Validation of Smartphone-Based Seismocardiography for Heart Rate Variability Analysis in the Kubios Application

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Abstract

Background & Objective: Heart rate variability (HRV) is a critical marker for physiological readiness. While traditionally measured via wearable sensors, smartphone-based seismocardiography (SCG) offers a wearable-free alternative using built-in accelerometers. This study validates the accuracy of smartphone-based SCG for HRV analysis, as implemented in the Kubios mobile application, against a gold-standard ECG reference and established consumer sensors.

Methods: The study included 57 healthy adult participants (aged 18–58 years; 75% male). For each participant, resting HRV was measured simultaneously using a reference ECG, Polar H10, Polar Verity Sense, and smartphone-based SCG (Apple and Samsung devices). Method agreement, error distribution, and automatic beat correction requirements were evaluated on time-aligned segments.

Results: Under controlled resting conditions, the need for automatic beat correction in phone-based SCG recordings was minimal (average <0.7%). Smartphone-based SCG demonstrated high agreement with the ECG reference across Mean HR, RMSSD, and PNS index ($r \geq 0.99$ for all). For RMSSD, mean absolute error values were 0.38 ms for Polar H10, 2.57 ms for Polar Verity Sense, and 2.01 ms for phone-based SCG. These findings indicate that SCG-based HRV analysis performed at a level comparable to optical sensor measurements.

Conclusion: Smartphone-based SCG in the Kubios app is a highly accurate and reliable method for HRV analysis. It provides a wearable-free, low-barrier approach to physiological tracking, offering immense practical value for scalable and high-compliance readiness assessment.

Introduction

Heart rate variability (HRV) is widely used to assess autonomic nervous system function, recovery status, and physiological readiness [1][2][3]. Traditionally, HRV is derived from electrocardiography (ECG) or photoplethysmography (PPG) based wearable heart rate (HR) sensors that measure beat-to-beat intervals [1][4]. While these wearable sensors provide accurate data, their daily use in team sports, large-scale research, or routine wellness monitoring is often hindered by logistical challenges, device management, user compliance, and financial costs. Therefore, there is a growing demand for accessible, highly scalable measurement solutions. Recent advances in smartphone accelerometer technology have unlocked a powerful alternative: seismocardiography (SCG). By capturing the subtle mechanical vibrations generated by cardiac activity on the chest wall, high-resolution smartphone accelerometers can detect inter-beat intervals directly. This makes accurate HRV estimation possible using built-in smartphone sensors, entirely eliminating the need for dedicated ECG or PPG hardware [5][6].

The Kubios mobile application enables HRV assessment using smartphone-based SCG. In readiness measurement mode, the smartphone's built-in accelerometer records cardiac-induced chest wall vibrations when the device is placed on the chest. Inter-beat intervals are automatically detected and processed to derive standard HRV metrics, including Mean HR, RMSSD, and the proprietary Kubios PNS index. The PNS index specifically reflects parasympathetic nervous system activity, providing a direct physiological window into cardiovascular recovery. These metrics are integrated into a readiness model that compares daily HRV values to an individual's long-term baseline. By tracking this autonomic nervous system balance, individuals and coaches can accurately assess training readiness, manage daily stress, and optimize recovery without the friction of external hardware.

The primary aim of this whitepaper is to validate the accuracy of the Kubios mobile application's smartphone-based SCG for HRV analysis and readiness estimation against a gold-standard reference ECG measurement. A secondary aim is to compare the accuracy of these smartphone-based SCG HRV metrics against commonly used reference devices, including the Polar H10 and Polar Verity Sense, to provide practical insight into the accuracy and real-world viability of the SCG approach.

Materials and methods

Subjects

The study included 57 participants, with a higher proportion of males than females (Table 1). Participants covered a broad adult age range (18 – 58 years), with body weight ranging from 51 to 118 kg and height from 157 to 189 cm. Overall, the sample included individuals with varying body sizes, providing a heterogeneous cohort for validation analyses. The study was approved by the Ethics Committee of Northern Savo Hospital District and all participants signed a written informed consent prior to participation.

Table 1: Participant characteristics. Values are presented as mean ± standard deviation (range). Gender distribution is reported as number and percentage.

