Estimating Respiration Rate from Actxa Core Smart Ring

Performance Validation White Paper

VERSION
V1.1

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Revision History

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Revised by Dr Yao Du, Chief Scientist

- Changed the citation style from APA author–date to IEEE numeric and reformatted the reference list.
- Updated the header, footer and fonts to the current Actxa corporate template.
- Clarified that hourly tracking is the primary measure of estimation accuracy, and removed the description of it as real-time.
- Corrected the per-night RMSE in the Conclusion (1.60 to 1.57 BPM) and the title of reference [8].
- Removed a repeated sentence on the confidence-interval method, standardised the product name to Actxa Core Smart Ring, and made typographical corrections.

V1.0

Prepared by Justin Tan, Data Scientist Intern

- Initial release.

Overview

The Actxa Core Smart Ring continuously tracks respiration rate (RR) during sleep, providing users with nightly insight into their breathing patterns. Respiration rate is measured in breaths per minute (BPM) and reflects the number of complete breathing cycles a person takes each minute. Monitoring respiration rate during sleep can help users better understand how lifestyle factors — such as physical activity, illness, or stress — affect their nighttime breathing [1, 2].

This white paper describes the performance validation of the respiration rate estimation algorithm embedded in the Actxa Core Smart Ring. The ring's green-light optical sensor captures photoplethysmography (PPG) signals from the finger, which are converted on-device to peak-to-peak interval (PPI) values — the time elapsed between successive heartbeats. These stored PPI values are then used to derive respiration rate by detecting the respiratory modulation of the cardiac cycle [3].

Performance was evaluated against Apple Watch's measured respiration rate as a reference standard, across 20 adult participants over multiple nights of home-based sleep recording. Performance is reported at the hourly level as the primary measure of estimation accuracy, and at the nightly level as the aggregated summary view experienced by users.

Introduction

Respiration rate is one of the four classical vital signs and a key indicator of physiological status. Normal resting respiration rate in healthy adults falls between 12 and 20 breaths per minute [1]. Elevated or irregular breathing during sleep can be associated with physiological stress, infection, or underlying cardiorespiratory conditions [4].

Despite its clinical relevance, respiration rate is among the least frequently monitored vital signs outside of acute care settings. Continuous overnight monitoring has historically required clinical-grade equipment such as polysomnography (PSG), limiting its use to laboratory or hospital environments. The emergence of consumer wearables has created an opportunity for passive, continuous respiration monitoring during sleep in real-world settings [5].

PPI-based respiration rate estimation relies on respiratory sinus arrhythmia (RSA) — the rhythmic fluctuation in heart rate that occurs in synchrony with the breathing cycle, where heart rate increases during inhalation and decreases during exhalation [6]. Because the ring stores only PPI values rather than the full PPG waveform, amplitude-dependent phenomena such as pulse amplitude variation and baseline wander are not available; RSA is the sole respiratory signal extracted from the PPI time series. This approach is well suited to ring-form wearables, which provide stable optical contact with the finger throughout the night and yield reliable beat detection for RSA analysis.

This white paper presents validation results for the Actxa Core Smart Ring's respiration rate feature, intended to provide transparency for business partners and stakeholders regarding the accuracy and reliability of this capability.

Algorithm Overview

Signal Acquisition

The Actxa Core Smart Ring uses a green-wavelength optical sensor to capture PPG signals from the finger during sleep. Green PPG is particularly sensitive to blood volume changes near the skin surface, making it well suited for overnight continuous measurement [7]. The PPG signal is processed on-device to extract peak-to-peak intervals (PPI) — the time between successive cardiac peaks — and these PPI values are what is stored and transmitted from the ring. Respiration rate estimation is performed entirely from the PPI time series; raw PPG waveform data is not retained.

Respiration Rate Derivation

Respiration rate is derived from the PPI time series by resampling at a uniform rate and applying a bandpass filter to isolate respiratory frequencies. Breathing cycles are identified through peak detection in the filtered signal, and the median instantaneous rate across detected cycles is computed as the respiration rate in breaths per minute. The algorithm produces a respiration rate estimate for each valid hourly window throughout the night, with periods of insufficient signal quality or excessive movement automatically excluded from the output. Hourly estimates are then averaged across the full sleep session to produce the nightly summary value presented to users.

Reference Standard

Algorithm performance was benchmarked against Apple Watch, which estimates sleep breathing rate from triaxial accelerometer data capturing fine body movements associated with respiration — not optical PPG [8].

