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Respiratory frequency does not track perceived fatigue independently of time-on-task during a half-marathon: a wearable-sensor field study

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Article

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Respiratory frequency does not track perceived fatigue independently of time-on-task during a half-marathon: a wearable-sensor field study

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Abstract

Breathing pattern is suggested to reflect physical load and stress, but field evidence is limited. This study examined whether breathing pattern, measured with a wearable sensor shirt, tracks perceived fatigue during a half-marathon. Fifteen recreational runners (12 analyzed) completed a 21.1 km time trial while ratings of fatigue (ROF) were recorded every 5 min. Respiratory frequency (f_R) increased +7.9 ± 6.8 breaths/min between the first and last quarters of the run, ribcage contribution to breathing increased by about 25% from seated rest to peak, and thoraco-abdominal coordination averaged −16.6 degrees (-4.6 to -34.3; abdomen precedes thorax). Runners performed locomotor-respiratory coupling (LRC) for 47.1 ± 26.0% of the run, most commonly at a 4:1 step-to-breath ratio. f_R was strongly correlated with ROF ($\rho = 0.71$), but this association disappeared after adjusting for time-on-task ($\rho = 0.11$, 95% CI −0.08–0.29). Physiological variables did not classify ROF better than the majority-class baseline, but time-on-task did, and runners differed substantially in how their breathing pattern tracked fatigue. Because perceived fatigue and respiratory frequency both increase with time during a continuous self-paced run, their association cannot be separated from time-on-task in such protocols. Future field studies should use designs that dissociate fatigue from elapsed time.

Keywords

locomotor-respiratory coupling; respiratory inductance plethysmography; time-on-task; rating of fatigue; wearable sensors

Introduction

Physical exercise triggers marked acute physiological and psychological responses in humans, including substantial changes in respiratory function. Pulmonary ventilation increases from an average 4-8 L/min at rest to approximately 150-200 L/min at maximal intensity [1]. This ventilatory response is driven by numerous physiological and psychological mechanisms such as exercise intensity, metabolism, environmental stress, movement frequency and rhythm. Ventilation may also be more sensitive to exercise tolerance and acute changes in intensity than other frequently reported metrics such as oxygen consumption or heart rate (HR) [2]. Nevertheless, a growing body of evidence suggests that more important than *how much* an athlete breathes might be *how* breathing is achieved; this concept is termed "breathing pattern".

Breathing pattern describes the temporal and mechanical aspects of how ventilation is achieved. Examples of breathing pattern variables include respiratory frequency (f_R), depth (tidal volume), coordination (between ribcage compartments and with movement), and airway utilization (nasal vs. oral). It was previously believed that breathing pattern automatically and continuously adjusts to minimize the metabolic work of breathing, termed the "principle of minimal effort" [3]. Recent work has countered this with a new "differential control" model suggesting that during exercise f_R adjusts quickly to changes in central command and muscle afferent activity, while breathing depth adapts slowly secondary to f_R to maintain biochemical homeostasis [2]. Monitoring f_R may therefore be especially valuable given its association to subjective ratings of perceived exertion (RPE). During exercise, in the high/very high intensity domain the f_R-RPE correlation was reported as high as 0.89 while minute ventilation ($r = 0.80$) and HR ($r = 0.81$) were lower [4,5]. This is likely because at relatively high exercise intensities, both "physical effort" (central motor outflow) and f_R are regulated by similar neural feedback loops [2]. These governing mechanisms are also fast-acting. Billat, et al. [6] reported that a disproportionate increase in f_R was the only valid predictor variable of the well-known "hitting the wall" phenomenon during a marathon run. However, most studies of exercise breathing pattern utilized incremental protocols inside a laboratory; there are limited field studies reporting both breathing pattern and RPE in the field. Events such as marathon or half marathon are valuable field study settings, because they induce substantial metabolic and peripheral stress but also require pacing that could affect the (in-) stability of breathing pattern. One study found a decrement in pulmonary function of 15-25% after marathon running [7], which may affect the evolution of breathing pattern during the run, although this was not reported. In incremental, time-to-exhaustion and time-trial protocols alike, perceptual ratings and f_R both rise with elapsed time, so their association may partly reflect time-on-task rather than a specific link between breathing and perception. How much of this association remains once elapsed time is accounted for has rarely been quantified, and not, to our knowledge, during self-paced running in the field.

Beyond f_R there might be additional diagnostic value in monitoring other breathing pattern variables. Thoraco-abdominal coordination (TAC), the time-domain synchrony of different ribcage compartments, was reported to increase with fatigue during steep (> 30% gradient) outdoor trail running [8]. The upper ribcage relative contribution to tidal volume (%RC) may increase 10% across a maximal 10 km treadmill run [9]. Notably, %RC depends heavily on the

relative gain of the multiple sensor bands, which is posture specific and may drift during prolonged exercise [10,11]. Breathing variability and complexity may also change, since central command influences both the perception of fatigue [12] and breathing rhythm [13]. Indeed, during exercise quantitative and correlated variability decrease as intensity increases [14]. Finally, locomotor-respiratory coupling (LRC), defined as the frequency and/or phase synchronization of f_R to cadence, may offer additional insights to monitoring use cases and running-related fatigue. Between 40-80% of runners express some degree of LRC, most often at ratios of 4:1 or 6:1 steps per breath [15]. Some reports suggest it is more prevalent at higher relative intensities [16,17]; this could be an adaptive response since LRC may contribute up to 10-12% minute ventilation [18]. While these "step-driven flows" could influence the metabolic cost of breathing and perceived effort, there is a paucity of data of LRC in the field.

Prolonged running generally increases acute fatigue, potentially blunting running's positive psychological benefits [19] or contributing to running-related injury [20]. However, fatigue is a complex phenomenon that may even protect a runner from negative consequences like injury. Fatigue has interdependent objective (e.g., speed) and subjective components (e.g., rating of fatigue) that manifest both peripherally (i.e., skeletal muscle) and centrally (i.e., central nervous system) [21,22]. Since the relationship between internal and external load is highly individual [23], there has been increased scientific attention towards understanding and monitoring acute fatigue factors before, during, and after running [24]. While performance fatigue during running can be quantified with pacing profiles and speed decrement [25], it should also be contrasted with perceived fatigue via self-report scales such as RPE [26] or rating of fatigue [27]. Employing holistic collection methods such as experience sampling during activity can increase the understanding of its evolution and relationship to key determinants.

