Energy Cost of Running Instability Evaluated with Wearable Trunk Accelerometry

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ABSTRACT

Maintaining stability under dynamic conditions is an inherent challenge to bipedal running. This challenge may impose an energetic cost (Ec) thus hampering endurance running performance, yet the underlying mechanisms are not clear. Wireless tri-axial trunk accelerometry is a simple tool that could be used to unobtrusively evaluate these mechanisms. Here, we test a *cost of instability* hypothesis by examining the contribution of trunk accelerometry-based measures (tri-axial root mean square, step and stride regularity, and sample entropy) to inter-individual variance in Ec (kcal.km^{-1}) during treadmill running. Accelerometry and indirect calorimetry data were collected concurrently from 30 recreational runners (16 men; 14 women) running at their highest steady-state running speed (80.65 ± 5.99% VO_2 max). After reducing dimensionality with factor analysis, the effect of dynamic stability features on Ec was evaluated using hierarchical multiple regression analysis. Three accelerometry-based measures could explain an additional 10.4% of inter-individual variance in Ec after controlling for body mass, attributed to anteroposterior stride regularity (5.2%), anteroposterior RMS ratio (3.2%), and mediolateral sample entropy (2.0%). Our results lend support to a *cost of instability* hypothesis, with trunk acceleration waveform signals that are 1) more consistent between strides anteroposterioly, 2) larger in amplitude variability anteroposterioly, and 3) more complex mediolaterally, are energetically advantageous to endurance running performance. This study shows that wearable trunk accelerometry is a useful tool for understanding the Ec of running, and that running stability is important for economy in recreational runners.

NEW & NOTEWORTHY

This study evaluates and more directly lends support to a *cost of instability* hypothesis between runners. Moreover, this hypothesis was tested using a minimalist setup including a single tri-axial trunk mounted accelerometer, with potential transferability to biomechanical and performance analyses in typical outdoor settings.

KEYWORDS

Wearable technology; trunk accelerometer; energy cost; running instability; running economy

GLOSSARY

AP	anteroposterior
BLa	blood lactate
BMI	body mass index
CPU	central processing unit
CoM	center of mass
Ec	energetic cost
g	acceleration due to gravity
HR	heart rate
ML	mediolateral
OBLA	onset of blood lactate accumulation
RER	respiratory exchange ratio
RMS	root mean square
V_{OBLA}	highest treadmill velocity prior to OBLA
VO_2	oxygen consumption
VO_2 max	maximal aerobic power
V_{peak}	peak treadmill speed
VT	vertical

INTRODUCTION

Running economy is widely accepted as a key determinant of endurance running performance. Running economy is also a complex, multifactorial phenomenon with numerous anthropometrical, demographic i.e. age- sex- and ethnic-related, physiological, biomechanical, and neuromuscular determining factors (5, 23, 28). Of these factors, establishing a biomechanical basis to running economy continues to be of interest to researchers and coaches. For example, using biomechanical principles such as drafting, lighter shoes, and course elevation drop has recently been proposed as quantifiable strategies needed to reduce energy cost and break the two-hour marathon barrier (17). A biomechanical basis for running economy is also intuitive from a running 'technique' standpoint. Although the majority (~80%) of running economy is determined by the cost to support body mass (4), a most recent review has revealed that superior running economy has its strongest direct links to running technique characteristics such as less leg extension at toe-off, larger stride angles, alignment of the ground reaction force and leg axis, and low activation of the lower limb muscles (28).

Despite the plethora of studies examining biomechanical or running 'technique' links to economy (4, 14, 22, 30, 34, 37, 46, 51), the upper extremity with respect to trunk control or dynamic postural stability has been largely ignored. Evolutionary theory suggests that while structural adaptations have allowed humans to have a more stable and less energetically costly running gait, human running remains unwieldly and prone to instability (9, 25). Indeed, trunk control has been identified as a critical component of locomotor efficiency (38). During ground contact a runner must activate muscles sufficiently to ensure adequate stability while also maintaining forward momentum (14). Electromyography has demonstrated that during human running, the back extensors activate early to control forward momentum during impact, while abdominal obliques' actively decelerate the thorax during second half of stance (35). The increased activation of these trunk muscles could help explain earlier findings relating trunk lean to running economy (51). For example, aside from a comprehensive set running gait characteristics, Williams and Cavanagh (51) showed that a group of distance runners with the best running economy exhibited greater mean forward trunk lean relative to the vertical compared to runners with middle and least economical groups (51). Other previous work indicates that larger horizontal plane lumbo-pelvic motion while running relates to augmented activity of both abdominal and the superficial multifidi muscles (38). Therefore, it is plausible that various characteristics of dynamic stability or trunk kinematics in 3D could influence the activation levels of these stabilizing muscles as well as running economy.

The effects of upper extremity posture on walking and running economy has been indirectly assessed by removing stability (2, 3, 48). For example, instability induced by supressing arm swing increases energetic cost (Ec) by 7.7% and 7.6% while walking (48) and running (3) respectively. The maintenance of lateral balance i.e. additional step width variability has been a primary yet refuted mechanism for this increase (3), reasoned that other unknown aspects of dynamic stability could account for this increased energetic cost. Alternative explanations may include compensatory strategies in torso rotation or increases in the free moment in the horizontal plane (3). Moreover, dynamic instability as reflected by larger lateral and horizontal total excursions or exacerbated accelerations of the CoM could also account for increased energy cost without arm swing (15).

Wearable trunk accelerometers provide a new level of analysis for dynamic stability of human locomotion. Accelerometers have improved from an accuracy, sensitivity, and computing power standpoint and have enabled more sophisticated analyses of motion. When mounted to the lower trunk, accelerometry unobtrusively estimates CoM motion and thus allows for several aspects of dynamic stability to be captured. These stability aspects, whether it function vertically i.e. body weight support, mediolaterally i.e. side-to-side balance control, or anteroposterioly i.e. braking and propulsion could more directly test various biomechanical hypotheses underpinning running economy. To the knowledge of the authors only two studies (26, 49) and one pilot study (32) have previously used trunk accelerometry-based measures to estimate energy expenditure while running. Unfortunately, these studies (26, 49) did not investigate submaximal running economy specifically, by including running intensities beyond aerobic i.e. ranging to maximal aerobic capacity in their regression analyses. Additionally, these studies either did not assess (32, 49) or did not delineate (26) inter-subject variations in running economy. Therefore, it remains unclear which trunk-accelerometry based aspects of dynamic stability may be economically favourable for endurance running. Several linear and non-linear stability aspects are worthy of investigation.

