

Assessment of Contact Pressure in Wrist Photoplethysmography and a Multi-Step Mitigation Scheme for Cardiac Measurement Accuracy Enhancements

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Abstract: Modern commercial wearables utilize photoplethysmography (PPG) sensors to track health metrics with a lightweight, compact design. However, PPG sensors are vulnerable to variations in contact pressure, which refers to the level of tightness of wearables on the wrist. This can cause deformation of PPG waveform morphology and result in inaccurate estimation of health metrics. Electrocardiography (ECG) sensors are the gold standard for heart rate measurement, but they contain certain flaws. We assessed how contact pressure affects wrist PPG heart rate accuracy. In this study, we conducted a secondary data analysis on the publicly available WF-PPG dataset. From the dataset, we computed heart rate from both PPG and ECG signals and compared them to calculate heart rate error. The values of heart rate error were distributed across categories based on PPG waveform morphology types, each associated with a range of contact pressure. Thus, the impact of skin composition on the effect of contact pressure was partially accounted for. Median heart rate error for each category was calculated. The results suggested that contact pressure has a profound impact on the accuracy of PPG sensors. Median wrist error was lowest for Type 2E + 2L (2.38 bpm), except for Type 3 (2.25 bpm), which has a low signal-to-noise ratio (SNR); finger error was lowest for Type 2L (1.36 bpm). Blood oxygen saturation (SpO_2), measured by a fingertip pulse oximeter, was found to be only negligibly correlated with contact pressure. The results highlight potential inaccuracy in consumer-grade medical data that should be considered during medical use. A multi-step engineering scheme was suggested to alleviate this challenge of modern wearables.

Keywords: Photoplethysmography (PPG), Electrocardiography (ECG), Contact Pressure, Wearables, Heart Rate, Waveform Morphology

Introduction

Advancements in modern technologies have propelled the transformation of traditional practices into a smaller, more convenient form, such as computers into smartphones and libraries into e-books. Health tracking is no exception to this trend. Modern wearables, such as smartwatches, track health metrics anywhere, anytime. They rely heavily on photoplethysmography (PPG) for tracking health metrics, especially to support their minimal size. PPG measures cardiac activity by emitting light, ranging from a single wavelength to a broad spectrum, into the skin. A portion of light is absorbed, and part of the remainder is reflected by the underlying microvascular bed back to a sensor. Each heartbeat creates a surge in microvascular blood volume, which increases light absorption, thus creating detectable variations that register individual cardiac cycles. By capturing these dynamic changes over time, PPG enables inference of key physiological metrics including heart rate (HR), heart rate variability (HRV), blood oxygen saturation (SpO_2), and blood pressure¹. Figure 1 shows where a PPG sensor is typically located on a smartwatch, marked by a red circle.



Figure 1 | Back of an Apple Watch and PPG sensor location. Photo by Mliu92 (CC BY-SA 3.0), cropped, with red circle added².

Electrocardiography (ECG) is another technique that provides non-invasive cardiac readings. ECG measures electrical signals generated from each heartbeat and is considered the ground truth for heart rate measurement³. Despite its superior accuracy compared to PPG, its integration into wearables remains a challenge. Limitations include the single-lead constraint and active tracking (the user must start each recording)⁴. Twelve leads are used in a standard clinical ECG, as shown in Figure 2, which enables a view of the heart from multiple angles; there is only a single angle for single-lead wearable ECG, and it cannot capture comprehensive vector information, thus creating blind spots that may cause it to miss structural abnormalities⁴. Active tracking suffers from noise created by motion artifacts, as electrodes move against the skin.



Figure 2 | Standard clinical ECG. Photo by P. Danilyuk⁵.

The health tracking capabilities of modern wearables have several purposes: continuous health monitoring, fitness and activity tracking, early detection and alerts, and chronic disease management^{6,7}. Therefore, failure of wearables to provide accurate data may lead to health issues, misdiagnosis, or disruption to preventive care; for instance, an inaccurate, underestimated heart rate reading could cause users with heart disease to miss vital medical attention.

