*dHealth 2026*
*G. Schreier et al. (Eds.)*
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*doi:10.3233/SHTI260087*

# Signal Quality and Reliability of Heart Rate Measurement Using Simultaneous PPG and Inertial Data in Healthy Adults

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**Abstract.** Background: Reliable estimation of heart rate and beat-to-beat intervals is essential for cardiovascular monitoring. Smartphone sensors such as photoplethysmography (PPG) and inertial measurement units (IMUs) offer accessible measurement possibilities, but their reliability depends on acquisition conditions.
Methods: In this observational pilot study, simultaneous PPG and accelerometer signals were recorded using smartphones across three acquisition configurations: single-device supine (M1), single-device seated (M2), and synchronized dual-device recordings (M3). RR intervals were derived using identical filtering and peak detection pipelines. Results: Agreement between accelerometer- and PPG-derived RR intervals differed significantly between configurations (Kruskal–Wallis $H = 15.98$, $p < .001$). The dual-device configuration showed lower median RR agreement error (38.33 ms) compared to single-device setups (median ≈ 107 ms). Conclusion: Acquisition configuration substantially influences agreement of smartphone-derived RR intervals. These findings highlight the importance of standardized acquisition setups for reliable smartphone-based cardiac monitoring.

**Keywords.** Photoplethysmography, Accelerometry, Heart Rat, RR Intervals, Signal Quality, Mobile Health, Signal Processing, Wearable Electronic Devices

## 1. Introduction

Heart rate and beat-to-beat interval dynamics provide fundamental information about cardiovascular function and form the basis for numerous applications in cardiovascular research and mobile health. Reliable estimation of heart rate and RR intervals is a prerequisite for rhythm characterization, heart rate variability analysis, and the

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development and validation of signal processing algorithms. Although electrocardiography (ECG) represents the reference standard for cardiac timing analysis, its applicability in large-scale or long-term monitoring scenarios is limited due to hardware requirements, setup complexity, and user burden [1, 2].

Against this background, scalable and low-threshold measurement approaches are of increasing interest, particularly as rhythm irregularities may remain undetected when monitoring is infrequent or of short duration. Smartphone-based sensing technologies enable unobtrusive and repeated acquisition of physiological signals and have demonstrated technical feasibility for large-scale rhythm-related data collection in real-world settings [3, 4].

Photoplethysmography (PPG) has emerged as a widely used non-invasive technique for heart rate and beat-to-beat interval estimation, mainly due to its suitability for long-term and large-scale monitoring. PPG measures blood volume changes in microvascular tissue and can be implemented using the built-in camera and light source of consumer-grade devices such as smartphones and wearables. Previous studies and systematic reviews have shown that PPG-based approaches allow accurate estimation of heart rate and inter-beat intervals under controlled conditions, supporting their applicability in mobile measurement scenarios [5, 6].

Large population-based investigations further highlight the scalability of smartphone-based technologies for rhythm-related data acquisition outside controlled laboratory environments [3]. At the same time, advances in machine learning (ML) have improved the analysis of physiological time series, particularly with respect to the extraction of rhythm-related features from RR interval dynamics. Several studies emphasize that the performance of such data-driven approaches critically depends on the reliability and consistency of the underlying signal acquisition and RR interval estimation [6, 7].

In addition to optical sensing, inertial sensor data acquired from smartphone accelerometers have been increasingly explored for cardiac timing estimation. Subtle mechanical body movements induced by cardiac activity can be captured by accelerometers and used to derive inter-beat (RR) intervals under controlled conditions. Previous work has demonstrated that accelerometer-based heart rate estimation using smartphones is feasible and shows good agreement with electrocardiographic reference measurements, indicating its potential as a complementary sensing modality to PPG, particularly when optical signal quality is affected by motion or contact conditions [8, 9].

However, both PPG- and accelerometer-derived heart rate parameters are sensitive to motion-related disturbances and acquisition conditions. Signal quality, sensor placement, device configuration, and user movement strongly influence the reliability of derived timing features. While many previous studies have focused on algorithmic performance or application-oriented outcomes, fewer have systematically investigated the robustness and agreement of heart rate and RR interval estimates derived from different sensor modalities under varying acquisition setups. Such methodological analyses are essential for the development of reliable smartphone-based heart rate measurement systems and for the interpretation of rhythm-derived features in downstream applications [2, 6].

Reliable and scalable sensing technologies are a key prerequisite for digital health and telemedicine applications. In large-scale remote monitoring scenarios, smartphones represent one of the most accessible sensing platforms available to the general population. Understanding how acquisition configurations influence signal stability and RR interval

estimation is therefore relevant for the design of future mobile health systems where physiological signals may be acquired opportunistically using consumer devices.

