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Title;

Profiling movement quality and gait characteristics according to body-mass index in children (9-11y) - *Original Research Article*

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Abstract

Obese children move less and with greater difficulty than their normal-weight counterparts. Whilst the effect of high BMI on cardiovascular fitness is well known, the effect on movement quality characteristics during a standardised fitness test has not been investigated. The aims of this study were, to characterise the movement quality of children performing the multi-stage fitness test (MSFT), and, report how movement quality characteristics cluster according to weight status. One hundred and three children (10.3±0.6y, 1.42±0.08m, 37.8±9.3kg, BMI; 18.5±3.3 kg·m^2) performed the MSFT whilst wearing an ankle mounted accelerometer. BMI groups were used to classify children as underweight (UW), normal weight (NW), overweight (OW) and obese (OB). Characteristics of movement were profiled using a clustering algorithm. Spearman's rho was used to assess relationship with BMI group, and a Mann-Whitney U test was used to assess differences between BMI groups. Obese children had significantly lower spectral purity than every other group and significantly lower time to exhaustion (TTE) than UW and NW children (P<0.05). BMI was clustered with stride profile and TTE with spectral purity. Significant negative correlations (P<0.05) were found between BMI and TTE (r=-0.25), spectral purity (r=-0.24), integrated acceleration (r=-0.22), stride angle (r=-0.23) and stride variability (r=-0.22).This was the first study to report the spectral purity of children's gait. Further analysis unveiled key performance characteristics that differed between BMI groups. These were (i) representative of children's performance during the MSFT and, (ii) significantly negatively correlated with BMI.

Keywords

BMI; Clustergram; Accelerometer; Spectral purity; Multi-stage fitness test

1. Introduction

Physical inactivity is one of the most widespread non-communicable diseases worldwide (WHO, 2010), and despite recognition of the importance of physical activity, the use of the appropriate measurement and analytical techniques is currently limited, especially with regard to gait and movement quality characteristics that make up physical activity. Accelerometers are the *de facto* standard in objectively measuring physical activity (Mathie et al., 2004; Van Hees et al., 2012) that cover the range of acceleration amplitudes and frequencies required to capture human movement (Bhattacharya et al., 1980). However commercial accelerometers have limitations, for example high frequency movement and noise information can escape the bandpass filter which in turn adds unexplained variation in activity counts (Brond & Arvidson, 2015). In addition, variations in epoch length, cut points and device type further add to the lack of clarity in the literature (Bassett, Rowlands, & Trost, 2012; Edwardson & Gorely, 2010; Strath, Bassett, & Swartz, 2003). This is further confounded by the fact that commercially available accelerometers only provide manufacturer-dependent output values that are computed by unpublished and proprietary signal processing techniques, resulting in a unit of measure termed, 'activity counts'. Activity counts summarize data in an epoch, reducing the burden of data management, analysis, and interpretation; however, information about the raw accelerometer signal is irretrievably lost and a full picture of physical activity overlooked. In the assessment of human movement a central body position is the best accelerometer placement for capturing overall quantity of activity and best predicts energy expenditure (Boerema et al., 2014; Crouter, Churilla, & Bassett, 2008). However, the location of an accelerometer should be dependent on what researchers are attempting to investigate. Mannini et al. (2013) asserted that for gait quality characteristics, an ankle-mounted monitor had greatest validity, with a classification accuracy of 95%. Furthermore detailed information about gait quality during ambulation, gait phase detection, walking speed estimation, with an ankle mounted device would be far more revealing (Clark et al., 2016; Mannini et al., 2013).

The quantity of physical activity has been linked to various comorbidities, such as hypertension and obesity. (Katzmarzyk et al., 2015; Vale et al., 2015) The quantity of physical activity is useful in studies interested in measuring energy expenditure. The problem is that energy expenditure takes one simple measure from the accelerometer trace, the area under the curve. In contrast, there are numerous other features that can be derived from accelerometer data. For example quality characteristics can provide specific, contextualised feedback, but these have not been well utilised. The best known use of raw accelerometry to ascertain qualities of movement is in fall detection and the mobile gait analysis of older adults (Aziz et al., 2014; Aziz & Robinovitch, 2011; Kangas et al., 2015) whereby specific monitoring of walking and balance quality has been used to determine patients' safety and control during ambulation. As novel and robust analytics develop quantity and quality data will be derived from accelerometer traces (Clark et al., 2016).

