Original Article

Smartphone-based health monitoring in India: Data collection and evaluation for pulse rate estimation

Achal Shetty[1], Sanjana S. Narasimhamurthy[2], KS Nataraj[3], Srilakshmi M. Prabhu[4], Neha Jagadeesh[5], Kunal Katre[6], Sumit Kumar[5], Neelesh Kapoor[2], Sudhir P. Haladi[1], Sankalp Gulati[7]

[1]Department of Community Medicine, Father Muller Medical College, Mangalore, Karnataka, India, [2]Medical Affairs, Eka Care, Bengaluru, Karnataka, India, [3]Department of Electronics and Communication Engineering, Indian Institute of Information Technology, Dharwad, Karnataka, India, [4]Department of General Medicine, Father Muller Medical College, Mangalore, Karnataka, India, [5]Engineering, Eka Care, Bengaluru, Karnataka, India, [6]Design, Eka Care, Bengaluru, Karnataka, India, [7]Data Science, Eka Care, Bengaluru, Karnataka, India

Abstract

Introduction: Over the past decade, monitoring of body vitals has gained significant popularity, specifically during and post the recent COVID pandemic. Advancements in smartphones and wearables have been pivotal, providing accessible and cost-effective solutions for at-home health monitoring. Their development often requires a large corpus of labeled datasets, but such large and diverse datasets for developing smartphone-based vital estimation systems, particularly adapted to Indian context, are scarce. **Aims and Objectives:** This observational study focuses on development of such a dataset in a diverse Indian context and evaluation of smartphone-based pulse rate estimation based on this dataset. **Methods:** Data collection considered Indian patients with various medical conditions, body mass index profiles, blood pressure levels, ages, and smoking habits, reflecting a broad demographic spectrum. As part of this study, an algorithm was implemented to estimate the photoplethysmogram (PPG) signal from video recordings of fingers placed on the smartphone camera and subsequently to estimate pulse rate using the acquired PPG data. Smartphone-based pulse rate estimates were compared with readings from pulse oximeters to assess accuracy and feasibility. **Results:** The smartphone-based PPG algorithm provides reasonably accurate estimations of pulse rate when compared to traditional pulse oximeters under varied healthcare settings (mean absolute error < 5, intraclass correlation coefficient > 0.90). **Conclusion:** Results indicate that the smartphone-based PPG signal captures sufficient information of the cardiac cycle to reliably estimate the pulse rate. Furthermore, system accuracy is consistent across varied subjects and settings, highlighting the importance of tailored data collection for development and evaluation of vital estimation algorithms.

Keywords: Machine learning, oximeter, photoplethysmogram, pulse rate, smartphone

Address for correspondence: Dr. Sanjana S. Narasimhamurthy, 3M 683, 3rd Main, Lakshmamma Layout, OMBR Layout, Bengaluru, Karnataka, India.
E-mail: sanjana.sn@eka.care

Received: 23-07-2024 **Revised:** 03-09-2024
Accepted: 17-09-2024 **Published:** 13-01-2025

Access this article online	
Quick Response Code:	**Website:** http://journals.lww.com/JFMPC
	DOI: 10.4103/jfmpc.jfmpc_1257_24

Introduction

Point-of-care devices such as pulse oximeters and digital blood pressure monitors have empowered individuals to monitor their health conveniently.[1] However, systematic logging and sharing of these biomarkers with healthcare providers is still a challenging task[2-4] as this both requires stakeholders to

How to cite this article: Shetty A, Narasimhamurthy SS, Nataraj KS, Prabhu SM, Jagadeesh N, Katre K, *et al.* Smartphone-based health monitoring in India: Data collection and evaluation for pulse rate estimation. J Family Med Prim Care 2025;14:348-55.

be on the connected digital ecosystem and demands a basic digital literacy. Also, carrying diagnostic devices is inconvenient compared to smartphones. Smartphone-based solutions offer cost-effectiveness and address challenges related to mobility, connectivity, and data-sharing.

Background

Photoplethysmography, which detects blood volume changes in the microvascular bed of tissue, is a cost-effective method in medical devices for various vital measurements like pulse rate and oxygen saturation.[5] A reliable estimation of photoplethysmogram (PPG) signal has been feasible through smartphone camera recordings of a fingertip,[6] and Figure 1 illustrates the fundamental principle of the same. The smartphone's flash light reflects off venous blood and other tissues, resulting in low-frequency fluctuations in the PPG signal.[7] Pulsatile changes in the signal mirror the changes in the arterial blood volume, with the rising segment representing systolic and the descending segment representing diastolic phases of heartbeat. Signal processing algorithms and advancements in deep neural networks (DNNs) have expanded the possibilities for accurate vital parameter estimation from PPG signals.[8,9] However, development and evaluation of such algorithms require large volumes of labeled gold standard PPG datasets.

