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The Relationship Between Cardiorespiratory and Accelerometer-Derived Measures in Trail Running and the Influence of Sensor Location

Craig A. Staunton, Mikael Swarén, Thomas Stöggl, Dennis-Peter Born, and Glenn Björklund

Purpose: To examine the relationship between cardiorespiratory and accelerometer-derived measures of exercise during trail running and determine the influence of accelerometer location. ***Methods:*** Eight trail runners (7 males and 1 female; age 26 [5] y; maximal oxygen consumption [$\dot{V}O_2$] 70 [6] $mL \cdot kg^{-1} \cdot min^{-1}$) completed a 7-km trail run (elevation gain: 486 m), with concurrent measurements of $\dot{V}O_2$, heart rate, and accelerations recorded from 3 triaxial accelerometers attached at the upper spine, lower spine, and pelvis. External exercise intensity was quantified from the accelerometers using PlayerLoad™ per minute and accelerometry-derived average net force. External exercise volume was calculated using accumulated PlayerLoad and the product of average net force and duration (impulse). Internal intensity was calculated using heart rate and $\dot{V}O_2$-metrics; internal volume was calculated from total energy expenditure (work). All metrics were analyzed during both uphill (UH) and downhill (DH) sections of the trail run. ***Results:*** PlayerLoad and average net force were greater during DH compared with UH for all sensor locations ($P \le .004$). For all accelerometer metrics, there was a sensor position × gradient interaction ($F_{2,14}$29.003; $P < .001$). The upper spine was lower compared with both pelvis ($P \le .003$) and lower spine ($P \le .002$) for all accelerometer metrics during both UH and DH running. Relationships between accelerometer and cardiorespiratory measures during UH running ranged from moderate negative to moderate positive ($r = -.31$ to .41). Relationships were stronger during DH running where there was a nearly perfect correlation between work and impulse ($r = .91$; $P < .001$). ***Conclusions:*** Simultaneous monitoring of cardiorespiratory and accelerometer-derived measures during trail running is suggested because of the disparity between internal and external intensities during changes in gradient. Sensor positioning close to the center of mass is recommended.

Keywords*:* athlete, hilly terrain, IMU, inertial measurement unit, undulating terrain

Trail running is a popular leisure activity and growing competitive sport, characterized by large positive and negative elevation changes.[1,2] In trail running, the majority of exercise is performed on uneven surfaces, consisting of dirt roads, gravel, and often includes sections with obstacles such as rocks and trees.[3]

Traditionally, trail runners and their coaches rely on global navigational satellite system (GNSS) technology, cardiorespiratory measures, such as heart rate (HR), or subjective ratings of perceived exertion (RPE) for monitoring the intensity and volume of training.[4] GNSS systems are limited because basic measurement of locomotion velocity is not a necessarily a valuable measure of exercise intensity in trail running, particularly during downhill (DH) sections.[5] This is because running DH requires less mechanical effort compared with flat or uphill (UH) running due to the effect of gravity. In addition, the large ground reaction forces experienced during DH running[6] likely causes large amounts of mechanical stress, which is not reflected by running speed alone. Furthermore, previous research has identified that the physiological response during DH running is substantially reduced compared with UH running at an equivalent velocity.[7]

Physiological measures, such as HR, might be useful to indicate internal exercise intensity. However, measurements of HR are associated with a delayed response at the onset of changes in exercise intensity due to periods of cardiorespiratory acceleration and deceleration.[8] This means that measures of HR lack the sufficient resolution to reflect exercise intensity during intermittent exercise,[5,9,10] such as trail running. Therefore, measurements with a higher resolution are required to accurately reflect instantaneous exercise intensity and tailor competition-specific training programs.

While RPE might be a useful tool to monitor internal exercise intensity, this metric provides limited information for coaches to prescribe exercise intensity for the purpose of replicating competition demands. Furthermore, RPE scores are subject to emotion[11] and a variety of external influences, such as psychological factors.[12] Therefore, subjective perceptual measures should be monitored during exercise in combination with other measures of intensity or volume.[13] As a consequence, an objective measurement is required to isolate the external components of perceived exertion from the actual exercise volume and intensity completed by athletes. In addition, monitoring of RPE provides no continuous ability to understand fluctuations in exercise intensity experienced over the duration of exercise.

Wearable accelerometers offer a measurement system to quantify external exercise intensity and volume in a manner that can overcome the limitations of other monitoring tools, such as GNSS, cardiorespiratory measures, and subjective perceptual measures.

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This is because accelerometers have a sufficient measurement resolution to reflect instantaneous changes in exercise intensity during intermittent activity.[14,15] In addition, wearable accelerometers offer a measurement system, which might be able to quantify biomechanical stress in additional locomotor activity.[14,16] Accordingly, accelerometer-derived metrics, such as PlayerLoad™ (PL), have readily been used for athlete monitoring in team sports, such as basketball,[17,18] soccer,[19,20] and Australian football.[21,22]

Some authors have claimed the validity of PL for athlete monitoring because of strong correlations to other measures, such as HR, $\dot{V}O_2$, and RPE.[20,23–26] However, it is unknown how accelerometer-derived metrics relate to cardiorespiratory responses during trail running. This is because running on hilly terrain is known to influence the relationships between HR, $\dot{V}O_2$, and running speed.[5] Therefore, the expected relationships between internal and external measures of exercise intensity are likely to be distorted during trail running.