Characteristic	Value
Participants	57
Age (years)	32.8 ± 8.6 (18.0–58.0)
Height (cm)	173.7 ± 8.3 (157.0–189.0)
Weight (kg)	75.6 ± 12.4 (51.0–118.0)
BMI (kg/m²)	25.0 ± 3.6 (18.1–35.2)
Male / Female	43 (75%) / 14 (25%)

Measurements

HRV measurements were obtained simultaneously using a reference ECG system (Biopac MP150, Biopac Systems Inc., USA), a Polar H10 (Polar Electro Oy, Kempele, Finland) chest strap, a Polar Verity Sense (Polar Electro Oy, Kempele, Finland) optical sensor, and phone-based seismocardiography. The Biopac MP150 ECG served as the reference method for all comparisons.

The reference ECG was sampled at 250 Hz. Polar H10 and Polar Verity Sense devices were used in online recording mode, and the device-detected RR intervals (H10) and pulse-to-pulse intervals (Verity Sense) were used for HRV analysis. Smartphone-based SCG data acquisition and HRV analysis were performed using the readiness measurement mode of the Kubios mobile application (Kubios Oy, Kuopio, Finland), which integrates accelerometer-based signal capture, automated inter-beat interval (IBI) detection, preprocessing of the IBI series, and HRV analysis. SCG measurements were performed using two smartphones: Apple iPhone 13 mini (Apple Inc., Cupertino, CA, USA) and a Samsung Galaxy A36 (Samsung Electronics Co., Ltd., Suwon, South Korea). Two separate 3-minute recordings were obtained per participant: one using the Samsung device and one using the Apple device.

All measurements were performed with participants in a supine resting position. The first recording was obtained after a 5-minute stabilization period. Subjects were instructed to remain completely still, avoid talking, and breathe spontaneously during the measurements. The smartphone was positioned on the participant's chest to capture cardiac-induced chest wall vibrations. These instructions were consistent with the Kubios mobile application's readiness measurement protocol used for SCG recordings.

For device comparisons, analyses were performed using time-aligned segments. Specifically, the same time intervals recorded with the smartphone were extracted from the reference ECG, Polar H10, and Polar Verity Sense recordings. HRV metrics were calculated for these synchronized segments, and measurements from each device were directly compared with the corresponding ECG-derived reference values. In total, 57 subjects contributed 114 matched samples. Five samples from the Polar Verity Sense were excluded due to a technical error related to sensor placement.

Reference ECG data from Biopac MP150 and beat-to-beat interval data from H10 and Verity Sense were processed using Kubios HRV Scientific software version 4.3 (Kubios Oy, Kuopio, Finland). Identical preprocessing and artifact correction settings were applied across all devices to ensure methodological consistency. The following HRV parameters were analyzed: Mean HR, root mean square of successive differences (RMSSD), and the PNS index. For smartphone-based SCG, HRV metrics were obtained directly from the Kubios mobile application (readiness measurement mode), where inter-beat intervals were detected and processed automatically within the application.

Statistical analysis

Agreement between smartphone-based SCG and ECG reference measurements was evaluated using correlation and Bland–Altman analyses. For each parameter (Mean HR, RMSSD, and PNS index), Pearson correlation coefficients (r) were calculated to assess linear association between methods. Ninety-five percent confidence intervals (95% CI) for correlation coefficients were derived using Fisher's z-transformation.

Method agreement was assessed using Bland–Altman analysis. Mean bias (Device − ECG) and standard deviation (SD) of the error were calculated for each parameter. Bland–Altman plots were used to evaluate systematic bias and potential proportional effects across the measurement range.

For device-level comparisons (Polar H10, Polar Verity Sense, and smartphone-based SCG), errors were calculated relative to ECG reference values. Bias and SD of error, median error with 2.5th–97.5th percentiles, mean absolute error (MAE), and Pearson correlation coefficients (r) were computed to describe linear association, systematic bias and random error components.

Associations between absolute error in SCG-derived HRV metrics (Mean Heart Rate, RMSSD, and PNS index) and participant characteristics (age, height, weight, and BMI) were assessed using Pearson correlation analysis. Paired differences in error between Apple and Samsung devices were evaluated using the Wilcoxon signed-rank test. Statistical significance was defined as $p < 0.05$.