Despite widespread use, the accuracy of PPG sensors is impaired in real-world conditions. One condition is periodic motion artifacts from rhythmic movements, such as running, which cause erroneous variability⁸. To mitigate this variability, researchers are actively developing mathematical algorithms and multi-channel, multi-wavelength sensors⁹. Yet, few studies exist that investigate the overarching impact of contact pressure, which varies with rhythmic movement as well as with wrist posture at rest¹⁰. Scardulla et al. conducted a study in which 17 subjects wearing a PPG wristband exercised at three different levels of contact pressure, and the PPG data were compared to the ECG chest strap reference¹¹. Yet, the study used only three distinct pressure values (12, 33, and 54 mmHg), which does not reflect real-world data. They found that 54 mmHg gave the most accurate heart rate and that each subject's best contact pressure gave reliable readings, but they still noted that a system to adjust the device's tightness is needed¹¹.

Ho et al. used the WF-PPG dataset to show that PPG waveform morphology changes in a consistent order as contact pressure increases: Type 1 and Type 2E appear at low pressure, Type 2L at an optimal range, and Type 1L and then Type 3 at higher pressure¹⁰. They also found that heart rate and heart rate variability errors were minimal when both the wrist and finger sensors were at optimal pressure, but that wrist errors were significantly higher than finger errors under sub-optimal wrist pressure¹⁰. However, they estimated these errors from eight-second windows and did not compare heart rate error between individual morphology types.

With the aim of filling these research gaps, we perform a cycle-by-cycle comparison of wrist PPG heart rate and finger PPG heart rate values against the corresponding synchronized values from the ECG ground truth across five waveform morphology types and from 27 subjects in the WF-PPG public dataset by Ho et al.¹⁰. Additionally, the correlation of SpO₂ values with variation in contact pressure was tested. The aim of the study is to assess the level of impact of contact pressure on the accuracy of wrist PPG readings and propose solutions to mitigate the consequent inaccuracy. Specifically, we asked whether heart rate error differs across waveform morphology types, which represent different contact pressure ranges, for wrist and finger PPG. This work paves the way for a new perspective into the wearable sensor industry and provides a baseline comparison between PPG and ECG sensors for future studies.

Methods

Research Design

We conducted a secondary data analysis on the WF-PPG dataset by Ho et al.¹⁰.

Participants

The dataset comprises 27 young, healthy participants. There were 16 males and 11 females, and their mean age was 24.3 ± 2.7 years (range 20–32)¹⁰.

Data Collection

Conducting a literature review on papers regarding PPG sensors, we found the WF-PPG dataset by Ho et al.¹⁰, which contains recordings of PPG light intensity values and ECG signals across varying pressure values. In the experiment by Ho et al., subjects underwent six experimental sessions. Dual-channel optical PPG signals were captured simultaneously using MAXM86161 optical modules: Wrist PPG was measured via a sensor mounted on a mechanical clamp fitted with an FX1901 load cell sensor to apply, adjust, and continuously record contact pressure. Finger PPG was measured via a sensor attached to a fingertip of the same hand using a strap to maintain a constant reference pressure. A Polar H10 ECG chest band was used to measure ground truth ECG values. SpO₂ was measured separately with a medical-grade fingertip pulse oximeter (Vibeat Oxylink) at 0.25 Hz, and blood pressure was measured once per session with a cuff-based monitor (Omron Complete). During each session, raw PPG and ECG signals were recorded¹⁰. Each session consisted of three steps: a blood pressure measurement, an adjustment of the clamp to set the wrist contact pressure, and a four-minute recording while the participant remained still. The contact pressure was gradually increased across the six sessions, and some recordings are slightly shorter than four minutes because poor-quality segments were removed. The PPG sensors recorded green, red, and infrared light; the cycle indices and morphology labels provided in the dataset, which were used in this study, were derived from the green channel¹⁰.