Only one study to date has investigated how accelerometer-derived metrics and cardiorespiratory responses change during the course of a trail running event.[27] This study is severely limited because it is a case study of just one participant. Nevertheless, the authors reported increased accelerometer metrics during DH running and increased HR responses during UH running. This is not a surprising result because running UH is known to impose a greater physiological stress,[28] and running DH is associated with increased ground contact forces,[29] which is linked to accelerations. Regardless, it is important for trail runners and their coaches to understand how these metrics relate for the purposes of athlete monitoring and the development of new wearable devices and metrics for trail running.

Importantly, the above-mentioned case study utilized a single accelerometer positioned on the upper spine. This sensor positioning is common for devices, which also contain a GNSS receiver for the purpose of improving signals with overhead satellites.[26] However, it is generally accepted that in order to measure the acceleration of a body, referred to as the overall dynamic body acceleration, the center of mass is considered as the criterion anatomical location.[30] Furthermore, it is known that sensor location influences the accelerometer data during treadmill running.[26,31] However, it is currently unknown how sensor location influences accelerometer metrics during trail running.

Therefore, the aims of this study were to examine: (1) the relationship between accelerometer-derived metrics and cardiorespiratory responses during trail running and (2) the influence of sensor location on accelerometer-derived metrics.

Methods

Participants

Eight elite runners (7 males and 1 female; age 26 [5] y; stature: 180 [9] cm; body mass: 70 [8] kg; maximal $\dot{V}O_2$ uptake: 70 [6] $mL{\cdot}kg^{-1}{\cdot}min^{-1}$) who regularly compete in trail and road running were recruited to participate in this study. All participants provided written informed consent and completed all requirements of the study. Data collected for this research were part of a larger project, some of which has been previously published.[5,6] The regional ethical review board in Umeå, Sweden (registration number: 2014-171-31M) preapproved the research techniques and experimental protocol. All research was conducted in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki).

Design

This investigation was a retrospective observational study. All participants completed a preliminary testing session as well as one maximal-effort trail-run time trial. The preliminary testing session was conducted 2 days prior to the trail-run time trial and included measurements of anthropometry, a maximal $\dot{V}O_2$ uptake test, as well as a low-intensity familiarization with the specific trail to be used.

Methodology

The runners' maximal $\dot{V}O_2$ uptake was determined with an incremental treadmill (RL3000 Rodby; Innovation AB, Vänge, Sweden) test in the morning, 3 hours following a light breakfast. For the trail familiarization, the athletes were instructed to apply their usual routine, which involved scouting the trail-running track and identifying critical sections of the route. Athletes were instructed to maintain an easy running pace so that they were well prepared for the trail-run time trial 2 days later. For all data collection athletes were well hydrated, refrained from strenuous exercise and alcohol for at least 24 hours, and refrained from food and caffeine consumption for 3 hours beforehand.

During the trail run, the MyoMotion (Noraxon Inc, Scottsdale, AZ) 3D motion analysis system was used to investigate kinematic variables. The MyoMotion system consisted of 12 inertial measurement units (IMUs) attached to various points of the body recording at 100 Hz. The MyoMotion system acts as an attitude and heading reference system, which provides attitude information of a body (technical specifications: accelerometer: ±16 g; gyroscope: $\pm 2000°{\cdot}s^{-1}$; magnetometer: ±1.9 gauss). The MyoMotion system has confirmed validity and reliability[32,33] for measuring 3-dimensional angular movements. Accelerations derived from 3 of the 12 IMUs were used for analysis in this study. Those were the 3 IMUs positioned along the spine and included the pelvis, lower spine, and the upper spine positions (Figure 1). These positions were chosen because they are commonly used attachment points for measuring exercise volume and intensity in sports.[15,26]

In addition, breath-by-breath respiratory parameters (MetaMax3B_R2; Cortex Biophysik GmbH, Leipzig, Germany) and HR (Polar Electro Oy, Kempele, Finland) were recorded to assess the cardiorespiratory responses during the trail run.

Running Course

The trail run was performed as a time trial on an off-road running course consisting of 2 laps, each with a length of 3524 m. A 2-minute rest period was provided between lap 1 and lap 2, which permitted the researchers to ensure correct fitting of all equipment. The running track had 6 distinct sections, including 3 UH and 3 DH sections, with a total elevation gain of 486 m. The running course was typical for trail running, including uneven surfaces, single tracks, dirt roads, gravel, and sections with obstacles such as rocks and wood. Before the start, the athletes followed their usual competition warm-up routine for 20 minutes, including moderate running, short high-intensity intervals, and light stretching. The course profile is displayed in Figure 2.

