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Quantifying Heart Rate Variability From Rr Intervals Derived From Smartphone Camera Ppg Signals: A Novel Approach To Non-Invasive Cardiovascular Monitoring

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Abstract:
Background*: Heart Rate Variability (HRV) has emerged as a valuable indicator of cardiovascular health, reflecting the dynamic interplay between the sympathetic and parasympathetic branches of the autonomic nervous system [1]. Traditionally, HRV assessment involves the analysis of RR intervals derived from electrocardiogram (ECG) signals, providing valuable insights into autonomic function, stress levels, and overall well-being [2]. This study aims to explore the possibility of utilizing PPG signals obtained from smartphone cameras to accurately derive HRV metrics, representing a novel and promising approach to non-invasive cardiovascular assessment.*
Materials and Methods*: In this prospective observational study involving 289 participants aged 18 to 70 without known cardiovascular disorders, we investigated the feasibility of quantifying Heart Rate Variability (HRV) using RR intervals derived from Photoplethysmography (PPG) signals obtained through smartphone cameras. Baseline demographic data were collected, and participants placed their index fingertip against the smartphone camera lens for non-invasive PPG signal acquisition. HRV metrics, including standard deviation of NN intervals (SDNN) and root mean square of successive differences (RMSSD), were calculated. Simultaneous HRV recordings using Polar H9 were obtained for validation, enabling a comparative analysis of HRV metrics. Descriptive statistics, correlation analyses, and Bland-Altman plots were employed for data analysis, and ethical approval was secured from the institutional ethics committee. The study aimed to assess the accuracy and reliability of smartphone-derived HRV metrics, presenting a novel approach to non-invasive cardiovascular monitoring with potential implications for widespread accessibility and convenience in healthcare. Limitations, such as environmental factors and technological constraints, were duly acknowledged in interpreting the study outcomes.*
Results*: The study included 289 diverse participants (mean age 42.12 ± 12.42 years), all successfully undergoing smartphone-based PPG signal acquisition for HRV assessment. Calculated HRV metrics, SDNN and RMSSD, showed positive correlation with polar H9 reference values ($r = 0.7607$, $p < 0.001$ for SDNN; $r = 0.51$, $p < 0.001$ for RMSSD). Bland-Altman plots indicated good agreement between smartphone-derived HRV metrics and polar H9 reference data. These results underscore the accuracy of smartphone-derived PPG signals in HRV quantification, highlighting its non-invasive nature for widespread cardiovascular monitoring. Acknowledging study limitations, including potential environmental influences and variations in smartphone camera quality, the findings suggest a promising and convenient avenue for non-invasive cardiovascular assessment with implications for both clinical and personal health.*
Conclusion: *In conclusion, our study demonstrates the efficacy and reliability of smartphone-derived PPG signals in quantifying Heart Rate Variability (HRV) during cardiovascular monitoring. The positive correlation observed between smartphone-derived HRV metrics (SDNN and RMSSD) and polar H9 reference values, along with good agreement revealed by Bland-Altman plots, supports the accuracy of this non-invasive approach. While acknowledging study limitations, including potential environmental influences and variations in smartphone camera quality, our findings suggest that smartphone-based HRV assessment holds significant promise for convenient and widespread non-invasive cardiovascular monitoring in both clinical and personal health applications.*
Key Word*: Heart rate variability; Sdnn; Rmssd; Photoplethysmograph; cardiovascular, non-invasive.*

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I. Introduction

The increasing integration of smartphones into our daily lives has prompted a paradigm shift in healthcare, offering novel opportunities for non-invasive physiological monitoring [3]. This study explores the feasibility and accuracy of utilizing smartphone-derived Photoplethysmography (PPG) signals to quantify Heart

Rate Variability (HRV), a valuable metric for assessing autonomic nervous system modulation [1]. With a diverse cohort of 289 participants, we investigate the correlation between HRV metrics derived from smartphone-based PPG signals (SDNN and RMSSD) and concurrently recorded Heart Rate Variability (HRV) and RR intervals reference values from polar H9 connected with elite hrv application. Bland-Altman plots are employed to evaluate agreement between the two methods. Subgroup analyses by age and gender further examine the consistency of results. Acknowledging potential limitations, including environmental influences and variations in smartphone camera quality, this research aims to contribute to the growing field of mobile health technologies, paving the way for convenient and accessible non-invasive cardiovascular monitoring.