In the original study, raw PPG signals underwent fifth-order low-pass Butterworth filtering (cutoff 10 Hz) followed by baseline wander (DC component) removal using cubic spline interpolation fitted to waveform feet and troughs. Signals were cycle-by-cycle synchronized with ECG R-peaks and resampled to a uniform sampling rate of 100 Hz (10 ms per sample)¹⁰.

Raw ECG signals were originally sampled at 130 Hz using the Polar H10 ECG chest band. Resampling to 100 Hz matched the ECG to the PPG sampling rate, and the two signals were synchronized cycle by cycle rather than sample by sample¹⁰. Then, in this study, R peaks were extracted using a prominence-thresholding peak detection algorithm.

Variables and Measurements

Everyone has different skin composition, including different skin thickness, arteries, and blood vessels¹⁰. Unfortunately, this makes it impracticable to compare raw contact pressure directly to heart rate error to see a relationship. Therefore, the waveform morphology measured by the PPG sensor, which is affected and deformed at varying scales by varying contact pressure, was divided by Ho et al. into five categories and used to approximately represent different levels of contact pressure to normalize across subjects.

In the original study, the preprocessed PPG data was used to create waveforms for each heartbeat cycle, which were then divided into the five categories based on shape¹⁰. Table 1 shows the categories, their typically associated contact pressure level, and a description of the appearance of their waveform curve.

Table 1 | Classification of PPG waveform morphologies. Adapted from Ho et al.¹⁰.

Morphology Type	Typical Contact Pressure Level	Curve Description
1	Low	A single, centralized peak occurs later than 25% of the waveform's width.
2E	Slightly Low/Insufficient	Two peaks with an amplitude difference of less than 10%.
2L	Ideal/Optimal	Ideal PPG waveform from the literature, with two peaks where the left peak is at least 10% larger than the right, and a dirotic notch lies between them.
1L	Excessive	Similar to Type 2L graph's morphology, yet it is missing a diastolic peak, and its prominent systolic peak occurs at or before 25% of the waveform's width.
3	Extremely High/Low	Typically corrupted by noise or motion artifacts. Does not fit into any of the other classes. Corresponding heart rate is unpredictable.

Heart rate was calculated from the PPG preprocessed data according to equations 1 and 2.

For each pulse cycle in the indices files, s denotes the start sample index of a cycle, e denotes the end sample index of a cycle, and F_s denotes the sampling frequency.

$$\text{Inter-Beat Interval} = \Delta t_{\text{PPG}} = (e - s) / F_s. \quad (1)$$

$$\text{Instantaneous PPG Heart Rate} = \text{HR}_{\text{PPG}} = 60 / \Delta t_{\text{PPG}}. \quad (2)$$

Heart rate was calculated from ECG preprocessed data with equations 3 and 4, where p_i and p_{i+1} are sample indices of consecutive R-peaks and F_s denotes the sampling frequency.

$$\text{Inter-Beat Interval} = \Delta t_{\text{ECG}} = (p_{i+1} - p_i) / F_s. \quad (3)$$

$$\text{HR}_{\text{ECG}} = 60 / \Delta t_{\text{ECG}} = (60 \times F_s) / (p_{i+1} - p_i). \quad (4)$$

Each PPG cycle was then paired with an ECG heart rate. To account for fluctuations in skin thickness and anatomical variability in bodily composition that could differently affect the impact of the same pressure value on individual participants, min-max normalization was applied to pressure for each subject using equation 5, following Ho et al.¹⁰:

$$\text{Normalized Pressure} = (\text{Raw Pressure } P - P_{\text{min subject}}) / (P_{\text{max subject}} - P_{\text{min subject}}). \quad (5)$$

Here, P is the contact pressure of a cycle, computed from the load-cell readings within that cycle, and $P_{\text{min subject}}$ and $P_{\text{max subject}}$ are the lowest and highest pressures recorded for that subject.

