

# Passive Heart Rate Monitoring During Smartphone Use in Everyday Life

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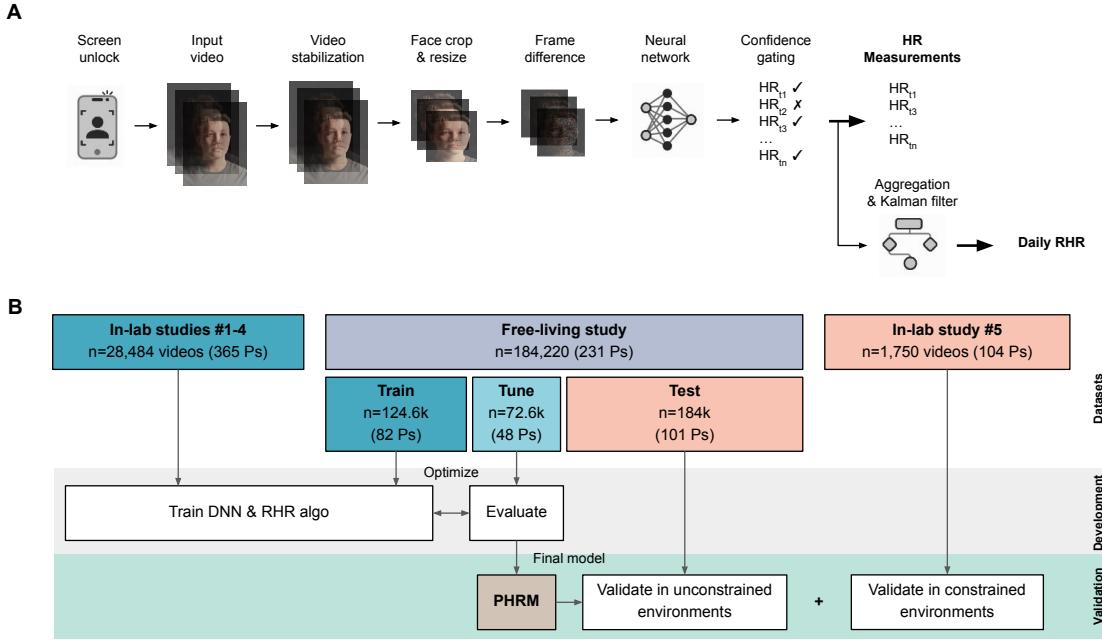
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Resting heart rate (RHR) is an important biomarker of cardiovascular health and mortality, but tracking it longitudinally generally requires a wearable device, limiting its availability. We present PHRM, a deep learning system for passive heart rate (HR) and RHR measurements during everyday smartphone use, using facial video-based photoplethysmography. Our system was developed using 225,773 videos from 495 participants and validated on 185,970 videos from 205 participants in laboratory and free-living conditions, representing the largest validation study of its kind. Compared to reference electrocardiogram, PHRM achieved a mean absolute percentage error (MAPE) < 10% for HR measurements across three skin tone groups of light, medium and dark pigmentation; MAPE for each skin tone group was non-inferior versus the others. Daily RHR measured by PHRM had a mean absolute error < 5 bpm compared to a wearable HR tracker, and was associated with known risk factors. These results highlight the potential of smartphones to enable passive and equitable heart health monitoring.

## 1. Introduction

Heart rate (HR) is an important and dynamic vital sign that varies based on numerous influences including physical and mental activity, sleep stages, and environmental factors (Ceconi et al., 2011). In addition, resting heart rate (RHR) is well-recognized as a biomarker of cardiovascular health and a prognostic for overall mortality (Alhalabi et al., 2017; Kannel et al., 1987; Raisi-Estabragh et al., 2020). Studies of longitudinal changes in RHR over long periods of time have reported that temporal increases in RHR were associated with higher mortality and major adverse cardiovascular events (Nauman et al., 2011; Seviiri et al., 2018; Vazir et al., 2018). The traditional method of measuring RHR relies on measurements taken after a period of rest, typically in a supine or sitting position. While relatively simple to perform, this limits the practicality of obtaining daily RHR measurements over time to evaluate longitudinal trajectories. As such, until the proliferation of consumer wearable devices equipped with HR sensors, the quantification of RHR was largely confined to clinical and research settings, with limited observation of RHR during individuals' daily lives. Considering the sensitivity of HR to various factors, the cardiovascular system might be better assessed through multiple measurements during daily life activities rather than brief measurements during standardized rest in an artificial and often stressful clinical environment (Dunn et al., 2021; Hansen et al., 2007; Johansen et al., 2013). Indeed, average HR throughout the day has been shown to be a strong independent predictor, even more so than RHR, for all-cause mortality (Korshøj et al., 2015). In addition, continuously measuring ambulatory HR throughout a day has demonstrated improved reproducibility compared to clinic-based RHR (Dunn et al., 2021; Palatini et al., 2000).