Results

Signal quality and beat correction between devices

In order to ensure high-quality IBI time series data for HRV analyses, beat correction was performed using the Kubios automatic beat correction algorithm [7]. IBI signal quality between the devices (Polar H10, Verity sense and Phone based-SCG) was assessed by quantifying the proportion of recordings requiring any correction and the percentage of corrected IBIs. The results are presented in Table 2.

The Polar H10 and Verity Sense devices produced the highest number of recordings without the need for beat correction (86/114 and 81/109 recordings, respectively). The average correction percentage was very low (<0.4%), with a maximum correction rate of 5%. The majority of detected corrections appeared to originate from ectopic beats rather than motion artifacts or signal noise.

Table 2: Beat correction percentages across devices. N indicates the total number of samples; Samp With Corr. denotes the percentage of samples requiring beat correction (>0%); Avg. Corr. represents the average correction percentage across samples; and Max Corr. indicates the maximum correction percentage observed.

Metric	H10	Sense	SCG
Samples (N)	114	109	114
Samp. with Corr. (%)	24.6	25.7	39.5
Avg. Corr. (%)	0.37	0.35	0.68
Max Corr. (%)	4.58	5.00	6.25

In contrast, smartphone-based SCG recordings required corrections more frequently. In 45 recordings, at least one outlier was detected and corrected. The average correction percentage was 0.68%, with a maximum of 6.25%.

HRV accuracy between devices

Figure 1 presents the agreement between smartphone-based SCG and reference ECG measurements for Mean HR, RMSSD, and PNS index, combining data from Apple and Samsung devices. Agreement between smartphone-based SCG and ECG was high across all metrics. Mean HR showed near-perfect correlation, with a mean bias of −0.06 bpm and error SD of 0.19 bpm. RMSSD demonstrated a correlation of r = 0.991, with a bias of −0.6 ms and SD of 4.09 ms; including four measurements where errors exceeded 10 ms. The PNS index showed a correlation of r = 0.996, with a bias of −0.01 and SD of 0.12. Across all parameters, errors were centered close to zero with no evident systematic bias.

Figure 2 illustrates the distribution of individual device errors (Polar H10, Verity sense and smartphone-based SCG) relative to reference ECG. A small number of outliers were observed, primarily affecting variability-related parameters (RMSSD and PNS), whereas heart rate measurements remained consistently aligned with the reference.

Table 3 summarizes agreement metrics for device-derived HRV parameters compared with the ECG reference. For Mean HR, all devices produced values closely aligned with the reference measurements, with minimal bias and narrow limits of agreement. For RMSSD and the PNS index, correlations with reference ECG were very high across all devices (r = 0.99–1.00). The Polar H10 produced values that were nearly identical to the ECG reference, with minimal bias and