Because the pressure was normalized within each subject, the normalized values have no units and do not depend on the units of the raw load-cell readings. Each cycle was also assigned the SpO_2 value recorded by the pulse oximeter during that cycle; because the oximeter updates only every four seconds, consecutive cycles often share the same reading.

Heart rate error was defined as the absolute difference between the ECG and PPG heart rates of each cycle, calculated separately for wrist and finger PPG with equation 6:

$$\text{Heart Rate Error} = |\text{HR}_{\text{ECG}} - \text{HR}_{\text{PPG}}|. \quad (6)$$

Data Analysis

The files in the dataset contained 27 subjects, each with 6 sessions. Each session had preprocessed data and indices data files, as shown in Figure 3. The preprocessed data contained the actual data, including PPG light intensity values, ECG signal values, raw pressure values, SpO_2 values, and the time recorded in milliseconds. Corresponding to the preprocessed data, the indices data provided the start and end points of pulse cycles and their morphology types¹⁰. From this information, a custom Python program was used to calculate the inter-beat interval and heart rate for each pulse cycle, for both PPG and ECG, as shown in equations 1, 2, 3, and 4. The absolute difference between ECG and PPG heart rate (heart rate error, equation 6) was calculated for each pulse cycle.

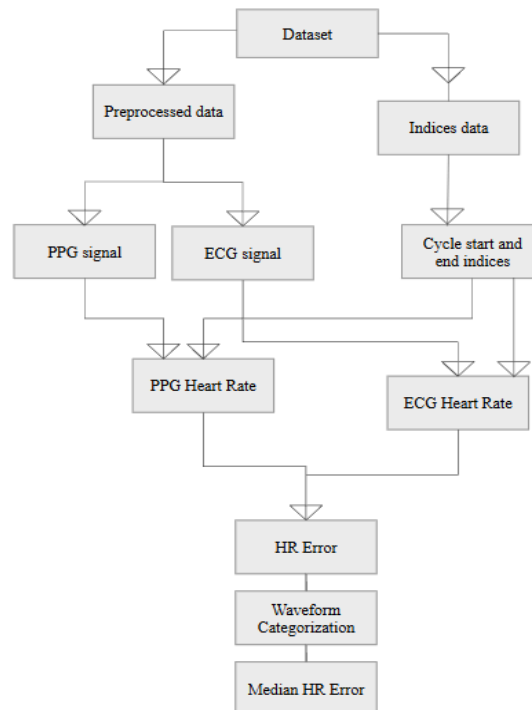


Figure 3 | Block diagram for data analysis.

Given the nature of the data collection, we used Tukey's fences to remove extreme outliers outside 3 times the interquartile range (IQR). The fences were applied to the PPG and ECG heart rate values on all pooled data.

Then, the morphology types in the indices data were used to categorize each cycle into one of the five categories, as shown in Table 1. These labels were assigned by Ho et al.'s classification algorithm¹⁰.

Median normalized pressure was calculated to be nearly equivalent for both Type 2E and Type 2L wrist morphology at 0.42, rounded to the tenth. Therefore, the wrist cycles of Type 2E and Type 2L morphology were merged as a single morphology class representing near-optimal dual-peak morphology. This merge was decided after the data were examined, mainly because only 43 wrist Type 2L cycles remained for analysis.