Firstly, higher amplitudes or variations of trunk accelerations expressed as the acceleration root mean square (RMS) could reflect excessive changes in momentum that are energetically wasteful (14). Vertically, this is plausible since runners with poor economy often demonstrate larger vertical oscillation of the pelvis (12) and CoM (12, 46, 51), which may translate to larger vertical accelerations. Horizontally, this is plausible since coordination patterns of the pelvis and spinal segments during running function to minimize both ML and AP changes in momentum (35, 38). Indeed, Folland et al.,(12) recently found that runners with greater minimum AP horizontal velocity of the pelvis i.e. more deceleration/braking were more energetically costly. Poor trunk coordination could therefore increase energetic cost via larger changes in horizontal momentum (15). In partial support, trunk accelerations in the ML and AP direction have shown to increase due to running induced fatigue (24, 40).

Secondly, the dominant autocorrelations of acceleration waveforms could empirically test whether the ability to maintain a global consistency either between steps or strides are influential on economy. Step regularity indicates bilateral (a)symmetry and could evaluate the notion that as occurring in cars, dynamic asymmetries could generate a higher energetic cost to travel a given distance (43). Stride regularity indicates consistency between strides, and sticking with the car analogy, inconsistencies thereof could be synonymous to a driver rapidly and/or more frequently applying accelerations i.e. “gas-brake-gas” that result in increased fuel consumption.

Thirdly, the sample entropy of trunk accelerations accounts for the complexity of the trunk acceleration signal waveform and could assess whether overall fluidity of a runner’s gait pattern is related to economy (1). Sample entropy is a non-linear measure that might be sensitive enough detect movement efficiencies masked by linear measures such as the RMS.

Here, we test a *cost of instability* hypothesis that proposes a link between a runner’s stability and running economy, and that this link can be assessed using measures derived from wearable tri-axial trunk accelerometry. Specifically, we hypothesize that runners running with less deviations in CoM motion such as 1) less amplitude variability (RMS); 2) higher symmetry; 3) higher consistency; and 4) less complexity have a running gait that is energetically advantageous. We experimentally evaluate these hypotheses using simple and non-linear measures including 1) the RMS; 2) inter-step 3) inter-stride regularity, and 4) the sample entropy of waveforms of each acceleration axis (vertical, ML, AP), each of which express unique aspects of dynamic stability during running. Additionally, since low-pass filtering of acceleration waveform is a common, yet often questioned pre-processing approach, we further assessed whether leaving accelerations unfiltered prior to calculating stability measures would explain more inter-individual variance in Ec.

METHODS

Subjects. Thirty recreational to moderately trained runners including 16 men and 14 women (aged 19-26 years with running experience of 5 - 10 years) volunteered to be part of this study. To be included in the study runners had to be running regularly (2 – 4 sessions per week; 15 – 40 km/week) and have prior experience with treadmill running. All subjects were screened to have no known history of metabolic, neurological, cardiovascular disease, or surgery to the back or lower limbs, and were symptom-free of any lower extremity injury for at least six months prior to the study. All runners provided written informed consent prior to participation in accordance with the Declaration of Helsinki. The local ethics committee of Stellenbosch University approved the study (# SU-HSD-002032).

Incremental treadmill running speed test. Subjects were asked to refrain from alcohol, caffeine, and vigorous physical activity for 24 h before the session. They were also instructed not to consume any food or drink, other than water, during the 90 min before the testing session. All subjects indicated “excellent” as their self-reported motivation for exercise testing on the day. Subjects performed a maximal incremental running test to exhaustion at 1% slope on a motorized treadmill (Saturn h/p/cosmos, Nussdorf-Traunstein, Germany), starting at a running speed of 2.22 m•s^{-1} or 2.5 m•s^{-1} depending on individual comfort and previous experience. A warm-up of four minutes’ equivalent to starting speed was first provided, after which treadmill speed was increased discontinuously in increments of 0.42 m•s^{-1} every four minutes interspersed by a one-minute rest until volitional exhaustion. This protocol was chosen based on pilot data that suggested four-minute intervals were sufficient to accommodate to each steady-state while also covering broader range of sub-maximal running speeds. Participants could run in their own relatively new (within three months of use) conventional shod running shoes. Treadmill gradient was maintained at 1% throughout submaximal assessments to reflect the energetic cost of outdoor running [22]. All tests were performed under similar laboratory conditions (20 – 25 ° C, 50 – 60% relative humidity at 130m of altitude). Rating of perceived exertion scores on a 6 – 20 point scale (8), as well as blood capillary samples from the finger (obtained with BLa concentrations using a portable lactate analyzer ; Lactate Pro 2 LT-1730, Japan) were obtained immediately after each stage. Heart rate (HR) was recorded by a heart rate monitor (Cosmed Quark CPET, Rome, Italy).

Participants were fitted with an adjustable safety harness during the entire treadmill test. Runners were considered to have achieved VO_2 max when at least two of the following criteria are fulfilled: 1) A plateau in the VO_2, defined as an increase of less than 1.5 ml•kg•min^{-1} in two consecutive workloads; 2) respiratory quotient (R- value) > 1.15); 3) maximal heart rate value (HR max) > 95% of the age-predicted maximum (220 - age); and 4) rating of perceived exertion (RPE) ≥ 19 on the 6-20 Borg scale. Additionally, peak treadmill speed (V_{peak}; in m•s^{-1}) was calculated as follows, taking every second into account:

$$V_{peak} = \text{completed full intensity } (\text{m}\bullet\text{s}^{-1}) + [(\text{seconds at final speed} \text{x} 240\text{s}^{-1}) \text{ x } 0.42 \text{ m}\bullet\text{s}^{-1}]$$

Running economy assessment. Pulmonary gas exchange was recorded through-out the incremental test using a breath-by-breath metabolic analyser (Cosmed Quark CPET, Rome, Italy). Gas analysers were calibrated before each session to 16% O_2, 4% CO_2 balance N_2 and the turbine flow meter is calibrated with a 3L calibration syringe before each test. VO_2 data collected from the last two minutes of each stage were checked for steady-state. Specifically, linear regressions were performed on the final two minutes of each speed increment to determine whether the VO_2 profile was not statistically different ($p < 0.05$) from the horizontal flat line. In other words, no additional rise in the slow component of VO_2 was to be detected during steady-state. V_{OBLA} was determined using this VO_2 criterion in addition to the highest stage which elicited a post-stage BLa below the onset of blood lactate accumulation (OBLA; BLa < 4mmol•L^{-1}) (Fig. 1).