Rationale and knowledge gap

There are a number of datasets available online that provide PPG signals from pulse oximeters,[10-14] but only a few offer PPG signals recorded using smartphone cameras.[11-14] The BUT PPG dataset[11] from Brno University of Technology includes PPG data from 12 healthy subjects (six males, six females, aged 21–61 years) captured using a Xiaomi Mi9 smartphone. It comprises 48 ten second PPG recordings with corresponding ECG signals for pulse rate calculation. The Welltory dataset,[12] obtained using Welltory Android app, has 21 PPG recordings (1–2 minutes) from 13 healthy subjects (aged 25–35 years). Reference pulse rates are computed using RR intervals from a Polar H10 ECG device. The MTHS dataset,[13] recorded with an iPhone 5s, features PPG data from 62 patients (35 males, 27 females) and provides pulse rate and SPO2 reference values from a pulse oximeter. The

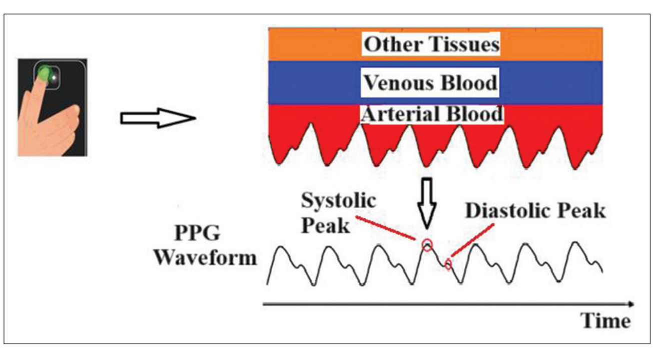

Figure 1: Principle of PPG using a smartphone camera; PPG, photoplethysmogram

K20-vPPG dataset[14] offers 2–10 minute PPG recordings from 20 healthy subjects (five females, 15 males, aged 16–36 years) using a smartphone camera. It also includes reference values for pulse rate, respiration rate, and SPO2. Given the physiological variabilities in individuals across age, gender, medical conditions, and other factors such as skin color, the above-mentioned datasets with few tens of subjects are far from representing the broader population.[15,16] Moreover, for developing machine learning algorithms, we require substantially large datasets, which are currently publicly unavailable.

Objective

We intended to curate a large-scale dataset of PPG signals labeled with different vital parameters and incorporate individuals of varied ages and anthropometric measurements and even with pre-existing health-related conditions to better represent physiological diversity in the Indian population. We intended to collect our data from pre-existing urban and rural Primary Health Centers (PHCs), a tertiary care outpatient center, and also an intensive care unit (ICU). This approach would ensure that the dataset captures the complexities of real-life situations, facilitating the development of more applicable and effective healthcare solutions. To facilitate our study, we developed a smartphone application designed to extract PPG signals from video recordings of fingers placed on the smartphone camera and to gather anonymized patient health information and associated vital parameters. Within the scope of the work, we also implemented and evaluated a pulse rate estimation algorithm.

To be concise, here are our objectives:

1) Development of a large-scale PPG dataset in a diverse Indian context.

2) Evaluation of smartphone-based pulse rate estimation based on this dataset.

Materials and Methods

Selection of Participants: For curation of our dataset, we used purposive sampling methodology and selected subjects who visited the health facility for at least a minor health-related issue. The ethics committee approval was taken and it was obtained on 14-08-2021. An informed written consent was taken from each of the participants above 18 years of age. For children between 13 and 18 years, we obtained the written assent, along with the parental/legal guardian consent.

Study area: Tertiary care medical college teaching hospital, Urban and Rural PHC.

Inclusion criteria : Participants above 13 years of age who gave consent.

Exclusion criteria: Pregnant women, lactating women, and patients with a cardiac pacemaker.

Study tool: We developed an android-based smartphone application to capture relevant data of the participants. The process consisted of two parts.

The first part involved collecting demographic information such as age and gender, enquiring about pre-existing diseases, taking anthropometric measurements, and recording body vitals. These vitals later served as the ground truth for development and evaluation of our algorithm. Note that no personal identifiers were recorded in this study at any point in time. History of pre-existing conditions such as diabetes, hypertension, bronchial asthma, chronic obstructive pulmonary disease (COPD), cancer, thyroid disorders, epilepsy, coronary artery disease, and cerebrovascular diseases was noted along with history of smoking habits in adults. In relation to anthropometry, only height and weight were measured. We measured vitals such as pulse rate and blood oxygen saturation level using a pulse oximeter. It was a hand-held, battery-operated, clip-type oximeter (Model 203, Dr Trust, USA), and it had an accuracy of ±1 beats per minute (bpm) for pulse rate. The subject's finger was sanitized and placed on the oximeter for at least 30 s to obtain reliable results. We also specifically took note of instances where the subjects had applied henna or nail paint as these factors could potentially impact the quality of the PPG signal recorded. Blood pressure was measured with the help of a digital sphygmomanometer, and respiratory rate was clinically assessed by observing the study subject for an entire one minute. Data were collected on the android mobile application by investigators who were trained prior to the study.

The second part of data collection involved capturing the PPG signals from subjects by placing their fingertips in front of the mobile rear camera for 40 s and recording a short video. Simultaneously, the smartphone's accelerometer sensor recorded the acceleration data along the three axes. All these data were secured in the smartphone SD card and later uploaded to cloud storage.

Estimation of Pulse Rate: An overview of the processing blocks used in the implementation of pulse rate estimation algorithm is shown in Figure 2. The PPG signal was extracted from the three channels of the video (Red, Green, Blue) of a user's fingertip on the smartphone camera using signal decomposition techniques. Note that we rejected PPG signals from our analysis when the contact between the camera lens and finger was not good. For determining if the contact is good, we used the mean pixel intensities of the three aforementioned video channels. We also utilized the accelerometer data to automatically detect sessions where severe motion was present and dropped those signals as well from our analysis.