As noted above, breathing monitoring is particularly valuable in part because RPE sensation and f_R are governed by similar neural pathways [13,28]; as such, concurrently monitoring fatigue and breathing patterns, particularly in combination with wearable sensors, could therefore substantially advance our understanding of these processes. Few studies have reported continuous breathing pattern and perceived fatigue during outdoor, self-paced exercise. Breathing may be different in outdoor environments not only because of pacing strategies, ambient air quality, and sensory stimulation, but also because spirometry masks, commonly used during indoor sports science studies, may perturb natural breathing patterns by the addition of instrumental dead space or use of nose clips [29,30]. Moreover, few studies have reported other valuable components of breathing pattern such as coordination or breathing variability. A half-marathon time trial does not dissociate fatigue from elapsed time. It does, however, represent the setting in which wearable fatigue monitoring would be applied, and therefore allows the size of this time-on-task confound to be quantified under realistic conditions. The main purpose of this study was to quantify how strongly breathing pattern tracks perceived fatigue during a self-paced half-marathon time trial, and how much of this association remains after accounting for time-on-task. Secondary aims were to describe continuous breathing pattern, thoraco-abdominal motion and locomotor-respiratory coupling during outdoor running, and to test whether physiological variables classify fatigue better than a no-information baseline and whether they improve classification beyond time-on-task alone.

Results

Data overview

Fifteen runners completed the half-marathon, from which 12 had complete breathing and gait data; 10 of these had complete rating of fatigue (ROF) data (172 ratings, 17 ± 3 per runner). These 10 ran for 93.6 ± 14.3 min at an average pace of 4:26 ± 0:41 min/km and relatively even speed (Figure 1b). Their ROF rose from 3.2 ± 2.1 at the first prompt to 9.1 ± 0.7 at the last (Figure 1a).

The ribcage/abdominal gain ratio K was 2.0 ± 1.0 (range 0.42–4.13). K derived after the run differed from the pre-run value by 41% on average and by more than 20% in 9 of 12 runners (range −53% to +99%; Supplementary Figure S1a). The validity gate passed a median 44% of breaths (range 8–96%; Figure S1b); in six recordings the two bands shared no common respiratory oscillation over most of the run, so relative ribcage contribution to breathing (%RC) and thoraco-abdominal coordination (TAC) rest on the remaining breaths.

f_R averaged 47.3 ± 10.8 breaths/min and increased by 7.9 ± 6.8 breaths/min between the first and last quarter of the run, while breath depth fell by 10.7 ± 11.3% (Figure 2a). %RC was 67.8 ± 9.0% during running, 25.4 ± 9.6 % higher than at seated rest (range +10.9 to +38.4; positive in all 12), and changed little across the run (+3.0 ± 3.9 %). TAC was −16.6 ± 9.0° (abdomen leading), with high within-breath phase concentration ($R \geq 0.92$). Runners were attached to a locomotor-respiratory coupling (LRC) ratio for 47.1 ± 26.0% (range 2.0–81.4) of time, most often at 4:1 (six runners) or 3:1 (four), and attachment increased from 40% to 59% between the first and last quarters (Figure 3).

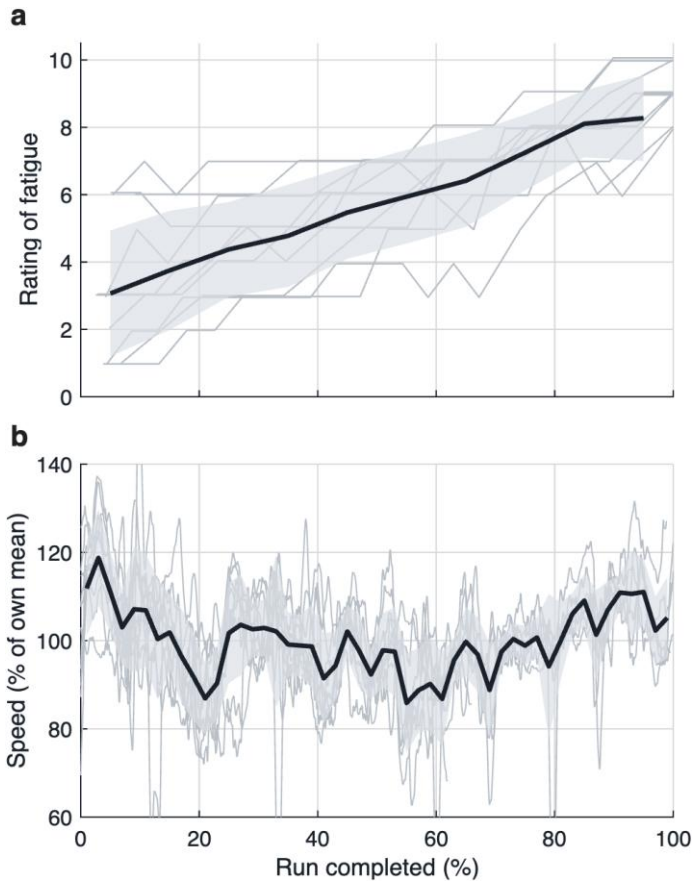


Figure 1. Rating of fatigue and pacing across the run. (a) Rating of fatigue (1–10) at each prompt. (b) Running speed relative to each runner's own mean (GPS, 60-s moving mean). Grey lines, individual runners (n = 10); black line and band, mean ± SD."