[FIGURE 1]

VO_2, VCO_2 and RER were averaged during the final minute of V_{OBLA}. Updated nonprotein respiratory equations were used to estimate substrate use (grams•min^{-1}) and the relative energy derived from fat and carbohydrate was calculated by multiplying by 9.75 and 4.07 respectively (19). Running economy was defined as gross absolute Ec (expressed as joules per meter), quantified as the sum of these values to reflect the mean energy content of the metabolized substrates during moderate to high-intensity exercise (19). This definition was chosen firstly to account for variations in substrate use when running at submaximal speeds i.e. energetic, rather than oxygen cost (44), and secondly to enable normalization and comparison between runners with different speed thresholds often determined by individual training level and/or gender e.g. running at similar relative intensity (different absolute speeds) rather than at a single fixed speed for all runners (11). Resting metabolic rate was not subtracted since it cannot be ascertained if resting metabolic demand continues at the same rate during the running (45).

Accelerometry-based measures of stability. Tri-axial accelerometry was acquired during the entire running test using a Shimmer3 wireless device (±16 g range, sampling at 1024 Hz, 16-bit resolution, 0.023 kg weight, Shimmer Sensing, Dublin, Ireland). The accelerometer was securely positioned over L3 spinous process of the trunk and directly mounted to the skin using double sided tape and adhesive spray. The accelerometer was securely tightened to individual comfort provided to minimize movement artefact using additional self-adhesive bandage (Cipla-Plast, Cipla, South Africa). Tri-axial accelerations signals expressed as g's were processed using customized software in MATLAB version 8.3 (The Mathworks Inc. Natick, MA, USA).

The sensing axis of the accelerometer may not be aligned with the axes of the world-reference orientation while running. Therefore, a trigonometric correction (27) of the dynamic acceleration signal was performed, a procedure consistently applied to CoM accelerations during walking (20, 27) and running (21, 26). In this study, calculated deviations of accelerometer axes were between 4.1 degrees to 12.5 degrees (anterior tilt) and 0.1 to 1.6 degrees (laterolateral tilt) prior to transformation. Accelerometry-based measures were then computed from the final twenty consecutive steps of acceleration signals at each runner's individual V_{OBLA} (Fig. 2). Standardizing acceleration epochs to amount of running steps as opposed to time windows was done to allow cross study comparison (39, 40).

[FIGURE 2]

Since filtering of body-worn accelerations is a common (40), yet disputed signal processing approach in terms of potentially eliminating physiologically related signal variance (36), we additionally assessed the effect of filtering by computing a second set of accelerometry-based measures after applying a zero-lag 4th order low-pass Butterworth filter (cut-off frequency 50 Hz).

Moreover, non-linear measures such as sample entropy can be sensitive to input signal length (N) (52) which would undesirably influence the outcome. To determine the optimal amount of continuous running steps required for steady-state sample entropy values, we performed a basic iteration analysis on VT, ML, and AP sample entropy values on N steps ranging from six to 160. Twenty steps were chosen as the optimal (minimal) number of steps required to achieve steady-state sample entropy values, and which appears in the APPENDIX.

Dynamic stability parameters were extracted from each acceleration axis (vertical, ML, AP) and quantified firstly using both absolute and ratio of each linear acceleration axis root mean square (RMS) relative to the resultant vector RMS to capture movement variability (26, 42); secondly using step regularity (inter-step symmetry) and stride regularity using the unbiased autocorrelation procedure, with perfect regularities equivalent to one (27); and thirdly using sample entropy to capture the waveform predictability, with values typically in range of 0 to 2 for physiological systems and higher values indicating less periodicity or more unpredictability (36). Detailed procedures and algorithm inputs for the computation and extraction of these dynamic stability parameters are the same as previously explained (40). Spatio-temporal parameters including step frequency (27, 39, 40) and contact time (13, 39) were additionally computed from vertical trunk accelerations.

Statistics. Sex differences were analysed with a 2-tailed independent t-test. Factor analysis was performed to reduce dimensionality and possible multicollinearity of the 17 respective accelerometry outcome measures. A scree-plot determined the number of extracted factors (eigenvalues > 1.0). VariMax rotation was used to optimize loadings of variables onto factors, and the most representative accelerometry measures were chosen as the measures which revealed the highest loading per factor. These representative measures were then entered in an a priori hierarchical multiple regression analysis to explain inter-individual variance in Ec. Specifically, body mass was entered first as block 1 into the model. Thereafter, block 2 was entered containing the most representative accelerometry measures from each factor. After the entry of each block, we evaluated the adjusted R^2 change to determine the proportion of additional variance explained and the significance from 0. This sequential order was based on an a priori hypothesis that the additional variance in Ec could be explained by dynamic stability and spatio-temporal parameters, after accounting for body mass that is well known as a primary determinant of running Ec (6). For each block the beta weights for the independent variables retained in the regression equations and the multiple correlation coefficients are presented. Beta weights further indicate the relative importance of each variable in explaining the variance in Ec. All statistical analyses were performed using SPSS (version 20.0; SPSS Inc, Chicago, IL), and data are reported as mean ± SD.