This methodological distinction was a key selection criterion: alternatives such as Garmin derive respiration rate via respiratory sinus arrhythmia (RSA) from an optical photoplethysmography (PPG) sensor, the same physiological pathway used by the Actxa Core Smart Ring. Benchmarking two PPG-RSA systems against each other may introduce shared measurement uncertainty due to the common sensing pathway, potentially obscuring true device performance [9]. Such dependence between measurement methods can also complicate the interpretation of agreement statistics in method comparison studies [10].
Apple Watch's accelerometer-derived signal provides a genuinely independent cross-check. Its credibility as a reference is further supported by its FDA 510(k)-cleared Sleep Apnea Notifications feature, validated against polysomnography in a clinical study [8], making it a practical and clinically grounded consumer-grade comparator for naturalistic multi-night home recording.

Study Design and Participant Characteristics

A total of 20 adult participants were enrolled in the study. Participants wore both the Actxa Core Smart Ring and an Apple Watch simultaneously during their regular sleep at home over multiple nights. No laboratory sleep study was required, reflecting the real-world consumer context of the feature.

Participants were recruited across a range of ages and included both male and female subjects. Table 1 summarises the key characteristics of the study population and dataset.

Characteristic	Value	Notes
Participants (n)	20	Adults
Age, mean (SD)	36.85 (12.39) years	Range: 25–61 years
Sex (% Female)	55.0%	11 Female, 9 Male
Sleep Data Breakdown		
Total Nights	62	Across all participants
Total Sleep Hours	458	Across all participants
Valid Sleep Hours*	444 (96.94%)	After signal quality filtering

Table 1. Study Population and Dataset Characteristics

*Valid Sleep Hours refer to periods during sleep when the PPI signal quality is sufficient to derive respiration rate using the RSA method.

Performance Evaluation

Evaluation Methodology

Algorithm performance was assessed by comparing Actxa Core Smart Ring respiration rate estimates against Apple Watch reference values across all valid recordings. Two primary metrics were used:

- **Mean Absolute Error (MAE):** the average absolute difference in breaths per minute between the ring estimate and the Apple Watch reference.
- **Root Mean Squared Error (RMSE):** a measure of error that penalises larger deviations more heavily, providing sensitivity to outlier performance.
- **95% Confidence Interval (CI):** a measure of the uncertainty around the estimated mean MAE/RMSE, computed using a subject-level t-statistic approach.

Performance is reported at two levels. The per-hour analysis, which is the primary measure of estimation accuracy, evaluates each individual hourly window across all recording nights, providing a granular view of how well the algorithm tracks breathing rate throughout sleep. The per-night analysis averages all hourly estimates within each sleep session to produce a single nightly value, which reflects what users see in the app.

Overall Results

Table 2 presents overall performance across both evaluation levels. At the per-hour level, the algorithm achieves an MAE of 1.49 BPM (95% CI: 1.10–1.94) and RMSE of 2.07 BPM (95% CI: 1.42–2.32), capturing the granular variability of hour-to-hour breathing patterns. When estimates are averaged to the nightly level, performance improves to an MAE of 1.16 BPM (95% CI: 0.71–1.64) and RMSE of 1.57 BPM (95% CI: 0.82–1.73), as short-term estimation variability averages out over the full night.

Evaluation Level	MAE (BPM)	95% CI — MAE (BPM)	RMSE (BPM)	95% CI — RMSE (BPM)
Per Hour	1.49	1.10–1.94	2.07	1.42–2.32
Per Night	1.16	0.71–1.64	1.57	0.82–1.73

Table 2. Overall Respiration Rate Estimation Performance Against Apple Watch Reference

MAE and RMSE are in breaths per minute (BPM). 95% CI computed using a subject-level t-distribution, where one MAE and RMSE value is derived per participant before computing the interval across subjects. This accounts for the correlated nature of repeated nightly measurements within the same individual.

Regression and Bland-Altman Analysis

Figure 1 presents the regression and Bland-Altman plots for the per-hour evaluation (N=20, 444 data points). The regression plot shows strong tracking of the reference along the identity line across the physiological range. The Bland-Altman plot confirms a consistent negative bias of −0.89 BPM with limits of agreement of −4.56 to +2.79 BPM, with no systematic widening of differences across the range of respiration rates.