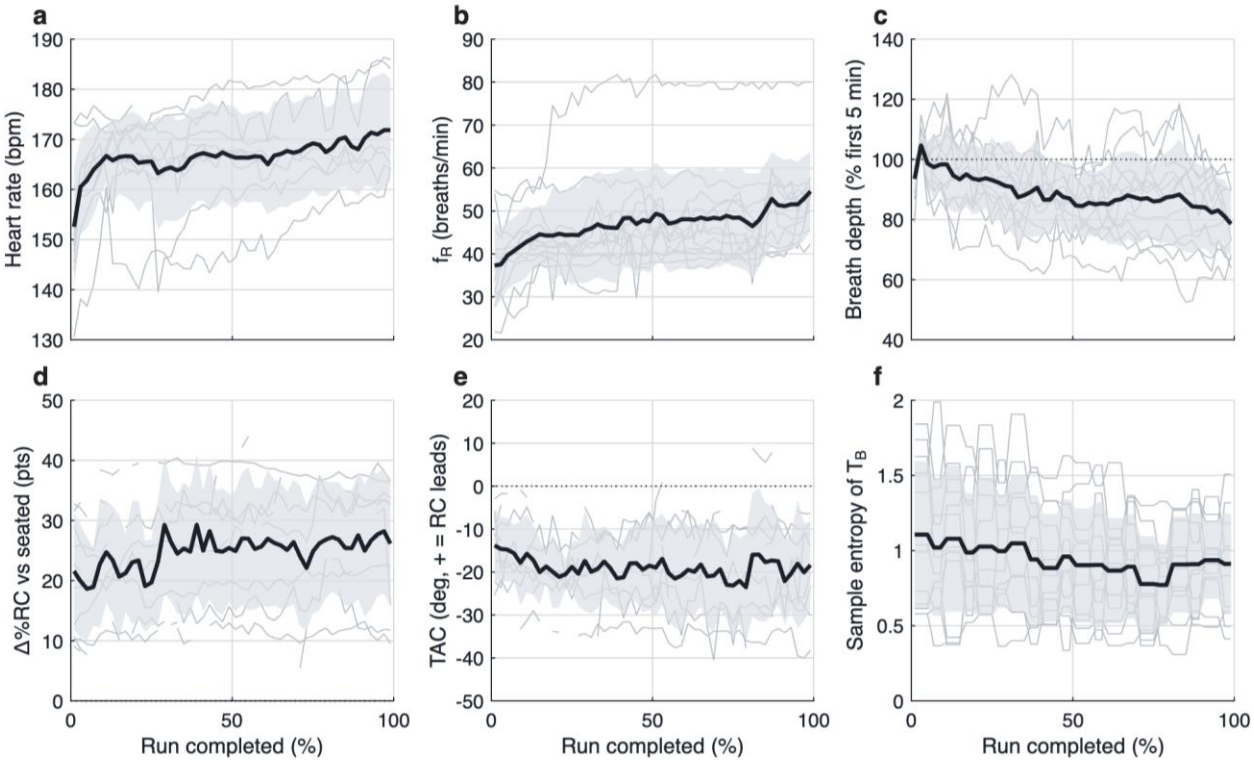


Figure 2. Breathing pattern across the run. (a) Heart rate. (b) Respiratory frequency. (c) Breath depth relative to the first 5 min of running. (d) Change in rib-cage contribution from seated rest (Δ%RC). (e) Thoraco-abdominal phase angle (TAC; positive = rib cage leads). (f) Sample entropy of breath cycle time. Δ%RC and TAC use only breaths passing the validity gate, in bins with at least 10 such breaths. Grey lines, individual runners (n = 12); black line and band, mean ± SD across runners in 2% bins of the run. f_R, respiratory frequency; %RC, relative ribcage contribution; TAC, thoraco-abdominal coordination.

