

1 **Title:**

2 Physical Activity, Motor Competence and Movement and Gait Quality: A Principal
3 Component Analysis.

4 **Running head:**

5 Quality of Movement in Children

6 **Author names and affiliations:**

7 Cain C. T. Clark ^{a, b*}, Claire M. Barnes ^{b, c}, Michael J. Duncan ^a, Huw D Summers ^{b, c}, Gareth
8 Stratton ^{b, d}

9 ^a Centre for Sport, Exercise and Life Sciences (CSELS), Coventry University, Coventry, CV1
10 5FB, U.K.

11 ^b Engineering Behaviour Analytics in Sport and Exercise (EBASE) Research group, School
12 of Sports and Exercise Sciences, Swansea University, Bay Campus, Fabian Way, Swansea,
13 SA1 8EN, U.K.

14 ^c Systems and Process Engineering Centre, College of Engineering, Swansea University, Bay
15 Campus, Fabian Way, Swansea, SA1 8EN, U.K.

16 ^d Applied Sport, Technology, Exercise and Medicine (A-STEM), College of Engineering,
17 Swansea University, Bay Campus, Fabian Way, Swansea, SA1 8EN, U.K.

18 **Corresponding author (*):**

19 Dr Cain C. T. Clark, email: cain.clark@coventry.ac.uk, Centre for Sport, Exercise and Life
20 Sciences, Coventry University, Coventry, CV1 5FB, U.K.

21

22

23 **Abstract**

24 *Objective*

25 While novel analytical methods have been used to examine movement behaviours, to date, no
26 studies have examined whether a frequency-based measure, such as spectral purity, is useful in
27 explaining key facets of human movement. The aim of this study was to investigate movement
28 and gait quality, physical activity and motor competence using principal component analysis.

29 *Methods*

30 Sixty-five children (38 boys, 4.3±0.7y, 1.04±0.05m, 17.8±3.2kg, BMI; 16.2±1.9 kg·m²) took
31 part in this study. Measures included accelerometer-derived physical activity and movement quality
32 (spectral purity), motor competence (Movement Assessment Battery for Children 2nd edition; MABC2),
33 height, weight and waist circumference. All data were subjected to a principal component analysis,
34 and the internal consistency of resultant components were assessed using Cronbach's alpha.

35 *Results*

36 Two principal components, with excellent internal consistency (Cronbach $\alpha > 0.9$) were found;
37 the 1st principal component, termed "*movement component*", contained spectral purity, traffic
38 light MABC2 score, fine motor% and gross motor% ($\alpha=0.93$); the 2nd principal component,
39 termed "*anthropometric component*", contained weight, BMI, BMI% and body fat% ($\alpha=0.91$).

40 *Conclusion*

41 The results of the present study demonstrate that accelerometric analyses can be used to assess
42 motor competence in an automated manner, and that spectral purity is a meaningful, indicative,
43 metric related to children's movement quality.

44 **Keywords:** Pre-School; Motor Competence; Principal Component Analysis; Physical
45 Activity; Motor Development

46 **Introduction**

47 Global physical activity guidelines advocate that pre-school aged children (3-5 years)
48 engage in at least 180 minutes of physical activity every day (Tremblay et al., 2012), with
49 variables such as demographic, biological, sociocultural, and motor competence, defined as a
50 child's ability to perform a wide range of motor skills in a proficient manner (Haga, 2008), all
51 influencing physical activity levels (Bingham et al., 2016; Lubans, Morgan, Cliff, Barnett, &
52 Okely, 2010). Recent studies have established that development of motor competence has
53 numerous tangible health and developmental benefits; for example, higher levels of motor
54 competence are shown to positively predict cardiorespiratory fitness (Vlahov, Baghurst, &
55 Mwavita, 2014), improve academic performance (Jaakkola, Hillman, Kalaja, & Liukkonen,
56 2015), and are protective against obesity (Rodrigues, Stodden, & Lopes, 2015). Concerningly,
57 studies have reported low levels of motor competence among primary school aged children
58 (Bryant, Duncan, & Birch, 2013; LeGear et al., 2012). These findings highlight the need to
59 examine motor competence during early years (3-5 years), which is considered a critical phase
60 for fundamental movement skills development (Gallahue & Donnelly, 2003) and a facilitator
61 for lifelong physically active lifestyles; moreover, children's perceptions of their competency
62 is asserted to influence this development (LeGear et al., 2012).