For example fast Fourier transformation (FFT), has been used to process the accelerometer signal and identify gait qualities; walking smoothness, walking rhythmicity, dynamic stability and stride symmetry (Bellanca et al., 2013; Brach et al., 2011). While FFT is an analytical technique used to characterise accelerometer data, cluster analysis involves the use of algorithms to separate a population into clusters or groups based on various parameters, such as activity behaviours, gait or movement qualities, stride profile, and BMI. Cluster analysis uses an iterative process of interactive, multi-objective optimization and has been used to inform animal movement and behaviour theory (Braun, Geurten, & Egelhaaf, 2010) and to identify and track cells (Tonkin et al., 2012). Given the nature of human movement, cluster analysis could be of great use in the understanding and analysis of gait and movement quality characteristics at a group level (Clark et al., 2016).

Fast Fourier transformation and cluster analysis can be combined to analyse movement in standardised settings. Moreover sensors can be attached to whole groups undertaking the same movement task. The multi-stage fitness test (MSFT) is a globally utilised test of cardio-respiratory, particularly used within school aged children, and is a component of the European battery of cardiorespiratory and motor tests (Eurofit, 1983). It is well reported that obese children move less and with much greater difficulty than normal-weight counterparts (Blakemore et al., 2013; McNarry, Boddy, & Stratton, 2014; Nantel, Brochu, & Prince, 2006; Nantel, Mathieu, & Prince, 2011; Shultz et al., 2010; Stratton et al., 2007). This compromised movement is attributed to greater force through joints, decreased mobility, modification of gait pattern, and changes in the absolute and relative energy expenditures for a given activity. Further, detrimental changes in gait pattern have been demonstrated at the ankle, knee, and hip, and modifications at the knee level affecting articular integrity (Nantel et al., 2011; Shultz, D'Hondt, Lenoir, et al., 2014). Although some recent work has examined the relationship between gross motor and fundamental movement skills and physical activity, in a standardised setting (incorporating accelerometry) (Laukkanen, Finni, et al., 2013; Laukkanen, Pesola, et al., 2013), however, there has been no attempt in the literature to use clustering algorithms to profile and compare derivatives of a raw acceleration trace signal during standardised fitness tests. There is clearly potential to derive more information from the signal from accelerometers to address current gaps in scientific knowledge. The aims of this study were first, to apply automated, novel analyses to characterise the movement quality of children during the MSFT (Clark et al., 2015; Mannini et al., 2013; Tonkin et al., 2012), and second, to report how movement quality characteristics of gait cluster according to BMI.

2. Methods;

2.1. Participants and settings

One hundred and three children (10.3±0.6y, 1.42±0.08m, 37.8±9.3kg, body mass index; 18.5±3.3 $kg{\cdot}m^2$) volunteered to take part in this study. Participants were a representative sub-sample of 822 children (10.5±0.6y, 1.42±0.08m, 27.3±9.6kg, body mass index; 18.7±3.5 $kg{\cdot}m^2$) from 30 schools in the City and County of Swansea. Mean and variance data were not significantly different between the whole sample and sub-sample (P>0.05). The participants attended an indoor training facility, had anthropometric recordings taken and took part in the MFST. Additionally, children were classified as either underweight (<5th percentile, n = 7), normal weight (5th to 85th percentile, n = 73), overweight (>85th to <95th percentile, n = 14) or obese (≥ 95th percentile. n = 9) (Cole & Lobstein, 2012). This research was conducted in agreement with the guidelines and policies of the institutional ethics committee.

2.2. Instruments and Procedures

After standard familiarisation and five minute warm-up, children performed the MSFT (Leger and Lambert (1982)), whilst wearing 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 40hz) (ADXL345 sensor, Analog Devices). It 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.

2.2.1. Anthropometrics

Standing and seated stature (measured to the nearest 0.01m) and body mass (to the nearest 0.1kg) were measured using a stadiometer (SECA, Hamburg, Germany), sitting stadiometer (Holtain, Crymych, UK) and digital scales (SECA, Hamburg, Germany), respectively, using standard procedures (Lohmann, Roche, & Martorell, 1988).