The total number of analyzed cycles differs across tables. The indices files provided in the dataset, which were used to identify pulse cycles according to varying morphology classes, only contained pulse cycles that were strictly filtered. Ho et al. only included heartbeat cycles where both the pulse start (s) and end (e) troughs were clearly identifiable and stable¹⁰. This filtering is already reflected in the 39,822 wrist cycles in Table 4, so the smaller numbers in Tables 2 and 3 come from the later steps of this study. Tukey's fences ($3.0 \times \text{IQR}$), which were used to eliminate PPG and ECG outliers, also filtered out a certain number of pulse cycles. Of the 39,822 wrist cycles in the indices files, 3,471 (8.7%) remained in the wrist analysis (Table 2), and 3,505 (8.8%) of the paired finger cycles remained in the finger analysis (Table 3). This reduction was uneven across wrist morphology types: 17.5% of Type 1 cycles remained, compared with 10.0% of Type 2E, 6.1% of Type 3, 3.0% of Type 1L, and only 1.3% of Type 2L. Since $3.0 \times \text{IQR}$ fences remove only extreme values, most of this reduction likely occurred when PPG cycles were matched to ECG R-peaks.

Statistical Analysis

The median heart rate error was chosen over mean HR error because noise in the signals produced extreme heart rate error values, making the mean value unreliable. Differences in heart rate error and in normalized pressure across morphology types were tested with the non-parametric Kruskal–Wallis H-test, and the effect size was calculated as $\varepsilon^2 = H / (N - 1)$. The relationships of SpO_2 with normalized pressure and with heart rate error were tested with Pearson and Spearman correlations. A significance level of $\alpha = 0.05$ was used. Each cycle was treated as an independent observation.

Ethical Considerations

This study is a secondary analysis of the publicly available, de-identified WF-PPG dataset¹⁰. No new data were collected from human participants for this study, and the original data collection protocol underlying the WF-PPG dataset is described in Ho et al. (Singapore Management University Institutional Review Board, approval number IRB-23-207-A141-1223). All participants gave informed consent in the original study, and their data were shared under anonymous IDs¹⁰.

Results

Wrist PPG Heart Rate Error

In Table 2, median heart rate error for the wrist - the median absolute difference of wrist PPG against the ground truth ECG - was computed across the four morphological categories.

A non-parametric Kruskal–Wallis H-test indicated a statistically significant overall difference in HR error across morphology classes ($H(3) = 52.74$, $p < 0.001$, $N = 3,471$; $\varepsilon^2 = 0.015$). A

non-parametric Kruskal–Wallis H-test on normalized pressure indicated a statistically significant overall difference in normalized pressure across the four morphology classes ($H(3) = 842.16$, $p < 0.001$; $\epsilon^2 = 0.243$).

Table 2 indicates that 49.93% of analyzed cycles belong to the Type 1 morphology, 25.76% to Type 2E, 1.24% to Type 2L, 7.92% to Type 1L, and 15.15% to Type 3.

Table 2 | Median heart rate error for wrist PPG across four morphologies.

Wrist Morphology	Analyzed Cycles (N)	Median HR Error (bpm)	Median Normalized Pressure
Type 1	1733	2.71	0.36
Type 2E + Type 2L	937 (894+43)	2.38	0.42
Type 1L	275	3.24	0.48
Type 3	526	2.25	0.34

Table 2 shows a greater median heart rate error for Type 1 with reduced pressure at 0.36 median normalized pressure and Type 1L with excessive pressure at 0.48 median normalized pressure, in comparison to Type 2E + Type 2L with near-optimal pressure at 0.42 median normalized pressure, by differences of 0.33 bpm and 0.86 bpm, respectively. However, Type 3, which is typically corrupted by noise, showed the lowest median heart rate error at 2.25 bpm, 0.13 bpm lower than Type 2E + Type 2L.

Finger PPG Heart Rate Error

Table 3 summarizes median heart rate error for the finger (the median absolute difference of the finger PPG against the ground truth ECG) across the five morphological categories.

A non-parametric Kruskal–Wallis H-test indicated a statistically significant overall difference in HR error across morphology classes ($H(4) = 214.85$, $p < 0.001$, $N = 3,505$; $\epsilon^2 = 0.061$). Pressure readings were not collected for finger PPG data.