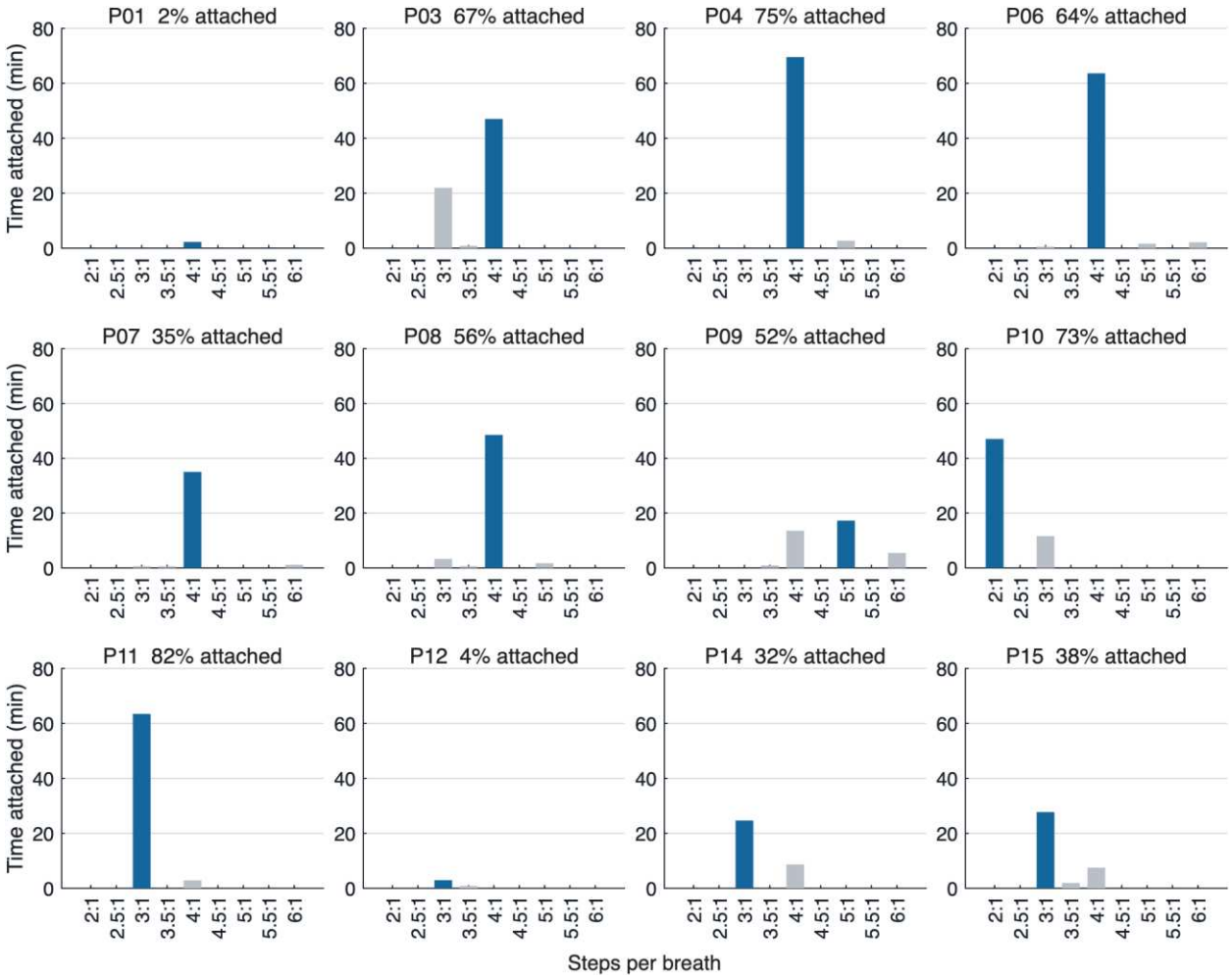


Figure 3. Locomotor-respiratory coupling by runner. Total time attached to each whole- or half-integer steps-per-breath ratio; the dominant ratio is highlighted. Panel titles give the percentage of breaths attached over the whole run.

Model performance

The 172 ratings fell into the low (35), medium (94) and high (43) classes, so always predicting 'medium' gave an accuracy of 0.56 ± 0.17 (Table 1). Physiological variables alone did not exceed this baseline with any learner (accuracy 0.47–0.56, κ 0.06–0.25; all $p \geq 0.47$). Time-on-task alone did (naive Bayes 0.75 ± 0.16, $\kappa = 0.57$, $p = 0.014$; boosted trees 0.72 ± 0.19, $p = 0.018$), and adding physiology to time did not improve on it (0.61–0.70). Complete model outputs are in Supplementary Tables S6-S9.

Table 1. Leave-one-participant-out classification of rating-of-fatigue class (low 1–3, medium 4–7, high 8–10). Values are mean ± SD across the 10 held-out runners; p, one-sided Wilcoxon signed-rank test of accuracy against the no-information baseline.

Predictors	Learner	Accuracy	Cohen's κ	Weighted F1	p vs baseline
None (baseline)	Majority class	0.56 ± 0.17	0.00	0.41	—
Time-on-task	Naive Bayes	0.75 ± 0.16	0.57	0.77	0.014
	Random forest	0.67 ± 0.11	0.44	0.69	0.051
	Boosted trees	0.72 ± 0.19	0.54	0.73	0.018
Physiology	Naive Bayes	0.53 ± 0.20	0.24	0.51	0.54
	Random forest	0.47 ± 0.14	0.06	0.41	0.89
	Boosted trees	0.56 ± 0.19	0.25	0.52	0.47
Physiology + time	Naive Bayes	0.61 ± 0.15	0.35	0.60	0.28
	Random forest	0.68 ± 0.15	0.44	0.68	0.061
	Boosted trees	0.70 ± 0.18	0.51	0.71	0.034

Within-participant associations and sensitivity

Within runners, f_R was strongly associated with ROF ($\rho = 0.71$, 95% CI 0.44–0.86, $p < 0.001$), as were HR ($\rho = 0.73$) and, inversely, breath depth ($\rho = -0.68$) and LRC ratio ($\rho = -0.65$), the latter largely mirroring f_R because the steps-per-breath ratio is cadence (stable) divided by f_R (Figure 4, Supplementary Table S2). After adjustment for time-on-task, none of the 11 variables was associated with ROF (f_R $\rho = 0.11$, 95% CI −0.08–0.29, $p = 0.21$; all $q \geq 0.35$). The design was sensitive to adjusted mean associations of about $|\rho| \geq 0.26$.

Time-on-task alone explained 63% of the variance in ROF. Adding within-participant f_R did not improve the model ($\beta = 0.007$ per breath/min, $p = 0.74$), whereas without the time term f_R appeared highly significant ($\beta = 0.24$, $p < 0.001$). Three variables were associated with ROF beyond time in both linear and ordinal intercept-only models (TAC, BD RMSSD, and sample entropy, all $q < 0.05$), but none remained when including per-individual random slopes (all $p \geq 0.07$, $q \geq 0.41$, in linear and ordinal models). Between-runner slope variance was significant for f_R ($p < 0.001$), HR, breath depth, Δ%RC, BD RMSSD, sample entropy and both LRC measures (Supplementary Tables S3-S5): runners differed in how these variables tracked fatigue.

