessed using Cronbach's alpha (α), and reported according to (Nunnally & Bernstein, 1994);$\alpha < 0.5$ is unacceptable, $\alpha \geq 0.5$ but < 0.6 is poor, $\alpha \geq 0.6$ but < 0.7 is questionable, $\alpha \geq 0.7$ but < 0.8 is acceptable, $\alpha \geq 0.8$ but < 0.9 is good, and $\alpha \geq 0.9$ is excellent. All statistical analyses were conducted using JASP statistical package (JASP Team, 2018, jasp-stats.org).

3. Results

Two principal components, with excellent internal consistency (Cronbach $\alpha > 0.9$) were found; the 1st principal component, termed "*movement component*", contained Spectral purity, traffic light MABC-2 score, fine motor% and gross motor% ($\alpha = 0.93$; Table 1); the 2nd principal component, termed "*anthropometric component*", contained weight, BMI, BMI% and body fat% ($\alpha = 0.91$; Table 1). The percentage of variance, defined by the Eigenvalues, is displayed in Table 2, whilst the PCA structure is displayed in

Table 1
Principal components, Eigenvalues and internal consistency.

	Component				
	1	2	3	4	5
Age	–	–	0.789	–	–
Height	–	–	0.897	–	–
Weight	–	0.777	0.569	–	–
Sex	–	–	–	0.695	–
BMI	–	0.950	–	–	–
BMI%	–	0.932	–	–	–
Waist circumference	–	–	–	–	0.916
Body fat%	–	0.897	–	–	–
Activity counts	–	–	–	0.638	–
MVPA	–	–	–	−0.596	–
Spectral purity	0.866	–	–	–	–
Traffic light score	0.882	–	–	–	–
Fine motor%	0.718	–	–	–	0.342
Gross motor%	0.790	–	–	–	−0.364
Eigen Value	3.7	2.6	1.6	1.2	1.1
Cronbach α	0.93[b]	0.91[b]	0.81[a]	0.24	0.21

Note. Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotated component matrices supressed < 0.3.

[a] Denotes good internal consistency.

[b] Denotes excellent (≥0.9) internal consistency.

Table 2
Principal components and variance explained.

	Initial eigenvalues			Extraction sums of squared loadings		Rotation sums of squared loadings			
	Total	%var.	Cum.%	Total	%var.	Cum.%	Total	%var.	Cum.%
1	3.782	27.018	27.018	3.782	27.018	27.018	3.333	23.810	23.810
2	2.683	19.163	46.180	2.683	19.163	46.180	2.666	19.043	42.853
3	1.627	11.623	57.803	1.627	11.623	57.803	2.030	14.502	57.355
4	1.281	9.149	66.952	1.281	9.149	66.952	1.336	9.540	66.894
5	1.113	7.953	74.905	1.113	7.953	74.905	1.121	8.011	74.905

Note. Extraction Method: Principal Component Analysis. %var.: percent of variance; Cum.%: cumulative percentage.

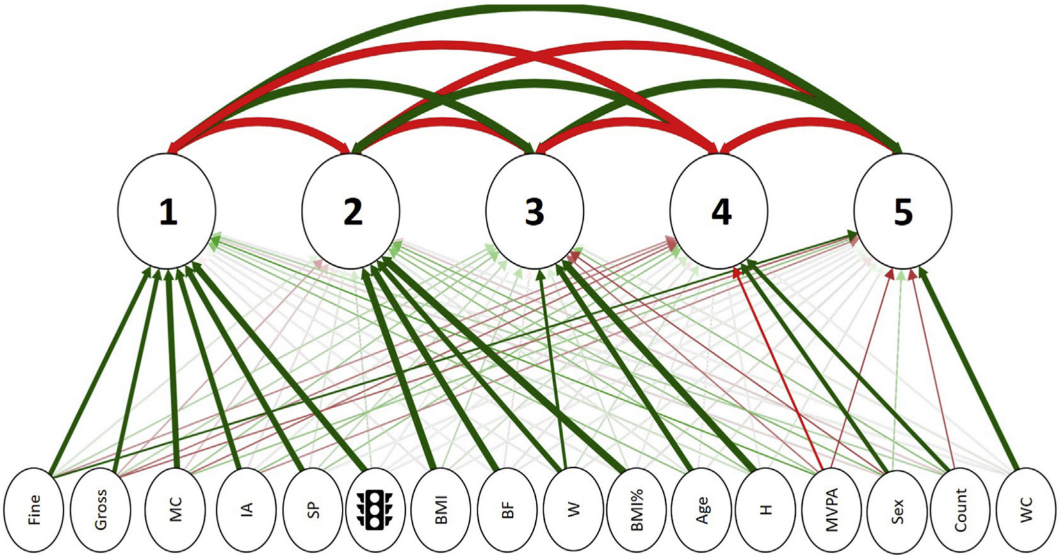

Fig. 1. PCA structure.
Note. The sign of the correlations are indicated by colour; positive correlations are green, negative are red. The thickness of the lines indicates strength of correlation (thicker = stronger). *Fine*: fine motor%; *Gross*: gross motor %; *MC*: motor competence; *IA*: integrated acceleration; *SP*: spectral purity; *traffic light symbol*: traffic light classification; *BMI*: body mass index; *BF*: body fat%; *W*: weight; *H*: height; *MVPA*: moderate-to-vigorous physical activity; *count*: activity count; *WC*: waist circumference. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 1.