II. Material And Methods

This prospective, observational study was carried out at the Ear, Nose, and Throat (ENT) Out-patient Department of IPGMER and SSKM Hospital in Kolkata, India. Approval for the study design was obtained from the ethics committee of Institute of Post-Graduate Medical Education and Research (IPGMER). The study enrolled out-patients visiting the ENT Department, who were selected based on predetermined inclusion and exclusion criteria. Informed consent was obtained from the participants before their inclusion, and subjects were enrolled and initiated their participation in the study on the same day.

Study Design: Prospective open label observational study

Study Location: Institute of Post-Graduate Medical Education and Research and Seth Sukhlal Karnani Memorial (IPGMER and SSKM) Hospital, Bhowanipore, Kolkata, West Bengal

Study Duration: January 2024 to February 2024.

Sample size: 753.

Subjects & selection method: For this study, subjects were selected from individuals who fit the inclusion criteria, which include adults who are at least 18 years old and have never had a history of cardiovascular disease. The selection process prioritized obtaining a diverse sample to ensure representation across different demographics, including age and gender, to enhance the generalizability of the study findings. Subjects who showed interest in the study were approached during their clinic appointment and encouraged to participate. All recruited subjects were fully informed about the objectives, procedures and any discomforts of the study prior to receiving their consent. Participation was voluntary. The recruitment process was conducted with careful adherence to ethical principles for human research.

Inclusion criteria:

1. Subjects who are willing to participate and capable of providing informed consent.
2. Either sex.
3. Aged ≥ 18 years but ≤ 70 years.
4. The subject can sit still for the duration of the reading (maximum 2 minutes per reading).

Exclusion criteria:

1. Pregnant women.
2. Patients whose health was judged to be deteriorating and unstable by the doctor.
3. Subjects who consumed alcohol/coffee/tea in the past hour.
4. Subjects who have shaky hands due to nervous disorder or tremors.
5. Subjects who have non-functioning arm(s).

III. Procedure Methodology

The trial was conducted under the ethical clearance from IPGMER and SSKM Hospital in Kolkata, West Bengal, India. The volunteers participated in the trial with their self-consent. Subjects' participation starts once they have signed the Informed Consent Form and when the subjects have understood the entire procedure of the trial. After written informed consent was obtained, a well-designed questionnaire was used to collect the data of the recruited patients retrospectively. The questionnaire included socio-demographic characteristics such as age, gender, height (cm), weight (kgs). The body mass index (BMI) was calculated as the weight in kilograms divided by height in meters squared.

Smartphone-based PPG readings will be compared with Predicate Device (Polar H9 chest strap) that is FDA approved and CE Certified to monitor the heart rate variability [4].

Each participant was instructed to sit at rest. Both the hands were kept at rest on the surface of the table. One hand index finger was placed on the rear camera covering the flash light area. While each participant wore a polar chest strap (Polar H9 Heart Rate Sensor) connected with Elite HRV monitoring app via Bluetooth. Participants were then instructed to stay steady for 1 min till the completion of the scan. Both methods of heart rate variability measurements were used simultaneously on the subject and the data was captured over a recording length of 1 minute.