Data Analyses

Accelerometer data from the pelvis, lower spine, and upper spine IMUs were downloaded using the manufacturer software (MyoResearch version 3.6.2; Noraxon Inc, Scottsdale, AZ). MyoMotion

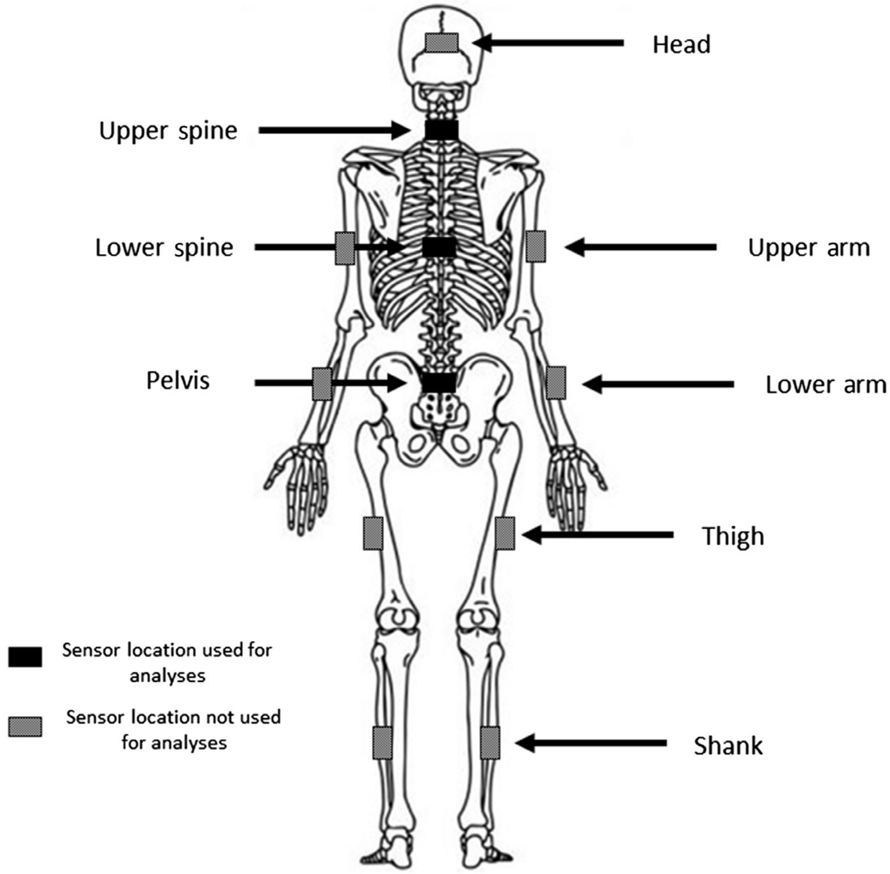

Figure 1 — Depiction of the inertial measurement unit's sensor locations during the trail run.

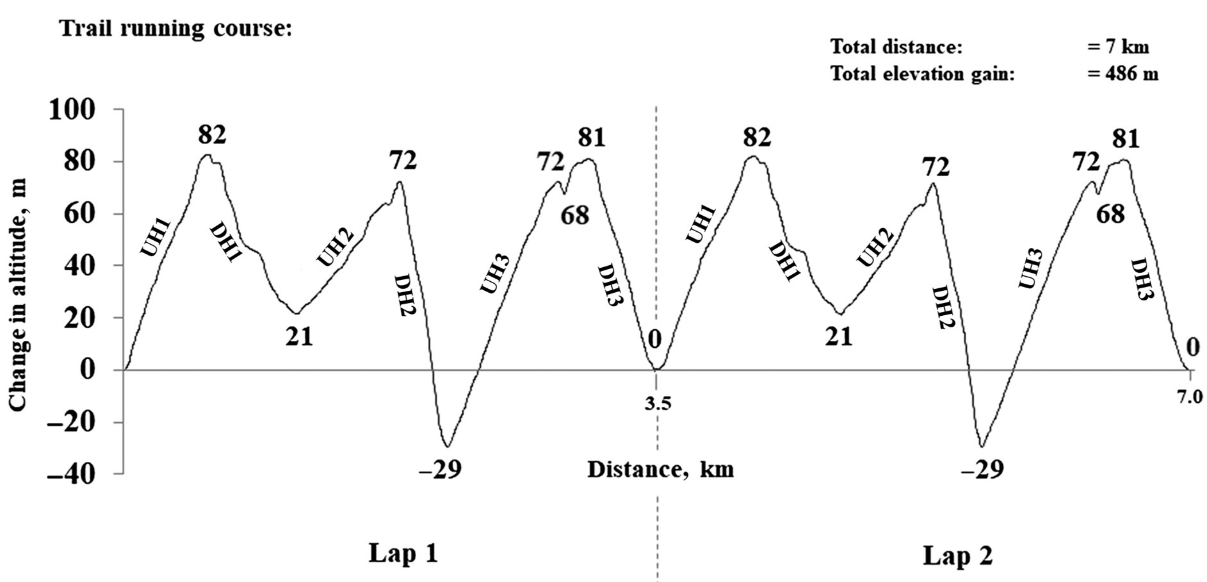

Figure 2 — Schematic illustration of the trail-running course and the specific UH and DH sections. Figure adapted from Born, Stöggl, Swarén, and Björklund.[5] Near-infrared spectroscopy: more accurate than heart rate for monitoring intensity in running in hilly terrain. *Int J Sports Physiol Perform*. 2017;12(4):440–447. DH indicates downhill; UH, uphill.