The signal conditioning involved bandpass filtering to eliminate low-frequency baseline wandering and high-frequency noise components. Post filtering, the signal was normalized using the average magnitude of the PPG waveform to ensure consistent parameter estimation across different recordings. After preprocessing, a filtered PPG signal was used to obtain an estimate of pulse rate. In this study, we employed the peak-to-peak intervals within the filtered PPG signal for pulse rate estimation. We experimented with both time- and frequency-domain features. Frequency-domain features such as short time Fourier transform (STFT) were also used to obtain a measure of the signal quality, which was further used to mask poor-quality segments in the PPG signal.

Statistical Methodology: The implementation of algorithm and statistical calculations was performed using Python 3 (version 3.9.13) (RRID: SCR_008394). In those cases in which the reference data were not available or PPG was not recorded, we removed them from the analysis. We first describe demographic characteristics of our data corpus and calculated the overall mean and SD values of vital parameters. Mean pulse rates across different cohorts based on gender, smoking habits, ICU admission, and medical conditions were compared using independent t-tests, and the significance was defined as a P value of <0.05. To evaluate our pulse rate estimation algorithm, we have used mean absolute error (MAE) and intraclass correlation coefficient between the estimated rate and the rate measured by the pulse oximeter for each subject.

Results

Our dataset comprises 7409 subjects; the mean age of participants is 49.4 years with a healthy gender ratio (43% males, 57% females). The majority of the patients fall in the age bucket of 40 to 70 years. The mean (SD) body weight and height of the study population are 62.1 (13.28) kg and 1.59 (0.1) m, respectively. The calculated body mass index (BMI) using the mean values is within the normal range (24.64 kg/m^2). A detailed distribution

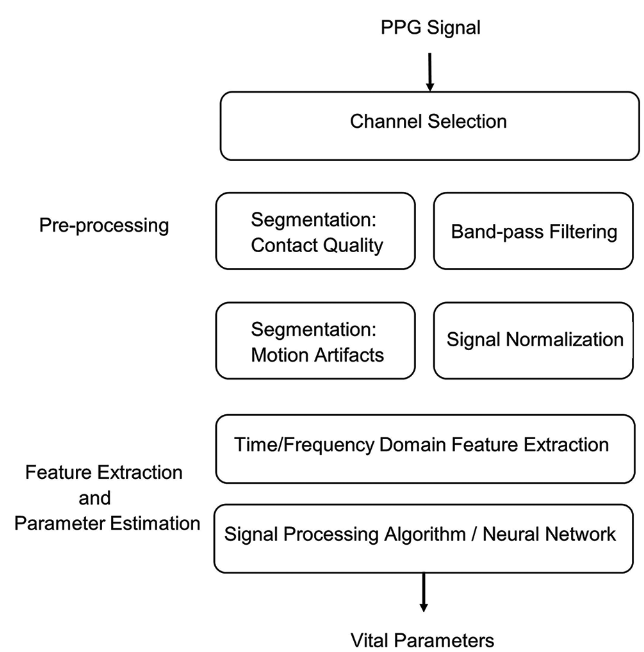

Figure 2: Estimation of vital parameters from the PPG signal; PPG, photoplethysmogram

of these body parameters and demographics is presented in Figure 3a-c. The mean and SD values of vital parameters such as pulse rate, respiratory rate, saturation, temperature, and blood pressure are in the normal range. The only exception was the respiratory rate, whose mean (SD) is 21.2 (3.34) cycles/min.

Distribution of the pre-existing diseases among subjects is shown in Figure 3d. The most common conditions are hypertension (37.2%) and diabetes mellitus (25.3%), wherein nearly 90% of both the groups are on regular medication. As could be expected, the hypertensive subjects have a higher mean systolic blood pressure (145.91 mm Hg) and a higher mean diastolic blood pressure (81.91 mm Hg) compared to the overall mean values. Other vitals among these patients are nearly similar to the rest of the subjects with no statistically significant difference.

A total of 163 participants are smokers with a mean of 17.7 years of smoking and 8 cigarettes per day. Upon investigation of their vitals, only the mean systolic pressure (137.16 mmHg) and the mean diastolic pressure (80.21 mmHg) are higher than the overall mean values of the other subjects in the dataset.

Mean pulse rates, between pulse oximeter and smartphone-based PPG data, were compared based on gender, BMI, and smoking and also based on presence or absence of various diseases such as diabetes, hypertension, bronchial asthma, COPD, cancer, thyroid disorders, epilepsy, coronary artery disease, and cerebrovascular diseases. Out of these, comparison among some important groups is given in Table 1. To evaluate our pulse rate algorithm using MAE, we selected 5710 participants out of 7409. The PPG recordings of other subjects were dropped owing to poor finger contact, motion artifacts, and bad signal-to-noise ratio (SNR). Note that this selection is done fully automatically by the algorithm and hence does not impact the precision metric. We have obtained an MAE of 4.08 bpm with a strong positive intraclass correlation coefficient (ICC) of 0.92. A scatter plot of reference and estimated pulse rates is shown in Figure 4.