During a 1-minute finger scan using the smartphone's back camera, the flashlight emits light into the skin, and the photodetector (smartphone primary back camera) measures the amount of light absorbed and reflected by the underlying blood vessels. As blood volume changes with each heartbeat, the smartphone camera detects fluctuations in light absorption, generating a waveform that corresponds to the blood flow. We capture video frames using the smartphone camera and employ digital image processing along with various algorithms to convert these frames into the desired format. Simultaneously, we identify quadrants within the frames which extract the best signal intensity components and compute ratios between them. Subsequently, after finalizing the required intensity, our primary algorithm is run to determine heart rate and measure the interval between successive heartbeats, known as N-N intervals. From these intervals, we calculate SDNN (Standard Deviation of N-N intervals) and RMSSD (Root Mean Square of the Successive Differences).

Statistical analysis

We presented the results of the paired t-test analysis comparing the HRV metrics (SDNN and RMSSD) obtained from the predicate device and the experimental device. Additionally, Bland-Altman plots are utilized to visually assess the agreement between the two sets of measurements. Furthermore, demographic analysis details and study cohort distribution are provided to offer a comprehensive understanding of the study population.

IV. Result

Demographic analysis and study cohort distribution

Table 1 presents the demographic characteristics of the study participants, including age, gender distribution, and relevant clinical parameters. The study cohort comprised 289 participants aged 18 to 70 years, with a balanced distribution of gender.

Table 1: Shows demographic characteristics of the study participants.

Characteristics	Total Participants (n=289)	Male (n= 93)	Female (n = 196)	Minimum	Maximum
Age (years)	42.12 ± 12.42	45.51 ± 13.12	40.52 ± 11.78	18	70
Height (cms)	154.84 ± 11.94	160.45 ± 10.9	152.18 ± 11.5	49	182
Weight (kgs)	61.05 ± 15.36	62.99 ± 15.01	60.13 ± 15.47	32	170

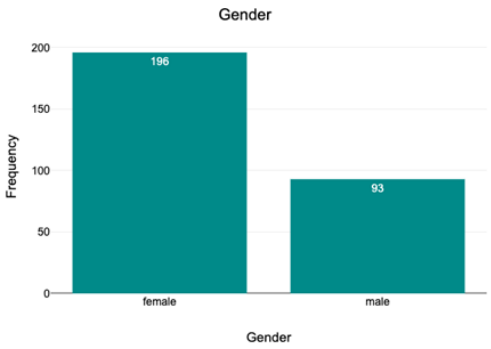

Figure 1 : Gender Distribution

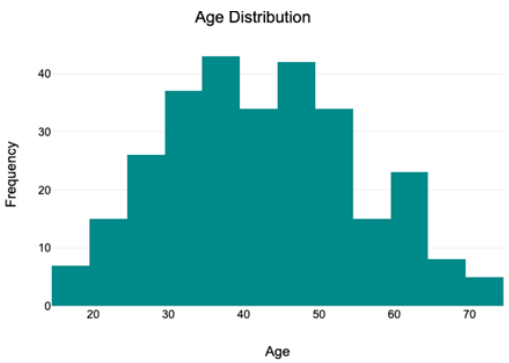

Figure 2 : Age Distribution

Figure 1: Gender distribution - Our study cohort comprised 289 participants, with a distribution between genders. Specifically, there were 93 male participants and 196 female participants, ensuring representation from both sexes.

Figure 2: Age distribution - Regarding age distribution, participants ranged from 18 to 70 years old, reflecting a broad spectrum of age groups. The mean age of the participants was calculated to be 43.79 years, with a standard deviation of 12.78. This indicates a diverse age distribution within the study population.

Table 2 summarizes the descriptive statistics of the HRV metrics for both devices which includes the mean of the sample and the standard deviation, along with the gender wise statistics. In Figure 4 and Figure 5, we present the age-wise correlation of RMSSD and SDNN values respectively obtained from the predicate device and the experimental device. Each data point represents an individual participant, with their respective SDNN values plotted against their age.

Table 2: Shows descriptive statistics of the HRV metrics for both devices.