63 Motor competence in the early years is traditionally assessed using subjectively scored
64 observation tools in a controlled setting, most commonly, the movement assessment battery for
65 children (MABC2 (Henderson, Sugden, & Barnett, 2007)) or the test of gross motor
66 development (TGMD (Ulrich, 2000)). Although empirical and conceptual evidence exists to
67 support the reciprocal relationship between motor competence and PA (Stodden et al., 2008),
68 there is a limited evident base of motor competence related to PA measurement in pre-school
69 children, largely due to the complexity in examining such constructs in this age group (Adamo
70 et al., 2016; Goldfield, Harvey, Grattan, & Adamo, 2012). When studies have investigated PA

71 and motor competence they tend to examine this as a relationship, where large variability in
72 not only motor competence, but also PA, is reported, which can conceivably mask, or indeed
73 create spurious, responses or relationships (Adamo et al., 2016; Clark, Barnes, Swindell, et al.,
74 2018).

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

95 hierarchically clustered with cardiovascular fitness (Clark, Barnes, Holton, Summers, &
96 Stratton, 2016a).

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

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

113 **Methods**

114 **Participants and Settings**

115 Sixty-five children (38 boys, 4.3 ± 0.7 y, 1.04 ± 0.05 m, 17.8 ± 3.2 kg, body mass index;
116 16.2 ± 1.9 kg·m² (underweight, N = 3; normal weight, N = 40; overweight, N = 13; obese, N =
117 9)) volunteered to take part in this study. Prior to research commencing, informed parental
118 consent and child assent was attained. In order to be included in this study, each participant
119 had to be free from any physical or neurological impairment that may hinder normal movement.
120 This research was conducted following approval of the institutional research ethics committee
121 and conformed to the Declaration of Helsinki.

122 **Instruments and Procedures**

123 Children participated in free-play (100 ± 3 minutes per day), which in the context of
124 this work is synonymous with outdoor recess, where children had access to an enclosed
125 playground, whilst wearing a custom-built Micro Electro-Mechanical System (MEMS) based
126 device, which incorporated a tri-axial accelerometer with a ± 16 g dynamic range, 3.9mg point
127 resolution and a 13-bit resolution (with a z-axis amplitude coefficient of variation of 0.004 at
128 40 Hz (Clark, Barnes, Holton, Summers, & Stratton, 2016b); ADXL345 sensor, Analog
129 Devices). The MEMS device was housed in a small plastic case and affixed via a Velcro strap
130 to the lateral malleolar prominence of the fibula of the right leg and set to record at 40 Hz,
131 which has been validated in previous studies (Barnes, Clark, Holton, Stratton, & Summers,
132 2016; Clark, Barnes, et al., 2016a), and does not violate the Nyquist-Shannon sampling
133 theorem, which specifies that the sample must contain all the available frequency information
134 from the signal to result in a faithful reproduction of the analogue waveform signal (Farrow,
135 Shaw, Kim, P., & Billinge, 2011). Further, put simply, if the highest frequency component, in
136 Hz, for a given analogue signal is f_{max} , according to the Nyquist-Shannon sampling theorem,

137 the sampling rate must be at least $2f_{max}$, or twice the highest analogue frequency component.
138 Mannini and colleagues (2013) highlighted that for movement characteristics related to
139 ambulation, an ankle-mounted monitor may be most suitable, whilst Barnes and colleagues
140 (2016) systematically demonstrated that ankle affixed accelerometers can be used to accurately
141 compute locomotion. Data were stored locally on the device, with no incidences of data loss.

142 Physical activity was concurrently recorded using an ActiGraph GT3X+ device
143 (ActiGraph, Pensacola, FL, USA). The accelerometer measures $4.6\text{ cm} \times 3.3\text{ cm} \times 1.5\text{ cm}$, and
144 weighs 19 g. Its sampling frequency was set to 100 Hz, and the sampling interval (epoch) in
145 the present study was set to be 1-s (Østbye et al., 2013; Pate, Almeida, McIver, Pfeiffer, &
146 Dowda, 2006). Participants wore their accelerometer on the waist, above the right hip, affixed
147 using an elastic belt (Hesketh et al., 2014), in accordance with manufacturer guidelines
148 (Migueles et al., 2017). All children also completed the MABC2, using standardised
149 procedures as described below Henderson et al. (2007).