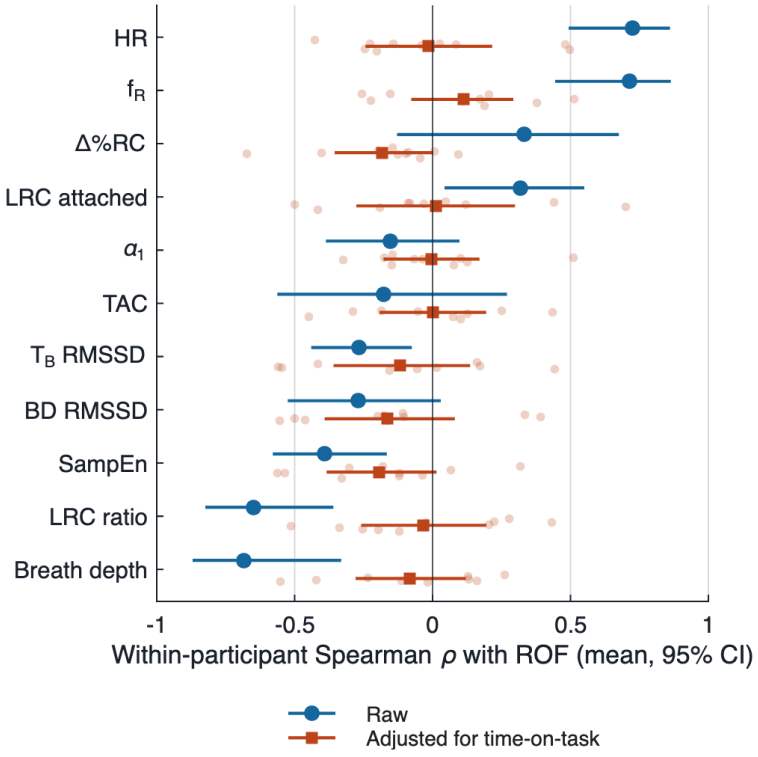


Figure 4. Association of each variable with rating of fatigue, before and after adjustment for time-on-task. Within-participant Spearman ρ, mean and 95% CI across 10 runners (Fisher z). Blue circles, raw; orange squares, partial correlation controlling for the proportion of the run completed; faint points, individual runners (adjusted). HR, heart rate; f_R, respiratory frequency; %RC, relative ribcage contribution; LRC, locomotor-respiratory coupling; TAC, thoraco-abdominal coordination; T_B, breath time; RMSSD, root mean square of successive differences; BD, breath depth; SampEn, sample entropy.

Discussion

This study is among the first to report and connect concurrent, continuous subjective fatigue and breathing pattern data during outdoor running with wearable sensors. Overall, breathing pattern variables were strongly associated with perceived fatigue, but these associations were mostly accounted for by time-on-task in correlation and classification analyses. Mixed models identified that three breathing variability variables (TAC, BD RMSSD, and sample entropy) were associated with ROF beyond time only, but these associations disappeared in when adding within-participant partial correlations and random slopes. Runners differed substantially in how their breathing tracked fatigue: some variables (e.g., thoraco-abdominal motion) show stability while others like f_R show monotonic trends. While these breathing pattern metrics have been reported and compared with fatigue or exertion in controlled lab settings, this is a unique description of these variables across time during field exercise and with peak exertion like that of competition. The continuous measurement with wearable sensors and experience sampling demonstrates the challenge and potential for executing ecologically valid studies in the field.

The observed group-level trends reflect the modern understanding of how breathing pattern responds during prolonged exercise: f_R showed a consistent increase related to time-on-task, which reflects increasing internal workload and fatigue perception. This occurred despite a flat course, stable weather, and negligible changes in pacing within participants. Breathing depth decreased secondary to f_R to maintain biochemical homeostasis at a given metabolic level [2]. f_R ($\rho = 0.71$) and HR ($\rho = 0.73$) had similarly close associations to ROF scores, but after adjustment to time-on-task both were near zero (0.11 and −0.01). Previous findings showed the ROF-f_R association to be greater than HR during various time-to-exhaustion tasks [4]. Hence, incremental or time trial protocols may be insufficient to study independent connections between breathing pattern and subjective exertion or fatigue; intermittent or sinusoidal protocols may be better for studying this mechanistic link [5].

These results show a higher LRC prevalence (47.1%, median 54%) than the ~35% reported in earlier outdoor running studies [31-34], despite employing a stricter criterion that indexes both frequency and phase synchronization. Furthermore, the observed LRC exceeded that expected by chance alone in all 12 runners (median 28.9%, tested against 100 time-shifted copies of each runner's breathing). The dominant ratio reported here (4:1 steps per breath) aligns with these previous studies. Runners also increased LRC later in the run, which was not previously reported. This may be due to increasing type III and IV afferent feedback [35], or an adaptive response to mitigate the accumulating effects of respiratory muscle fatigue across the run. Neurological, physiological, and perceptual factors respond to prolonged running and stimulate LRC [15]; thus, future studies manipulating these independent factors are needed to isolate these potential mechanisms and outcomes.

This is one of few reports of continuous thoraco-abdominal motion during field exercise. A recent study using gold-standard optoelectronic plethysmography (OEP) and a two-compartment ribcage model found that pulmonary contributions to total tidal volume averaged 78 ± 22% during running [36]. Hedge, et al. [37] found 63-67 %RC during incremental cycling tests to exhaustion with the Hexoskin shirt; their study reported %RC from raw oscillation counts, without any calibration. Volume-motion coefficients are an imprecise basis for this calculation as they vary ± 20 % between days [10]. In the current study %RC was 67.8 ± 9.0 % with subject-specific K-ratios; 3/10 runners decreased %RC with increasing ROF, but after time adjustment Δ%RC was not associated with ROF ($\rho = -0.18$, $p = 0.053$). The TAC values reported here also align with another report during field running with wearables: TAC was −16.6 ± 9.0° (range −4.6 to −34.3°), which is comparable to 12-16° during inclined trail running [8] and the 20° observed at maximal exhaustion [38,39]. Previous studies did not indicate sign convention, so it is unclear if they observed the abdominally-led breathing that is reported here. TAC had most consistent association with ROF in the intercept-only linear and ordinal mixed-models (both $p < 0.001$), but the association was eliminated with participant random slopes and within-participant partial correlations. Thus, the TAC-ROF relationship could be strong within some individuals but should be evaluated in higher-powered studies.

This study is limited in three ways. First, the half marathon run performed was only a race simulation – not an actual race. This was helpful to gather quality data such as ROF audio

collection and control for the external influence of other runners. Since the participants were not running together with others, it is possible that they did not run at the same intensity or perform the same pacing as they might in a large group. In addition, the sounds of others' footsteps, breathing, or ambient noise could affect runners' tendency for entrainment [40]. Second, the sample of runners studied here was a small (n = 10) group of moderately experienced runners. This challenges the ability to generalize our findings to runners in general, for example to beginners or elites. These participants were healthy and male, we do not expect identical findings in female runners, who have well-documented differences in breathing during exercise [41]. While this breathing pattern monitoring approach may be useful for clinical populations (such as patients with asthma), we would expect different normative values than reported here.