## 2. Methods

### 2.1. *Study Design & Data Acquisition*

In this study, simultaneously recorded ACC and PPG signals obtained from a smartphone-based measurement setup were analyzed. The dataset consisted of multiple measurement sessions conducted using different acquisition protocols, referred to as M1 (single-device, supine position), M2 (single-device, seated position), and M3 (synchronized dual-device acquisition in a supine position), used as an internal reference configuration. Even though electrocardiography (ECG) represents the clinical gold standard for RR interval estimation, the aim of this work was not to validate sensor accuracy against ECG but to investigate the agreement between two smartphone-based sensing modalities under different acquisition configurations. During all measurements, participants were instructed to remain still and to minimize voluntary movement. For PPG acquisition, the smartphone camera and flashlight were used in contact mode, with participants placing the fingertip gently over the camera lens. In the single-device configurations (M1, M2), the same smartphone was used to acquire both PPG and accelerometer signals simultaneously. In the dual-device configuration (M3), camera-based PPG was recorded on one smartphone, while accelerometer (ACC) data were recorded on a second, synchronized smartphone placed on the participant's upper torso. Supine measurements were conducted with participants lying flat, whereas seated measurements were performed with participants sitting upright and the device resting stably against the body. Measurements were conducted by five healthy adults using a total of eight smartphones available within the project environment. Devices were not selected to represent specific hardware characteristics but to reflect typical consumer-grade smartphones used during exploratory data acquisition. The unequal number of recordings resulted from practical constraints during data collection sessions, including varying device availability, differences in acquisition configurations across sessions, and occasional incomplete recordings due to technical interruptions. Since the analysis compares distributions rather than pooled averages, non-parametric statistical methods were used that are robust to unequal group sizes. The study involved five healthy adult participants between the ages of 24–31 years (2 male and 3 female. Measurements were recorded using a total of eight smartphones that were available within the project environment. Devices were not selected to represent specific hardware characteristics but reflect typical consumer-grade smartphones used during exploratory data acquisition.

### 2.2. *Signal Processing and Statistical Analysis*

All signal processing for this work was done in Python. Both ACC and PPG signals were processed using signal processing pipelines with identical filter types and peak detection logic, but different sampling frequencies. Algorithmic differences were intentionally minimized to isolate configuration effects. Signals were bandpass-filtered between 0.8 and 2.5 Hz using a 4th-order Butterworth filter with zero-phase application. Beat-related peaks were then detected using a distance- and prominence-based approach. The minimum peak distance was fixed at 0.4 s (24 samples for PPG, 80 samples for ACC),

and minimum peak prominence was set adaptively to 15% of the standard deviation of the filtered signal. These parameters were selected to reflect physiologically plausible heart rate ranges and were applied consistently to both sensor modalities. Inter-beat (RR) intervals were computed as the time differences between consecutive detected peaks. For each signal, RR intervals were summarized using the median RR interval to reduce sensitivity to outliers from occasional peak detection errors. M3 was treated as the reference acquisition configuration (dual-device setup) when comparing error distributions across measurement setups (M1, M2, M3). Due to non-normal and right-skewed distributions of RR interval differences, group comparisons between measurement configurations (M1, M2, M3) were performed using a non-parametric Kruskal–Wallis test. Post-hoc pairwise comparisons between measurement configurations were performed using the Mann–Whitney U test with Holm correction for multiple testing. Effect sizes were quantified using epsilon squared ($\varepsilon^2$) for the global test and Cliff's delta ($\delta$) for pairwise comparisons.

Descriptive statistics were used to summarize RR interval differences across measurement methods. Results are reported using median values and interquartile ranges to account for non-normal distributions. RR differences exhibited skewed distributions with pronounced outliers.

## 3. Results

### 3.1. *Method-Specific Differences in RR Agreement*

Across all measurement configurations, RR interval differences exhibited a wide and right-skewed distribution. As illustrated in Figure 1, the dual-device configuration (M3, 2 devices, supine) showed a lower median RR agreement error and a markedly narrower interquartile range compared to both single-device configurations. This indicates more consistent agreement between ACC- and PPG-derived RR summaries under the dual-device setup. In contrast, both single-device configurations (M1 and M2) demonstrated higher median errors and substantially greater dispersion. The y-axis represents an agreement error between ACC- and PPG-derived RR summaries and not the physiological RR interval itself.