4. Discussion

Developments in the field of objectively measured human movement are progressing expediently, with sensors now efficaciously being able to analyse gait patterns and determine safety, control, balance, variability and rhythmicity during ambulation (Aziz, Park, Mori, & Robinovitch, 2014; Aziz & Robinovitch, 2011; Bellanca, Lowry, Vanswearingen, Brach, & Redfern, 2013; Brach et al., 2011; Kangas, Korpelainen, Vikman, Nyberg, & Jamsa, 2015), through exploitation of the periodicity of raw signal outputs (Gage, 1964; Smidt, Arora, & Johnston, 1971). It is asserted that 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., 2016a). Feature extraction of such variables has the potential to yield unseen insights, with reduced dimensionality, while concurrently retaining the discriminative capability of the new set of feature variables (Jain et al., 2000; Mannini & Sabatini, 2010). Thus, the aim of this study was to investigate movement and gait quality, physical activity and motor competence using principal component analysis. In accord with the aim of this study, two principal components, with excellent internal consistency (Cronbach $\alpha > 0.9$) were found; the 1st principal component contained Spectral purity, traffic light MABC2 score, fine motor% and gross motor% ($\alpha = 0.93$; Table 1); the 2nd principal component contained weight, BMI, BMI% and body fat% ($\alpha = 0.91$; Table 1). The results of the current study are novel as no study has examined this issue in pre-school children. Moreover, the data we present are practically significant in that we demonstrate the efficacy of spectral purity as a meaningful metric related to children's movement.

4.1. Movement component

This study highlighted that accelerometric analyses of motor competence, and traditional assessment tools (MABC), represent one, distinct principal component, and as such, the authors strongly recommend further work be done investigated the veracity of accelerometer derived measures of motor competence as a time-saving, automated and accurate proxy for traditionally assessed motor competence. Such assertions are concordant to that of Clark et al. (2017), who highlighted that 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. The authors reported that spectral purity and motor competence (MABC2 classification) were more closely, cophenetically, linked (0.06) than integrated acceleration (0.19), which was previously unreported; whilst in older children, spectral purity was demonstrated to be indicative of fundamental aspects of movement (Clark, Barnes, Holton, et al., 2016a). Collectively, the current study, and antecedent findings, suggest that spectral purity may be a movement quality indicator in early years' children.

Ubiquitous sensors have been used with signal analysis to machine-score specific activities or components within a varied activity programme with reasonable success (Allen, Ambikairajah, Lovell, & Celler, 2006; Bisi et al., 2017; Clark et al., 2018; Rocha et al., 2019). Barnes and colleagues (Barnes et al., 2018) presented an alternative, process-oriented quantification of complex motion in which pairwise comparison of individuals is made using time trace correlations of position sensor data. Previous approaches using wearable sensors have focussed on identification of specific gestures (Akl, Feng, & Valaee, 2011) or discrimination between specific activities, e.g. walking or cycling (Mannini et al., 2013). Whilst Barnes et al. (Barnes et al., 2018) show that comparison of an automated, sensor-based method to the standard approach has a strong correlation to subjective human-assessed scores.

Previous examples of measurement variability within physical activity tests have reported correlation coefficients of 0.6 when comparing overall scores between different FMS tests (Lander, Morgan, Salmon, Logan, & Barnett, 2017), and 0.5–0.7 for comparison of process and product-oriented scores of individual skills (Logan, Barnett, Goodway, & Stodden, 2017). Moreover, comparison of inter-rater variability within a single test indicated κ values in the range of 0.2–0.6 for overhand throw and strike skills (Barnett, Minto, Lander, & Hardy, 2013). Thus, given novel, automated assessment appears not only accurate, but comprises one principal component with overall MC, further confirmatory assessment, and eventual adoption of such metrics is warranted.

