A PEDIATRIC CORRELATIONAL STUDY OF STRIDE INTERVAL DYNAMICS, ENERGY EXPENDITURE AND ACTIVITY LEVEL

Running head: Pediatric SI Dynamics, Energy & Activity

ABSTRACT

The strength of time-dependent correlations known as stride interval (SI) dynamics has been proposed as an indicator of neurologically healthy gait. Most recently, it has been hypothesized that these dynamics may be necessary for gait efficiency although the supporting evidence to date is scant. The current study examines over-ground SI dynamics, and their relationship with the cost of walking and physical activity levels in neurologically healthy children aged nine to 15 years. Twenty participants completed a single experimental session consisting of three phases: 10 minutes resting, 15 minutes walking and 10 minutes recovery. The scaling exponent (α) was used to characterize SI dynamics while net energy cost was measured using a portable metabolic cart, and physical activity levels were determined based on a 7-day recall questionnaire. No significant linear relationships were found between α and the net energy cost measures ($r<0.07$; $p>0.25$) or between α and physical activity levels ($r=0.01$, $p=0.62$). However, there was a marked reduction in the variance of α as activity levels increased. Over-ground stride dynamics do not appear to directly reflect energy conservation of gait in neurologically healthy youth. However, the reduction in the variance of α with increasing physical activity suggests a potential exercise-moderated convergence towards a level of stride interval persistence for able-bodied youth reported in the literature. This latter finding warrants further investigation.

Keywords: gait, stride-to-stride fluctuations, exercise, detrended fluctuation analysis

INTRODUCTION

The analysis of gait has become incredibly advanced with the development of technologies such as motion capture, electromyography, force plates, and portable gas analysis systems. However, limitations such as the cost of equipment, time required for data collection and the invasive nature of the equipment suggest the need for more practical means of quantifying gait abnormalities [33]. The measurement of stride interval dynamics is inexpensive, non-invasive, and has shown promise as a potential tool for gait analysis [14].

The stride interval (SI), defined as the time between consecutive heel strikes of the same foot, exhibits fluctuations from one stride to the next. Traditionally, it was believed that individuals exhibit a preferred average SI, around which any variation was identified as random noise. However, recent non-linear time series analyses have revealed time dependent correlations embedded in the variation of SI data [17]. Essentially, SI fluctuations up to an hour apart exhibit statistical persistence, which can be quantified by the scaling exponent, α, typically determined using detrended fluctuation analysis (DFA) [5]. An α value of 0.5 indicates that the stride times in the SI time series are uncorrelated, while $0.5<\alpha<1.0$ indicates statistical persistence in the time series [30]. Research has shown α to be sensitive to changes in neuromuscular function, age and speed [15, 16, 23].

To determine the stability of statistical persistence, Hausdorff et al. performed walking trials at participants' slow, comfortable and fast walking speeds [18]. Stride interval time series remained in the statistical persistent range regardless of walking speed. Subsequently, Jordan et al. corroborated this finding, and further, showed that the scaling exponent relates to speed in a U-shaped manner; with the lowest α value (0.70<α<0.75) occurring at the individual's comfortable walking speed [23].

Statistical persistence also exhibit a unique developmental profile, evolving from primitive patterns in toddlers to robust correlations by pre-adolescence. In a study of 50 healthy children 3 to 14 years of age, the scaling exponent was highest in the youngest children, and tended to decrease towards adult values in the oldest age group [16]. These findings suggest that SI dynamics may not be fully developed in children 7 years of age, although they are typically regarded as having mature gait [22]. Exploring the opposite end of the age spectrum, the gait of elderly participants has been shown to lack the statistical persistence characteristic of the younger adult population [15, 27].

Numerous studies have shown that some neurological disorders can affect stride interval correlations. The values for statistical persistence in participants with Huntington's disease (HD) [15], Parkinson's disease (PD) and cerebral palsy [6] differ from those values in healthy young adults. In fact, the scaling exponent decreased linearly with the degree of functional impairment in the HD population.