acceleration data were continuously transformed from sensor to world coordinates by applying a sensor fusion algorithm from the onboard gyroscopes and magnetometers. Accordingly, 1 g was subtracted from the vertical axis in order to remove the gravitational component from the acceleration signal. Following this, a low-pass fourth-order Butterworth filter with a cutoff frequency of 20 Hz was used to remove the noise component of the signal. This frequency was identified from visual inspection of the energy spectrum of the acceleration signal and is closely aligned with previous research, which has used similar low-pass filter frequencies during sports.[34,35]

External exercise intensity was quantified from the accelerometer signal for each section of the running track in 2 ways. First, PL per minute was calculated as previously described.[14] Briefly, PL is calculated as the square root of the sum of the squared instantaneous rate of change in acceleration in each of the 3 axes (*X*-, *Y*-, and *Z*-axes) and divided by 100. Subsequently, the accumulated PL for each section of the running track was divided by the section time to calculate PL per minute.

Second, accelerometry-derived average net force (AvF_{Net}) was calculated as previously described (Equation 1).[15,36–38] Briefly, the product of the filtered instantaneous resultant acceleration vector and participant's body mass was used to determine instantaneous net force, which was then averaged over user selected periods. This metric has confirmed construct validity to measure exercise intensity in basketball[15] and is strongly correlated with $\dot{V}O_2$ and running speed on flat surfaces.[15,36] Equation 1 is the accelerometry-derived average net force.

$$AvF_{Net} = BM \times \frac{\sum_{i=1}^{n}\left(\sqrt{a_{x_i}^2 + a_{y_i}^2 + a_{z_i}^2}\right)}{n}, \tag{1}$$

where AvF_{Net} = average net force, BM = body mass, a_x = acceleration in the x direction, a_y = acceleration in the y direction, a_z = acceleration in the z direction, n=number of samples.

External exercise volume was also quantified from the accelerometers for each section of the running track in 2 ways. First, the numerical integral of AvF_{Net} and exercise duration was used to calculate accumulated impulse (IMP), measured in Newton seconds.[37,38] Second, PL for each section of the running track was computed.

Internal exercise intensity was calculated for each section of the running track based on HR and $\dot{V}O_2$ data. Mean HR (in beats per minute), relative $\dot{V}O_2$ (in milliliters per kilogram per minute), and percentage of maximum $\dot{V}O_2$ was calculated. In addition, metabolic power (*P*) was calculated using the Weir equation[39] and was also expressed relative to body mass (relative power; in watts per kilogram). Internal exercise volume was calculated as the total metabolic work (*W*) completed for each section of the running track, which was calculated as the time integral of *P* and expressed in kilojoules.[39]

For the purposes of comparing UH and DH running, all metrics from the UH trail sections (sections 1, 3, and 5) were averaged and considered as UH; all metrics from the DH trail sections (sections 2, 4, and 6) were averaged and considered as DH.

Statistical Analyses

Statistical analyses were performed using IBM SPSS Statistics (version 27.0; IBM Corp, Armonk, NY) with level of significance set at $\alpha < .05$. Shapiro–Wilk tests confirmed that the assumption of normality was not violated and group data were expressed as mean (SD). A 1-way analysis of variance (ANOVA) was used in order to assess differences in section times and internal exercise intensity and volume between the first and second lap (ANOVA). Repeated-measures 2-way ANOVAs (within factors: gradient; sensor position) were used to identify if gradient (UH and DH) or sensor position (upper spine, lower spine, and pelvis) influenced the pattern of external exercise demands throughout the trail run. For all ANOVAs, effect sizes are presented as partial eta-squared statistic (η_p^2). Significant interactions were followed up with simple main effect analyses with pairwise comparisons using Bonferroni correction. Furthermore, Pearson correlation coefficients (*r*) were used to examine the strength of relationship between cardiorespiratory and accelerometer-derived metrics during UH and DH running at all sensor locations. To compare the strength of relationship between cardiorespiratory and accelerometer-derived metrics at all sensor locations, the *r* values were *z* transformed using Fisher *z* transformation.[40] This analysis identified that there was minimal differences in the strength of relationship between sensor locations. Accordingly, for simplicity, only the relationships obtained at the Pelvis sensor location are reported because this is considered as the criterion sensor location due to being closest to the centre of mass.[30] Strength of relationships were evaluated according to methods previously stated.[41] Very small correlations were .0 to .1; small correlations were .1 to .3; moderate correlations were .3 to .5; large correlations were .5 to .7; very large correlations were .7 to .9; and nearly perfect correlations were .9 to 1.0.

Results

Running times for each section of the trail run are presented in Figure 3. All section times, except for DH3, were faster on the first lap compared with the second lap ($P \leq .042$).

The internal exercise intensity and volume associated with each section of the trail run for both laps are presented in Table 1. For almost all trail sections, lap 2 was associated with a reduced internal exercise intensity and volume compared with lap 1. On the other hand, HR was greater on lap 2 during the first 2 track sections only.