Table 3 indicates 0.29% of analyzed cycles were identified as Type 1, 8.73% as Type 2E, 39.91% as Type 2L, 36.75% as Type 1L, and 14.32% as Type 3. Finger PPG has approximately 38.67 percentage points greater share of analyzed cycles in Type 2L (the optimal morphology) than wrist PPG.

Table 3 | Median heart rate error for finger PPG across five morphologies.

Finger Morphology	Analyzed Cycles (N)	Median HR Error (bpm)
Type 1	10	5.06
Type 2E	306	1.70
Type 2L	1399	1.36

Finger Morphology	Analyzed Cycles (N)	Median HR Error (bpm)
Type 1L	1288	2.67
Type 3	502	2.16

Table 3 shows a trend of increasing median heart rate error for finger PPG as waveform morphologies depart farther from the shape of the optimal curve. Here, departing farther from the optimal curve means moving from Type 2L to Type 2E, Type 1L, and Type 1, as the peaks become less like the ideal shape; noise-corrupted Type 3 (2.16 bpm) fell between Type 2E and Type 1L, and Type 1 included only 10 cycles.

SpO₂ Readings Across Wrist Morphology Classes

For Table 4, mean and median SpO₂, standard deviation, and range were calculated across five morphological categories. These SpO₂ values come from the fingertip pulse oximeter, instead of the wrist PPG sensor; in the dataset, its 4-second readings were resampled to 100 Hz. Table 4 includes all 39,822 wrist cycles in the indices files, because SpO₂ did not require matching with ECG, whereas Table 2 includes only the 3,471 cycles that remained for the heart rate analysis.

Table 4 | SpO₂ readings across five morphologies.

Wrist Morphology	Analyzed Cycles (N)	Mean SpO ₂ (%)	Median SpO ₂ (%)	SD SpO ₂ (%)	SpO ₂ Range (%)
Type 1	9906	97.91	98.03	1.27	88.0–99.4
Type 2E	8962	97.59	97.99	1.51	88.2–99.5
Type 2L	3316	97.56	97.95	1.49	88.9–99.5
Type 1L	9049	97.65	97.98	1.37	88.4–99.4
Type 3	8589	97.80	98.07	1.46	88.8–99.5

Table 5 shows the results of statistical tests on the correlation of SpO₂ with normalized contact pressure and heart rate error.

Table 5 | Results of statistical tests on SpO₂ readings against normalized contact pressure and heart rate error.

Comparison	Sample Size	Pearson Correlation (r)	R ² (Pearson)	Spearman Correlation (ρ)	Pearson p-value
SpO ₂ vs. Normalized Contact Pressure	39,822	0.0585	0.0034	0.0531	< 0.001
SpO ₂ vs. Heart Rate Error	39,822	0.0087	< 0.0001	0.0091	0.0836

Table 5 shows a statistically significant but negligible correlation between SpO_2 and normalized contact pressure ($r = 0.0585$, $p < 0.001$); contact pressure explained less than 1% of the variance in SpO_2 ($R^2 = 0.0034$). Additionally, it is shown in Table 5 that SpO_2 has no statistically significant relationship with heart rate error ($p = 0.0836$). The Spearman correlations led to the same conclusions ($p < 0.001$ and $p \approx 0.07$, respectively, estimated from ρ and the sample size).

Discussion

We quantified the impact of variations in contact pressure on the accuracy of PPG heart rate readings by performing a cycle-by-cycle comparison of wrist and finger PPG data to the matched chest ECG data across 27 participants in the WF-PPG dataset¹⁰.

The results show a statistically significant difference across morphology types: median heart rate error decreases as the morphologies approach an ideal curve for the finger PPG. This shows the potential impact of pressure on the accuracy of PPG sensors by deforming the morphology of PPG waveforms. For wrist PPG, however, the pattern was only partial: Type 1 and Type 1L had higher median errors than Type 2E + Type 2L, but Type 3 had the lowest error of all. One possible reason is that heart rate depends only on the timing of each cycle's start and end, not on its shape, and the dataset only includes cycles whose start and end troughs were clearly identifiable; future work should test this.