RESULTS

Descriptive. All tests were terminated by volitional exhaustion, and all subjects achieved VO_2 max by the set criteria. All highest stage steady-state slopes used for Ec analysis had a gradient < 0.2ml $O_2 \bullet s^{-1}$ (p >0.05) thus equating to < 24ml O_2 increase over the final 2 min of each stage. Descriptive characteristics and results for endurance markers combined and per sex are listed in Table 1. Height and mass were significantly greater in men compared to the women (both $p < 0.001$). Men also had significantly higher VO_2 max, V_{peak} and V_{OBLA} (all $p < 0.001$). However, the relative intensity at which V_{OBLA} occurred was not significantly different between sexes ($p = 0.294$) indicating similar running intensity, and thus all subsequent analyses with respect to the primary hypothesis pooled both sexes together. Men had significantly higher absolute Ec, but not when expressed relative to body mass ($p = 0.44$).

Table 1. *Descriptive results for endurance markers and running economy. Values are means* ± SD.

	All runners (n = 30)	Males (n = 16)	Females (n = 14)
Descriptive			
Age	21.75 ± 1.40	21.86 ± 1.88	21.64 ± 0.74
Body mass (kg)	68.18 ± 11.41	74.72 ± 11.24*	61.64 ± 7.19
Height (m)	1.73 ± 0.08	1.78 ± 0.08*	1.68 ± 0.06
BMI	22.56 ± 2.48	23.4 ± 2.51*	21.72 ± 2.23
Endurance markers			
VO_2 max (ml•kg^{-1}•min^{-1})	48.43 ± 6.30	52.17 ± 5.90*	44.70 ± 4.19
V_{peak} (m•s^{-1})	4.15 ± 0.54	4.50 ± 0.43*	3.80 ± 0.39
V_{OBLA} (m•s^{-1})	2.89 ± 0.43	3.09 ± 0.39*	2.67 ± 0.37
V_{OBLA} (% VO_2 max)	80.65 ± 5.99	79.5 ± 5.30	81.79 ± 6.60
Running economy and RER			
RER	0.95 ± 0.03	0.95 ± 0.03	0.94 ± 0.03
Ec (J•m^{-1})	314.59 ± 52.51	341.75 ± 52.89*	287.44 ± 36.69
Ec relative to body mass (J•kg•m^{-1})	4.64 ± 0.33	4.56 ± 0.25	4.68 ± 0.42

* *$p < 0.05$ significantly different between sexes*

Descriptive statistics for spatio-temporal and dynamic stability accelerometry measures combined and per sex are listed in Table 2. At V_{OBLA}, men had significantly shorter contact times ($p = 0.016$), lower dynamic stability in the ML direction for RMS ($p = 0.014$), RMS ratio ($p = 0.003$), step regularity ($p = 0.04$) and stride regularity ($p = 0.026$) as well as higher dynamic stability in the vertical direction for RMS ratio ($p = 0.001$).

Table 2. *Descriptive results for accelerometry-based dynamic stability measures at V_{OBLA}. Values are means* ± SD.

	Axis	All runners (n = 30)	Males (n = 16)	Females (n = 14)
Spatio-temporal				
Stance-time (s)	VT	0.21 ± 0.02	0.20 ± 0.02*	0.22 ± 0.02
Step frequency (steps•min-^{1})	VT	165.24 ± 10.81	168.50 ± 9.44	161.98 ± 11.43
Dynamic stability				
Acceleration RMS	VT	1.22 ± 0.22	1.29 ± 0.29	1.16 ± 0.10
	ML	0.53 ± 0.14	0.48 ± 0.13*	0.58 ± 0.13
	AP	0.41 ± 0.09	0.39 ± 0.07	0.43 ± 0.10
Ratio of acceleration RMS (unitless)	VT	0.87 ± 0.05	0.89 ± 0.04*	0.84 ± 0.05
	ML	0.38 ± 0.09	0.34 ± 0.09*	0.42 ± 0.08
	AP	0.29 ± 0.05	0.28 ± 0.04	0.31 ± 0.06
Step regularity (unitless)	VT	0.91 ± 0.04	0.92 ± 0.06	0.91 ± 0.02
	ML	0.74 ± 0.14	0.69 ± 0.16*	0.79 ± 0.09
	AP	0.72 ± 0.12	0.70 ± 0.13	0.74 ± 0.11
Stride regularity (unitless)	VT	0.92 ± 0.06	0.92 ± 0.08	0.92 ± 0.02
	ML	0.82 ± 0.09	0.78 ± 0.10*	0.85 ± 0.08
	AP	0.77 ± 0.11	0.75 ± 0.13	0.79 ± 0.08
Sample entropy (unitless)	VT	0.11 ± 0.03	0.10 ± 0.03	0.11 ± 0.03
	ML	0.24 ± 0.09	0.27 ± 0.08	0.22 ± 0.09
	AP	0.27 ± 0.09	0.30 ± 0.10	0.25 ± 0.08

* *$p < 0.05$ significantly different between sexes*

Factor analysis. Five components explained 86.3 % of total variance in unfiltered accelerometry measures. From the rotated matrix, factor one (eigenvalue (λ) = 5.79, 34.0 % of variance) included variables relating mainly to step symmetry and stride regularity from all axes. Factor two (λ = 3.89, 22.9% of variance) comprised mainly of dynamic stability parameters in the ML direction. Factor three (λ = 2.34, 13.8% of variance) was associated with variability (RMS) in the AP direction. Factor four (λ = 1.68, 9.9% of variance) was associated waveform complexity (sample entropy in all directions) with while factor five (λ = 1.01, 5.7% of variance) comprised of spatio-temporal measures. Variables with highest loading per factor are bolded in Table 3. These five representative accelerometry measures were therefore assessed for their relationship with Ec. Although not reported here, the total variance explained in filtered accelerometry measures was like unfiltered (86.05% variance explained), with the same five measures having the highest loadings per factor.

Table 3. *Factor analysis on unfiltered accelerometry-based measures revealed five primary factors (eigenvalues greater than one).*

Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Stride regularity AP (0.93)	**RMS ML (0.94)**	**RMS AP (0.94)**	**Sample entropy ML (0.93)**	**Stance time (-0.85)**
Step regularity AP (0.90)	RMS ratio ML (0.93)	RMS ratio AP (0.87)	Sample entropy VT (0.80)	Step frequency (0.84)
Stride regularity VT (0.84)	RMS ratio VT (-0.84)		Sample entropy AP (0.63)	
RMS VT (-0.84)	Step regularity ML (0.55)			
Stride regularity ML (0.68)				
Step regularity VT (0.67)				

Measures (loadings) are sorted from highest to lowest and measures with most representative (highest loading) per factor are bolded. Cross-loadings as well as loadings smaller than 0.4 are suppressed for brevity.