UH Running

There was a significant, moderate positive correlation between relative $\dot{V}O_2$ and AvF_{Net} (r=.41; 95% confidence interval [CI], .16 to .63; P=.005) and moderate negative correlations between *W* and PL (r=.31; 95% CI, −.55 to −.01, P=.040) as well as *W* and PL per minute (r=.31; 95% CI, .55 to .01, P=.039). Correlations between relative $\dot{V}O_2$ and all other accelerometer metrics were nonsignificant and small to very small ($r \leq .17$; $P \geq .265$). Correlations between all accelerometer metrics with percentage of maximum $\dot{V}O_2$ HR, *P*, relative *P*, and *W* were all nonsignificant and small or very small ($r \leq .23$; $P \geq .124$).

DH Running

Figure 4 displays the correlations and 95% CIs between all accelerometer-derived metrics with *W*. Of note, there were large negative correlations between *W* and AvF_{Net} ($P < .001$) as well as *W* and PL per minute (P<.001). Furthermore, there was a large positive correlation between *W* and PL ($P < .001$) and a nearly perfect correlation between *W* and IMP ($P < .001$). In addition, there was a significant, moderate positive correlation between *P* and AvF_{Net} ($r = -.35$; 95% CI, .05 to .58; P=.021). Correlations between percentage of maximum $\dot{V}O_2$, relative $\dot{V}O_2$, HR, and

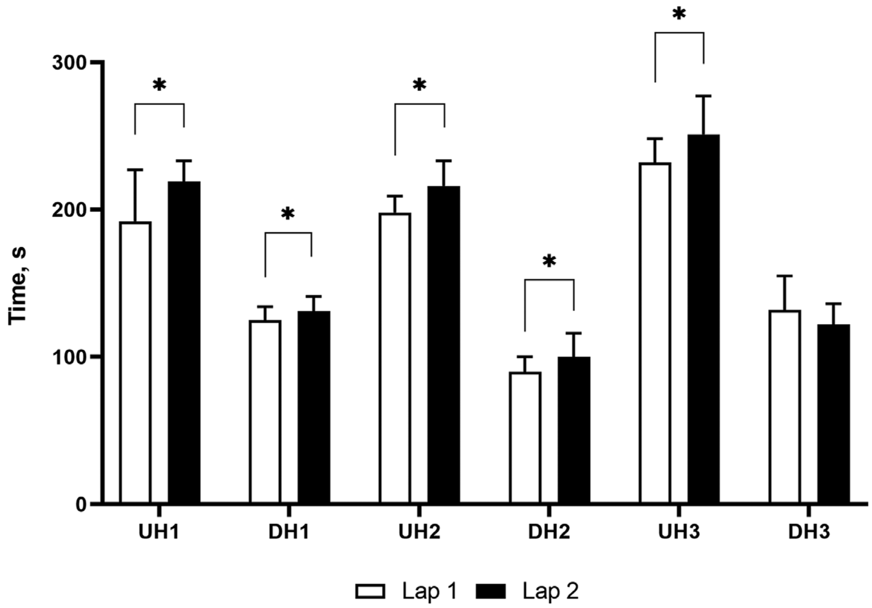

Figure 3 — Section times for each lap of the trail run. Values are represented as mean (SD). *Different between laps (P<.05). DH indicates downhill; UH, uphill.

relative P with all accelerometer metrics were nonsignificant and ranged from small negative ($r \geq -.25$; $P \geq .094$) to small positive ($r \leq .21$; $P \geq .156$).

Sensor Position

Figure 5 displays the mean and SD of all accelerometer metrics for each sensor position. For all accelerometer metrics, there was a sensor position × gradient interaction ($F_{2,14} \geq 29.003$; $P < .001$; $\eta_p^2 \geq .806$). All accelerometer-derived metrics were greater during DH compared with UH running for all sensor locations ($P \leq .004$). All accelerometer metrics for the upper spine were lower compared with the pelvis ($P \leq .003$) and the lower spine ($P \leq .002$) positions during both UH and DH running. The pelvis and lower spine metrics were not different during UH running ($P \geq .071$). During DH running, the pelvis was greater than the lower spine for AvF_{Net} ($P = .016$) and IMP ($P = .013$) but not for PL ($P = .135$) or PL per minute ($P = .168$).

Discussion

This study is the first to report the relationships between accelerometer-derived metrics and cardiorespiratory measures during trail running with multiple participants. Furthermore, this study is the first to report on the effect of sensor location on accelerometer-derived metrics during trail running.

The main findings of this study demonstrate that relationships between cardiorespiratory and accelerometer-derived metrics in trail running vary when running UH compared with running DH. Generally, relationships between accelerometer and cardiorespiratory measures were small during UH running, but were stronger during DH running. Consistently, AvF_{Net} and IMP metrics displayed stronger correlations with cardiorespiratory measures compared with PL and PL per minute. In fact, there was a nearly perfect correlation between W and IMP during DH running. Furthermore, this study demonstrated that sensor location affects accelerometer-derived metrics during both UH and DH running.

Previous studies have claimed the construct validity of PL because of strong correlations with cardiorespiratory measures such as $\dot{V}O_2$ and HR.[20,23–26] However, the present study demonstrates that these relationships might not be as strong during trail running, particularly during UH running.