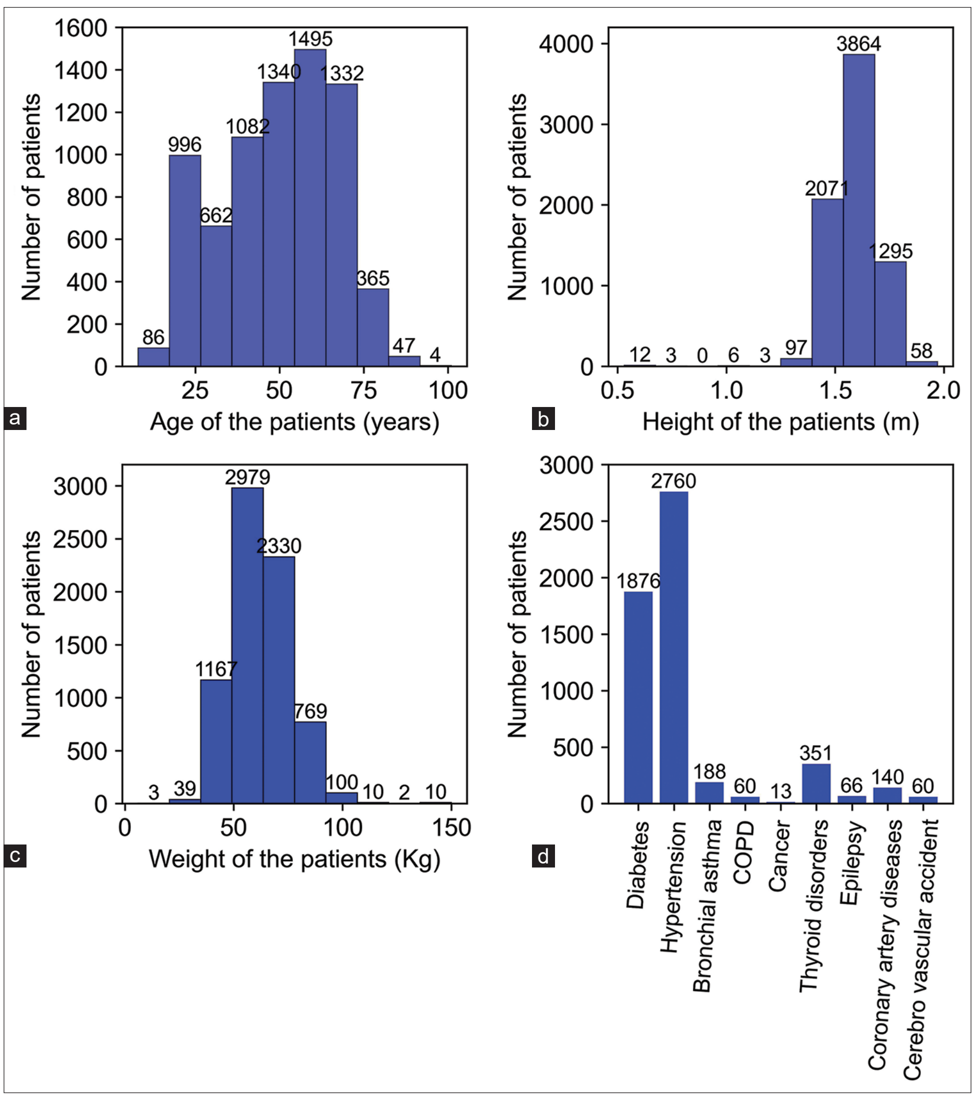

Figure 3: Distribution of parameters among participants based on age in years (a), height in meters (b), weight in kilograms (c), and proportion of participants having certain diseases (d). Participants (N) 7409. COPD, chronic obstructive pulmonary disease

Table 1: Pulse rate according to gender, presence or absence of smoking habits, and diseases

Group	Category	Condition	Mean (bpm)	SD (bpm)	*t*-statistic	Degree of freedom	*P*: Indepe-ndent *t*-test
Gender	Pulse oximeter*	Male	83.24	15.36	-8.195	3133	<0.001‡
		Female	86.24	13.96			
	Smartphone PPG†	Male	80.91	14.21	-9.038	2438	<0.001‡
		Female	84.34	12.94			
BMI	Pulse oximeter*	Normal	84.65	14.67	-0.294	3089	0.768
		Overweight	84.74	14.27			
	Smartphone PPG†	Normal	82.66	13.66	0.315	2435	0.752
		Overweight	82.65	13.34			
Hyper-tension	Pulse oximeter*	Yes	83.94	15.03	-4.829	2746	<0.001‡
		No	85.57	14.39			
	Smartphone PPG†	Yes	81.10	14.00	-8.065	2196	<0.001‡
		No	83.98	13.23			
Bronchial asthma	Pulse oximeter*	Yes	88.35	13.92	2.345	187	0.019§
		No	84.87	14.66			
	Smartphone PPG†	Yes	85.72	13.55	2.349	150	0.019§
		No	82.80	13.60			
COPD	Pulse oximeter*	Yes	82.95	13.00	-1.09	59	0.277
		No	84.98	14.66			
	Smartphone PPG†	Yes	80.60	9.32	0.129	47	0.897
		No	82.89	13.63			
Coronary artery disease	Pulse oximeter*	Yes	83.19	17.05	-1.012	139	0.312
		No	85.00	14.60			
	Smartphone PPG†	Yes	78.63	14.46	-2.078	108	0.038§
		No	82.96	13.57			