The differences in median heart rate error between wrist morphology types were small (at most 0.86 bpm), and the effect sizes of the Kruskal–Wallis tests were small ($\epsilon^2 = 0.015$ for wrist and 0.061 for finger PPG); with thousands of cycles, even small differences become statistically significant.

These results agree with Ho et al., who found that wrist PPG heart rate and heart rate variability errors were significantly higher than finger PPG errors when the wrist sensor was under sub-optimal contact pressure¹⁰. This study adds a cycle-level comparison across individual morphology types, which showed a clear pattern for finger PPG but only small differences for wrist PPG. Scardulla et al. also found that contact pressure affects PPG heart rate accuracy, with the most accurate results at 54 mmHg and average percentage errors of 2.4% to 3.8%¹¹; since this study reports error in bpm, the two sets of values cannot be compared directly.

SpO_2 was found to be only negligibly correlated with variation in contact pressure and showed no statistically significant correlation with heart rate error.

In order to mitigate the inaccuracy in cardiac readings caused by contact pressure, we propose a multi-step outline: First, implementation of minuscule force-sensing resistors underneath the optical sensors could enable measurement of pressure levels in real time. Then, a microcontroller within the wearable could calculate in real time min-max normalized pressure and accordingly provide users with haptic alerts; for instance, the wearable may vibrate and display “tighten the strap to the 3rd adjustment hole” when computed normalized pressure goes below a set threshold. To automate the process, adaptive straps utilizing air bladders or shape-memory alloy could be used to automatically adjust the tightness to remain within the optimal normalized pressure range instructed by the microcontroller. Additionally, neural networks integrated into the firmware could enable detecting and reconstructing distorted waveform morphologies (Type 1, 1L, 2E, 3) into the ideal Type 2L dual-peak morphology in real

time¹⁰. Because normalized pressure requires each wearer's $P_{\min}$ and $P_{\max}$, the wearable would first need a short calibration step to record the user's pressure range, similar to how Ho et al. adjusted the clamp from low to high pressure for each participant¹⁰. This outline should be evaluated in future studies.

However, several limitations should be discussed. First, the WF-PPG dataset consists of young, healthy adults (mean age 24.3 ± 2.7 years); future studies must evaluate the impact of contact pressure on older demographics with different body conditions, including stiffer vascular walls or hypertension. Second, participants were tested in a seated position throughout the whole experiment; future studies must assess contact pressure variations during dynamic, unconstrained physical exercise. Third, Ho et al. created the WF-PPG dataset partly as a benchmark for researchers to train deep-learning signal restoration models¹⁰. Due to this nature, the experiment intentionally manipulated contact pressure to produce cycles with distorted morphology, which can then be used to train artificial intelligence (AI) models to restore their ideal Type 2L morphology, which exists in finger PPG data. Consequently, the wrist PPG data has relatively few cycles (8.33%) of the ideal Type 2L morphology, which substantially undermines the reliability of the resulting calculated metrics. After the filtering in this study, only 43 of the dataset's 3,316 wrist Type 2L cycles remained for the heart rate analysis. Fourth, about 91% of the indexed cycles were excluded from the heart rate analysis, and the exclusion was uneven across morphology types, which may have affected the comparison between types. Finally, each cycle was treated as an independent observation, although cycles from the same participant and session are related, which makes the p-values smaller than they should be.

As commercial wearables show increasingly widespread usage as a device for measuring health metrics and detecting potential abnormalities, the importance of data integrity is paramount. Distortion of morphologies by contact pressure can potentially cause wearables to trigger false clinical alerts or miss critical signs of cardiac anomalies. By assessing the impact of contact pressure on waveform morphologies and thus on the accuracy of cardiac readings, and proposing a multi-step outline for mitigation methods, this study may help advance the reliability of consumer wearables toward a clinical-grade medical device for continuous health monitoring.

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