A possible explanation for the weaker correlations between cardiorespiratory and accelerometer-derived metrics, particularly during UH running, might be explained by altered HR and $\dot{V}O_2$ kinetics during trail running[5] or as a result to changes in gait.[6] Another explanation might be related to the fact that cardiorespiratory and accelerometer-derived metrics are measuring 2 separate constructs. Accelerometer monitoring of exercise likely reflects an external mechanical intensity and not an internal physiological intensity.[16] Because UH running is associated with high physiological responses[28] and reduced ground contact forces,[6,29] one might expect weak associations between cardiorespiratory and accelerometer-derived measures. Accordingly, the disassociation with internal intensity during UH running might actually demonstrate a level of discriminant validity for accelerometers to measure external exercise intensity during this exercise modality. Regardless, it seems clear that monitoring both internal and external exercise intensity is important for athlete monitoring in trail running.

In contrast to UH running, the relationships between cardiorespiratory and accelerometer-derived measures during DH running were strong. PL displayed a large correlation with W during DH ($r = .52$) and the relationship between W and IMP during DH was nearly perfect ($r = .91$). This finding indicates that IMP might provide an accurate estimate of total energy expenditure during DH running. Furthermore, AvF_{Net} and IMP consistently displayed stronger relationships with cardiorespiratory measures compared with PL and PL per minute. This might provide further evidence, which supports the notion the AvF_{Net} is a better measure of exercise

Table 1 Internal Exercise Intensity and Volume for Both Laps of the Trail Run

	Lap 1						Lap 2					
Section	$\%\dot{V}O_2max$	Rel $\dot{V}O_2$, $mL \cdot kg^{-1} \cdot min^{-1}$	HR, bpm	*P*, W	Rel *P*, $W \cdot kg^{-1}$	*W*, kJ	$\%\dot{V}O_2max$	Rel $\dot{V}O_2$, $mL \cdot kg^{-1} \cdot min^{-1}$	HR, bpm	*P*, W	Rel *P*, $W \cdot kg^{-1}$	*W*, kJ
UH1	91 (6)	64 (5)	165 (12)	1084 (161)	15 (1)	216 (23)	86 (5)*	60 (5)	175 (12)*	1035 (169)	15 (1)	227 (31)*
DH1	84 (6)	59 (6)	168 (15)	1432 (249)	20 (2)	262 (39)	73(3)*	51 (5)*	173 (15)*	1224 (225)*	18 (2)*	235 (29)*
UH2	90 (6)	63 (6)	174 (14)	1519 (254)	22 (2)	299 (43)	81 (5)*	56 (5)*	175 (13)	1323 (228)*	19 (2)*	285 (39)*
DH2	75 (7)	53 (7)	172 (15)	1304 (244)	19 (2)	116 (16)	65 (8)*	46 (6)*	170 (16)	1084 (242)*	16 (2)*	105 (12)*
UH3	88 (6)	62 (5)	176 (13)	1487 (265)	21 (2)	342 (53)	78 (6)*	54 (5)*	174 (12)	1287 (243)*	19 (2)*	326 (50)*
DH3	79 (8)	55 (7)	174 (14)	1295 (223)	19 (2)	282 (40)	73 (8)*	51 (7)*	176 (14)	1223 (257)*	18 (2)*	274 (42)

Abbreviations: bpm, beats per minute; DH, downhill; HR, heart rate; *P*, power; Rel *P*, relative power; Rel $\dot{V}O_2$, relative volume of oxygen uptake; UH, uphill; $\dot{V}O_2$, volume of oxygen uptake; $\%\dot{V}O_2max$, percentage of maximal oxygen uptake; *W*, work. Note: Values are presented as mean (SD).

*Different from lap 1 within condition ($P<.05$).