Interestingly, the previously mentioned conditions that induce changes in α are also known to affect the energy cost of walking. For example, an individual's preferred walking speed (PWS) is that at which the metabolic cost is minimized [9]; when walking at speeds slower or faster than the PWS, energy consumption increases in a U-shaped fashion. This relationship mirrors the reported behaviour of α at varied walking speeds [23].

To date, only two studies have examined α and the energy cost of walking. Most recently, an investigation of SI dynamics in children aged 4-7 years identified no correlation between α and energy cost [10]. However, this study only examined the gross energy cost of walking, which represents the total cost of walking inclusive of resting cost [32]. It is possible that between-participant variability in the resting state could mask metabolic trends due solely to walking. The net energy cost, the difference between the total cost and resting cost, is therefore more suitable than the gross cost as a measure of energy consumption due to walking [32]. Additionally, until age 7 a child's gait is not fully optimized with respect to physiological, neural and musculoskeletal systems [22]. With so many factors inducing energetic and temporal variability, it is perhaps not surprising that no correlation was found.

An earlier study looking at α and energy cost in both adult and elderly males found no association between the two measures [27]. However, the scaling exponents were estimated on the basis of only six minutes of walking data. Recent guidelines for use of DFA with gait data recommend a minimum of 600 strides for statistically stable estimation of α [8]. Given that healthy adults exhibit a preferred stride time of approximately 1s, a value that increases with age and pathology, it is unlikely that participants in Malatesta et al. achieved the recently recommended minimum number of strides [27]. While no relationship was found between α and energy cost, a positive correlation was identified between α and physical activity levels [27]. A more recent study identified the opposite relationship between SI dynamics and activity levels, in which trained runners tended to exhibit a lower α value than non-trained runners [29]. Hence, the current evidence is inconclusive about the relationship between alpha, energy cost and physical activity.

The present study aimed to develop a better understanding of the relationship between the strength of statistical persistence, the net energy cost of walking and activity levels in typically developing children, 9-15 years, an age at which gait is considered mature [9, 22]. A defined relationship between α and physical activity could also provide insight into the physiological mechanisms responsible for stride interval persistence, which to date remain unclear [10].

METHODS

Participants. Twenty able-bodied children (three male) from a community aquatics program and various neighborhood elementary schools volunteered to participate in the study. The children participated during the academic school year (September – April). Participants had no history of neurological, musculoskeletal or cardiovascular injury or illness that would affect their gait or respiration. The mean age of participants was 11.3 ± 1.9 years. Mean height and mass were 1.53 ± 0.13 m and 45.61 ± 10.66 kg, respectively.

The study was cleared by the Research Ethics Board of Holland Bloorview Kids Rehabilitation Hospital (Toronto, Canada). Participants and their guardians provided informed written assent and consent prior to participation in the study.

Instrumentation. Heel strike data were collected using paper-thin force sensitive resistors (FSR) secured under the heel of each shoe (Model 406, Interlink Electronics, USA). Information from the FSR's was recorded to a personal digital assistant (PDA; #X11-15454, Hewlett-Packard) at a rate of 250Hz. The wires from the sensors were clipped to the participant's pants or shorts to reduce interference with normal walking.

The energetic cost of walking was estimated using the Cosmed K4b^2 (Cosmed, Italy), a portable gas analysis system that measures oxygen consumption and carbon dioxide production on a breath-by-breath basis. The experimental setup is depicted in Figure 1, showing the equipment worn by participants during the session. The $K4b^2$ system consists of a data processing unit containing O_2 and CO_2 analyzers, a battery pack, and a silicon facemask that harbours the flow-rate turbine and gas sampling line. Facemasks were fitted to each participant to ensure an airtight seal around the nasal and oral cavities. Heart rate data were obtained via a heart rate transmitter fastened around the chest (WearLink 31, Polar Electro, Finland).