Third, sensor constraints and errors limited the scope of this study to be truly comprehensive. While we aimed to include speed and pacing data, GPS data was missing or corrupted for many individuals, and thus not used in this analysis. If these data were correct, we could add an analysis of pacing and speed to include "performance fatigue" in contrast to perceived fatigue [21]. Since there is an interplay of intensity, pacing, efficiency, and fatigue, it is necessary to consider these internal and external components carefully to better understand how breathing patterns respond. It is likely that intensity and pacing directly affected ROF and breathing pattern, but this mechanism is not certain here. A wearable RIP shirt was chosen instead of mobile spirometry since the added dead space of oro-nasal masks may influence gas kinetics and breathing patterns [29,30]. While RIP can be used to estimate tidal volume [42]; this was not performed in this study due to equipment unavailability. Future studies should consider this step since minute ventilation may provide additional information regarding ventilatory threshold shifts and intensity domains during prolonged exercise [43]. Using RIP during running is inherently difficult since footstrike introduces motion artifact into both bands. The band coherence validity gating used here rejected about half of breaths for thoraco-abdominal motion metrics. An isovolume maneuver would be superior to the quiet breathing calibration for deriving absolute %RC; thus Δ%RC was used as the primary rib-cage outcome here.

These findings demonstrate the potential of wearables for detailed breathing pattern analysis during field exercise. During a self-paced half-marathon, f_R and other physiological variables were strongly related to perceived fatigue, but the associations largely accounted for by time-on-task, and they did not classify fatigue better than elapsed time alone. Runners expressed LRC for about half of the run and had much greater %RC during running versus rest. Field studies of fatigue markers should adjust for time-on-task and consider individual response patterns.

Methods

Participants

A convenience sample of 15 healthy male recreational runners (age = 26.1 ± 5.0 years, height = 181.1 ± 7.2 cm, body mass = 74.9 ± 7.2 kg) volunteered to participate in this exploratory study. All had racing experience at various distances from 10 km to marathon. Of the 15 runners, three had respiration sensor problems, leaving 12 for breathing and gait analyses; rating of fatigue audio was usable for 10 of these. The human research ethics committee of École Polytechnique Fédérale de Lausanne approved the study (HREC 039-2018); work was performed in accordance

with relevant guidelines and regulations, and all participants provided written informed consent before the data collection in accordance with the Declaration of Helsinki.

Study design

This study was conducted during an individually performed 21.1 km half-marathon time trial in Rif, Austria, between 25 and 29 November 2020, as described previously [24]. The time trial was designed to simulate the demands of a half-marathon race: participants were instructed to run "all out" and complete the course as quickly as possible. However, participants ran individually rather than as part of a competitive field, allowing for standardized testing conditions and the collection of high-quality audio recordings while minimizing the potential influence of other runners. The course was flat, included exactly one change in direction, and had less than 10 m of elevation change. Weather conditions were cold and sunny, with temperatures ranging from 1 to 5 °C. Participants were instructed to avoid caffeine on the day of the run and to refrain from eating for at least two hours before the time trial. Before the run, basic anthropometric data were collected, and multiple sensors were fitted to each participant, including a sensor shirt. Before and after the run, participants sat quietly for 5 min wearing the sensor shirt; these recordings were used for calibration.

Instruments

Participants wore a Hexoskin shirt during the race and resting phases to gather breathing (dual thoracic and abdominal stretch sensors, two channel respiratory inductance plethysmography, 16-bit, 128 Hz), HR (1 Hz), and accelerometry (3-axis, 64 Hz, range ±16 g) data. Raw data were extracted via the HxServices application and the Hexoskin Online Dashboard. Participants also wore a global positioning system (GPS) sensor (Fieldwiz, ASI, Switzerland). Since GPS speed underestimated the known race distance, average pace was calculated from the race distance and running time, and GPS speed was used only to describe pacing relative to each runner's own mean.

Rating of fatigue (ROF) data were collected using a custom-built application on a smartphone as previously described [24]. The application reminded the runner to speak out their ROF on a scale of 1–10 [27] and recorded this audio with a timestamp. The application was configured to create a reminder every five minutes and subsequently record for a period of 30 s. Audio files were manually transcribed.

Data processing

All raw signals were processed in MATLAB R2026a (The MathWorks Inc., Natick, USA). The signal-processing functions are openly available on Github (*https://github.com/eharbss/hexoskin-rip-algorithms* and *https://github.com/eharbss/calc_LRC*). The data and a single live script that reproduces every result, table and figure in this article from the device recordings are archived on Zenodo (https://doi.org/10.5281/zenodo.23574436).

Claude (Anthropic) was used to refactor the analysis pipeline, improve readability, and prepare it for submission to the repository. All analyses were run, checked and interpreted by the authors, who take full responsibility for the content.

Calibration

Respiratory inductance plethysmography (RIP) records changes in ribcage and abdominal expansion with different gains, so the contribution of each compartment to tidal volume can be estimated only after calibration. From the seated recording made before the run, the gain ratio K was calibrated as described previously[44] with the formula:

$$K = SD(\Delta RC)/SD(\Delta AB)$$

where ΔRC and ΔAB are the per-breath excursions of the ribcage and abdominal bands, with a bootstrap 95% confidence interval. This K was used for all running data. K was estimated again from the seated recording after the run to check gain stability; a change of more than 20% was taken to indicate belt slippage or a change in sensor gain.

Breath detection and signal validity

Both RIP bands were screened for flat or disconnected segments and then band-pass filtered with a single fourth-order Butterworth filter (0.1–1.5 Hz, zero phase) applied identically to both, so that filtering could not introduce a phase difference between them. Inspiration and expiration onsets were detected on a weighted combination of the two bands, each weighted by its breathing-band signal-to-noise ratio, with the zero-crossing method of [45] and predetermined amplitude and minimum-breath-duration gates. An earlier version of this method showed less than 5% bias against reference measurements during running [45]. Abdominal onsets were then located within half-cycle windows defined by the thoracic onsets.

Ribcage contribution and thoraco-abdominal coordination are meaningful only when both bands record the same respiratory oscillation, so a two-step validity gate was applied (Supplementary Figure S1b). First, using a sliding 30 s window advanced in 10 s steps, the magnitude-squared coherence between the bands at the tracked breathing frequency, corrected for the bias of the Welch estimate, had to be at least 0.60. Because foot strike moves both bands mechanically and can itself produce high coherence, a window was also rejected when the tracked breathing frequency coincided with the stride frequency, or a subharmonic of it, obtained from the trunk accelerometer. Second, for each breath, the concentration R of the instantaneous phase difference between the bands had to be at least 0.70. Ribcage contribution and thoraco-abdominal coordination were calculated only from breaths that passed both steps; all other variables used every breath.