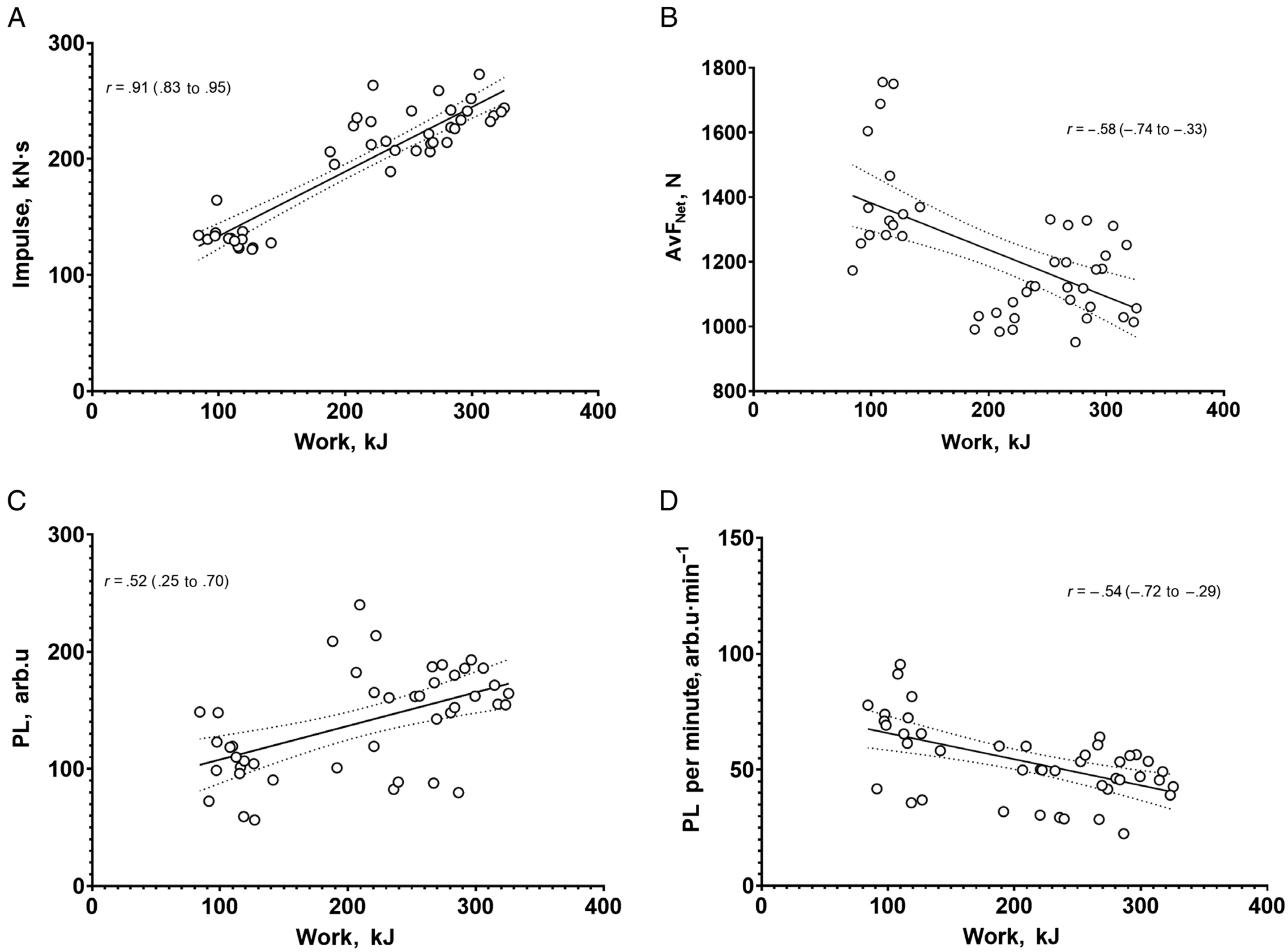

Figure 4 — Scatterplots displaying relationships between accelerometer-derived measures and work during downhill running. (A) IMP; (B) AvF_{Net}; (C) PL; and (D) PL per minute. arb.u indicates arbitrary units; AvF_{Net}, average net force; DH, downhill; IMP, impulse; PL, PlayerLoad; UH, uphill.

intensity compared with PL per minute.[15] It remains unclear why AvF_{Net} and IMP consistently displayed stronger relationships with cardiorespiratory measures compared with PL and PL per minute. However, this might be because AvF_{Net} considers the body mass of each athlete, whereas PL does not. By considering the body mass of each athlete, it might be that AvF_{Net} is a more individualized external intensity metric and more closely reflects physiological intensity. Another potential mechanism for differing associations with cardiorespiratory measures is that AvF_{Net} is a product of the vector acceleration. On the other hand, PL is a measure of the instantaneous rate of change in acceleration (otherwise referred to in classical physics as "jerk"). Although AvF_{Net} and PL are strongly related to each other, they are indeed measuring 2 separate time derivatives of the same mechanical construct (acceleration [in meters per second square] vs jerk [in meters per second cube]) and as such might explain different degrees of association to cardiorespiratory measures.

Finally, caution should be used when interpreting accelerations from units positioned on the upper spine. This sensor location is common in GNSS/IMU combined devices, where the device is positioned higher on the spine for better synchronization with overhead satellites.[26] In this study, unit positioning on the upper spine produced lower accelerometer-derived metrics during both UH and DH running, compared with positioning on the lower spine or pelvis. This finding is consistent with previous research, which has also identified that accelerations from a sensor located at the upper spine underestimates center of mass accelerations.[26]

A limitation of this study is the small sample size of athletes. Therefore, the results might not be generalizable to all trail runners. Nevertheless, these data represent a sample of elite-level trail runners competing at the highest level. This study presents correlations between cardiorespiratory and accelerometer-derived measures. A limitation of this approach is that these might be considered 2 separate constructs (biomechanical and physiological intensity, respectively). Future research could assess the relationships between accelerometer metrics with force data obtained from pressure insoles during trail running in order to make fair comparison between 2 measures of external intensity.