150 Stature (measured to the nearest 0.01m) and body mass (to the nearest 0.1kg) were
151 measured using standard procedures using a stadiometer and digital scales (SECA, Hamburg,
152 Germany), respectively (Lohmann, Roche, & Martorell, 1988). Skinfold measurements of the
153 left triceps and subscapular were made by trained researchers using calibrated skinfold callipers
154 (Harpenden, Baty International, U.K.), waist circumference was measured at the level of the
155 naval and measurements were subsequently used to estimate body fat percentage (Eisenmann,
156 Heelan, & Welk, 2004; Slaughter et al., 1988). Intra- and inter-observer technical error of
157 measurement (TEM) for waist circumference, triceps and subscapular skinfolds were evaluated
158 and relative TEMs were acceptable and indicative of 'skilful' anthropometrists (Perini, de
159 Oliveira, Ornelia, & de Oliveira, 2005)

160 Further, children were classified based on body-mass index percentiles as either;
161 underweight ($\leq 5^{\text{th}}$ percentile), normal weight (5^{th} to 85^{th} percentile), overweight ($>85^{\text{th}}$ to $<95^{\text{th}}$
162 percentile) or obese ($\geq 95^{\text{th}}$ percentile) (Cole & Lobstein, 2012).

163 **Data Analysis**

164 *Spectral purity (Movement quality):*

165 Raw acceleration data from the MEMS device were uploaded into MatLab (MATLAB
166 version R2016a), where spectral purity was derived (Barnes et al., 2016; Clark, Barnes, et al.,
167 2016a; Clark, Barnes, Summers, Mackintosh, & Stratton, 2018). The characteristics used for
168 analysis were derived from acceleration in the axis along the lower leg towards the origin of
169 motion, termed the radial axis (Barnes et al., 2016; Clark, Barnes, et al., 2016a). Acceleration
170 data were converted from the time into the frequency domain. To convert the data into the
171 frequency domain, a Fast Fourier transform (FFT) was applied to the data. The FFT computes
172 the discrete Fourier transform (DFT) of a sequence.

173 Let $x_0, \dots, x_{(N-1)}$ be a sequence of N complex numbers. The Fast Fourier transform
174 computes the Discrete Fourier transform

$$175 \quad X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i2\pi kn/N}, k \in Z$$

176 *Equation 1. Fast Fourier Transform*

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

182 To determine the quality of a child's movement - 'Spectral purity' was calculated from
183 the cumulative distribution function (CDF) of the frequency spectrum. The CDF plot is used
184 to generate a value for spectral purity. The empirical CDF $F(x)$ is defined as the proportion
185 of X values less than or equal to some value x . In this case, it is the number of values less than
186 or equal to some frequency in a spectrum being considered. A measure for spectral purity is
187 therefore considered to be the frequency at which the midway point of the CDF (0.5) occurs.
188 As a result, spectra that is 'clean', i.e. consisting of a tall narrow peak at the fundamental
189 frequency and only low amount of noise and small harmonics will have a different value to
190 spectra where there is lots of noise, a shorter wider peak, and higher peaks at the harmonics.
191 Spectral purity measures how tightly the frequency components of the raw accelerations are
192 distributed using fundamental frequency to harmonics and the frequency spectrum analysis is
193 directly related to the ambulation of a participant (Barnes et al., 2016; Clark, Barnes, et al.,
194 2016a).

195 *Actigraphy:*

196 ActiGraph acceleration data were analysed using commercially available analytics
197 (KineSoft version 3.3.67, KineSoft; www.kinesoft.org). Non-wear periods were defined as any
198 sequence of >20 consecutive minutes of zero activity counts (Tudor-Locke et al., 2015).
199 Sedentary behaviour was defined as <100 counts per minute, while 100, 2296 and 4012 counts
200 per minute were thresholds to define light, moderate and vigorous physical activity,
201 respectively (Evenson, Catellier, Gill, Ondrak, & McMurray, 2008; Trost, Loprinzi, Moore, &
202 Pfeiffer, 2011). Mean counts per minute during valid wear time and percentage of total time
203 spent in moderate-to-vigorous physical activity (MVPA) were used to define physical activity
204 (Migueles et al., 2017).