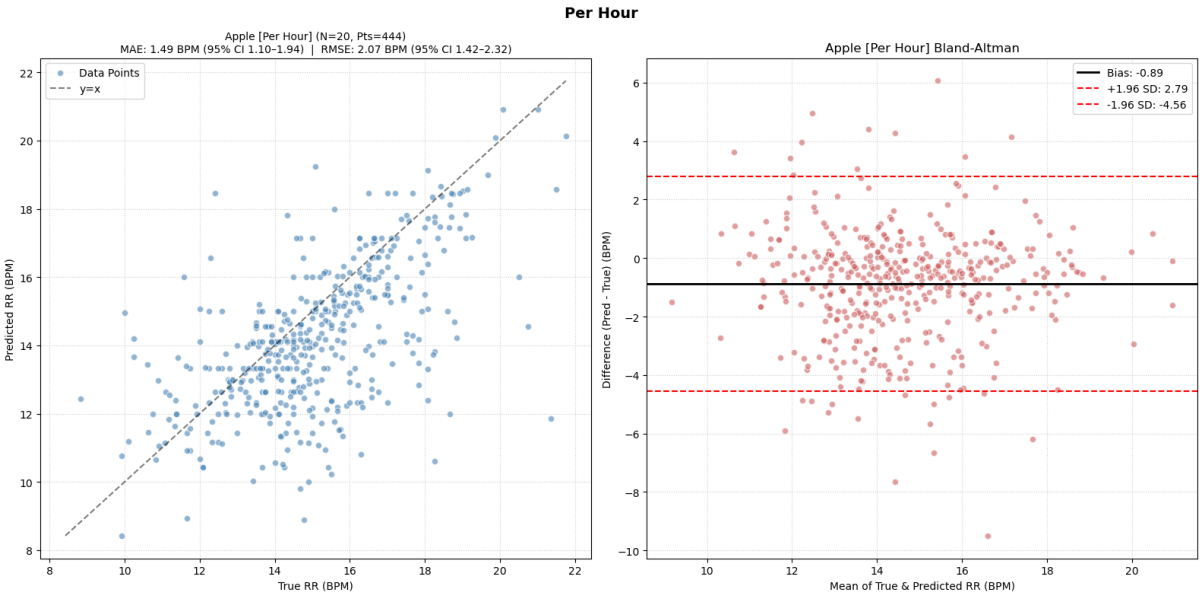


Figure 1. Overall Per-Hour Regression and Bland-Altman Plot (N=20, 444 data points; MAE 1.49 BPM, 95% CI: 1.10–1.94; RMSE 2.07 BPM, 95% CI: 1.42–2.32; Bias −0.89 BPM, LoA −4.56 to +2.79)

Figure 2 presents the per-night analysis. Averaging hourly estimates across each sleep session substantially narrows the limits of agreement to −3.43 to +1.68 BPM, with a bias of −0.88 BPM. The tighter spread reflects the reduction in estimation noise achieved by aggregating multiple hourly estimates.