Practical Applications

This research provides trail runners and their coaches with useful information pertaining to the use of wearable accelerometers for

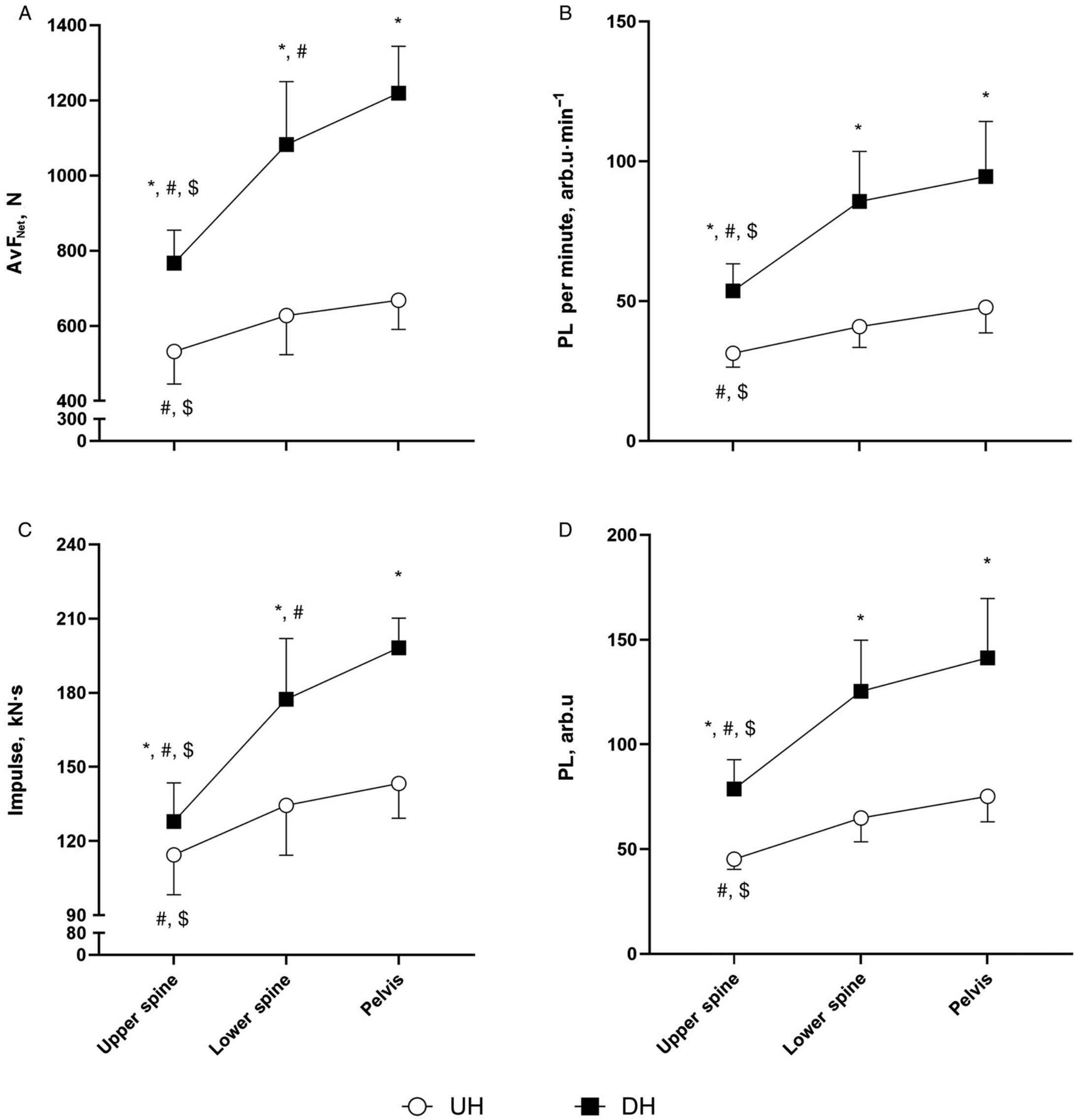

Figure 5 — Accelerometer metrics for all sensor positions during UH and DH running. (A) AvF$_{Net}$, (B) PL per minute, (C) IMP, and (D) PL. Values are represented as mean (SD). arb.u indicates arbitrary units; *Different between UH and DH ($P < .05$). #Different from pelvis ($P < .05$). $Different from lower spine ($P < .05$).

athlete monitoring. First, it appears that AvF$_{Net}$ and IMP are more useful metrics for quantifying exercise intensity and volume, respectively, compared with PL and PL per minute. This is because these metrics consistently displayed stronger correlations with cardiorespiratory measures. In particular, it seems that accelerometer-derived metrics are particularly useful for measuring exercise volume during DH running, with nearly perfect correlations between IMP and *W*. However, relationships between cardiorespiratory and accelerometer-derived measures of exercise volume and intensity during UH running were generally weak. Accordingly, coaches and athletes should consider that accelerometer monitoring is reflective of the mechanical intensity associated with trail running and not physiological intensity. Because of this, simultaneous monitoring of the mechanical and physiological intensity during trail running is recommended because of the disparity in internal and external intensities due to changes in gradient. Second, coaches and athletes should be cautious when interpreting accelerometer metrics from devices worn on the upper spine. This is because this sensor position produced systematically lower accelerometer-derived metrics over the course of the trail run.

Conclusions

Correlations between cardiorespiratory and accelerometer-derived measures varied depending on the gradient. In general, associations between cardiorespiratory and accelerometer-derived metrics were stronger during DH running compared with UH running. AvF$_{Net}$ and IMP are more useful metrics for quantifying exercise during trail running compared with PL because these metrics consistently displayed stronger correlations with cardiorespiratory measures. Sensor position on the upper spine produced lower accelerometer-derived measures over the course of the trail run. Therefore, sensor positioning close to the center of mass is recommended.

Acknowledgments

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