BMI, body mass index; bpm, beats per minute. *- n=7409, †- n=5710. ‡- Highly significant P (<0.01), §- Significant P (< 0.05). BMI - normal (BMI 18.5 – 25 kg/m^2) and overweight (BMI >25 kg/m^2)

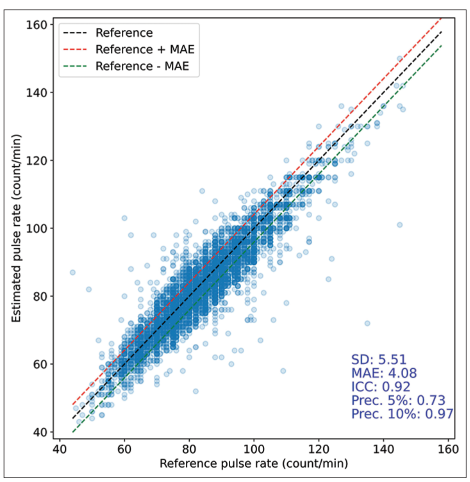

Figure 4: Beats per minute correlation plot. Note: Number of participants 5710. MAE, mean absolute error; SD, standard deviation; ICC, intraclass correlation; Prec, precision

Overall, the mean value of estimated pulse rates is 82.88 beats per minute (bpm) and that of actual pulse rates is 84.11 bpm. The difference between the two is significant according to the paired *t*-test (P < 0.001). The same parameters have been used for the evaluation of subgroups of the study population based on age and based on presence or absence of certain conditions [Table 2]. For these subgroups as well, the results are similar to the ones on the entire population, that even though the majority of mean values showed a significant difference (P < 0.05), the MAE is small, indicating accurate estimation. Furthermore, the application of nail paint or henna in 128 participants did not seem to interfere with results on either device (P = 0.096).

The heart rate measurement functionality is integrated into the Ayushman Bharat Digital Mission (ABDM)-certified[17] Eka Care mobile application, freely available on both Android and iOS operating systems [Figure 5].

Discussion

Key findings and strengths

In our study, even though the mean values of pulse rates measured by pulse oximeters and smartphone-based PPG show a significant difference when compared using a paired *t*-test, the MAE obtained is lower (≤5 bpm)[18] and the ICC is even better (0.92). Note that the popular fitness trackers such as Apple watch (Model: Series 3) and Fitbit could have an MAE of >5 bpm in several conditions.[19] Additionally, agreement between the two sources of readings when tested across age groups had a strong correlation in every instance. The maximum MAE was of only 5.06 bpm (<20 years group), and with increasing age, the MAE was getting lesser, with the least being 3.80 bpm (>80 years group).

When individuals with attributes such as their gender[20] or pre-existing illnesses such as bronchial asthma[21] and hypertension[22] are compared, the differences are statistically significant and are captured by both the pulse oximeter and

Table 2: Comparison of estimated pulse rate with those measured by a pulse oximeter based on presence/absence of certain conditions

Group	Condition	*n*	Mean Actual (bpm)	Mean Estimated (bpm)	MAE (bpm)	*t*-statistic	Degree of freedom	*P*: paired *t* -test	ICC
Gender	Male	2439	82.26	80.91	3.94	12.41	2438	<0.0001*	0.93
	Female	3270	85.48	84.34	4.18	11.63	3269	<0.0001*	0.91
BMI	Under-weight	332	87.57	86.42	4.21	3.85	331	0.0001*	0.93
	Normal	2942	83.74	82.66	4.12	10.49	2941	<0.0001*	0.92
	Over-weight	2436	84.08	82.65	4.01	12.94	2435	<0.0001*	0.92
Smoking	Yes	120	84.34	82.71	3.87	3.48	119	0.0007*	0.93
	No	5590	84.10	82.88	4.08	16.56	5589	<0.0001*	0.92
Diabetes	Yes	1510	85.29	83.57	3.69	13.12	1509	<0.0001*	0.93
	No	4200	83.68	82.63	4.21	12.12	4199	<0.0001*	0.92
Hyper-tension	Yes	2197	83.12	81.10	3.73	19.64	2196	<0.0001*	0.94
	No	3513	84.72	83.98	4.29	7.50	3512	<0.0001*	0.91
Bronchial asthma	Yes	151	87.66	85.72	4.15	5.04	150	<0.0001*	0.94
	No	5559	84.01	82.80	4.07	16.34	5558	<0.0001*	0.92
COPD	Yes	48	82.31	80.6	2.83	3.24	47	0.002*	0.93
	No	5662	84.12	82.89	4.09	16.71	5661	<0.0001*	0.92
Thyroid disorders	Yes	257	86.01	83.95	4.27	6.20	256	<0.0001*	0.92
	No	5453	84.02	82.82	4.07	15.95	5452	<0.0001*	0.92
Coronary artery disease	Yes	109	81.03	78.63	3.81	5.90	108	<0.0001*	0.96
	No	5601	84.17	82.96	4.08	16.35	5600	<0.0001*	0.92
Cerebrovascular accident	Yes	44	88.00	86.27	3.82	1.88	43	0.067	0.95
	No	5666	84.08	82.85	4.08	16.77	5665	<0.0001*	0.92
Nail paint	Yes	101	86.55	85.66	4.06	1.68	100	0.096	0.94
	No	5609	84.06	82.83	4.08	16.80	5608	<0.0001*	0.92