Hierarchical multiple regression analyses. Three unfiltered accelerometry measures were retained in the multiple regression after accounting for block one (body mass) which, as expected, accounted for most of Ec variance (80.8%). Specifically, stride regularity (AP), RMS (AP) and sample entropy (ML) significantly ($p < 0.05$) and independently accounted for an additional 5.2%, 3.2%, and 2.0% of the variance in Ec respectively. Remaining unfiltered accelerometry measures including RMS (ML) as well contact time were not retained as significant predictors (all $p > 0.05$). The final unfiltered regression model accounted for 91.2% variance in Ec. The spread of the partial regression plots is shown in Fig. 3 B, C, and D with individual beta coefficients in Table 4. Partial regression plots were generated to more accurately reflect the scatter of partial correlations (31). For example, the partial regression plot in Fig. 3 B reflects the individual residuals of Ec (dependent variable) on body mass, RMS AP and sample entropy ML (remaining explanatory variables) versus individual residuals of AP stride regularity (target explanatory variable) on body mass, RMS AP and sample entropy ML (the remaining explanatory variables). Thereafter, individual residuals are added to the group mean values e.g. of Ec and Stride regularity AP (from Table 1 and 2) on both axes to aid interpretation of understandable values. When filtered accelerometer measures were entered in the regression for model two, sample entropy (ML) was no longer retained in the model as a significant predictor of Ec. The final filtered regression model accounted for 88.8% of variance in Ec.

[FIGURE 3]

Table 4. *Three unfiltered and two filtered accelerometry-based measures were retained in the hierarchical multiple regression analyses for explaining inter-individual Ec after controlling for body mass.*

Predictor		Unique contribution B	SE B	β	R^2 change	Overall model R^2
Model 1: Unfiltered accelerations						0.912
Body mass	–	0.894	0.071	0.810**	0.808	–
Stride regularity	AP	-29.219	6.852	-0.279**	0.052	–
RMS	AP	-27.981	8.650	-0.199**	0.032	–
Sample entropy	ML	-20.382	8.464	-0.144*	0.020	
Model 2: Filtered accelerations						0.888
Body mass	–	0.892	0.078	0.813**	0.800	–
Stride regularity	AP	-37.069	10.037	-0.266**	0.045	–
RMS	AP	-30.523	9.673	-0.210**	0.043	–

β = standardized coefficients; */** $p < 0.05$ / $p < 0.001$; constant for multiple regression equations were 53.269 (unfiltered) and 56.935 (filtered)

DISCUSSION

The current study tested a *cost of instability* hypothesis that proposes a link between running stability and running Ec using wearable tri-axial trunk accelerometry. Our results lend support to this *cost of instability* hypothesis, with three accelerometry stability measures explaining an additional 10.4% inter-individual variance in Ec over and above that needed to support body mass (80.8%). Our findings build on limited evidence (3, 9, 25) by suggesting new dynamic instability mechanisms that imposes an Ec to running which could hamper endurance performance.

The first determining accelerometry measure, namely stride regularity AP, explained an additional 5.2% of running economy. The direction of the slope in Fig. 3 B was as expected, indicating that runners with poor consistency from stride to stride have a more energetically costly gait. Since this measure is directed anteroposterioly, it could reflect intermittency or alternate decelerations and accelerations corresponding to braking and propulsive forces, analogous to alternately applying “gas-brake-gas” while driving a car. The trunk muscles could be compensating for this instability since they play a critical role by eccentrically contracting to decelerate lumbo-pelvic motion anteroposteriorly during running (35, 38). Electromyography assessment evaluating relationships between muscle activity, stability and economy would help elucidate on the underlying mechanisms.

The second determining accelerometry measure, namely RMS AP, explained a slightly less but additional 3.2% of running economy. However, the direction of the slope as shown in Fig. 3 C is unexpected, since it was hypothesized that runners with higher RMS AP would have the poorest running economy due to larger changes in momentum. Our data counterintuitively suggest that higher amplitudes or variability of AP trunk accelerations while running is a kinematic adjustment advantageous to economy. On the one hand this confirms previous paradoxical evidence that greater changes in horizontal velocity of the CoM were related to better economy in elite female runners (50). On the other hand this contradicts more recent work (12) showing that endurance runners with smaller minimum AP horizontal velocity of the pelvis i.e. less deceleration/braking velocity were more energetically costly. Additionally, Ijmker et al., (18) showed a decrease in Ec, and variability in horizontal plane trunk accelerations when external balance support was provided during walking. Notably, the RMS measure used in the current study considers all amplitude variability during the running step and perhaps more knowledge could be gained from detecting and separately calculating RMS during breaking and propulsive phases of stance. For example, Chang and Kram (10) revealed that increases and decreases in propulsive impulses were primarily linked to costs and savings in Ec when impeding or aiding horizontal forces were externally applied to the individual. However, Heise et al., (14) revealed that neither braking nor propulsive impulses showed sensitivity to inter-individual differences in Ec. Therefore, it remains inconclusive how AP changes in momentum explain economy between runners and further research is needed.

The third determining measure, namely sample entropy of ML trunk accelerations explained an additional 2.0% of running economy when accelerations were left unfiltered. Sample entropy is becoming an increasingly popular complexity measure to capture both performance-related (32, 40) and pathologically-related (47) non-linear dynamics of human gait. Unexpectedly, lower sample entropy ML values i.e. less complexity, were related with costlier running gait (Fig 3. D). Although, this relationship may be supported from a dynamical systems perspective, suggesting that a reduction or “freezing” in the interacting degrees of freedom contributing to ML trunk control of stability is associated with poorer movement economy (7). Murray et al., (32) similarly found, in one of their six subjects, a decrease in sample entropy of ML trunk accelerations to be retained as a determinant of higher submaximal VO_2 with increasing running speed. However, their pilot sample was too small to conduct inter-individual group statistics, and it is possible that both oxygen consumption and sample entropy correlates were similarly detecting correlations with intra-individual changes in running speed. Here, for the first time, we show a relationship between ML sample entropy of movement and Ec of running in a larger sample of runners, while accounting for running speed effects by expressing running economy per unit distance .