2.2.2. Twenty-metre Multi-Stage Fitness Test

Participants completed the MFST by running back and forth along a 20m course, and were required to touch the 20m line at the same time that a sound signal was emitted from a pre-recorded audio disk. The frequency of the sound emissions increased in line with running speed. The test stopped when the participant reached volitional exhaustion and was no longer able to follow the set pace, or participants were withdrawn after receiving two verbal warnings to meet the required pace (Leger et al., 1988).

2.3. Data analysis

Raw acceleration data was uploaded into MatLab (MATLAB version R2016a), where the subsequent movement quality characteristics; integrated acceleration, stride profile quotient, stride variability, stride frequency, stride angle, spectral purity, and time to volitional exhaustion were derived. The MSFT was broken down into its respective running speed section. 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, in addition, three complete gait cycles were removed from the analyses prior to and post the point of turning during the test to reduce the effect the altered gait pattern had on the overall analyses. The maximum impact force generated upon foot strike, F_{max}, corresponds to the peak positive value of acceleration (force vector pointing from foot to knee) and was calculated by subtracting the background static acceleration and multiplying by the participant's weight. The stride angle, α_{max} was obtained from the peak acceleration value in the negative direction. This point represented the maximum leg lift and when dynamic acceleration was zero, the radial acceleration was wholly determined by the vector component of the gravitational field, as determined by the angle of the accelerometer relative to the vertical axis. Therefore determining the angle to which the subject's leg swings, the minimum point during the acceleration trace of the stride, A_{radial} was used in the following equation (Equation 1):

$$\alpha_{max} = acos(A_{radial}/g)$$

Equation 1. Maximum angle of foot lift

Where, α_{max} is the stride angle; $acos$ is the inverse of cosine; A_{radial}, is the minimum point during the acceleration trace of the stride; and g, is gravity.

The integrated acceleration was also determined, using an integration of the rectified signal and correspondent to the computation used to derive the standard 'activity counts' by other commercial devices (van Hees et al., 2010).

Fundamental frequency was derived by first applying a discrete FFT to the data. The fundamental frequency of motion was identified as the highest amplitude component. The Stride Profile Quotient (*Q*), is a multi-dimensional measure derived from the mean stride frequency and mean stride angle of each child during the first and last section of running that each child completed. The absolute of the two measures between the two sections was derived and normalised. These values were then used in the following equation (equation 2), where a score of *1* would equate entirely to changes in stride frequency, and a score of *0* would equate to changes entirely in foot lift angle.

$$Q = \sin(\operatorname{atan}(D1/D2))$$

Equation 2. Stride profile quotient.

Where Q, is the stride profile quotient; $\sin$, represents the sine function; atan, represents the inverse of the tangent; $D1$, is the = absolute difference in frequency and $D2$, is the absolute difference in foot lift angle.

Spectral purity was calculated from the cumulative distribution function (CDF) of the frequency spectrum and is the gradient of the CDF at high frequency, i.e. it measures how tightly the frequency components of the gait cycle are distributed. Finally, time to volitional exhaustion (TTE), derived by converting events into seconds based on the sampling frequency (40 Hz) was also recorded as a measure of overall performance.

2.3.1. Cluster analysis

In order to carry out further analysis of the cohort and identify areas of interest within the sample we applied a clustering to the dataset. The derived characteristics (integrated acceleration, stride profile quotient, stride variability, stride frequency, stride angle, and spectral purity) from the raw acceleration traces (described above) 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 3. 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, stride quotient, stride variability, stride frequency, spectral purity, TTE, BMI) 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 dendogram were joined was analysed using cophenetic distance, to demonstrate the similarity between two clusters (Saracli, Dogan, & Dogan, 2013; Schonlau, 2002; Sokal & Rohlf, 1962). The values for the dendogram linkages were subsequently normalised. The cophenetic distance ratio for the overall clustergram was also measured to demonstrate how successfully the dendogram preserved the pairwise distances between the original unmodeled data points (where 1 is maximum). As data were not normally distributed non-parametric methods were used to analyse the data, and were presented as mean, median and upper and lower quartiles. The Kruskall-Wallis test was used to determine general differences between the various characteristics and the Mann-Whitney U test (with continuity correction and tie adjustment (Gibbons & Chakraborti, 2011)) was used to determine specific differences between BMI groups. The Spearman's rho test was used to identify correlation coefficients between BMI within each characteristic. For all statistical tests an alpha level of 0.05 was applied. Data were reported in graphical and tabular format.