The processing unit of the $K4b^2$ was worn on the chest, while the battery pack and PDA were carried on the participant's back. All equipment was affixed using an adapted version of the harness provided by Cosmed. The total weight of the equipment was approximately 1.8kg. All equipment was calibrated according to manufacturer's specifications. Prior to each trial, the turbine was calibrated with a 3-1 syringe, and a two-point calibration of the O_2 and CO_2 analysers was carried out using ambient air and a standard calibration gas mixture.

Physical Activity Questionnaire. Participants filled out the physical activity questionnaire for older children (PAQ-C), a 7-day physical activity recall to assess general activity levels [26]. This questionnaire was developed as a method of discerning physical activity levels in school-aged children. In the case that a participant was of high school age, or did not have recess at their school, the PAQ-A was administered. The PAQ-A is a slightly modified version of the PAQ-C with the "recess" item removed, making it applicable to high school students. The questionnaires consist of eight (PAQ-A) to nine (PAQ-C) questions related to activity habits during the school week. The first question of both the PAQ-C and PAQ-A consists of a checklist of 22 common physical activities, with 2 additional lines to specify "other" activity choices. Each activity is rated on a 5-point ordinal Likert scale that reflects the frequency of that activity in the last 7 days (1 = activity performed 0 times; 5 = activity performed 7 times or more). The overall score for this question is the mean rating across all activities. The remaining questions probe general physical activity on a time-of-day or day-of-the-week basis, also on a scale of 1 to 5. The average of all individual question scores yields a final physical activity score between 1 and 5. The PAQ-C and PAQ-A have been tested for various psychometric properties and have shown moderate to moderately high test-retest reliability ($r = 0.30$), internal consistency (Cronbach's $\alpha = 0.72$-0.88), sensitivity to age and gender differences, and concurrent validity when compared against an activity monitor (Actigraph, $r = 0.47$, $p<0.05$) [21, 26, 28].

Procedure. All participants wore comfortable walking shoes and were familiarized with the experimental equipment and protocol. The participant's age, height and mass (m) were recorded. No pre-session fast was requested, as this study examined the net cost of walking, which subtracts the resting level, and thus mitigates the effect of feeding-induced thermogenesis [32].

Study sessions consisted of three phases: rest, walk, and recovery. Each experiment began with the resting phase in which children were suited with the equipment and asked to sit quietly for 10 minutes while watching cartoons. During this time, resting oxygen uptake data were collected. Schwartz et al. found that 10 minutes of data collection was required to reliably estimate resting energy [32]. Before the walking phase began, investigators accompanied participants on two warm up laps around the rectangular path (84.9m long, 2.43m wide) to ensure familiarization with the equipment. If equipment was restricting normal walking in any way, adjustments were made and warm up laps were repeated until the participant could walk comfortably.

The walking phase involved 15 minutes of walking at a comfortable pace. Comfortable pace was described to the participants as the pace they would walk if they were on their way home from school. As children exhibit an average stride interval time of approximately 1.0s, fifteen minutes of continuous walking was required to ensure enough strides were collected to obtain stable estimates of α [8]. The time required to complete each lap was measured using a hand-held timer, and speed (*v*) was determined by dividing the average lap time by the distance covered in each lap (84.9m). Researchers walked behind participants to avoid influencing walking speed.

The recovery phase was similar to the resting phase; participants sat quietly watching cartoons for 10 minutes while oxygen uptake data were collected. Upon completion of the recovery phase, all equipment was removed, and participants were asked to complete the questionnaire.

Data Analysis. Stride intervals were extracted from the heel strike data using a probabilistic SI extraction algorithm that locates heel strike times through changes in magnitude and slope of the force [6]. From the extracted stride intervals, strides that fell outside 0.01% and 99.99% of a gamma distribution fit were eliminated. These strides were considered as unphysiologically long or short and were likely due to occasional sensor noise [10]. To minimize 'start up' and 'end' effects, 30 seconds of data were trimmed from the beginning and the end of each time series. Then, the scaling exponent was determined using DFA from the remaining 14 minutes of data [8]. A detailed description of DFA can be found in [30]. Briefly, the root-mean-square fluctuations of integrated and detrended data are measured in observation windows of various sizes, and then plotted against the size of the window on a log-log scale [20]. The scaling exponent, α, represents the slope of this line on a log-log plot. The variance of the SI time series was evaluated using the coefficient of variation (CV).