Characteristics	Total Participants (n=289)	Male (n= 93)	Female (n = 196)	Minimum	Maximum
SDNN CarePlix App (msec)	22.41 ± 11.08	25.57 ± 13.14	20.93 ± 9.63	3.5	80.2
RMSSD CarePlix App (msec)	27.64 ± 13.6	32.16 ± 16.05	25.52 ± 11.72	4.96	114.82
SDNN Polar H9 (msec)	22.76 ± 12.59	25.2 ± 13.33	21.63 ± 12.07	2.61	87.91
RMSSD Polar H9 (msec)	16.34 ± 12.78	19.1 ± 13.67	15.05 ± 12.14	1.17	89.75

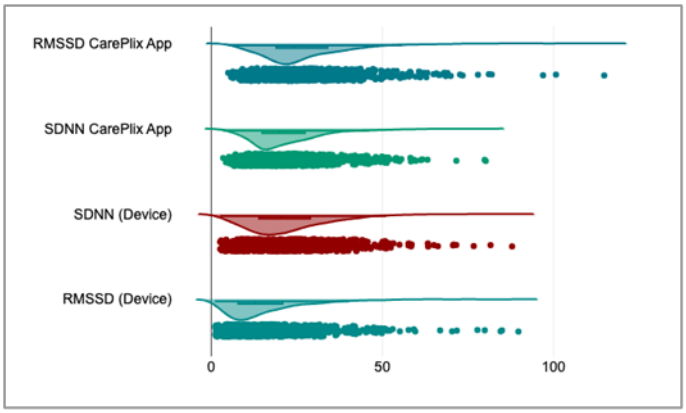

Figure 3: Raincloud plot for HRV metrics

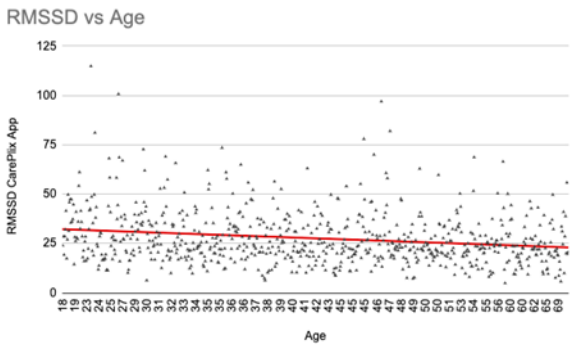

Figure 4: Scatterplot distribution of Rmssd vs Age

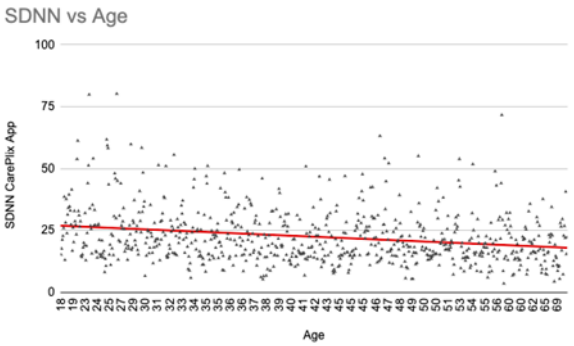

Figure 5: Scatterplot distribution of Sdnn vs Age

Pearson Correlation Coefficient Analysis

The Pearson correlation coefficient was calculated to assess the relationship between the HRV metrics obtained from the predicate device and the experimental device. Table 3 summarizes the correlation coefficients for SDNN and RMSSD.

Table 3: Shows Pearson Correlation Coefficient(r) of the HRV metrics for both devices.

Metric	Pearson Correlation Coefficient (r)
SDNN	r = 0.7607, (p < .001)
RMSSD	r = 0.51, (p < .001)

The Pearson correlation coefficient analysis revealed a significant positive correlation between the HRV metrics obtained from the predicate device and the experimental device for both SDNN and RMSSD ($p < 0.001$). The correlation coefficients indicate the strength and direction of the linear relationship between the two sets of measurements.

