Real-World Heart Rate Dynamics During Daily Running: Associations with Resting Heart Rate, Temperature, and Time

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Abstract

Background: Wearable heart-rate (HR) data enable high-frequency monitoring of cardiovascular strain during endurance training, but real-world HR patterns may reflect both physiologic responses and training behaviors.

Purpose: To analyze running HR in conjunction with ambient temperature, evaluate associations between daily resting HR and running HR, and describe temporal trends across a winter-to-spring transition in the Philadelphia metropolitan area.

Methods: This observational study analyzed 2,635 daily runs from 31 semi-competitive adult runners across 85 consecutive days (Feb 3–Apr 28, 2025). Running HR was obtained from Strava activity posts automatically uploaded from electronic running watches. Resting HR was measured each morning immediately or shortly after rising using a standardized two-minute seated protocol; the lowest HR observed during the two-minute window was recorded as resting HR. Ambient temperature (°F) was linked to each runner-day observation.

Results: Mean resting HR was 47.9 ± 4.8 bpm and mean running HR was 145.8 ± 14.4 bpm; mean HR ratio was 306.1% ± 28.3. Running HR correlated with resting HR ($r = 0.57$). Ambient temperature was inversely associated with running HR ($r = -0.49$), with an estimated −0.46 bpm per 1°F increase. Mean running HR increased from the first to last 14 days (+14.6 bpm), and HR ratio increased by +17.6 percentage points.

Conclusion: In this free-living cohort, higher temperatures were associated with lower running HR while running HR increased over time, suggesting that training intensity/workload selection and contextual or measurement factors influenced field HR patterns beyond ambient temperature alone.

Introduction

Heart rate (HR) is a practical proxy for cardiovascular strain and "internal load" during endurance exercise. During running, HR reflects the integrated response of metabolic demand, autonomic regulation, and circulatory requirements for both working muscle perfusion and heat transfer. Thermoregulation is tightly linked to cardiovascular control because blood flow is a primary pathway for moving heat from exercising muscles to the skin surface; as thermal load rises, the cardiovascular system must support both locomotor and heat-loss demands [1]. In many contexts, warm or hot conditions are expected to increase physiological strain during prolonged exercise, partly through mechanisms related to cardiovascular drift—characterized by a progressive rise in HR accompanied by reductions in stroke volume and blood pressure regulation challenges under sustained effort [2]. Hydration status and environmental conditions (temperature, humidity, wind, sun exposure) can further influence thermoregulatory and cardiovascular

responses during exercise [3].

At the same time, the direction and magnitude of field-observed HR changes across seasons are not determined by temperature alone. Training adaptation and heat acclimation can reduce physiological strain for a given workload, including reductions in exercise HR and improvements in circulatory efficiency [4]. Moreover, in free-living settings, runners often adjust pace, route, clothing, and workout intensity in response to weather and training goals. As a result, temperature-associated changes in running HR can be confounded by intentional or unintentional changes in external workload (e.g., easier "recovery" runs on warmer days, harder workouts later in a training block). These realities motivate analyses that pair ambient conditions with a runner-specific baseline metric—such as daily resting HR—to help contextualize day-to-day variation in exercise HR.

The proliferation of consumer wearables and platforms that store activity data (e.g., Strava) has created an opportunity to examine HR dynamics with high ecological validity. However, wrist-worn HR measurement is not equivalent to clinical electrocardiography and can be influenced by device model, sensor placement, motion artifact, and individual characteristics; therefore, careful reporting of measurement procedures and potential sources of error is essential [5]. In validation work, wrist-worn photoplethysmography (PPG) devices show, on average, small errors at rest and during treadmill walking/running, but performance varies by device and activity type [6]. Laboratory-based comparisons have also demonstrated that device accuracy may decline during movement and can differ by device and participant characteristics [7]. These considerations are particularly relevant when interpreting small-to-moderate associations between ambient conditions and running HR in observational datasets.

Despite growing access to wearable HR data, relatively few longitudinal field datasets include both (a) a standardized daily resting HR measure and (b) daily running HR across a contiguous season-transition period within a consistent geographic region. The Philadelphia metropolitan area offers a meaningful natural experiment window from late winter into spring, with wide day-to-day variability in temperature. Understanding how running HR covaries with ambient temperature—while simultaneously tracking resting HR and temporal trends—may help runners and coaches interpret HR signals more appropriately in real-world training.

Study aims: Using an 85-day observational dataset of daily runs from semi-competitive adult runners in the Philadelphia metropolitan area, we aimed to:

a) quantify the association between ambient temperature and running HR

b) evaluate the relationship between daily resting HR and running HR

c) describe temporal changes in running HR and the running-to-resting HR ratio across the observation period.