On a technology level, it is often argued that signal waveforms should be left unfiltered when assessing complexity measures such as sample entropy (36), and our current findings support this notion. Specifically, sample entropy ML was no longer retained as a significant predictor of Ec when accelerations were low-pass filtered prior to calculation. This result suggests that filtering either “washed out” or “masked” some inherent physiological variations in the signal needed to explain some variance in Ec. Clearly, the choice to filter is important because in contrast to the other two significant (linear) predictors, this complexity measure is not robust to low-pass filtering and researchers should carefully consider this approach. Additionally, based on incremental iteration tests, we recommend that 20 running steps is optimal for calculating sample entropy measures from both an accuracy and computing stand-point (see APPENDIX).

In terms of generalizability, men displayed some significantly different aspects of dynamic stability compared to women. For instance, women had higher RMS ML as well as higher step- and stride- regularity in the ML direction. This sex difference could be attributed partly to female breast biomechanics since larger ML breast accelerations have translated to larger

ML trunk displacements and ground reaction forces while running (41). Notwithstanding, none of the stability measures retained in the regression models showed significant sex effects. Although not presented here, sex-specific regression models were checked but retained the same determining stability measures. Therefore, it is possible that relationship between running stability and Ec is generalizable to both sexes. With respect to the calibre of our recreational to moderately trained participants, we suggest future studies assess and extend the generalizability of our findings to more elite distance runners whom are expected to have superior running stability. Furthermore, it is equally possible that the goal of the recreational runner might be to increase energy expenditure, rather than save it. Thus, trunk accelerometry could be proposed as a tool to test paradigms which deliberately attempt to increase the Ec of instability experimentally through training e.g. irregular surfaces, external perturbations, or unstable types of footwear.

Implications and future directions. Arguably, explaining an additional 10.4% inter-individual variance in Ec might be considered relatively low. However, the measures examined in this study were not expected to account for the majority of variance in Ec since the remaining variance could be attributed to numerous other factors. Nonetheless, using the final multiple regression equation of unfiltered accelerations, we estimated the energy cost for the runners using the lowest and highest values of these three accelerometry measures in our sample while holding body mass constant in the equation (by using group mean value of 68.18 kg). Hypothetically, the runner with poorest of all three stability measures i.e. 51% lower stride regularity AP, 56% lower RMS AP, and 76% lower sample entropy ML would correspond to a total additional energy cost of 49% or 125 J•m^{-1} (57.46 J•m^{-1} + 42.15 J•m^{-1} + 25.67 J•m^{-1} respectively) compared to the runner with the best of these three stability measures (see dotted lines on the x-axis of Fig. 3 B, C, D for visual comparison of maximum and minimum). Quantitatively, however, it remains unclear how much this additional energetic cost would translate to impaired outdoor endurance performance as has been shown by adding shoe weight (16), but warrants an interesting question for future research. Notably, other accelerometry measures that loaded together in factor one of the factor analysis correlated strongly with stride regularity AP. Therefore, these other measures could have been substituted as inputs in the multiple regression analysis, and shouldn't necessarily be excluded from future investigations.

Further interpretation is needed with regards to how a runner could collectively target these accelerometry measures and apply them to practice. For instance, an immediate question raised by our findings is why the first two results appear to contradict each other: higher stride regularity AP implies that higher consistency is good, while higher RMS AP implies higher amplitude or variability is good for economy. One plausible explanation for our results is that RMS amplitudes could be influenced by the different individual speeds used, given that speeds were chosen as relative intensity rather than absolute. However, neither RMS AP nor the other two retained accelerometry measures were correlated to running individual speed at V_{OBLA} (*a posteriori* Pearson's correlation r values between -0.03 and 0.04; all $p > 0.05$), indicating that individual speed was not an influencing factor on the relevant accelerometry parameters. Since these accelerometry measures were uncorrelated and resided on independent Factors (see Table 3), they seem to represent different constructs of dynamic stability. Nevertheless, a combined recommendation for a recreational runner based on these three measures would be target larger overall acceleration amplitudes (RMS AP), provided these amplitudes are consistent between strides (stride regularity AP) and are maintained to produce high complexity in ML control of movement (ML entropy) possibly by exploring multiple movement strategies.

The Ec of dynamic instability could be influenced by altering the task from treadmill to over ground running, especially in self-paced situations. Subject to the laboratory limitations of this study, stability measures identified here may be used as a potential basis for examining stability of an individual in relation to Ec in more ecological i.e. over-ground outdoor settings. In addition, the relationships with stability observed here could be subject to the specific types of parameters extracted and thus other parameter selections or combinations thereof could yield different insights in the future.

Using trunk accelerometry as a tool to continuously examine the instability of running could reveal more about how and when this instability arises at the individual level and how this instability could be used to predict early decline in uneconomical performance. As previously highlighted (29), it is also plausible that running economy could be improved by training dynamic stability, requiring intervention studies. Indeed, it has been shown that dynamic postural stability training reduces the level of coactivation needed during functional tasks (33), which would improve economy. How stability measures change with various types of endurance training could elucidate further on how runners "self-optimize" their stability patterns to innately reduce Ec and is a focus of ongoing research.

Conclusions. Our results suggest that male and female recreational runners with lower stride regularity AP, lower RMS AP, and lower sample entropy ML have a more energetically costly running gait at similar relative intensities. Stated differently, characteristics of dynamic stability may be an adaptation to improved endurance running performance. Additionally, sample entropy ML was no longer retained as a significant predictor of Ec when accelerations were low-pass filtered prior to calculation, indicating that researchers should carefully consider this signal processing step when analysing acceleration waveform complexity.

Overall, targeting these stability characteristics non-invasively and unobtrusively with a simple accelerometer in real competition settings could be useful for coaches and practitioners identifying athletes with favourable economy potential.