Bland-Altman Analysis

Bland-Altman plots were constructed to assess the agreement between the HRV measurements obtained from the predicate device and the experimental device. Figure 6 and Figure 7 depicts the Bland-Altman plots for SDNN and RMSSD respectively, along with the limits of agreement (LOA) and bias and random error (BAR).

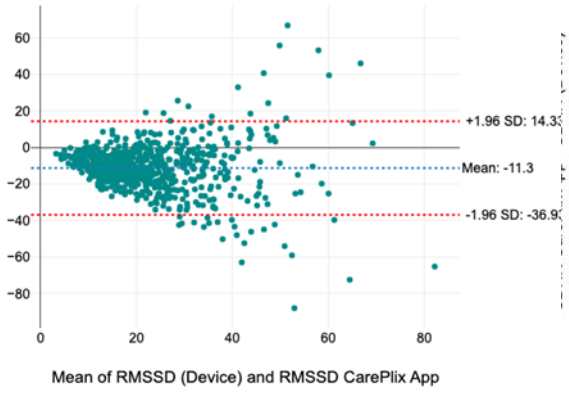

Figure 6: Bland-Altman plots for RMSSD

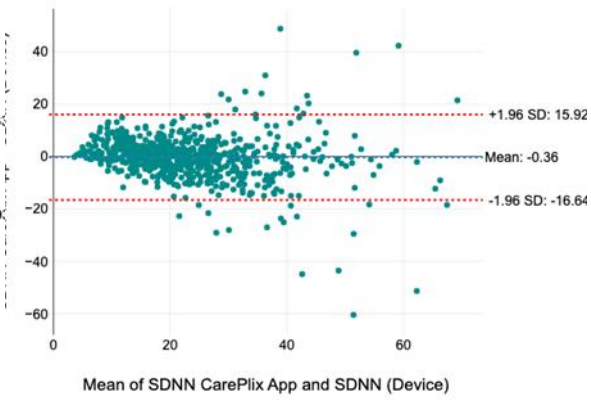

Figure 7: Bland-Altman plots for SDNN

The Bland-Altman analysis provides insightful observations regarding the agreement between measurements obtained from the predicate device and the experimental device when compared with the Polar H9 device. While the wide limits of agreement (LOA) may initially appear substantial, it's crucial to contextualize these findings and consider factors that may influence HRV measurements as shown in Figure 8.

One significant factor to consider is the difference in heart rate measurements between the predicate and experimental devices. We observed that the heart rate recorded by the two devices could differ by up to 5 beats per minute (bpm). This variance in heart rate can directly impact the calculation of inter-beat intervals (IBIs) and subsequently influence HRV metrics such as SDNN and RMSSD. Since SDNN and RMSSD are measured in milliseconds, even slight deviations in heart rate can result in significant variations in these metrics.

Despite the differences in heart rate measurements, we found a correlation between the IBIs obtained from the predicate and experimental devices. This correlation suggests a degree of agreement in the temporal sequence of heartbeats captured by the two devices. However, the slight deviation in heart rate measurements could contribute to the wide range of LOA observed in our study.

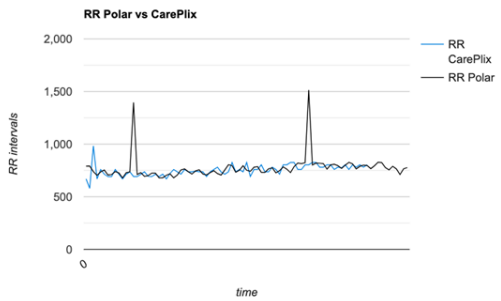

Figure 8: Correlation between RR intervals between two devices and factors influencing HRV measurements.