ICC, Intraclass correlation coefficient; MAE, mean absolute error; bpm, beats per minute; BMI, body mass index. *- Highly significant *P* (<0.01). BMI - underweight (BMI <18.5 km/m^2), normal (BMI 18.5 – 25 kg/m^2) and overweight (BMI >25 kg/m^2)

our algorithm. This suggests that our algorithm is effective in capturing variations in vital signs across diverse characteristics. These observations not only validate that the characteristics of our dataset are in line with those found in other studies.

Strengths and limitations

This is the first study, to the best of our knowledge, to include a large diverse Indian population with various conditions and diseases for smartphone-based PPG evaluation. But, as this study was conducted entirely in clinical settings, we cannot rule out the effects of white coat hypertension. The motion artifact due to the movement of finger on the smartphone camera could potentially have had an adverse influence on our findings, leading to a higher mean absolute error (MAE). Nevertheless, despite this, our MAE remained within the acceptable range. The limitation of our study however was the absence of simultaneous measurements of pulse rate on both, the smartphones and the pulse oximeters, a method employed in certain recent studies.[23] Our future work aims to mitigate these confounding factors.

Comparison with similar research

A study conducted by Cheatham *et al*.[24] had analyzed various pulse rate monitoring devices and had found an average ICC of >0.90 when the smartphone-based PPG and a pulse oximeter were compared. Similarly, the overall ICC in our study is 0.92. A study conducted by Avram *et al*.[25] had compared the pulse rate measured by smartphone-based PPG with those calculated from an ECG, and they obtained an ICC of 0.90 bpm too. Their study had shown that both people with BMI > 30 kg/m2 and the ones with BMI < 18.5 kg/m2 had a high pulse rate compared with those with normal BMI. In our study, we have found a similar phenomenon when the pulse oximeter's readings are considered [Table 2]. But the smartphone's readings have shown a higher pulse rate in only those with lower BMI. Even though the study conducted by Avram *et al*. had considered patients with various illnesses for their study, unlike us, they had not compared the readings from both the sources in people with such conditions. The pulse rate measured in the subset comprising women is higher compared to men. This agrees with previously done studies.[20] Patients with bronchial asthma were shown to have a higher pulse rate compared to the rest,[21] which is observed in our study as well.

Interpretation

The low MAE observed in pulse rate estimation may be attributed to effective signal conditioning and the selection of high-quality PPG segments. The pulse rate among women is higher compared to men, and this is attributed to the lower stroke volume among females.[20] Patients with bronchial asthma would be expected to have a higher pulse rate compared to those who did not[21] owing to the sympathetic stimulation, and this is observed in our study too. Additionally, the patients with BMI < 18.5 kg/m2 have shown a higher pulse rate when measured by both the pulse oximeter and smartphone. This indicates the effect of the sympathetic nervous system on BMI and pulse rate.[26]