We hypothesized that running HR would (a) correlate positively with resting HR and (b) show measurable variation with ambient temperature, while also acknowledging that real-world training behaviors could modify or obscure simple physiological expectations.

Methods

Study Design and Setting

This study was a longitudinal, observational analysis of daily running heart rate (HR), morning resting HR, and ambient temperature in a real-world training setting. Data were collected across 85 consecutive days from February 3, 2025 through April 28, 2025, with runs occurring in the Philadelphia (Pennsylvania, USA) metropolitan area.

Participants

The analytic cohort included 31 adult runners described as semi-competitive. Participant age was 33.1 ± 7.9 years (range: 18–49). Each participant contributed one run per day across the observation window, yielding 2,635 total run observations (31 runners × 85 days).

Data Sources and Data Compilation

Running HR values were obtained from Strava activity posts. Participants recorded runs using electronic running watches; HR data were captured by the watch during the activity and automatically uploaded to Strava. The study compiler extracted the per-run HR summary value from Strava for each runner-day and compiled it into a structured dataset.

Resting Heart Rate Measurement Protocol

Resting HR was collected each morning immediately or shortly after rising from bed using the participant's watch. The participant attached the watch to the wrist, sat down, minimized physical activity, and observed HR continuously for two minutes. The lowest HR observed during that two-minute period was recorded as the resting HR for that day (bpm). This approach was used to standardize resting HR collection and reduce the influence of early-morning movement and transient elevations.

Running Heart Rate Definition

Running HR (bpm) was defined as the single summary running HR value reported for the activity on Strava (as generated by the

wearable device/platform). One running HR value was recorded per runner per day, corresponding to that day's run.

Ambient Temperature

Ambient temperature was recorded in degrees Fahrenheit (°F) and linked to each runner-day entry as the outdoor temperature corresponding to the run day in the Philadelphia metropolitan area. Temperature values were compiled alongside the HR data to evaluate weather-related trends.

Derived Variable: HR Ratio

To contextualize exercise HR relative to baseline physiology, an HR ratio was calculated as:
HR ratio (%) = (Running HR / Resting HR) × 100.
In the dataset, this derived measure was stored as a percent value (unitless percent).

Dataset Structure and Data Handling

The final dataset contained four variables per observation: Resting HR, Running HR, HR ratio, and ambient temperature, with one row per runner per day (n = 2,635 rows). The analytic dataset contained no missing values for these variables. Descriptive summaries were computed for all observations and included mean (SD), median (IQR), and min–max values.

Statistical Analysis

Analyses were primarily descriptive and association-focused. Relationships between (1) resting HR and running HR and (2) ambient temperature and running HR were evaluated using Pearson correlation coefficients. The temperature–running HR association was additionally summarized with ordinary least-squares linear regression to estimate the expected change in running HR per 1°F difference in ambient temperature.

To describe contrasts across weather conditions, runs were stratified into temperature quartiles based on the empirical distribution of temperatures in the dataset; the coolest quartile was defined as ≤36°F and the warmest quartile as ≥59°F. Mean running HR was compared between these quartiles.

To describe time trends over the season-transition period, outcomes were summarized for the first 14 days versus the last 14 days of the 85-day window (each segment comprising 14 days × 31 runner-days). Primary outcomes for these comparisons were mean running HR and mean HR ratio.

Ethical Considerations and Consent

This project was conducted as a non-interventional observational study using volunteer participant fitness data. All participants were adults and provided informed consent for their de-identified data (resting HR logs and Strava-derived run HR summaries) to be included in the analysis. No direct identifiers were retained in the analytic dataset, and results were reported in aggregate to protect participant privacy. No medical interventions were performed, and the analysis was intended for research/training insights rather than clinical diagnosis or treatment.

Results

Sample and Dataset Overview

The analytic dataset included 31 semi-competitive adult runners (age: 33.1 ± 7.9 years; range: 18–49) in the Philadelphia metropolitan area. One run per runner per day was compiled across 85 consecutive days (February 3 to April 28, 2025), yielding 2,635 run-level observations (Figure 1).

Descriptive Statistics

Across all 2,635 runs, mean resting HR was 47.9 ± 4.8 bpm and mean running HR was 145.8 ± 14.4 bpm. The mean running-to-resting HR ratio was 306.1% ± 28.3%. Mean ambient temperature across the study period was 47.6 ± 15.2°F (Table 1).

Table 1: Descriptive statistics across all runs (n = 2,635).