Steady state values of metabolic data were determined after 2 minutes of acclimatization to the sitting and walking tasks [1]. Determination of steady state breaths followed the procedure proposed by Schwartz [32]. For the measurement at each breath, we formed a window of observation encompassing recordings within ±90s of the breath under consideration. For each 180s window of data, we tested the null hypothesis of steadiness using Kendall's Tau. If the null hypothesis was not rejected, the recording under consideration would be labeled as occurring within a "steady state breath". The overall steady state value for each condition (resting, walking or recovery) was then defined as the average of all values coinciding with steady state breaths. From the oxygen uptake data, the following variables were calculated:

Net Energy Consumption

$$\dot{V}O_2^{net} = \dot{V}O_2^{gross} - \dot{V}O_2^{rest} \times 20.1\,\mathrm{J/mL\ O_2}$$

Net Energy Cost

$$VO_2^{net} = \left(\frac{\dot{V}O_2^{gross} - \dot{V}O_2^{rest}}{v} \times 20.1\,\mathrm{J/mL\ O_2} \right)$$

Mass Specific Net Energy Cost

$$VO_2^{net}/\mathrm{kg} = \left(\frac{\frac{\dot{V}O_2^{gross} - \dot{V}O_2^{rest}}{v} \times 20.1\,\mathrm{J/mL\ O_2}}{m} \right)$$

where, as previously denoted, *v* is the speed of walking, and *m* is the mass of the participant. VO_2^{net} was determined in the pre-exercise phase, where the participant was sitting quietly for ten minutes, allowing resting energy cost to be measured. Resting VO_2 values were recorded during sitting.

An energy equivalent of 20.1 J/mL O_2 was used to convert oxygen uptake data into energy consumption [3]. The use of a constant term for conversion of oxygen to energy values has been validated in children older than 6 years of age [31, 35].

Participants were divided into two groups based on activity levels. The ‘high activity’ group included children with activity scores above three, and those with activity scores below three were deemed the ‘low activity’ group (no scores were equal to three). A score of three was used as the divisor, as it represented both the mid-point of the activity scale and the mean of the study population’s activity scores.

The Mann-Whitney test was used to test for differences in energy and stride variables between low and high activity subgroups. A linear regression analysis is used to explore potential trends between the variables. In all analyses, results were considered statistically significant if $p<0.05$.

RESULTS

Table 1 provides descriptive statistics of the study population, and Tables 2 and 3 summarize the results of the between-group analysis. No variables in Tables 2 and 3 exhibited statistical difference between the two activity levels (minimum $p>0.059$). A linear regression analysis revealed no statistical dependence between the scaling exponent and any other variable ($p > 0.129$). Lastly, activity level shared no dependence with the net energy cost measures, $\dot{V}O_2$ ($p=0.602$), VO_2 ($p=0.788$), VO_2/kg ($p=0.082$).

However, the between-participant variability of α was markedly reduced as activity levels increased (Figure 2). The reduction of variance was quantified by performing an F-test between the alpha values of the low and high activity groups. The difference in the variance of the two groups approached significance (F=3.66, p=0.054).

A linear regression analysis was used to identify any age effects on the considered variables. Height, mass, average SI time, CV, and VO_2/kg ($p < 0.039$) were all associated with age, whereas speed, activity score, α, $\dot{V}O_2$, VO_2 exhibited no significant linear relationship with age ($p > 0.456$).Similarly, the regression analysis revealed that activity levels were not associated with any other variables ($p > 0.082$).

DISCUSSION

In an effort to better understand the relationship between the strength of statistical persistence, energy cost and physical activity levels, this study examined overground walking in children at an age at which gait is generally considered to be mature. No simple linear relationships were identified between the energy cost of walking, physical activity and α. However, the variance in α tended to decrease as activity levels increased across the study population. All variables, including energy cost, α and the speed of walking were within the normal range reported for individuals of the same age [9, 16, 38].