205 *2.3.3 Motor competence:*

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

228 2.3.4 Statistical analysis:

229 All data were subjected to a principal component analysis using ‘*one*’ as the prior
230 communality estimate (Kline, 2000; Pearson, 1901). Varimax orthogonal transformation was

231 used to convert the set of physical and anthropometric variables into a set of linearly
232 uncorrelated variables, termed principal components. The number of distinct principal
233 components was equal to either, the number of original variables or the number of observations
234 minus one (whichever is smallest). This transformation was defined in such a way that the first
235 principal component had the largest possible variance (that is, accounts for as much of the
236 variability in the data as possible), and each succeeding component in turn has the highest
237 variance possible under the constraint that it is orthogonal to the preceding components. The
238 resulting vectors were an uncorrelated orthogonal basis set. Principal components with Eigen
239 values greater than one were retained (Kline, 2000; Nunnally & Bernstein, 1994). The internal
240 consistency of components were assessed using Cronbach's alpha (α), and reported according
241 to (Nunnally & Bernstein, 1994); $\alpha < 0.5$ is unacceptable, $\alpha \geq 0.5$ but < 0.6 is poor, $\alpha \geq 0.6$ but
242 < 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
243 excellent. All statistical analyses were conducted using JASP statistical package (JASP Team,
244 2018, jasp-stats.org).

245 **Results**

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

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

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

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

255 **Discussion**

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

276 *Movement component*

277 This study highlighted that accelerometric analyses of motor competence, and
278 traditional assessment tools (MABC), represent one, distinct principal component, and as such,

279 the authors strongly recommend further work be done investigated the veracity of
280 accelerometer derived measures of motor competence as a time-saving, automated and accurate
281 proxy for traditionally assessed motor competence. Such assertions are concordant to that of
282 Clark et al (2017), who highlighted that the frequency and harmonic content of movement is
283 reflective of movement characteristics such as gait pattern and overall physical activity, in
284 addition to cardiorespiratory fitness. The authors reported that spectral purity and motor
285 competence (MABC2 classification) were more closely, cophenetically, linked (0.06) than
286 integrated acceleration (0.19), which was previously unreported; whilst in older children,
287 spectral purity was demonstrated to be indicative of fundamental aspects of movement (Clark,
288 Barnes, et al., 2016a). Collectively, the current study, and antecedent findings, suggest that
289 spectral purity may be a movement quality indicator in early years' children.

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

300 Previous examples of measurement variability within physical activity tests have
301 reported correlation coefficients of 0.6 when comparing overall scores between different FMS
302 tests (Lander, Morgan, Salmon, Logan, & Barnett, 2017), and 0.5 – 0.7 for comparison of
303 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 minutes 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.

325

326 *Anthropometric component*

327 The present study found one principal component containing weight, BMI, BMI% and
328 body fat% ($\alpha=0.91$), which is indicative of groups of variables that measure the same

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

351 *Limitations, recommendations, and practical implications*

352 Although this study employed novel signal analytics of accelerometer data, in the form
353 of spectral purity, there are further analytics that could be employed and should be the focus of

354 future research, for example, the intensity gradient (Rowlands et al., 2018), Euclidean Norm
355 Minus One (ENMO) (van Hees et al., 2013) and Mean Amplitude Deviation (MAD) (Vaha-
356 Ypya, Vasankari, Husu, Manttari, et al., 2015; Vaha-Ypya, Vasankari, Husu, Suni, & Sievanen,
357 2015). Furthermore, although we utilised a reasonable sample size in this work, larger samples
358 will be required in order to better generalise, and indeed validate, our approach. Another
359 potential limitation is the use of varying demarcations for variables such as BMI grouping,
360 MVPA cut-points and MABC2 traffic light score. However, we presented the information
361 according to literature norms; nevertheless, we acknowledge that, as this field of analytics
362 progresses, harmonization of data outputs will become necessary. Although the findings of the
363 present study are useful, further work must be conducted in order to affirm the utility of
364 movement quality measurement, and indeed, track changes and development longitudinally
365 and in response to interventions. Whilst practically, the implications of being able to robustly
366 quantify movement quality using an automated sensor is extremely advantageous, particularly
367 when standard assessment batteries necessitate a time and resource consumptive approach,
368 with limited reliability.