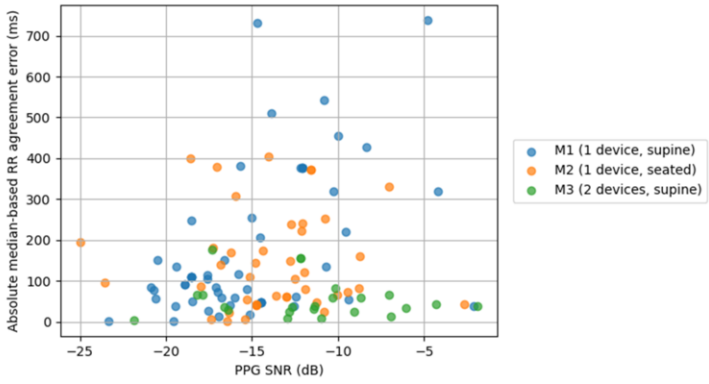


**Figure 1.** Distribution of the absolute median-based RR agreement error between accelerometer (ACC) and photoplethysmography (PPG) across measurement configurations (M1: 1 device, supine; M2: 1 device, seated; M3: 2 devices, supine), computed as |median RR_ACC − median RR_PPG|.

A global Kruskal–Wallis test indicated a statistically significant difference in RR interval agreement between the three measurement configurations ($H = 15.98$, $p < .001$, $\varepsilon^2 \approx 0.12$). Post-hoc pairwise comparisons using the Mann–Whitney U test with Holm correction revealed significant differences between the internal reference configuration (M3) and both single-device configurations (M1 vs. M3: p_Holm < .001, Cliff's $\delta \approx 0.54$; M2 vs. M3: p_Holm < .001, Cliff's $\delta \approx 0.53$). No statistically significant difference was observed between the two single-device configurations (M1 vs. M2: p_Holm = 0.851, Cliff's $\delta \approx 0.02$).

**Table 1.** RR interval agreement between ACC- and PPG-derived signals across measurement configurations. Values are reported as median and interquartile range (IQR). Effect sizes refer to pairwise comparisons against the dual-device internal reference configuration (M3). Measurements classified as unknown were excluded.

| Method | n | Median RR difference [ms] | 95% CI (lower) [ms] | 95% CI (upper) [ms] | IQR RR difference [ms] | Δ vs. M3 (Cliff's δ) |
|---|---|---|---|---|---|---|
| M1 (1 device, supine) | 54 | 107.08 | 73.33 | 135.42 | 201.67 | 0.54 |
| M2 (1 device, seated) | 42 | 107.08 | 70.00 | 164.17 | 160.42 | 0.53 |
| M3 (2 devices, supine) | 23 | 38.33 | 31.67 | 66.67 | 39.17 | 0.00 |

Regarding RR interval differences, the dual-device (M3) configuration showed the lowest median RR agreement error and the narrowest interquartile range, indicating more consistent agreement between ACC- and PPG-derived signals. Both single-device configurations exhibited higher median errors and substantially greater dispersion. Statistical testing confirmed significantly lower RR agreement errors for M3 compared to both single-device configurations, while no significant difference was observed between M1 and M2.

## 4. Discussion and outlook

The results indicate that the dual-device setup yields lower RR agreement errors and substantially reduced dispersion compared to single-device recordings, suggesting improved agreement between ACC- and PPG-derived RR intervals under the internal reference configuration. These differences were statistically significant; however, their interpretation is limited by the exploratory study design and the smaller number of dual-device measurements. Therefore, the findings should be understood as evidence of improved measurement consistency rather than definitive proof of methodological superiority. The small performance difference observed between supine and seated single-device measurements suggests that body posture may have a minor influence on measurement stability, although this effect appears secondary compared to the choice of acquisition configuration. Several limitations should be considered. Firstly, the number of dual-device (internal reference configuration) measurements was smaller than the number of single-device recordings, which limited statistical power for between-group comparisons. Secondly, RR interval estimation was based on automated peak detection, which may be sensitive to noise and artifacts, particularly in lower-quality signals. The present study should be interpreted as a methodological pilot investigation. The number of participants was small, and measurements were not collected under strictly controlled

experimental conditions. Therefore, the results do not support population-level conclusions regarding heart rate measurement accuracy but rather highlight how acquisition configuration can influence signal stability and agreement between smartphone-derived sensor modalities. Future studies should include larger participant cohorts, standardized device placement, ECG-based reference measurements, and more advanced signal processing approaches such as adaptive filtering, signal quality indices, or machine learning-based peak detection to further improve robustness.

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