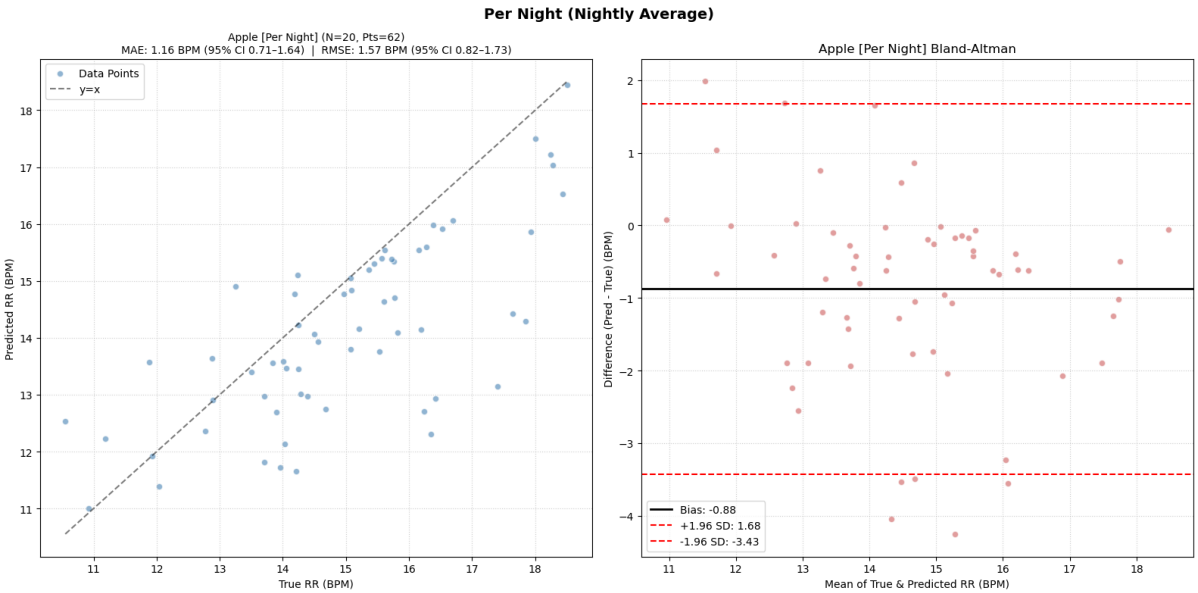


Figure 2. Overall Per-Night Regression and Bland-Altman Plot (N=20, 62 nights; MAE 1.16 BPM, 95% CI: 0.71–1.64; RMSE 1.57 BPM, 95% CI: 0.82–1.73; Bias −0.88 BPM, LoA −3.43 to +1.68)

Discussion

The Actxa Core Smart Ring demonstrates strong agreement with Apple Watch respiration rate estimates across both evaluation levels. The per-hour analysis is the primary measure of estimation accuracy, with an MAE of 1.49 BPM (95% CI: 1.10–1.94) and RMSE of 2.07 BPM (95% CI: 1.42–2.32) showing how closely the algorithm tracks breathing rate hour by hour through the night. The per-night result — an MAE of 1.16 BPM (95% CI: 0.71–1.64) and RMSE of 1.57 BPM (95% CI: 0.82–1.73) — reflects the nightly summary value experienced by users.

A consistent negative bias of approximately −0.89 BPM was observed across both evaluation levels, indicating that the ring's estimates are systematically slightly lower than the Apple Watch reference. This minor systematic offset is expected given the fundamental difference in sensing modalities: the Actxa Core Smart Ring derives respiration rate from PPI values captured via finger-based optical PPG, while Apple Watch estimates breathing rate from wrist accelerometer motion during sleep [8]. These two approaches measure different physiological signals and a small systematic offset between them does not represent algorithmic error.

The reference standard in this study was Apple Watch's consumer-grade respiration rate measurement rather than clinical polysomnography. This choice reflects the consumer context of the Actxa Core Smart Ring: the goal is to provide users with an accurate and actionable nightly respiration rate estimate consistent with other leading consumer wearables, not to replicate clinical diagnostic instrumentation. This feature is intended for general wellness monitoring and is not designed or validated for clinical or diagnostic use.

Limitations of this study include the relatively small participant sample (n=20), the use of a consumer device rather than a clinical gold standard as the reference, and the home-based recording environment which, while ecologically valid, introduces variability absent from controlled laboratory settings. It is important to note that the ring's respiration rate feature is designed as a personal wellness metric, not a diagnostic tool. The feature does not account for individual symptoms or medical history, and users experiencing breathing difficulties during sleep or any health concerns should consult a physician. The absence of an abnormal reading should not be interpreted as the absence of a sleep-related breathing condition.

That said, continuous nightly monitoring represents a meaningful advantage over traditional clinical assessments such as polysomnography, which capture only one or a few nights in a controlled setting. By tracking respiration rate passively across many nights in the home environment, the Actxa Core Smart Ring enables users to observe trends over time — something that single-night clinical tests cannot provide. The companion app surfaces these trends clearly, prompting users to seek professional guidance where relevant, and supporting more informed conversations with healthcare providers.

Conclusion

The Actxa Core Smart Ring estimates respiration rate during sleep from PPI values derived from its green-light optical sensor — the ring captures PPG, converts it to PPI on-device, and uses those PPI values to compute breathing rate. At the per-hour level the algorithm achieves an MAE of 1.49 BPM (95% CI: 1.10–1.94), and when estimates are aggregated to a nightly summary the per-night MAE improves to 1.16 BPM (95% CI: 0.71–1.64) with an RMSE of 1.57 BPM against Apple Watch as a reference standard. A valid data capture rate of 96.94% across all recording hours demonstrates robust overnight signal acquisition.

Respiration rate is available as a nightly metric within the Actxa platform, enabling users to monitor trends in their breathing patterns and relate them to lifestyle and health factors over time. Actxa continues to invest in algorithm refinement and expanded validation to support the ongoing development of the Actxa products' health monitoring capabilities.

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