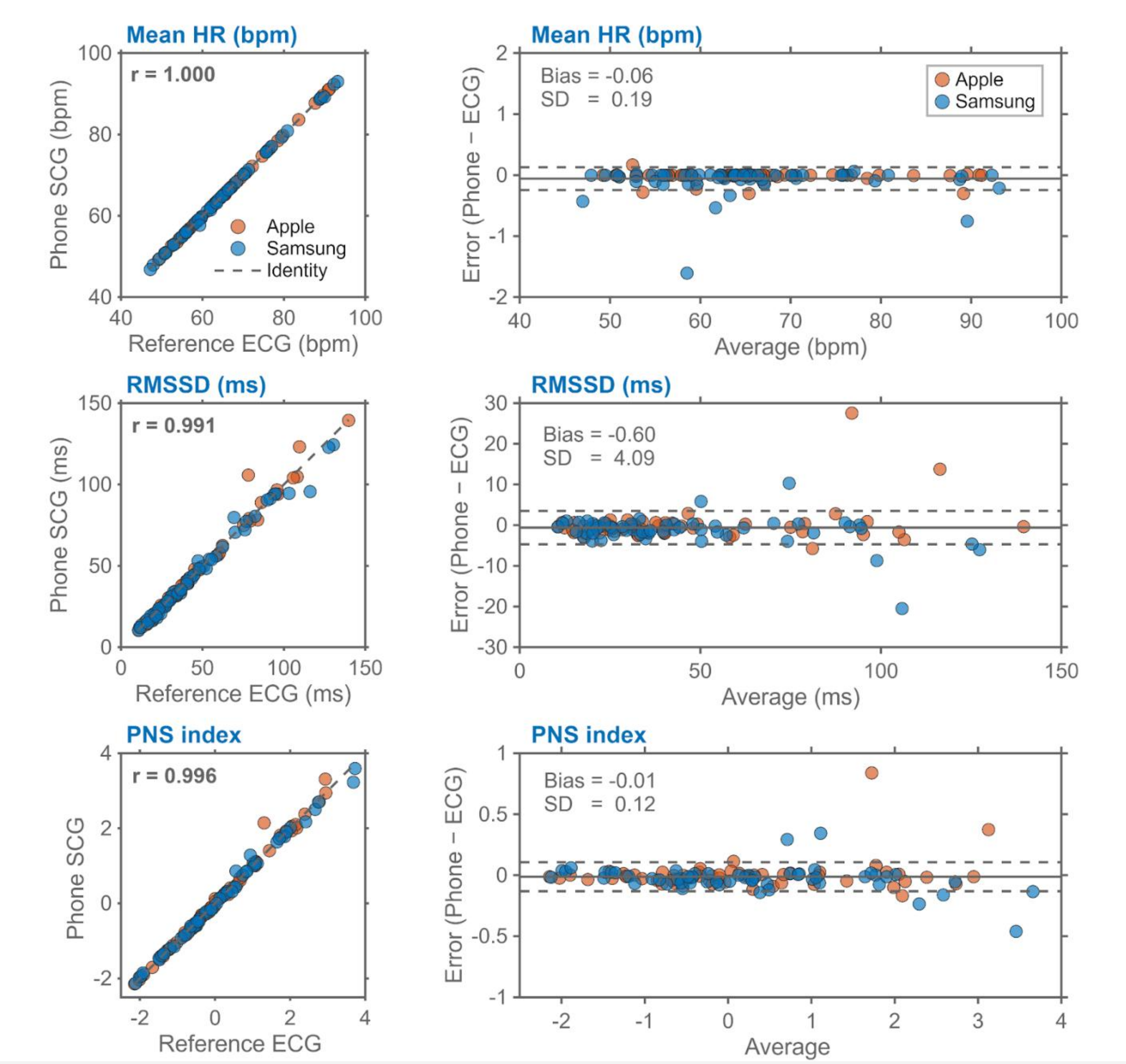

Figure 1. Agreement between smartphone SCG-based HRV metrics and reference ECG measurements. Left panels show correlation plots between Phone SCG-based estimates and ECG for Mean Heart Rate, RMSSD, and PNS index. Right panels present Bland–Altman analyses displaying the error (Phone – ECG) against the mean of the two methods. Solid horizontal lines represent the mean bias, and dashed lines indicate SD of error.

narrow limits of agreement. Polar Verity Sense and smartphone-based SCG showed slightly larger deviations, with SD of RMSSD error being ±4.09 ms for Verity Sense and ±3.90 ms for smartphone-based SCG. A similar pattern was observed for the PNS index

Exploratory Analysis of Subject- and Device-Related Factors in Phone-Based SCG

Correlation analysis was performed to evaluate whether HRV parameter accuracy derived from the smartphone-based SCG was associated with participant characteristics. A small positive correlation was observed between mean HR error and BMI ($r = 0.24$, $p < 0.05$). However, the magnitude of mean HR error was low overall, with the largest absolute error being 1.61 bpm. No significant correlations were found between RMSSD or PNS index errors and participant characteristics, including age, height, weight, and BMI.

When comparing the two smartphone models used for SCG measurements, mean HR absolute error differed significantly between devices ($p < 0.05$), with a lower mean absolute error observed for Apple (0.03 bpm)