Breathing pattern

For each breath the following variables were calculated (Figure 5):

- Breath cycle time (T_B, s): from one inspiration onset to the next, and respiratory frequency, $f_R = 60/T_B$ (breaths/min).
- Breath depth (BD): the sum of the peak-to-trough excursions of the two bands within the breath [46]. Because RIP amplitude depends on shirt fit and torso geometry, BD was expressed relative to each runner's median over the first 5 min of running (100%).
- Ribcage contribution (%RC): $\Delta RC / (\Delta RC + K \cdot \Delta AB) \times 100$, using the pre-run K.
- Change in ribcage contribution (Δ%RC): %RC during running minus the median %RC of the same runner's seated pre-run recording, both computed with the same K. A within-

runner change is far less sensitive to error in K than the absolute level, so Δ%RC was the primary rib-cage outcome.

- Thoraco-abdominal coordination (TAC, °): the circular mean over the breath of the instantaneous phase difference between the bands obtained from the Hilbert transform. Positive values indicate that the rib cage leads, 0° synchrony and ±180° paradoxical motion [47,48]. The within-breath concentration R (0–1) was retained as the confidence of each value.

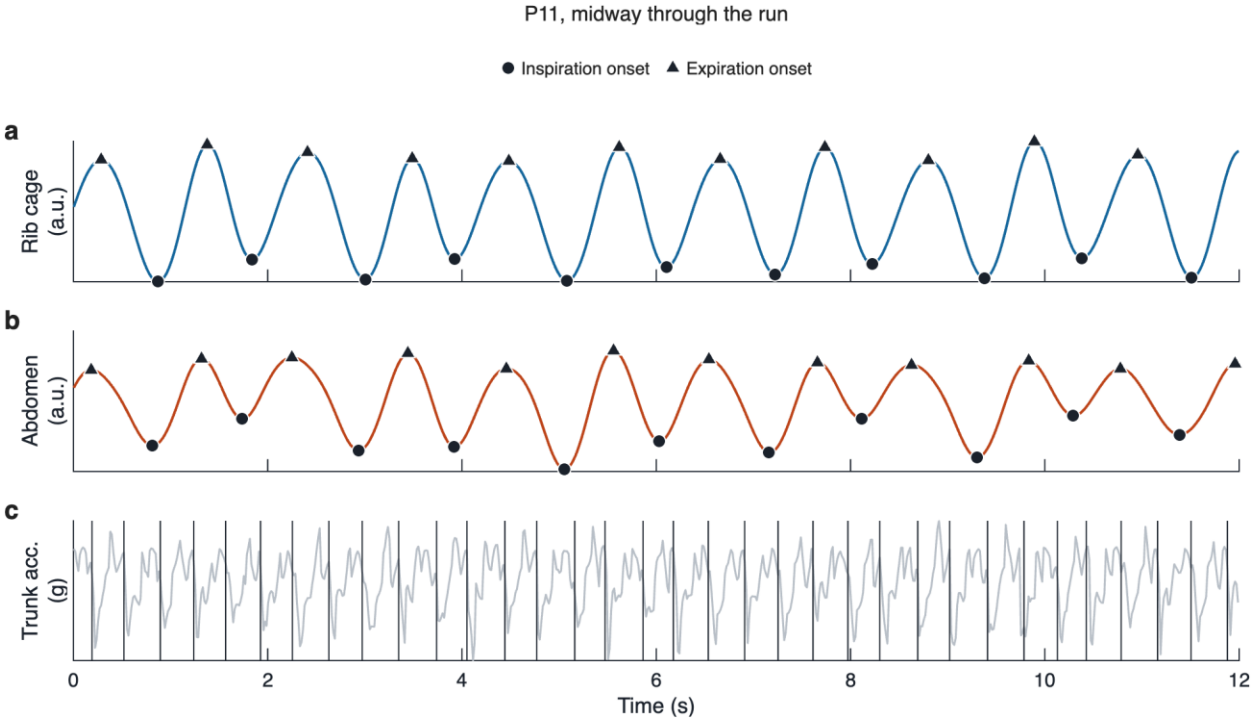


Figure 5. Respiratory inductance plethysmography and trunk acceleration during running (participant 11, 12 s at mid-race). (a) Ribcage and (b) abdominal bands after identical band-pass filtering, inverted so that upward = inspiration, with detected inspiration (circles) and expiration (triangles) onsets. (c) Vertical trunk acceleration with detected foot contacts (vertical lines)."

Breathing variability

Within each analysis interval (below), variability of T_B and BD was quantified as the root mean square of successive differences (T_B RMSSD, BD RMSSD); complexity of T_B as sample entropy ($m = 2$, $r = 0.2 \times SD$) [49]; and correlation structure of T_B as the short-term scaling exponent α_1 of detrended fluctuation analysis (box sizes 4–9 breaths) [50]. Sample entropy and α_1 required at least 20 and 30 breaths, respectively.

Steps and locomotor-respiratory coupling

Foot contacts were detected from the trunk accelerometer with an adapted version of the algorithm of Benson, et al. [51]. For each breath, steps were counted with soft boundaries: a step within 15% of a breath period of a breath boundary was shared between the adjacent breaths.

The phase of each inspiration and expiration onset within the step cycle (0° = foot contact) was summarized by the resultant vector length R (0–1) as a measure of phase coupling [52].

Attachment, defined as LRC at a fixed ratio [53], was detected in windows of five consecutive breaths. A window was attached to a candidate ratio (whole or half integers from 1:1 to 10:1) when at least 80% of its breaths lay within ±0.5 steps per breath of that ratio, and when breath onsets held a stable phase within the step cycle (defined as a phase concentration of the corresponding synchrogram of at least 0.3 over the surrounding 20 breaths). The phase criterion distinguishes LRC from step and f_R that is simply near an integer ratio; on surrogate data with shuffled inter-breath intervals, it reduced false-positive attachment from 18–60% to 0–10% (see *https://github.com/eharbss/calc_LRC*). A half-integer ratio was preferred only when it was supported by at least 10% more of the window's breaths than the nearest integer. Attached windows with the same ratio less than 10 s apart were merged, and episodes shorter than 30 s were discarded. Coupling prevalence was expressed as the percentage of time attached, and each runner's dominant ratio as the ratio with the greatest total attached time.