The image highlights key factors influencing heart rate variability (HRV) measurements when comparing data from predicate and experimental devices. It emphasizes the impact of differences in heart rate between devices, which can lead to varying lengths of RR intervals, subsequently affecting HRV metrics. Additionally, abnormal RR intervals, and ensuring accurate time synchronization between devices are crucial considerations.

V. Discussion

The implications of the findings of this study are noteworthy in the realm of non-invasive cardiovascular monitoring. The aim of this study was to evaluate and quantify heart rate variability metrics of SDNN and RMSSD obtained from smartphone-based PPG signals. The successful estimation of SDDN and RMSSD highlights the potential of smartphone-based PPG signals in providing comprehensive cardiovascular monitoring outside traditional clinical settings. Our approach aligns with previous research emphasizing the efficacy of smartphone PPG signals in capturing physiological data. For instance, studies by Zhang et al. [5] and Fan et al. [6] demonstrated the accuracy and reliability of smartphone-based PPG for heart rate measurement and cardiovascular assessment.

However, several limitations warrant discussion. First of all, the limited sample size in our study restricted the generality of our conclusions. Future research with larger and more diverse populations is needed to validate our results across different demographic groups and clinical conditions. Furthermore, technical elements like ambient lighting conditions, motion or movement artifacts, and camera resolution could have affected how accurately we acquired and processed the PPG signal. Resolving these technical issues could improve the validity and dependability of HRV assessments using smartphones even more.

One of the most important methodological considerations in our study was choosing the colour channel for photoplethysmography (PPG) signal extraction from video frames captured by smartphones. The quality and reliability of the PPG signal can be strongly impacted by the color channel selection (red, green, or blue, for example). Traditionally, the green channel has been favored for PPG signal extraction due to its higher sensitivity to blood volume changes and reduced sensitivity to motion artifacts compared to other color channels. This is because hemoglobin absorbs the green light most efficiently [7,8,9]. In our study, we opted to analyze all three color channels (red, green, and blue) to assess their respective suitability for PPG signal extraction. By comparing the PPG signals obtained from different color channels, we were able to evaluate their performance in terms of signal quality, robustness to motion artifacts, and agreement with reference measurements.

In our study, we also acknowledge the potential effect of fingertip pressure on smartphone camera sensor during photoplethysmography (PPG) measurements. Research has shown that excessive pressure can distort blood flow dynamics and compromise signal quality. While standardized protocols were employed to minimize this effect, further research is needed to optimize pressure standardization techniques for reliable PPG signal acquisition [10,11]. A stable measuring environment was maintained, and participants were advised to apply gentle, consistent pressure to the sensor area during data collection.

When using smartphone cameras, motion artifacts presented a serious problem that could have an impact on the precision and consistency of the PPG signals[12]. Motion artifacts arise from the movement of the body or the smartphone during data acquisition, leading to distortions in the PPG signal. Detrimental effects of motion artifacts on PPG signal quality, including signal degradation and erroneous measurements have been explored in previous researches [13,14].Our study was conducted in controlled environments with minimal motion interference. We implemented measures such as instructing participants to maintain stillness during data collection and employing stabilization techniques to minimize disturbances caused by motion. These efforts aimed to ensure the integrity of our data by reducing the influence of motion-related artifacts on photoplethysmography (PPG) signal quality. A number of techniques, such as signal processing algorithms, motion-tolerant sensors, and data fusion with other sensor modalities, have been proposed to reduce these artifacts [15,16]. In spite of these initiatives, additional study is required to create robust motion artifact correction algorithms for smartphone-based PPG, guaranteeing precise and trustworthy cardiac monitoring in practical settings.

Despite the limitations, our study underscores the potential of smartphone camera PPG signals for non-invasive HRV assessment, offering a cost-effective and user-friendly approach to cardiovascular monitoring.

VI. Conclusion

In conclusion, our study demonstrates a positive correlation and good agreement between the HRV measurements obtained from the predicate device and the experimental device. These findings underscore the utility of the experimental device for HRV assessment in clinical practice and research settings.

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