3. Results

The results from this study demonstrated that neither overall integrated acceleration nor overall stride variability were significantly different across BMI groups (Table 1, Figure 2 and Figure 3).

There were significant differences found in TTE between UW and OB (P=0.03) and OB and NW (P=0.05) (Table 1, Table 2, Figure 1). The OB group had significantly lower spectral purity than every other group (OB and OW: P=0.02, OB and NW: P=0.01, OB and UW: P<0.001) (Table 1, Table 2). The OB group had significantly lower stride angle than NW (P=0.04) and UW (P=0.04) groups (Table 1). Further, stride profile quotient was significantly different between UW and NW (P=0.01) and UW and OB (P=0.03) (Table 1, Table 2, Figure 4).

Significant differences between BMI groups were found for stride profile quotient (P=0.03) and spectral purity (P=0.02). The clustergram illustrated that spectral purity and TTE (cophenetic distance: 0.3), stride profile quotient and BMI group (cophenetic distance: 0.6), and stride profile characteristics (integrated acceleration, stride angle and stride variability: cophenetic distance 0.57) were clustered together (Figure 5), with a cophenetic distance ratio for the overall clustergram of 0.86.

Following the Spearman's rho test, significant (P<0.05) relationships were found between integrated acceleration (r=-0.22), stride variability (r=-0.22), stride angle (r=-0.23), TTE (r=-0.25) and spectral purity (r=-0.24) and BMI.

Table 1. Differences in movement quality characteristics between BMI groups.

Group	Q	MRV	SV	SF	SA	TTE	SP
UW-NW	0.01*	0.30	0.23	0.99	0.59	0.26	0.21
UW-OW	0.07	0.17	0.15	0.36	0.15	0.09	0.11
UW-OB	0.03*	0.33	0.33	0.80	0.04*	0.03*	<0.001*
OB-NW	0.13	0.74	0.87	0.60	0.04*	0.05*	0.01*
OB-OW	0.16	0.87	0.51	0.51	0.87	0.33	0.02*
OW-NW	0.51	0.20	0.37	0.09	0.10	0.35	0.75

Q: Stride profile quotient, MRV: maximum radial velocity, SV: stride variability, SF: stride frequency, SA: stride angle, T spectral purity. UW: underweight, NW: normal weight, OW: overweight, OB: obese, * denotes significant difference (*P*

Table 2. Descriptive data for time to exhaustion, spectral purity and stride profile quotient.

Group	TTE	SP	Q
UW	328s (Med: 293, UQ: 402, LQ: 256)	2.97 (Med: 2.95, UQ: 3.02, LQ: 2.93)	0.15*Q* (Med: 0.11, UQ: 0.25, LQ: 0.05)
NW	279s (Med: 263, UQ: 352, LQ: 190)	2.91 (Med: 2.9, UQ: 2.81, LQ: 2.97)	0.51*Q* (Med: 0.48, UQ: 0.88, LQ: 0.25)
OW	254s (Med: 227, UQ: 288, LQ: 177)	2.90 (Med: 2.89, UQ: 2.94, LQ: 2.84)	0.5*Q* (Med: 0.35, UQ: 0.86, LQ: 0.19)
OB	203s (Med: 182, UQ: 258, LQ: 168)	2.80 (Med: 2.8, UQ: 2.88, LQ: 2.72)	0.71*Q* (Med: 0.91, UQ: 0.99, LQ: 0.51)

TTE: time to volitional exhaustion, SP: spectral purity, Q: stride profile quotient, UW: underweight, NW: normal weight, Median value, UQ: upper quartile value, LQ: lower quartile value.

4. Discussion

The aims of this investigation were; first to characterise movement qualities using novel analyses of children performing the MSFT, and second, to report how these movement qualities of gait clustered according to BMI group.

The principal findings of this study were; that children from the OB group had significantly lower spectral purity than every other group and significantly lower TTE than UW and NW children. The clustergram linked TTE and spectral purity at a cophenetic distance of 0.3 and BMI and stride profile quotient at a cophenetic distance of 0.6. Further, significant negative correlation coefficients were found between BMI and TTE, spectral purity, integrated acceleration, stride angle and stride variability.