369 **Conclusion**

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

379 **Acknowledgments**

380 We would like to express our sincere gratitude to the schools, parents, guardians and children
381 involved in this study.

382 **Authors' Contributions**

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

389 **Competing Interests**

390 The authors declare that they have no competing interests.

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394

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597 Table 1. Principal components, Eigenvalues and internal consistency

	Component				
	1	2	3	4	5
Age	-	-	.789	-	-
Height	-	-	.897	-	-
Weight	-	.777	.569	-	-
Sex	-	-	-	.695	-
BMI	-	.950	-	-	-
BMI%	-	.932	-	-	-
Waist circumference	-	-	-	-	.916
Body fat%	-	.897	-	-	-
Activity counts	-	-	-	.638	-
MVPA	-	.-	-	-.596	-
Spectral purity	.866	-	-	-	-
Traffic light score	.882	-	-	-	-
Fine motor%	.718	-	-	-	.342
Gross motor%	.790	-	-	-	-.364
Eigen Value	3.7	2.6	1.6	1.2	1.1
Cronbach α	0.93**	0.91**	0.81*	0.24	0.21

598 Note. Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser

599 Normalization. Rotated component matrices suppressed <0.3. ** denotes excellent (≥ 0.9) internal consistency.

600 *denotes good internal consistency.

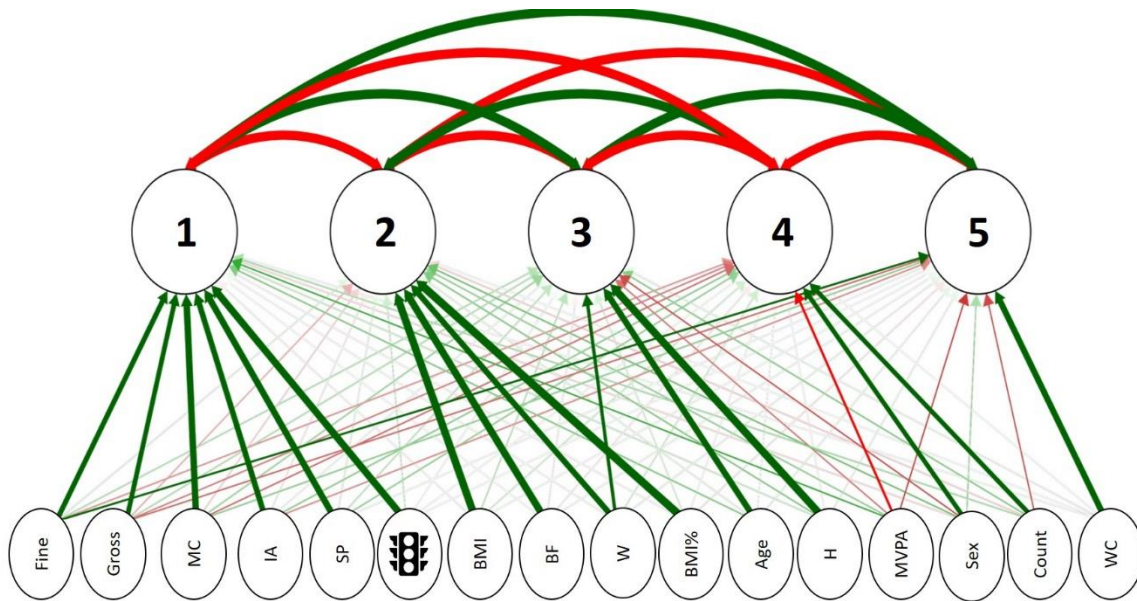
601 Table 2. Principal components and variance explained

602

603

	Initial Eigenvalues			Extraction Sums of Squared			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.



604

605 **Figure 1. PCA structure.**

606 Note. The sign of the correlations are indicated by colour; positive correlations are green, negative are red. The
 607 thickness of the lines indicates strength of correlation (thicker = stronger). *Fine*: fine motor%; *Gross*: gross
 608 motor %; *MC*: motor competence; *IA*: integrated acceleration; *SP*: spectral purity; **TL**: traffic light classification;
 609 *BMI*: body mass index; *BF*: body fat%; *W*: weight; *H*: height; *MVPA*: moderate-to-vigorous physical activity;
 610 *count*: activity count; *WC*: waist circumference.

611