The scaling exponent demonstrated no dependence on age, suggesting that SI dynamics as described by the statistical persistence were mature in the individuals studied. We further explored this finding by comparing the α values obtained in this study with those from previous reports. We found that the α values reported in this study are well within the published range for healthy adults. Thus, we contend that SI dynamics appear to be mature in children over the age of 9 years.

The lack of correlation found between α and the physiological cost of walking is consistent with that of previous studies in younger children [10] and the elderly [27]. This finding could be partially attributed to the relatively small data set, though participants exhibited a range of energy cost and α values similar to those of other studies [9, 10, 16]. Therefore, corroborating previous investigations [10, 27], our present findings would suggest that SI dynamics are not reflected in the energy cost of walking in healthy, typically developing individuals.

Physical activity levels and α were not significantly correlated with each other. This finding may be a consequence of the homogeneity of the study sample in terms of physical activity levels. The majority of the children involved in this study were very active, and as such the range of physical activity scores was relatively small and may have only represented a limited region of the alpha-energy plane. It is conceivable that α may be robust to a range of variations of energy cost as a natural adaptive gait timing control mechanism, just as α is robust to dual-tasking, and peripheral feedback [13, 25]. Kiefer et al. suggested that a change in α due to dual-tasking may require the performance of a more attention-demanding assignment than tapping [25]. Perhaps, an α-energy dependence emerges only at extreme levels of energy expenditures. To explore this conjecture, a future study ought to include individuals known to have exaggerated energy costs during walking (e.g., children with spastic diplegic cerebral palsy).

The lack of correlation between activity level and scaling exponent may also be attributed to the limited sensitivity of the questionnaire. In particular, the PAQ-C/PAQ-A does not provide information regarding the duration or intensity of activity performed [26]. For example, an “after school activity" may be moderate intensity, such as a leisurely bike ride, or high intensity, such as a competitive soccer practice. This additional level of discernment would yield a more realistic physical activity score reflecting the frequency, duration and intensity of activity. Lack of sensitivity of the questionnaire would also help explain why children with higher physical activity levels were found to exhibit a higher cost of walking in this study. We suggest that future investigations utilize either a questionnaire with both time and intensity data, or more objective measures of daily physical activity such as heart rate monitors or accelerometers [2].

Although physical activity level did not exhibit a simple linear relationship with α, an interesting pattern in α variation was observed. Generally, the between-participant variation in α decreased as activity levels increased. In fact, between participants with the lowest and highest activity levels, the variation in α dropped by approximately 60%. This interesting finding could suggest that the locomotive practice facilitated by physical activity further refines SI scaling properties after maturation. Furthermore, previous work has demonstrated that an alteration in joint/muscle function is observed to be accompanied by a greater physiological cost of walking. It is plausible that limb/trunk mechanics may be additional parameters that have shared variance with the physiological cost of walking.

Training has been shown to improve efficiency, optimize muscle activation, and decrease variability in interlimb coordination [34]. Specifically, practice refines intended movements by reducing SI variability as measured by the coefficient of variation (CV) [12, 29]. The findings of the current study are exceptional in that the reduction in variability is not reflected in the CV of the SI, but in the variance of the scaling exponent of the participants. A potential explanation for this discrepancy could be that the aforementioned studies investigated the effect of task-specific practice, thereby reducing the task-specific CV, employing target movements, whereas the current study examined daily physical activity as a form of general locomotor practice, thus minimally affecting SI variability, but more broadly impacting motor timing [12]. The apparent exercise-moderated reduction in the variance in α may represent the convergence of SI dynamics to previously reported normal levels [20].

The reduction in the variability of α with respect to activity level is supported by the common core hypothesis of human movement [39]. This hypothesis states that "all forms of rhythmic human movement share a similar neural control, which can be thought of as a common core composed of oscillatory neurons that drive the basic motor pattern"[39]. Thus, participation in any activity involving rhythmic movement (i.e., cycling, skating, and swimming) would translate into training of the common core. Furthermore, the neuronal group selection theory suggests that practice can optimize the selection of motor commands, reducing the variability of the output [11].