APPENDIX

Non-linear measures such as sample entropy are known to be sensitive to length of input signal used (52). Therefore, we computed sample entropy values as a function of number (N) running steps over averages ranging from six to 160 consecutive running steps (see Fig A1 for visual example of one participant). We observed that sample entropy values stabilized i.e. less variable or levelled off from around 20 running steps (range of 16 - 20 in all runners). Knowing when this biomechanical "steady-state" occurs is useful in two ways. Firstly, steady-state eliminates the influence of average N steps used on the outcome thus improving accuracy, and secondly minimizes the computational time, better suited to achieve outputs for real-time application.

[FIGURE A1]

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DISCLOSURES

No conflicts of interest, financial or otherwise, are declared by the author(s)

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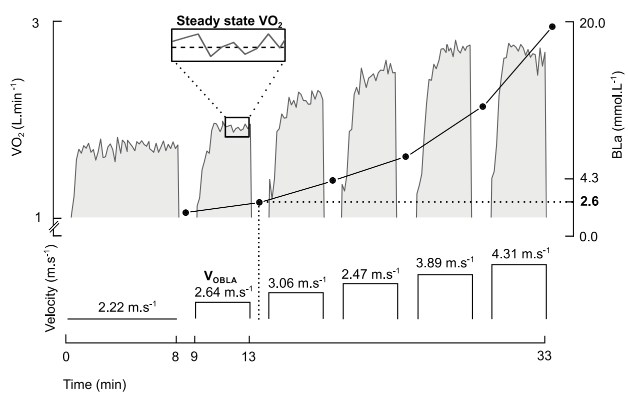
FIGURE CAPTIONS

Figure 1. Representative example of determining the highest sub-maximal steady-state stage for estimating energetic cost (Ec) of running. Ec was extracted from the final two minutes of stage two (here 2.64 m•s^{-1}), which demonstrated a running velocity at which 1) the oxygen uptake (VO_2) curve was not drifting i.e. statistically significant ($p > 0.05$) from the horizontal (flat dashed line shown in steady-state VO_2 box), and 2) a post stage blood lactate (BLa) that was less than the velocity required to elicit onset of blood lactate accumulation (V_{OBLA}; BLa < 4 mmol•L^{-1}), here 2.6 mmol•L^{-1}.

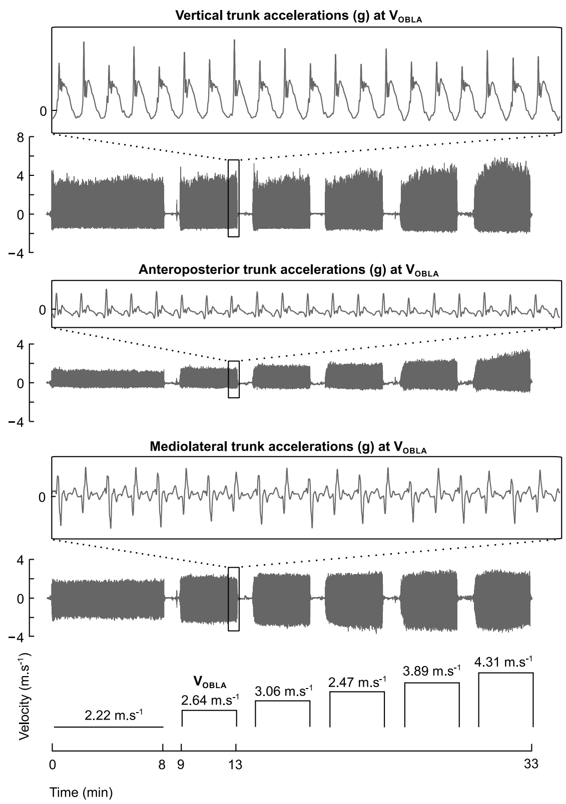
Figure 2. Representative example of tri-axial trunk accelerations extracted for computing dynamic stability measures of running. Accelerations used for analysis represented the final 20 running steps at V_{OBLA} for each runner (here 2.64 m•s^{-1} for the same female runner as shown in Figure 1).

Figure 3. Three unfiltered accelerometry-based dynamic stability measures contributed significantly and independently to the inter-individual energetic cost (Ec) of running after controlling for body mass (n = 30). Partial regression plots were scaled by adding regression-residuals to group mean values (from Table 1 and 2) on both axes to enhance interpretation (31). Each plot represents the true correlation coefficient for the specific predictor on Ec, while controlling for the remaining three predictors e.g. in panel **B** the relationship of stride regularity AP to Ec is shown while controlling for body mass (panel **A**), root mean square (RMS) AP (panel **C**), and sample entropy ML (panel **D**). Minima and maxima highlight the range of the spread on each axis (dashed lines). The final regression equation revealed Ec (J•m^{-1}) = 3.740•BM – 122.252•Stride regularity AP -117.071•RMS AP – 85.279•Sample entropy ML + 222.878.

