# Expansion of Smartwatch Use in Daily Life Activities: Reliability in Heart Rate Variability Measurement

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**Abstract**

*This study investigates the reliability of the smartwatch in assessing heart rate variability (HRV) under everyday conditions. Two protocols were compared: LTL (lying–treadmill–lying) and STS (sitting–treadmill–sitting), both lasting 19 minutes and comprising three phases (rest, walking, and recovery). Seven participants were monitored using a smartwatch (fs-S = 100 Hz), and the analyzed parameters included Mean RR, SDNN, and RMSSD (time domain), as well as LF, HF, and LF/HF (frequency domain). The results showed significant differences in the time domain during phases 1 and 3, especially for Mean RR (phase 1: p = 0.007; phase 3: p = 0.020) and SDNN (phase 1: p = 0.043). The frequency domain did not show significant differences between the protocols in any phase. Data collection in a natural context allows for more realistic inferences about autonomic physiology, highlighting the potential of smartwatches in remote telemonitoring.*

## 1. Introduction

Wearable devices operate through a sensor equipped with a photoplethysmography (PPG) system, which uses a non-invasive optical technique to analyze blood pulsation in peripheral regions of the body and, from that, provides physiological monitoring data to the user. Although this technique has great potential and various applications, its physiological origin is still under investigation. However, with advancements in computational modeling and imaging technologies, it has become possible to better understand the interaction between light and tissue (skin) [1].

Due to their wide range of functions, ease of portability, and usability, the use of wearable devices has been growing and gaining popularity in recent years. Among the physiological variables that can be monitored through a smartwatch is heart rate variability (HRV), which is an important marker of the autonomic modulation of the heart. HRV reflects the balance between the parasympathetic and sympathetic systems and can be associated with several physiological conditions, such as stress, fatigue, physical performance, cardiovascular risk, and post-exercise recovery [2]. Therefore, its measurement must be accurate, as it is essential for clinical interpretation. In addition to HRV, wearable devices can also assess blood pressure, oxygen saturation, and monitor body position and speed in real time through embedded gyroscopes and accelerometers [3].

However, when using photoplethysmography, it must be considered that it is highly sensitive to movement, making it prone to motion artifacts [4].

Given its broad utility, this technology has increasingly been incorporated into users' daily routines. Nonetheless, it still presents challenges, such as limited storage capacity for extended use, the need for a secondary device to analyze signals/data collected during daily activity, battery life that may not support full-day or overnight recording, water resistance requirements for specific environments, as well as issues related to motion artifacts, lighting, and skin pigmentation [5].

Despite these challenges, measurements obtained from wearable devices often exhibit variability in both reliability and accuracy when compared with data acquired from gold-standard instruments such as the electrocardiogram (ECG). ECG enables precise detection of RR intervals, which serve as the foundation for calculating key HRV indices across both the time and frequency domains. [1].

Therefore, it is essential to develop specific protocols tailored to the monitoring of daily activities. Considering the integration of accelerometer and gyroscope technologies, this study aimed to evaluate the reliability of HRV data obtained exclusively from a smartwatch during real-life conditions using two distinct protocols, and to determine whether these measurements are comparable in accuracy to those derived from an electrocardiogram

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(ECG).

### 1.1. Hypothesis and objective

We hypothesized that HRV measurements obtained through smartwatch show a high correlation when compared to ECG measurements under resting conditions accuracy decreases during activities greater body movement due to motion artifacts. The objective is to expand the application of the smartwatch to daily activities in uncontrolled environments, i.e., during the participant's routine.

## 2. Materials and methods

### 2.1. Materials

The participants in this study were recruited voluntarily. The tests were conducted at the Polyclinic of the University of Mogi das Cruzes (UMC), SP, Brazil.

### 2.2. Sample

The study sample comprised 7 participants (4 females and 3 males), aged between 23 and 46 years, mean age (34.1 ± 10.1) years old. Participants had no comorbidities or physical or mental limitations. The participants in this study were recruited voluntarily (CEP CAAE: 64561022.7.0000.5497. 3)

### 2.3. Protocol

Participants completed two experimental protocols using a smartwatch operating at a sampling frequency of 100 Hz, each composed of three consecutive phases. In the LTL protocol, participants remained lying down for 6 minutes (Phase 1), walked on a treadmill at 3.5 km/h for 6 minutes (Phase 2), and then lay down again for 7 minutes (Phase 3). In the STS protocol, the same structure was followed, but participants began sitting, performed the same 6-minute treadmill walk, and ended sitting again for the recovery period. Each protocol lasted 19 minutes per participant.

Phase 1 represented a resting condition in a quiet environment, allowing the establishment of a baseline HRV measurement under autonomic stability, with minimal body movement.

Phase 2 consisted of continuous treadmill walking, considered a light physical activity sufficient to elicit physiological changes in HRV. This phase aimed to test the smartwatch's signal reliability under motion, one of the main limitations of phase PPG-based devices.