In the present study, it would be presumptive to say that α is converging towards optimal levels, as no optimal α value has been prescribed in the literature. The α values reported in this paper fall within the same range of α values previously reported in the literature for healthy adults, leaving no discernible 'optimal' value for the scaling exponent. This is in large part due to the different lengths of data studied, and different window sizes used for analysis. For α to become useful as tool for monitoring disease progression and assessment of therapeutic interventions, it is necessary to identify normative values for the populations studied. That being said, it is highly recommended that future studies of SI scaling properties follow methodological guidelines (such as those outlined in [8]) in order to facilitate accurate comparisons across studies.

The health benefits of physical activity are irrefutable. Regular exercise has been shown to be a powerful preventative tool against cardiovascular disease, diabetes, hypertension, obesity and depression to name a few [37]. The findings of this study suggest that habitual physical activity may also help to tune the complex temporal coordination of walking. However, future investigations of the effect of physical activity on α with larger populations and more varied habitual activity levels among participants are necessary to better elucidate this relationship. Specifically, prospective studies of the effect of exercise interventions on α, such as those in the cardiovascular literature, could provide insight into the effects of physical activity as well as the mechanisms controlling the complex SI fluctuations.

Lastly, it should be pointed out that while resting VO2 values were estimated in a seated posture, we do not expect gross differences between resting energy expenditure in sitting and standing positions, as suggested by a recent study with adult participants [40]. One third of the participants in that study showed no difference between resting energy expenditure values estimated from quiet standing and sitting. Only 18% of participants showed elevated energy expenditure during standing. For the remainder, standing energy expenditure started at higher levels but approached sitting levels during the latter half of the measurement. Overall, the average increase in energy expenditure was less than 6%. A future pediatric study would be required to confirm definitively the equivalence of sitting and standing resting energy estimates in children. We do reiterate that for practical purposes (given the pediatric population), a sitting rest energy expenditure measurement was logistically more convenient.

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Captions of Tables

Captions of Figures

TABLE 1

Variable	Minimum	Maximum	Mean	SD
Average SI time	0.910	1.220	1.075	0.078
SI coefficient of variation (CV)	0.016	0.047	0.029	0.007
Speed (m/s)	0.990	1.510	1.260	0.138
Activity score	2.052	3.926	2.999	0.576
α	0.649	1.071	0.853	0.117
$\dot{V}O_2$ (J/s)	51.03	160.3	116.3	37.08
VO_2 (J/m)	41.91	118.0	91.56	19.80
VO_2/kg (J/kg/m)	1.466	3.175	2.045	0.418

TABLE 2

Variable	Low activity (n = 8)	High activity (n = 12)	*p*
Age (yrs)	11.25 ± 1.981	10.83 ± 2.125	0.662
Height (cm)	154.5 ± 13.98	151.5 ± 13.34	0.589
Mass (kg)	49.75 ± 11.54	42.85 ± 9.528	0.105
Average SI time	1.098 ± 0.062	1.060 ± 0.086	0.297
SI coefficient of variation (CV)	0.028 ± 0.007	0.030 ± 0.007	0.787
Speed (m/s)	1.234 ± 0.153	1.278 ± 0.130	0.487
α	0.882 ± 0.157	0.833 ± 0.082	0.464
$\dot{V}O_2$ (J/s)	112.2 ± 33.51	118.9 ± 91.23	0.616
VO_2 (J/m)	90.84 ± 23.24	92.04 ± 18.24	0.847
VO_2/kg (J/kg/m)	1.831 ± 0.294	2.188 ± 0.437	0.059

FIGURE 1:

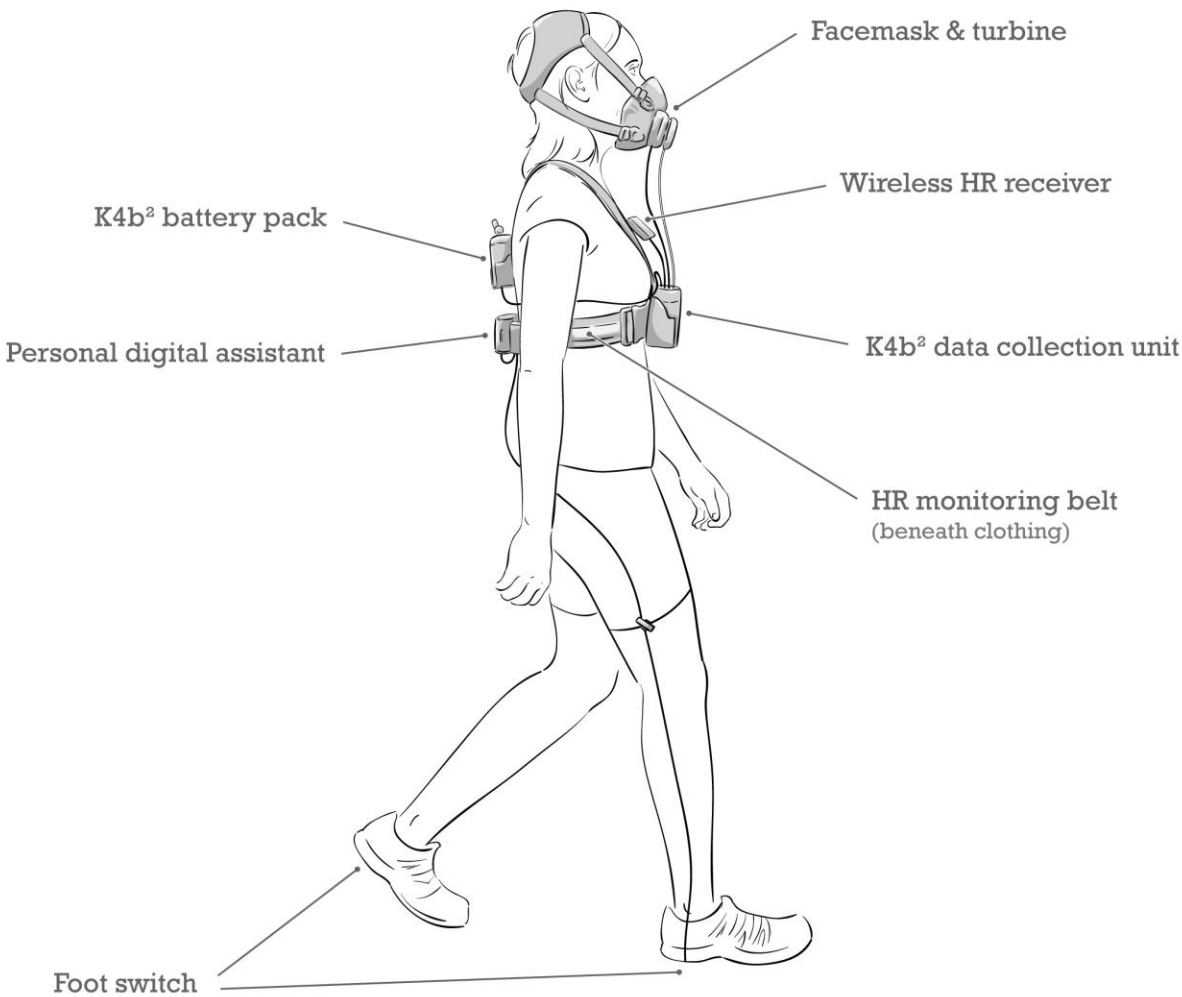
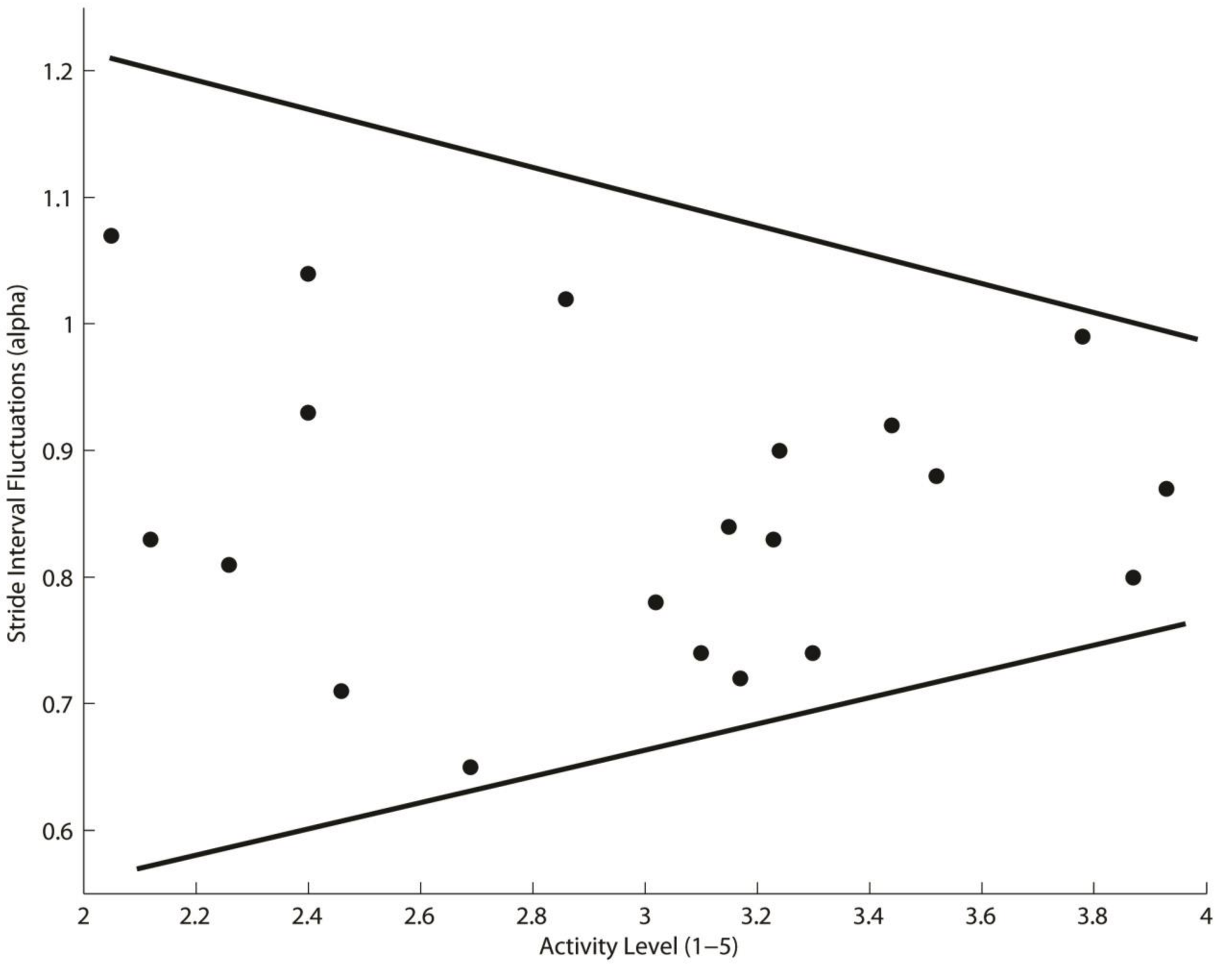

Facemask & turbine
Wireless HR receiver
K4b² battery pack
Personal digital assistant
K4b² data collection unit
HR monitoring belt
(beneath clothing)
Foot switch

FIGURE 2


Stride Interval Fluctuations (alpha)
1.2
1.1
1
0.9
0.8
0.7
0.6
2
2.2
2.4
2.6
2.8
3
3.2
3.4
3.6
3.8
4
Activity Level (1–5)