4.1. Clustergram overview

In order for a clustergram to be considered successful a cophenetic distance ratio of 0.75 is required (Bradley, 2003). The clustergram in this study had a cophenetic distance ratio of 0.86, indicating confidence in the veracity of clusters identified. The clustering algorithm hierarchically linked each characteristic (integrated acceleration, stride profile quotient, stride variability, stride frequency, stride angle, spectral purity, and TTE), 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 BMI and stride profile quotient: 0.6, time until volitional exhaustion and spectral purity: 0.3). This cophenetic distance ratio indicated that movement characteristics can be successfully, and reliably, clustered.

4.2. Body-mass index, harmonic content and overall performance

The finding that higher BMI had lower overall TTE (Figure 1, Table 1), and by extension cardiovascular fitness, agrees with similar studies (Brunet, Chaput, & Tremblay, 2007), and that obesity has a highly deleterious effect on fitness and motor skill development (Ceschia et al., 2015).

Our results are also novel. While spectral purity represents a measure of the motor control of ambulation (Bellanca et al., 2013; Brach et al., 2011), it has not been used in standardised fitness tests. Results from this study demonstrate that spectral purity, and performance score/fitness indicator (TTE) were cophenetically linked. Therefore spectral purity is a characteristic of movement quality in children performing the MSFT (Figure 5).

Further the frequency and harmonic content of the accelerometer output derived from the MSFT, spectral purity, was negatively correlated with BMI ($r=-0.24$, $P=0.02$). While the harmonic content of ambulation is related to movement quality (Doi et al., 2013; Lowry et al., 2009), its relationship with BMI has not been reported in the literature. This is a novel finding and indicates that the frequency and harmonic content of ambulation, and by extension, performance (TTE) during the MSFT, differs by BMI.

This study indicated that overall performance during the MSFT, as well as the frequency and harmonic content of movement, differs by BMI group. This study shows spectral purity can be used as an indicator of overall performance, as well as being significantly related to BMI.

4.3. Body-mass index and stride characteristics

Stride frequency and stride angle may be independently used to provide an in depth assessment of gait, in different age, body mass and gender groups. For higher BMI individuals, higher frequencies have been linked with greater knee-joint loads and deleterious to the biomechanics of ambulation (Shultz, D'Hondt, Fink, et al., 2014; Shultz, D'Hondt, Lenoir, et al., 2014). The quotient metric we derived from stride frequency and angle to assess movement quality is reflective of children’s running approach when performing the MSFT. This quotient has not yet been reported in the literature. We report that this stride profile quotient was an important contributor to the hierarchical clustering algorithm and was clustered with BMI (Figure 5).

The stride profile of children in different BMI groups illustrated contrasting approaches to the MSFT (Figure 4). The mean stride profile quotient for the BMI groups showed that NW and OW children altered their gait in an analogous fashion (NW: 0.5, OW: 0.51), indicating that these children responded to the stimulus of an increase in running speed during the MSFT by increasing stride angle and frequency. In contrast the stride profile quotient for UW and OB children presented different responses (UW: 0.15, OB: 0.71) whereby OB children, increased stride frequency but not stride angle. In addition, the clustergram provided a novel illustration of this finding, with children of NW/OW BMI displaying similarly low stride profile quotient scores, while the reverse occurred for OB children (Figure 5).

Children in the OB group predominantly altered stride profile through increases in stride frequency, as opposed to stride angle. Our findings that OB children develop a different gait have also been reported elsewhere, and has been shown to be exacerbated with increases in running speed (Nantel et al., 2006; Nantel et al., 2011; Shultz, D'Hondt, Lenoir, et al., 2014). The inability to alter stride angle is reflective of OB children’s reduced articular range of motion in hip flexion, hip adduction, and knee flexion, compared to NW children (Joao et al., 2014). The alteration in stride profile was associated with BMI ($r=0.18$, $P=0.09$).

Reduction or impairment in range of motion (ROM) would detrimentally affect movement quality and performance during the MSFT (Joao et al., 2014; Nantel et al., 2011; Shultz, D'Hondt, Lenoir, et al., 2014). In fact OB children, who displayed a greater stride profile quotient score, also had a significantly lower TTE than every other BMI group (Table 1, Table 2). This indicates that overall performance on a standardised fitness test may be effected by stride profile.