Product-oriented assessments evaluate the outcome of a movement (e.g. how fast, how many), offer an objective evaluation of the outcome of the task, but do not allow interpretation on how it was achieved. On the other hand, process-oriented motor competence assessments analyse how a movement is performed and with which strategy, with the advantage of allowing the identification of specific skill components that may need improving (Barnett et al., 2013). A particular limitation of process-oriented assessment is that it is time consuming and requires the involvement of numerous trained observers to ensure reliability. In general, the use of combined process and product assessments is suggested, if a complete and comprehensive capture of the motor development of the child is to be made (Logan et al., 2017). Thus, of further, contemporary interest, is the time saving capability of novel metrics such as spectral purity. Bisi et al. (2017) report a tangible reduction in assessment, per person, of 13 min when using sensor-based analytics, vs. traditional assessment in the TGMD2. Given the retention in accuracy of automated assessments using novel metrics, concomitant to marked time saving, both in terms of analyses and human time, and the findings of the current study, where automated novel analytical outputs are related to MC; this may act as a valid and useful alternative, or addition, to the assessment of MC and PA in children.

4.2. Anthropometric component

The present study found one principal component containing weight, BMI, BMI% and body fat% ($\alpha = 0.91$), which is indicative of groups of variables that measure the same underlying dimensions of a data set (Davis, 2001). This finding is unsurprising and congruent with previous literature, where BMI and body fat percentage have been shown to be cophenetically clustered (Clark et al., 2017; Clark, Barnes, Holton, et al., 2016a) and significantly positively correlated (Cui, Truesdale, Cai, Koontz, & Stevens, 2013; Lindsay et al., 2001). Furthermore, Pasco et al. (Pasco, Nicholson, Brennan, & Kotowicz, 2012) reported an exact agreement between BMI and waist circumference criteria for categorising normal, overweight and obese groups in males and females, whilst BMI was correlated to other indices of adiposity in both men and women. Pietrobelli et al. (1998) identified that body fat (in kilograms) and percent of body weight as fat (BF%) were estimated by dual energy x-ray absorptiometry (DEXA) in 198 healthy Italian children and adolescents between 5 and 19 years of age. BMI was strongly associated with TBF ($R^2 = 0.85$ and 0.89 for boys and girls, respectively) and BF% ($R^2 = 0.63$ and 0.69 for boys and girls, respectively), and asserted that BMI as a fatness measure in groups of children and adolescents. Further, Jelena et al. (2016) reported the correlation between BMI and %BF was very strong, positive, among young girls ($r = 0.975$) and boys ($r = 0.752$). However, this study was not seeking to support the veracity of one anthropometric variable over another, but has reiterated the already well-established linear relationship between such anthropometric indices (i.e. BMI, BMI percentile, BF%), utilising principal component analyses. As such, given all of the anthropometric measures, independently and strongly correlated with the overall, rotated principal component (Table 1.), the authors would suggest the choice of which measures to take be carefully considered according to researcher and participant time and resource constraints, and following transparent reporting practices.

4.3. Limitations, recommendations, and practical implications

Although this study employed novel signal analytics of accelerometer data, in the form of spectral purity, there are further analytics that could be employed and should be the focus of future research, for example, the intensity gradient (Rowlands et al., 2018), Euclidean Norm Minus One (ENMO) (van Hees et al., 2013) and Mean Amplitude Deviation (MAD) (Vaha-Ypya et al., 2015; Vaha-Ypya, Vasankari, Husu, Suni, & Sievanen, 2015). Furthermore, although we utilised a reasonable sample size in this work, larger samples will be required in order to better generalise, and indeed validate, our approach. Another potential limitation is the use of varying demarcations for variables such as BMI grouping, MVPA cut-points and MABC2 traffic light score. However, we presented the information according to literature norms; nevertheless, we acknowledge that, as this field of analytics progresses, harmonization of data outputs will become necessary. Although the findings of the present study are useful, further work must be conducted in order to affirm the utility of movement quality measurement, and indeed, track changes and development longitudinally and in response to interventions. Whilst practically, the implications of being able to robustly quantify movement quality using an automated sensor is extremely advantageous, particularly when standard assessment batteries necessitate a time and resource consumptive approach, with limited reliability.

5. Conclusion

Firstly, the results of the present study are practically significant in that we demonstrate the efficacy of spectral purity as a meaningful, indicative metric related to children's movement quality Secondly, one of the primary functions of PCA is to reveal groups of variables that measure the same underlying dimensions of a data set, indeed, we have demonstrated that spectral purity, a quantitative measure of movement quality, comprises a principal component with overall, and derivatives of, motor competence, indicating that movement quality may inform the level of motor competence in children. Moreover, the measure of movement quality requires comparatively little time and resource, accompanied by an automated analytical procedure.

Authors' contributions

CC conceptualized and designed the study, collected the data, analysed the data, wrote the first draft of the manuscript and revised the manuscript; CB conceptualized the study, analysed the data and revised the manuscript; MD critically revised the manuscript; HS supervised and critically revised the manuscript; GS supervised and critically revised the manuscript. All authors have read and approved the final version of the manuscript, and agree with the order of presentation of the authors.

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Declaration of Competing Interest

The authors declare that they have no competing interests.

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Appendix A. Supplementary data

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