Phase 3 served as the recovery period, assessing HRV behavior after physical exertion and verifying the smartwatch's ability to maintain signal consistency comparable to the resting condition.

### 2.4. Data processing

The data were collected and exported in **.**csv format for subsequent processing. Signal preprocessing was performed using PyBios software, which allowed for artifact filtering and generation of clean data samples [6]. The resulting dataset was then segmented by phase to enable phase-specific HRV analysis [7].
Data from both protocols LTL and STS were organized in a spreadsheet and categorized by HRV parameter and experimental phase. Statistical analyses were conducted using GraphPad Prism v10.4**,** applying the Mann–Whitney U-test to assess differences between protocols.

## 3. Results

The results were analyzed phase by phase for each parameter.

### 3.1. Phase 1: Resting condition

Table 1 summarizes the HRV results obtained during the resting phase. Significant differences were observed in the time-domain parameters.

Mean RR was significantly higher in the LTL protocol (0.869 ± 0.195 ms) compared with STS (0.817 ± 0.154 ms; $p$= 0.007), indicating greater parasympathetic activity in the lying position. Conversely, SDNN was lower in LTL (0.037 ± 0.014 ms) than in STS (0.049 ± 0.021 ms; $p$ = 0.043), suggesting higher overall variability while sitting. RMSSD values were nearly identical between protocols (LTL: 0.009 ± 0.002 ms; STS: 0.009 ± 0.003 ms; $p$= 0.662). No significant differences were detected in the frequency-domain indices, including LF ($p$= 0.560), HF ($p$= 0.560), and LF/HF ratio ($p$= 0.421).

Table 1: Mean Values and Standard Deviations Between LTL and STS Protocols for HRV Parameters (*) $p < 0.05$.

| **Parameter** | **LTL (mean ± SD)** | **STS (mean ± SD)** | ***p*-value** |
|---|---|---|---|
| | **Time domain** | | |
| **Mean RR (ms)** | 0.86 ± 0.19 | 0.81 ± 0.15 | 0.01* |
| **SDNN (ms)** | 0.03 ± 0.01 | 0.04 ± 0.02 | 0.04* |
| **RMSSD (ms)** | 0.01 ± 0.00 | 0.01 ± 0.00 | 0.66 |
| | **Frequency domain** | | |
| **LF (norm)** | 85.78 ± 5.77 | 87.75 ± 6.23 | 0.56 |
| **HF (norm)** | 14.21 ± 5.77 | 12.24 ± 6.23 | 0.56 |
| **LF/HF** | 7.28 ± 3.76 | 9.24 ± 5.27 | 0.42 |

## 3.2. Phase 2: Walking on treadmill

In Table 2, representing the walking phase, none of the parameters showed statistically significant differences between protocols. Mean RR (LTL: 0.561 ± 0.081 ms; STS: 0.570 ± 0.102 ms; $p$= 0.637), SDNN (LTL: 0.033 ± 0.021 ms; STS: 0.024 ± 0.009 ms; $p$= 0.367), and RMSSD (LTL: 0.002 ± 0.008 ms; STS: 0.003 ± 0.001 ms; $p$= 0.633) remained comparable across conditions. Similarly, LF, HF, and LF/HF ratio did not differ significantly (LF: $p$= 0.411; HF: $p$= 0.411; LF/HF: $p$= 0.976).

These results indicate that the body posture preceding walking (lying or sitting) did not affect autonomic response during light exercise, as reflected by similar HRV patterns between the two protocols.

Table 2: Mean Values and Standard Deviations Between LTL and STS Protocols for HRV Parameters.

| Parameter | LTL (mean ± SD) | STS (mean ± SD) | *p*-value |
|---|---|---|---|
| | Time domain | | |
| Mean RR (ms) | 0.56 ± 0.08 | 0.57 ± 0.10 | 0.64 |
| SDNN (ms) | 0.03 ± 0.02 | 0.02 ± 0.01 | 0.38 |
| RMSSD (ms) | 0.00 ± 0.01 | 0.00 ± 0.00 | 0.63 |
| | Frequency domain | | |
| LF (norm) | 87.06 ± 6.14 | 82.93 ± 8.60 | 0.41 |
| HF (norm) | 12.93 ± 6.14 | 17.06 ± 8.60 | 0.41 |
| LF/HF | 8.00 ± 3.33 | 8.13 ± 9.28 | 0.98 |

## 3.3. Phase 3: Recovery phase

Table 3 summarizes the results for the recovery phase.