This work is supportive of laboratory based findings that OB children have an altered gait and impaired articular ROM; this is reflected by the in-field movement quality characteristic, stride profile quotient, and demonstrates that during a standardised fitness test, stride profile is linked to BMI.

4.3.1. Stride characteristics

Three stride characteristics, integrated acceleration, stride angle and stride variability were clustered together, at a cophenetic distance of 0.57. Spearman's rho test also demonstrated very similar relationships for all three characteristics with BMI (integrated acceleration: r=-0.22, *P*=0.02, stride angle: r=-0.23, *P*=0.03, stride variation: r=-0.22, *P*=0.03) The weak negative correlation coefficient between BMI and integrated acceleration is also supported by previous literature, where OB children have been shown to move less and with greater difficulty than their NW counterparts (Shultz et al., 2010), in addition to demonstrating a reduced velocity compared to NW children (Hill & Parker, 1991; McGraw et al., 2000; Shultz et al., 2010). The difficulty in movement in OB compared to NW children is also reflected in their inability to effectively alter stride angle, which further diminishes TTE.

Although similar relationships were found between integrated acceleration, stride angle and stride variability with BMI (Table 1), there were underlying differences between these characteristics. Stride angle was found to be significantly different between OB and UW, and OB and NW (Table 1). Further, despite the significant relationship between integrated acceleration and BMI, it was not significantly different between groups (Table 1, Figure 2). Neither were there any significant differences in stride variation between any groups (Table 1, Figure 3).

The movement quality characteristics of integrated acceleration, stride angle and stride variability were close cophenetically linked characteristics, as illustrated in the clustergram (Figure 5) These data provided novel insights into children's movement quality when performing the MSFT. For example, although stride angle was significantly different between OB and NW and OB and UW children, the quantity and variability remained consistent across BMI groups (Table 1, Figure 2). Furthermore, although high stride frequency affected gait in obese children (Shultz et al., 2010), this study did not find any statistical differences between BMI group for stride frequency or stride variation (Table 1, Figure 3). Therefore, neither stride frequency, nor stride variation, precluded high TTE in the MSFT. Stride angle appears to play a pivotal role in the stride profile and performance of children taking part in the MSFT. In conclusion multiple characteristics drawn from an accelerometer signal can be used to build a broader picture of children's movement quality during a standardised fitness test and these may also be applicable to measures of habitual physical activity.

4.4. Limitations

There were a number of limitations to this study. First the clustering algorithm was structured using hierarchical methods pairing characteristics by proximity. However this means it may not be instinctively obvious if characteristics are anti-correlated, for instance there was a clear negative association between BMI and spectral purity. On the other hand, this can be overcome with careful interpretation of the clustergram and in addition to other correlation analyses (i.e. Spearman's rho). This study sought to employ novel analysis techniques to assess movement quality characteristics, and although TTE was recorded, no inferences to physiologic outputs (e.g. estimated $\dot{V}O_{2max}$, peak $\dot{V}O_2$, heart rate variability) or psychological aspects were made as this was beyond the scope and aims of the study. Finally, this study did not incorporate analysis of gait characteristics at the point of turning, there is body of literature specifically investigating turning strategy and including it in our analyses would have detrimentally impacted mean and standard deviation values and thus, the authors' recommend that this be investigated further.

5. Conclusion

The first aim of this study was to apply automated, novel analyses to characterise the movement quality of children during the MSFT. This investigation found that key gait characteristics of children's running performance during the MSFT could be derived.

The second aim was to report how movement quality characteristics of gait cluster according to BMI. This study has shown clustering between a performance/fitness outcome, frequency and harmonic content of movement and BMI during a standardised fitness test and, that movement quality in children of higher BMI (OB), is characterised by significantly lower stride angle, significantly lower TTE and significantly lower spectral purity than OW, NW and UW counterparts.

Finally further investigations into age, gender and movement characteristics other than running are required before the relationship between movement quality characteristics and performance/fitness in children can be elucidated. This research will provide further insights into the development of physical competency and fitness in children.

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7. Conflict of Interests

The authors declare that there are no conflict of interests regarding the publication of this paper.

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