Data segmentation

Each ROF prompt was used to define discrete analysis intervals: from the start of the run to the first prompt, between consecutive prompts, and from the last prompt to the end of the run. Breathing pattern variables were summarized within each interval by their median (circular mean for TAC), and HR and speed by their mean. %RC and TAC were summarized only when at least 10 breaths in the interval passed the validity gate. Every prompt was retained as a separate observation. Time-on-task was expressed as the proportion of the run completed at each prompt.

Statistical analysis

Descriptive data are reported as mean ± SD across participants unless stated otherwise. Statistical significance was set at $\alpha = 0.05$ (two-sided unless stated).

Because ROF and most physiological variables increase with time during a run, a within-runner correlation between them could reflect elapsed time alone. The association of each of 11 variables (f_R, HR, BD, Δ%RC, TAC, T_B RMSSD, BD RMSSD, sample entropy, α_1, LRC ratio and time attached) with ROF on its original 1–10 scale was therefore estimated in two ways within each runner: as a Spearman rank correlation, and as a partial Spearman correlation controlling for time-on-task. Runner-level coefficients were Fisher z-transformed, averaged, and tested against zero with a one-sample t test ($df = n - 1$); means and 95% confidence intervals were back-transformed. The Benjamini–Hochberg procedure controlled the false discovery rate across the 11 variables, separately for the raw and the time-adjusted associations [54].

The same question was addressed with linear mixed models fitted by maximum likelihood to all 172 prompts, with each variable (x) centered within runner so that its coefficient estimates the within-runner association. Whether x adds to time-on-task was tested by likelihood-ratio test ($\chi^2(1)$) of *ROF ~ time + x + (1 | runner)* against *ROF ~ time + (1 | runner).* Because runners may differ in how x tracks ROF, the test was repeated with a correlated random intercept and slope, *ROF ~ time + x + (1 + x | runner)* against *ROF ~ time + (1 + x | runner).* Between-runner slope variance was tested by comparing the random-intercept and random-slope models. Because

a variance is tested at its lower bound of zero, p was taken from a 50:50 mixture of $\chi^2(1)$ and $\chi^2(2)$[55]. The variance in ROF explained by time-on-task was reported as marginal R^2 (fixed effects) and conditional R^2 (fixed effects and runner intercepts)[56]. For comparison with earlier studies, models without the time term were also fitted.

Because ROF is an ordinal rating, the analysis was repeated with cumulative-logit mixed models on all ten ROF levels and on three classes (low 1–3, medium 4–7, high 8–10). Each variable was centered and scaled to its within-runner SD, so β is the change in log-odds of a higher rating per within-runner SD. Models had a random intercept per runner and, for the ten-level outcome, a correlated random slope. They were fitted by maximum likelihood, with random effects integrated by Gauss–Hermite quadrature, and tested with the same likelihood-ratio tests. For all mixed-model tests, the Benjamini–Hochberg procedure controlled the false discovery rate across the 11 variables[54]. All tests are summarized in Supplementary Table S5 and detailed in Supplementary Tables S3 and S4.

To test whether physiology could classify fatigue beyond what elapsed time predicts, ROF was grouped into low (1–3), medium (4–7) and high (8–10) classes and classified with naive Bayes (kernel densities), random forest (300 trees, minimum leaf size 3) and boosted trees (AdaBoost.M2, 100 learning cycles, trees with at most four splits, learning rate 0.1). Each learner was trained on three predictor sets: time-on-task alone, the 11 physiological variables, and both, and compared with a no-information baseline to predict the majority class of the training data. Performance on unseen runners was evaluated by leave-one-participant-out cross-validation, with median imputation and standardization fitted to the training folds only. Accuracy, Cohen's κ and weighted F1-score were computed for each held-out runner and summarized as mean ± SD, and accuracy was compared with the baseline by one-sided Wilcoxon signed-rank test. The per-runner accuracy difference (physiology + time minus time alone) was summarized for each learner as mean with t-based 95% CI and tested with two-sided Wilcoxon signed-rank and paired t tests. Sensitivity was checked with per-fold feature filtering, per-fold hyperparameter tuning, 20 random seeds, classification of all ten ROF levels, and exclusion of P10. See Supplementary Tables S6–S10 for more information.

Because the sample size was fixed (n = 10), sensitivity was evaluated for the mean within-participant association. Participant-specific Spearman correlations were Fisher z-transformed, and the between-participant standard deviation on the Fisher-z scale was used as the variability estimate. This post-hoc sensitivity analysis was used to characterize the detectable magnitude of the mean within-participant association, not to perform an a priori sample size calculation.

The minimal detectable mean effect was calculated on the Fisher-z scale as

$$\Delta_z = \left(t_{0.975,n-1} + t_{0.80,n-1}\right) \times \frac{s_z}{\sqrt{n}}$$

where s_z denotes the between-participant standard deviation of the Fisher-z transformed correlations. The resulting value was back-transformed to the correlation scale as $\rho_{\mathrm{MDE}} = \tanh(\Delta_z)$.

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Declarations

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Competing interests
No conflicts of interest, financial or otherwise, are declared by the authors.

Ethics approval and consent to participate
The human research ethics committee of École Polytechnique Fédérale de Lausanne approved this study (HREC 039-2018). The study was performed in accordance with the Declaration of Helsinki, and informed consent was obtained from all subjects.

Data and code availability
The data and the complete analysis code that reproduces all results and figures are openly available on Zenodo (https://doi.org/10.5281/zenodo.23574436). The signal-processing functions are available on Github (*https://github.com/eharbss/hexoskin-rip-algorithms* and h*ttps://github.com/eharbss/calc_LRC*).

Author contributions
GP and SA conceived and designed research; EH and SK analyzed data; EH drafted manuscript; EH, GP, SA, SK, and GT edited and revised manuscript; all the authors approved the final version of the manuscript.

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