Table 3: Mean Values and Standard Deviations Between LTL and STS Protocols for HRV Parameters (*) $p < 0.05$.

| Parameter | LTL (mean ± SD) | STS (mean ± SD) | *p*-value |
|---|---|---|---|
| | Time domain | | |
| Mean RR (ms) | 0.85 ± 0.14 | 0.80 ± 0.15 | 0.02* |
| SDNN (ms) | 0.05 ± 0.03 | 0.05 ± 0.03 | 0.31 |
| RMSSD (ms) | 0.01 ± 0.00 | 0.01 ± 0.00 | 0.76 |
| | Frequency domain | | |
| LF (norm) | 85.26 ± 7.59 | 89.93 ± 2.11 | 0.18 |
| HF (norm) | 14.73 ± 7.59 | 10.06 ± 2.11 | 0.18 |
| LF/HF | 7.88 ± 5.10 | 9.29 ± 2.01 | 0.54 |

A significant difference was observed in Mean RR, with higher values in LTL (0.854 ± 0.137 ms) compared to STS (0.797 ± 0.148 ms; $p$= 0.020), suggesting a more effective reactivation of parasympathetic activity in the lying condition. SDNN was slightly higher in LTL (0.059 ± 0.033 ms) than in STS (0.046 ± 0.027 ms; $p$= 0.311), whereas RMSSD remained similar between protocols (LTL: 0.008 ± 0.002 ms; STS: 0.008 ± 0.003 ms; $p$= 0.756).

In the frequency domain, LF, HF, and LF/HF ratio did not exhibit significant differences between conditions, showing only minor variations.

## 4. Discussion

The results presented in this study demonstrate that the LTL protocol elicited a different autonomic response compared to the STS protocol, particularly in the phases where participants remained at rest namely, Phase 1 and Phase 3 in the time domain. The analysis of the Mean RR, which can be considered a marker of parasympathetic activity, showed significantly higher values in the LTL protocol during Phase 1 ($p$= 0.007) and Phase 3 ($p$= 0.020). This suggests a vagal predominance when the participant is lying down. These results are consistent with previous studies comparing smartwatch and ECG measurements, which demonstrate strong correlation at rest and partial agreement during mild movements [1,2].

Although direct comparison with ECG was not performed in this study, the observed reliability pattern follows that reported in the literature, indicating that under low-motion conditions, smartwatch derived HRV indices are comparable to those from ECG.

Although SDNN presented higher values in the STS protocol during Phase 1 ($p$= 0.043), this pattern did not persist in the other phases. Greater variability while sitting may represent postural parasympathetic activity. The RMSSD parameter remained low in both protocols, which may be related to the short duration of data collection possibly insufficient to capture this metric or due to the limited sensitivity of the method when applied to a relatively simple protocol.

In Phase 2, during treadmill walking at 3.5 km/h, both the time and frequency domain parameters showed similar values between protocols. This indicates that the physical effort involved was mild and resulted in a standardized autonomic response, regardless of the participant's prior posture lying or sitting. Time domain values between LTL and STS ranged from ($p$= 0.367 to 0.637), and in the frequency domain, values ranged from ($p$= 0.411 to 0.976).

In the frequency domain, the LF, HF, and LF/HF parameters did not exhibit significant differences, suggesting that postural changes between LTL and STS had a stronger effect on time domain parameters, which reflect overall autonomic nervous system activity both sympathetic and parasympathetic.

Unlike previous studies, in which data collection was conducted in a controlled environment that may have induced a certain degree of participant stress, the use of the smartwatch with a 100 Hz sampling rate in an uncontrolled, real-life context demonstrated that this tool provides highly reliable data under such conditions.

In the present study, we were able to evaluate the effectiveness of both protocols and concluded that the LTL protocol was more effective, as it elicited a greater parasympathetic response during the resting period. This finding may be particularly relevant for studies focused on post-exercise recovery or activities aimed at assessing autonomic balance.

This study reinforces the strong potential of using the smartwatch as a tool for remote telemonitoring, allowing for continuous and non-invasive data collection across different postural positions, and increasing the ability to assess physiological data under various conditions[8], [9]. The applicability of the smartwatch can be extended to athletes, older adults, individuals with chronic diseases, and those undergoing rehabilitation.

Furthermore, the similarity of HRV parameters between sitting and lying positions during recovery suggests that body posture has a secondary influence on autonomic regulation once heart rate has stabilized. A key implication of this finding is that smartwatches can be used in longitudinal monitoring or home-based follow-ups, as they capture reliable HRV patterns even in semi-controlled environments. However, motion artifacts remain a limiting factor for accurate signal acquisition during more intense activities.

In future work, we aim to explore protocols involving the Valsalva maneuver a physiological test that enables the assessment of the normal functioning and responsiveness of the autonomic nervous system, particularly parasympathetic and sympathetic activity. The protocol consists of a forced expiration against a closed airway, typically lasting around 15 to 20 seconds, which induces controlled changes in intrathoracic pressure and heart rate [10].

Future studies should include simultaneous ECG recordings to establish correction factors and increase the reliability of smartwatch data for clinical diagnostics.

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