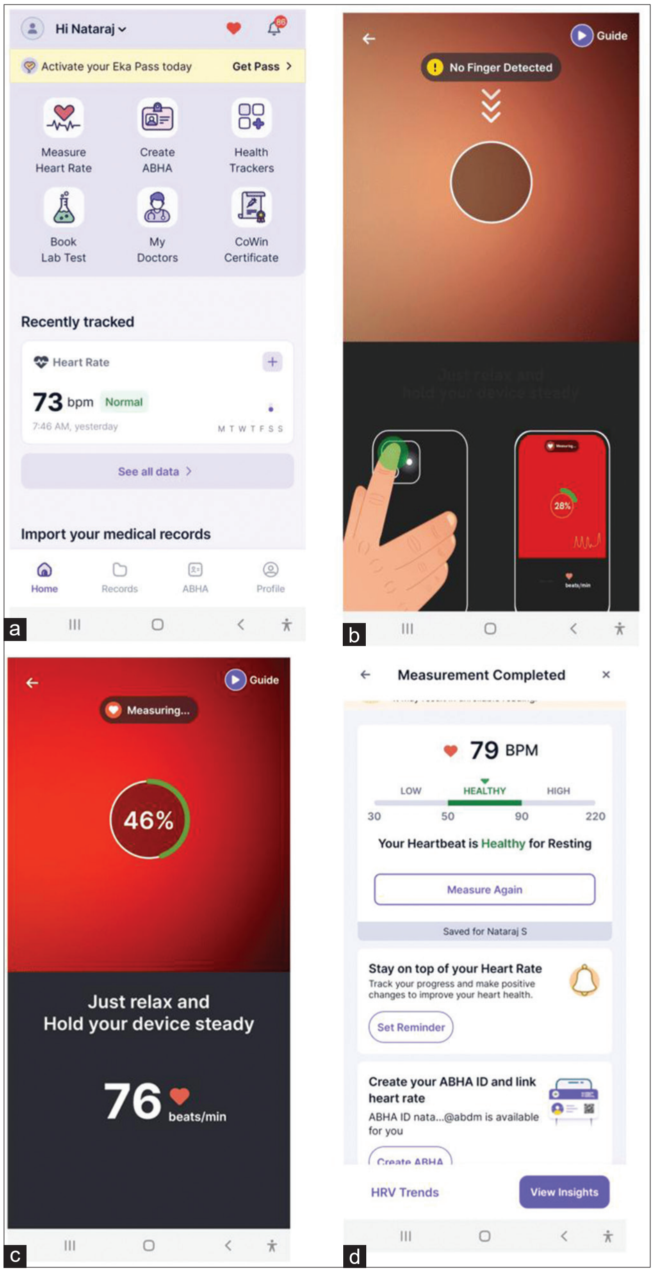

Figure 5: Eka Care mobile application. Note: This figure shows the interface for heart rate monitoring, including screens and features. a) Main screen b) Heart rate measurement screen c) Measurement progress screen d) Result and feedback

As our study was conducted in the clinical settings, the effect of white coat hypertension might have been present. In this phenomenon, there is a stimulation of the sympathetic system[27] and this might have led to the respiratory rate being outside the normal upper limit of 20 cycles/minute[28] (mean (SD) = 21.2 (3.34) cycles/min). The mean pulse rate in our study is 84.96 beats/min, and compared to a similar study using portable pulse oximeters,[29] ours is higher. This can be because they had an elderly population as their study subjects, and because of a decline in sympathetic modulation, the rate is expected to be lesser in them.[30] Additionally, the effect of white coat hypertension could have been absent as the study was conducted in their residences.

Implications and future research directions

We are at a pivotal moment in the evolution of healthcare with increasing involvement and advancements in artificial intelligence (AI). To enable AI systems to effectively generalize and make informed decisions about patients, it is imperative that they are trained on datasets that truly represent the diverse real-world population. However, there is a dearth of openly accessible extensive datasets pertaining to smartphone-based photoplethysmography for the Indian population. Our study addresses this gap, and the dataset which we have made available stands as a crucial reference for researchers, promoting collaborative efforts and driving advancements in mobile health monitoring.

Conclusion

With the aim to fill the gap of smartphone-based photoplethysmography based on Indian population, we curated and tested our algorithm in a dataset sourced from a wide array of local healthcare settings (ranging from a primary care center to an ICU), with the study population exhibiting diverse medical conditions, body compositions and smoking habits. The algorithm developed in this study has shown promise based on our analysis. The same has been deployed and is successfully running in a freely available android and iOS application called EkaCare. At the time of writing this article, this application is already being used by millions of users in India to check their pulse rates over tens of millions of times empowering users to track their cardiovascular health and tailor and correct their lifestyle habits, literally placing peoples' health in peoples' hands. In conclusion, as technology and healthcare coalesce in their advancement, it is not inconceivable that the symbolic "apple" may become a more potent instrument for safeguarding your health than the literal fruit.

Acknowledgement

We would like to express our sincere gratitude and thanks to data collectors Shraddha Udaya Shetty, Aysha Samrath H.R, Naila Anwar and the medico-social workers Asha M Monis, Gautham Rao B, Prabhavathi Nayak, Ashwita Dsouza, Jenifer Rodrigues and Iral R Dsouza who were instrumental in the data collection process and completion of this project.

Financial support and sponsorship

Funding used to cover the expense associated with performing the research was contributed to Sudhir P Haladi by Orbi Health Pvt. Ltd. (Eka Care), grant number FMRC/CT/21/22.

Conflicts of interest

This research is sponsored by the company (Orbi Health Pvt. Ltd) which may be affected by the research reported in the enclosed paper. The authors affiliated to the company have also provided writing assistance and played an active role in the analysis of the data. We have in place an approved plan for managing any potential conflicts arising from this arrangement,

the manuscript has undergone a thorough scrutiny by other authors of the study.