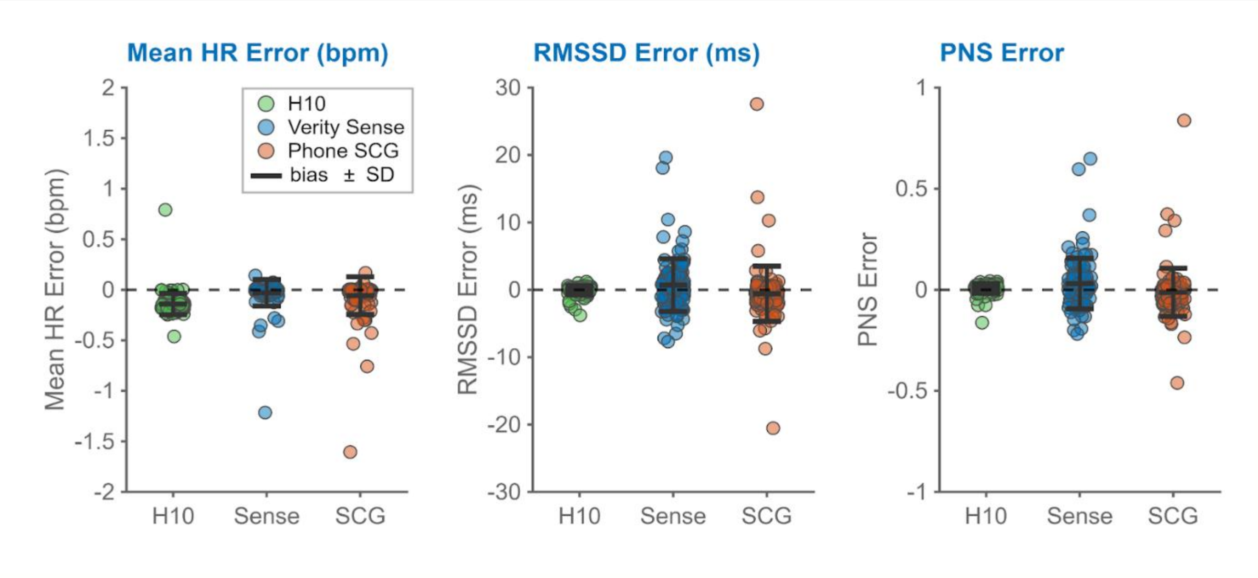

Figure 2. Comparison of device-level error distributions relative to ECG reference measurements. Errors (Device − ECG) are shown for Mean HR, RMSSD, and PNS index across three devices: Polar H10, Polar Verity Sense, and smartphone-based SCG. Individual data points represent sample errors, while solid horizontal lines present bias and bias ± SD.

Table 3: Agreement metrics for device-derived HRV measures compared with ECG reference. For each parameter and device, mean bias with SD of error, median error with 2.5th–97.5th percentiles, mean absolute error (MAE) and Pearson correlation with 95% confidence interval are reported.

HRV metric (Device)	Bias ± SD	Median [P2.5–P97.5]	MAE	r ± 95% CI
Mean HR (bpm)				
H10	-0.14 ± 0.11	-0.15 [-0.24, -0.00]	0.1546	1.00 [1.00, 1.00]
Verity Sense	-0.03 ± 0.13	-0.00 [-0.34, 0.03]	0.0383	1.00 [1.00, 1.00]
Phone SCG	-0.06 ± 0.19	-0.00 [-0.50, 0.01]	0.0629	1.00 [1.00, 1.00]
RMSSD (ms)				
H10	-0.08 ± 0.68	0.05 [-2.35, 0.81]	0.3797	1.00 [1.00, 1.00]
Verity Sense	0.69 ± 3.90	0.49 [-6.22, 10.01]	2.5696	0.99 [0.99, 0.99]
Phone SCG	-0.60 ± 4.09	-0.61 [-5.94, 8.72]	2.0053	0.99 [0.99, 0.99]
PNS index				
H10	0.01 ± 0.02	0.01 [-0.07, 0.04]	0.0167	1.00 [1.00, 1.00]
Verity Sense	0.03 ± 0.13	0.02 [-0.18, 0.34]	0.0838	1.00 [0.99, 1.00]
Phone SCG	-0.01 ± 0.12	-0.01 [-0.17, 0.33]	0.0596	1.00 [0.99, 1.00]

compared with Samsung (0.09 bpm). However, the absolute errors were minimal for both devices. No statistically significant differences were observed between devices for RMSSD or PNS index absolute errors.

Discussion

This study evaluated the accuracy of smartphone-based SCG for HRV analysis, as implemented in the Kubios mobile application, against an ECG reference. Overall, SCG-derived HRV showed high agreement with ECG-derived Mean HR, RMSSD, and PNS index. Heart rate measurements demonstrated minimal deviation from the reference, while variability-related parameters exhibited small differences and a limited number of outliers. Comparisons with established wearable devices suggested that the Kubios app's SCG–based HRV analysis performed at a level comparable to optical sensor–based measurements.