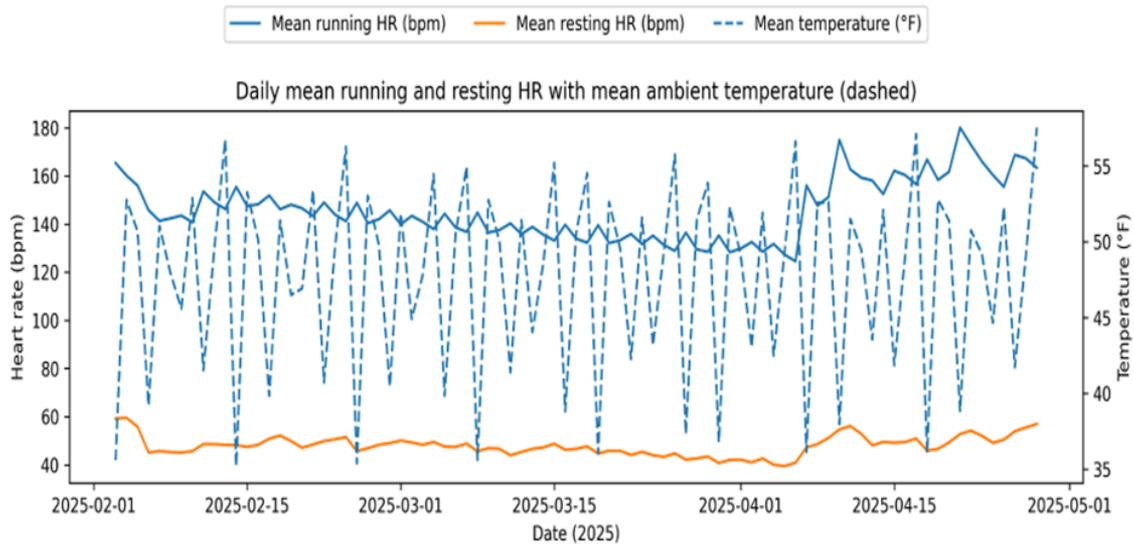| Measure	Mean (SD)	Median (IQR)	Min-Max
Resting HR (bpm)	47.9 (4.8)	47.0 (45.0–51.0)	34.0–62.0
Running HR (bpm)	145.8 (14.4)	144.0 (135.0–155.0)	116.0–210.0
HR ratio (Running/Resting, %)	306.1 (28.3)	304.9 (286.0–322.9)	238.5–465.9
Ambient temperature (°F)	47.6 (15.2)	50.0 (36.0–59.0)	12.0–75.0

Figure 1: Daily mean running and resting heart rate with mean ambient temperature (dashed).

Association Between Resting HR and Running HR

Running HR tracked with resting HR across the study period (Pearson r = 0.57), indicating that higher daily resting HR values tended to coincide with higher running HR values.

Temperature and Running HR

Ambient temperature was inversely associated with running HR (Pearson r = −0.49). In linear regression, running HR decreased by an estimated 0.46 bpm per 1°F increase in temperature (slope = −0.46 bpm/°F; 95% CI: −0.50 to −0.43) (Figures 2 & 3).

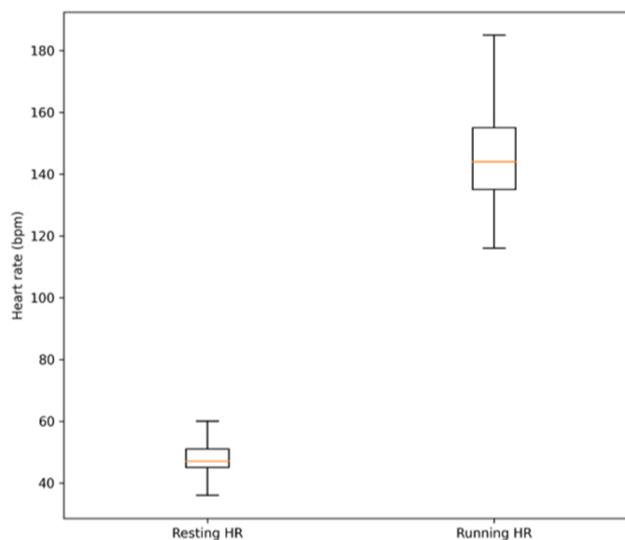**Figure 2:** Distribution of resting vs running HR (boxplots; whiskers exclude extreme outliers).