References

1. Ashwin V, Menon A, Devagopal AM, Nived PA, Gopinath A, Gayathri G, *et al.* Cost-effective device for autonomous monitoring of the vitals for COVID-19 asymptomatic patients in home isolation treatment. In: Thampi SM, Gelenbe E, Atiquzzaman M, Chaudhary V, Li K-C, editors. Advances in Computing and Network Communications. Singapore: Springer Singapore; 2021. p. 3–13.
2. Saha R, Kumar G, Kumar N, Kim T-H, Devgun T, Thomas R, *et al.* Internet of things framework for oxygen saturation monitoring in COVID-19 environment. IEEE Internet Things J 2022;9:3631–41.
3. Luks AM, Swenson ER. Pulse oximetry for monitoring patients with COVID-19 at home. Potential pitfalls and practical guidance. Ann Am Thorac Soc 2020;17:1040–6.
4. Vindrola-Padros C, Sidhu MS, Georghiou T, Sherlaw-Johnson C, Singh KE, Tomini SM, *et al.* The implementation of remote home monitoring models during the COVID-19 pandemic in England. EClinicalMedicine 2021;34:100799.
5. Allen J. Photoplethysmography and its application in clinical physiological measurement. Physiol Meas 2007;28:R1–39.
6. Lovisotto G, Turner H, Eberz S, Martinovic I. Seeing red: PPG biometrics using smartphone cameras. In: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). Seattle, WA, USA: IEEE; 2020. p. 3565–74.
7. Bagha S, Shaw L. A real time analysis of PPG signal for measurement of SpO2 and pulse rate. Int J Comput Appl 2011;36:45-50.
8. Hsu Y-C, Li Y-H, Chang C-C, Harfiya LN. Generalized deep neural network model for cuffless blood pressure estimation with photoplethysmogram signal only. Sensors 2020;20:5668.
9. Reiss A, Indlekofer I, Schmidt P, Van Laerhoven K. Deep PPG: Large-scale heart rate estimation with convolutional neural networks. Sensors (Basel) 2019;19:3079.
10. Wang W, Mohseni P, Kilgore KL, Najafizadeh L. PulseDB: A large, cleaned dataset based on MIMIC-III and VitalDB for benchmarking cuff-less blood pressure estimation methods. Front Digit Health 2023;4:1090854.
11. Nemcova A, Vargova E, Smisek R, Marsanova L, Smital L, Vitek M. Brno University of Technology Smartphone PPG Database (BUT PPG): Annotated dataset for PPG quality assessment and heart rate estimation. BioMed Res Int 2021;2021:1–6.
12. Neshitov A, Tyapochkin K, Smorodnikova E, Pravdin P. Wavelet analysis and self-similarity of photoplethysmography signals for HRV estimation and quality assessment. Sensors 2021;21:6798.
13. Samavati T, Farvardin M, Ghaffari A. Efficient deep learning-based estimation of the vital signs on smartphones. arXiv; 2022. doi: 10.48550/arXiv. 2204.08989.
14. Mehmood A, Sarauji A, Rahman MMU, Al-Naffouri TY. Your smartphone could act as a pulse-oximeter and as a single-lead ECG. arXiv; 2023. Available from: http://arxiv.org/abs/2305.12583.
15. Shin G, Jarrahi MH, Fei Y, Karami A, Gafinowitz N, Byun A, *et al.* Wearable activity trackers, accuracy, adoption, acceptance and health impact: A systematic literature review. J Biomed Inform 2019;93:103153.
16. Kos M, Li X, Khaghani-Far I, Gordon CM, Pavel M, Jimison HB. Can accelerometry data improve estimates of heart rate variability from wrist pulse PPG sensors? 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Seogwipo: IEEE; 2017.
17. NHA | Official website Ayushman Bharat Digital Mission. Available from: https://abdm.gov.in/our-partners. [Lst accessed on 2024 Feb 08].
18. Ayesha AH, Qiao D, Zulkernine F. Heart rate monitoring using PPG with smartphone camera. In: 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). Houston, TX, USA: IEEE; 2021.
19. Nelson BW, Allen NB. Accuracy of consumer wearable heart rate measurement during an ecologically valid 24-hour period: Intraindividual validation study. JMIR Mhealth Uhealth 2019;7:e10828.
20. Gillum RF. Epidemiology of resting pulse rate of persons ages 25-74 - Data from NHANES 1971-74. Public Health Rep 1992;107:193-201,
21. Simonsson BG, Jacobs FM, Nadel JA. Role of autonomic nervous system and the cough reflex in the increased responsiveness of airways in patients with obstructive airway disease. J Clin Invest 1967;46:1812–8.
22. Mancia G, De Backer G, Dominiczak A, Cifkova R, Fagard R, Germano G, *et al.* 2007 Guidelines for the management of arterial hypertension. Eur Heart J 2007;28:1462-536.
23. Jung H, Kim D, Lee W, Seo H, Seo J, Choi J, et al. Performance evaluation of a wrist-worn reflectance pulse oximeter during sleep. Sleep Heal [Internet] 2022;8:420-8. Available from: https://doi.org/10.1016/j.sleh.2022.04.003.
24. Cheatham SW, Kolber MJ, Ernst MP. Concurrent validity of resting pulse-rate measurements: A comparison of 2 smartphone applications, the polar h7 belt monitor, and a pulse oximeter with bluetooth. J Sport Rehabil 2015;24:171–8.
25. Avram R, Tison GH, Aschbacher K, Kuhar P, Vittinghoff E, Butzner M, *et al.* Real-world heart rate norms in the Health eHeart study. NPJ Digit Med 2019;2:58.
26. Molfino A, Fiorentini A, Tubani L, Martuscelli M, Fanelli FR, Laviano A. Body mass index is related to autonomic nervous system activity as measured by heart rate variability. Eur J Clin Nutr 2009;63:1263–5.
27. Smith PA, Graham LN, Mackintosh AF, Stoker JB, Mary DASG. Sympathetic neural mechanisms in white-coat hypertension. J Am Coll Cardiol 2002;40:126–32.
28. Nakao M, Nomura S, Shimosawa T, Fujita T, Kuboki T. Blood pressure biofeedback treatment of white-coat hypertension. J Psychosom Res 2000;48:161–9.
29. Pope CAI, Dockery DW, Kanner RE, Villegas GM, Schwartz J. Oxygen saturation, pulse rate, and particulate air pollution: A daily time-series panel study. Am J Respir Crit Care Med 1999;159:365–72.
30. Tanaka H, Monahan KD, Seals DR. Age-predicted maximal heart rate revisited. J Am Coll Cardiol 2001;37:153–6.