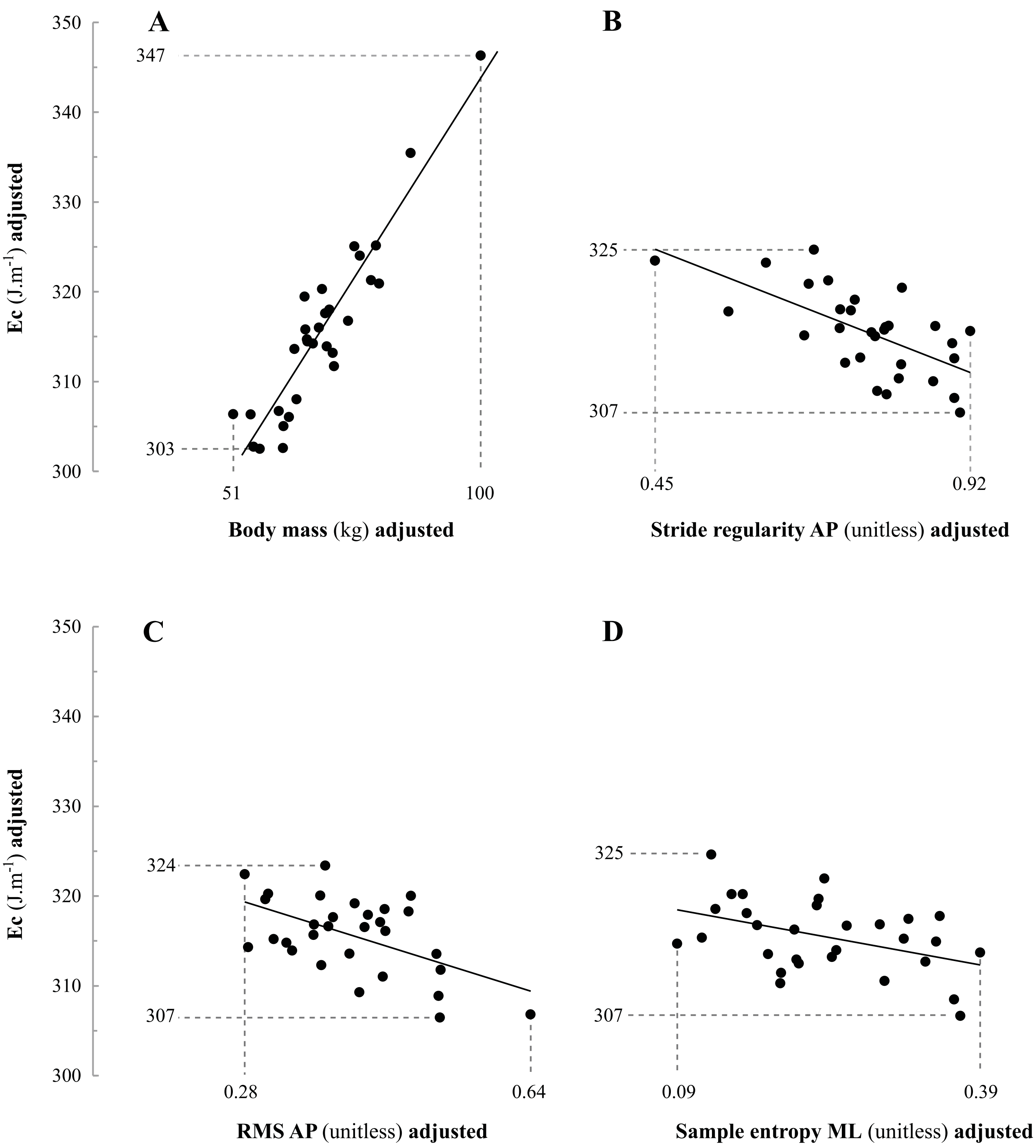
Fig A1. Non-linear sample entropy values were highly variable when averaged at a low number of steps but stabilized from around 20 running steps (interval time of 6.9 seconds and 7115 acceleration samples), with a combined computation time of approximately 0.8 sec on an Intel Core i5 CPU.

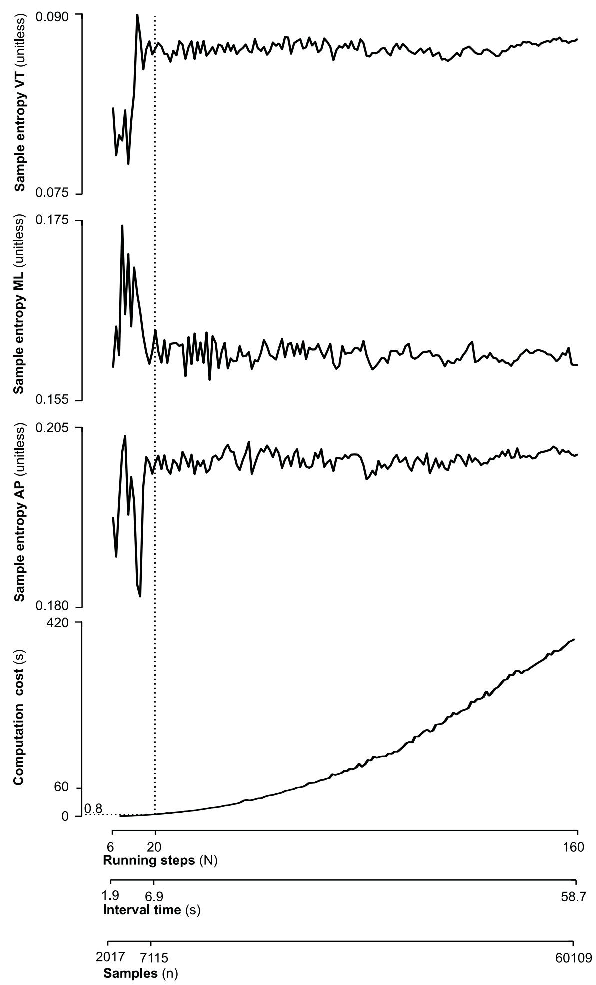


Steady state VO2
3
1
VO2 (L.min-1)
20.0
4.3
2.6
0.0
BLa (mmol.L-1)
Velocity (m.s-1)
2.22 m.s-1
VOBLA
2.64 m.s-1
3.06 m.s-1
2.47 m.s-1
3.89 m.s-1
4.31 m.s-1
0
8
9
13
33
Time (min)



Vertical trunk accelerations (g) at V OBLA
0
8
4
0
−4
Anteroposterior trunk accelerations (g) at V OBLA
0
4
0
−4
Mediolateral trunk accelerations (g) at V OBLA
0
4
0
−4
Velocity (m.s-1)
2.22 m.s-1
V OBLA
2.64 m.s-1
3.06 m.s-1
2.47 m.s-1
3.89 m.s-1
4.31 m.s-1
0
8
9
13
33
Time (min)


A
B
C
D
Ec (J.m-1) adjusted
350
340
330
320
310
300
347
303
325
307
324
51
100
0.45
0.92
0.28
0.64
0.09
0.39
Body mass (kg) adjusted
Stride regularity AP (unitless) adjusted
RMS AP (unitless) adjusted
Sample entropy ML (unitless) adjusted



0.090
Sample entropy VT (unitless)
0.075
0.175
Sample entropy ML (unitless)
0.155
0.205
Sample entropy AP (unitless)
0.180
420
Computation cost (s)
60
0
0.8
6
20
160
Running steps (N)
1.9
6.9
58.7
Interval time (s)
2017
7115
60109
Samples (n)