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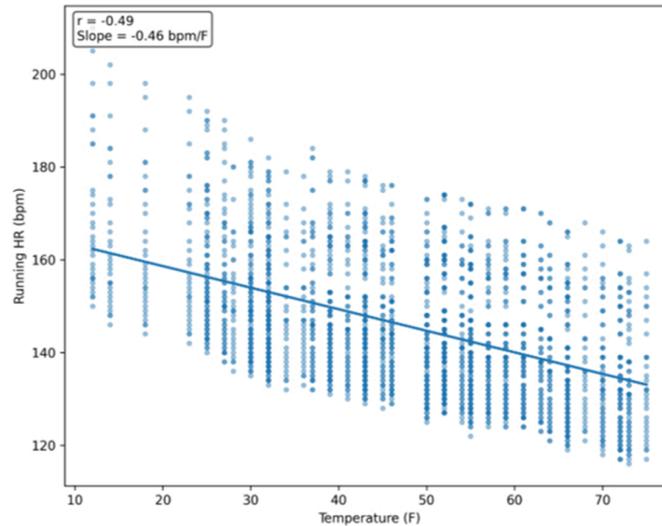
Figure 3: Relationship between temperature and running HR across all runs (least-squares fit).

Temperature Quartile Comparison

Runs performed in the warmest quartile of temperatures (≥59°F; n = 713) showed lower mean running HR than runs in the coolest quartile (≤36°F; n = 682): 137.8 bpm versus 155.1 bpm (difference = −17.3 bpm).

Time Trends Across the Observation Window

Mean running HR increased when comparing the first 14 days versus the last 14 days of the study window: 149.6 bpm in the first 14 days versus 164.3 bpm in the last 14 days (difference = +14.6 bpm). Over the same comparison, the mean HR ratio increased from 305.5% to 323.2% (difference = +17.6 percentage points).

Mean resting HR also increased from 49.3 bpm (first 14 days) to 51.1 bpm (last 14 days), while mean temperature was similar (47.3°F vs 48.0°F).

Runner-Level Patterns and Age (from Report Figure)

Runner-level mean running HRs were tightly clustered (approximately 145–146 bpm across runners), indicating relatively small between-runner differences compared with within-runner variability. Age-stratified runner means (Figure 4) similarly showed tight clustering of runner-level mean running HR across the adult age range.

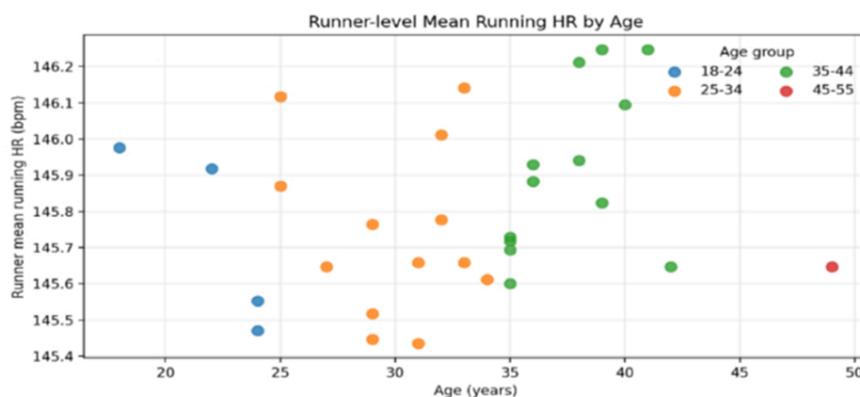**Figure 4:** Runner-level mean running HR by age (points colored by age group).

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Discussion

Principal Findings

In this observational dataset of 2,635 daily runs from 31 semi-competitive adult runners in the Philadelphia metropolitan area, running HR showed a moderate positive association with daily resting HR (r = 0.57) and an inverse association with ambient temperature (r = −0.49; ~−0.46 bpm per 1°F). Over the 85-day window, mean running HR and the running-to-resting HR ratio increased when comparing the first versus last 14 days. Taken together, these patterns indicate that real-world running HR reflects a combination of baseline physiologic state, environmental context, and time-varying training behavior.

Resting HR as Context for Interpreting Running HR

Resting HR can fluctuate with recovery, hydration status, and other stressors that also influence exercise HR. The observed correlation between resting HR and running HR supports the practical value of tracking resting HR alongside run HR to contextualize unusually high (or low) exercise HR days [3].

Temperature–Running HR Relationship: Why Might Warmer Days Show Lower HR Here?