Overall, the percentage of beat correction was low across all devices, with maximum correction values remaining below 6.25%. The majority of recordings required little to no post-processing adjustments. Beat correction percentages were marginally higher in phone-based SCG recordings compared with the other devices. This was expected, as SCG signals are mechanically derived and inherently more sensitive to movement artefacts. Even minor body movements or changes in chest position can introduce disturbances that result in missed or irregularly detected beats requiring correction. Importantly, when participants remained completely still in the supine resting position, the majority of SCG recordings required no correction at all. In recordings where correction was applied, the magnitude was generally low, suggesting that reliable HRV metrics can be obtained under controlled resting conditions.

The Kubios app's SCG-based HRV results showed strong agreement with the ECG across Mean HR, RMSSD, and PNS index. A small number of outliers were identified, primarily affecting the RMSSD and PNS index. Detailed inspection of the five largest deviations revealed that most (three) RMSSD and PNS errors were attributable to nondetected beats, in which the corresponding IBI value was corrected with the automatic correction algorithm. One case was associated with two misaligned beats that were not automatically corrected, while another case involved a longer corrupted signal segment at the beginning of the recording. This corrupted segment was subsequently excluded from the analysis by the signal quality detection algorithm.

Agreement between device-derived HRV metrics and the ECG reference was high across all evaluated parameters. The Polar H10 produced values that were nearly identical to the ECG reference, which was expected given that the H10 directly measures ECG signals. The optical Polar Verity Sense demonstrated slightly wider limits of agreement compared with the H10 but remained closely aligned with the reference. Smartphone-based SCG showed a comparable level of agreement to the Polar Verity Sense across Mean HR, RMSSD, and PNS index. The findings indicate that the Kubios app's SCG-based HRV analysis performed at a level comparable to the optical sensor during resting measurements.

Analysis of subject characteristics indicated no meaningful associations between SCG-derived RMSSD or PNS index errors and age, height, weight, or BMI. A small positive correlation was observed between mean HR error and BMI; however, the magnitude of this heart rate error remained low across all participants, suggesting limited practical relevance.

In the comparison between smartphones, a statistically significant difference was observed in mean HR absolute error, with the Apple device showing slightly lower error than the Samsung device. Nevertheless, the errors related to mean HR were very small, suggesting again limited practical relevance. No significant differences were detected between smartphones for RMSSD or PNS index errors, indicating comparable HRV performance across phone models. Overall, these results suggest that SCG-based HRV estimation is robust across the tested subject characteristics and smartphone platforms.

Practical observations from the beta phase of the SCG readiness application provide additional context for real-world use. Apple devices consistently recorded SCG signals at 100 Hz, whereas Android device sampling frequencies varied between approximately 100 and 500 Hz depending on the model. While higher sampling frequencies did not negatively impact analysis, hardware variability across Android models was more pronounced. In some older or lower-end Android devices, accelerometer noise levels were sufficiently high to prevent reliable beat detection. In such cases, the Kubios application automatically indicated that the measurement could not be analyzed due to insufficient signal quality. When SCG signal quality is inadequate, the recommended alternative is to use a Bluetooth heart rate belt for HRV measurement. These observations highlight the need for built-in signal quality control mechanisms.

Conclusion

The present validation demonstrates that smartphone-based SCG for HRV analysis, as implemented in the Kubios mobile application, provides agreement comparable to optical sensor–based measurements under resting conditions. Reliable HRV metrics can be obtained when the user remains completely still during measurement, as SCG signals are sensitive to movement artefacts. Under controlled resting conditions, deviations are small and within acceptable limits for readiness monitoring.

Smartphone-based SCG readiness assessment can be effectively used for individual stress and recovery monitoring in daily practice. Its practical advantages are particularly evident in team environments, such as football or cycling teams, where rapid, sensorless measurements simplify large-scale readiness assessment. The absence of external sensors reduces setup time, logistical complexity, and device management challenges. Similar benefits apply to wellness professionals monitoring multiple clients, as well as researchers conducting group-based HRV assessments, where ease of deployment and scalability are critical.

Beyond convenience, smartphone-based SCG enables low-barrier access to HRV monitoring without the need for dedicated wearable hardware. This may support higher measurement compliance, simplified data collection in field settings, and broader accessibility for routine physiological monitoring.

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