From a physiology standpoint, increasing heat load can increase cardiovascular strain at a fixed workload because the cardiovascular system must support both muscle perfusion and heat transfer to the skin [1]. During prolonged exercise, cardiovascular drift can further elevate HR over time even when external workload is stable [2], and hydration status can meaningfully influence thermal and cardiovascular strain during exercise [3]. However, this study was conducted under free-living conditions in which workload was not controlled. The inverse association observed here (higher temperature → lower running HR) is therefore plausibly explained by behavioral and contextual confounding: runners may slow pace, shorten sessions, or choose easier routes on warmer days, reducing average running HR despite higher heat strain at a given pace [1,3]. Additionally, "temperature" alone does not fully capture environmental heat stress; humidity and other factors alter evaporative potential and can change both cardiovascular strain and self-selected pacing/effort in the heat [8].

Reconciling the Time Trend with the Temperature Association

Mean running HR increased from the first to the last 14 days despite similar average temperatures across those windows, suggesting that temperature alone cannot explain the longitudinal rise. A likely explanation is a shift in external workload over time

(e.g., more workouts, faster pacing, longer runs), seasonal progression of training goals, and/or accumulated fatigue from sustained daily running. Changes in hydration behaviors and heat acclimation across weeks could also influence HR responses [3,4]. In addition, because HR values were derived from consumer wearables, measurement variability is a plausible contributor: wrist-worn photoplethysmography (PPG) is sensitive to motion artifact and signal quality challenges under real-world conditions [6,7,9]. Cold exposure and peripheral vasoconstriction can also alter PPG waveform characteristics and signal properties, which may affect wearable HR estimation in colder conditions or when coverage/clothing and perfusion differ [10]. Without pace, elevation, duration, workout type, humidity, and device-model stratification, the most conservative interpretation is that the time trend reflects changing training demands and/or training state, with some contribution from measurement variability.

Runner-Level Patterns and Age

Runner-level mean running HR values were tightly clustered, suggesting relatively small between-runner differences compared with within-runner day-to-day variability. The runner-level age plot similarly suggested no strong separation of mean running HR across the adult age range represented. In this cohort, day-to-day factors (training choice, recovery, environment, and measurement conditions) likely contributed more to observed differences than age-related between-person variation.

Limitations

Several limitations are important. First, causal inference is not possible in an observational design; temperature–HR associations are likely confounded by self-selected pace, route, duration, and workout type. Second, HR data came from consumer wearables uploaded to Strava; wrist-worn devices have known limitations and variable accuracy during activity depending on conditions, motion, and device characteristics [5-7,9]. Third, ambient temperature does not represent total environmental heat stress (e.g., humidity and solar load were not included), which can materially affect thermoregulation and cardiovascular strain [1,3,8]. Finally, additional influences on resting and exercise HR (sleep, illness, travel, stress, cross-training) were not measured.

Practical Implications and Future Directions

For runners and coaches, these data reinforce that running HR is best interpreted with baseline context (resting HR) and environmental context (weather). To better isolate physiologic temperature effects from behaviorally driven workload changes, future analyses should incorporate pace, elevation gain, duration, humidity/dew point, and session type, and apply modeling approaches (e.g., mixed-effects models) to separate within-runner

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responses from between-runner differences [1,3,8]. Device-model stratification or cross-validation with chest-strap HR in a subset could further clarify the role of wearable measurement variability [5-7,9,10].

Conclusion of Discussion

In this real-world daily running cohort, running HR was moderately aligned with daily resting HR and inversely associated with ambient temperature, while increasing over time across the observation window. The combined pattern is most consistent with a mixture of physiologic responses, shifting training workload/intent, humidity/thermal context, and wearable measurement variability in uncontrolled field conditions [1-10].

Conclusion

This observational analysis of 2,635 daily runs from 31 semi-competitive adult runners in the Philadelphia metropolitan area identified meaningful, real-world patterns in heart-rate behavior across a winter-to-spring transition. Running HR was moderately aligned with daily resting HR, supporting the value of pairing a baseline physiologic measure with exercise HR when interpreting day-to-day cardiovascular strain. Ambient temperature was inversely associated with running HR, while mean running HR and the running-to-resting HR ratio increased over the observation window, indicating that seasonal time trends were not explained by temperature alone. In combination, these findings suggest that training behaviors and workload selection (e.g., pace, route choice, and session intent), along with unmeasured environmental factors and wearable measurement context, likely contributed to the observed patterns. Future work incorporating external workload metrics (pace, elevation, duration), additional weather variables (humidity/solar load), and runner-level modeling would better isolate physiologic temperature effects from behavioral confounding and strengthen the interpretability of field-derived HR signals.

Data Availability

The de-identified run-level dataset and associated analytic files are available from the author upon reasonable request. Data are not publicly posted to protect participant privacy and to respect participant consent regarding data sharing.

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