With the availability of consumer wearable devices integrated with photoplethysmogram (PPG) sensors, daily RHR derived from combining multiple HR measurements throughout the day can now be automatically tracked (Russell et al., 2019). Daily RHR tracking might provide a measure of an individual's overall cardiovascular status and capture changes over weeks in cardiovascular fitness, or over days due to illness or other significant physiological triggers (Alexander et al., 2022; Mishra et al.,



**Figure 1 | System overview, development, and validation of the deeplearning system for passive heart rate (HR) and daily resting HR (RHR) measurements (PHRM) during smartphone use.** (A) In our research study with consented participants, upon a screen unlock event, the PHRM passively captures, processes, and analyzes 8-sec facial video using a deep neural network (DNN) to estimate HR and associated prediction confidence to determine if the measurement is valid. To compute daily RHR, the PHRM aggregates valid HR measurements from intermittent 8-sec video clips throughout a single day and applies a Kalman filter to improve estimates. (B) Workflow diagram of the different studies used to develop and validate the PHRM system. We used data from five independent, prospective laboratory studies and a prospective free-living study to develop and validate the PHRM.

2020; Quer et al., 2020). However, the adoption and consistent utilization of consumer wearable devices remains limited, and there is lower adoption by those who are most likely to benefit from these technologies (Dhingra et al., 2023). Smartphones provide an attractive alternative to develop daily RHR monitoring capabilities as the vast majority (90%) of US adults already have a smartphone and global smartphone penetration is estimated at 69% (Gelles-Watnick, 2024). Moreover, Americans check their phones an average of 144 times per day and the majority use their phones within the first 10 minutes of waking up (Kerai, 2023). In our work, we leverage the smartphone to provide a platform for opportunistically measuring HR across the day during normal phone use and aggregate the HR measurements across the day to derive RHR.

The principles of measuring the blood volume pulse from a distance via video-based, remote photoplethysmography (rPPG) are well established (Sun and Thakor, 2016; Wang et al., 2016). rPPG has been demonstrated to be capable of measuring HR (Liu et al., 2020; Poh and Poh, 2017; Qiao et al., 2022; Yan et al., 2017) and screening for irregular heart rhythms such as atrial fibrillation (Yan et al., 2018) via analysis of video images of the human face captured using front-facing smartphone cameras. However, most rPPG studies to date comprised small sample sizes or were conducted in controlled environments, limiting the generalizability to real-world conditions. Furthermore, the accuracy of current rPPG methods drops significantly for the darkest skin tones due to a larger concentration of melanin which absorbs more light (Nowara et al., 2020). The growing concern that

Table 1 | Baseline characteristics of participants across studies.

Conditions	Train Laboratory	Free-living	Tune Free-living	Test Laboratory	Test Free-living
No. videos	28,484	124,683	72,606	1,750	184,220
No. participants	365	82	48	104	101
Heart rate, BPM (mean ± STD)	92.8 ± 32.0	66.9 ± 34.5	69.3 ± 29.1	74.6 ± 13.4	70.2 ± 29.8
Age (mean ± STD)	40.5 ± 14.7	37.9 ± 9.8	37.4 ± 11.8	51.3 ± 14.8	38.1 ± 11.4
Age group	<40 years 40-59 years >59 years	196 (54.1%) 113 (31.2%) 53 (14.6%)	52 (61.9%) 30 (35.7%) 2 (2.4%)	32 (66.7%) 12 (25.0%) 4 (8.3%)	24 (23.1%) 43 (41.3%) 37 (35.6%)
No. female (%)		199 (55.0%)	45 (53.6%)	25 (52.1%)	71 (68.3%)
Skin pigmentation group: n (%)	Group 1 (Fitzpatrick I-III; MST 1-4) Group 2 (Fitzpatrick IV-V; MST 5-7) Group 3 (Fitzpatrick VI; MST 8-10)	165 (45.6%) 116 (32.0%)	30 (35.7%) 22 (26.2%)	18 (37.5%) 12 (25.0%)	44 (42.3%) 25 (24.0%)
		81 (22.4%)	32 (38.1%)	18 (37.5%)	35 (33.7%)
					39 (36.1%)

MST represents Monk skin tone.

accuracy of optical devices using PPG, particularly pulse oximeters, may vary by skin pigmentation has led to increased scrutiny from health governing bodies including the U.S. Food & Drug Administration (FDA) ([Center for Devices and Radiological Health, 2023](#)) and NHS ([Department of Health and Social Care, 2024](#)). This has prompted recommendations for clinical validation studies to be conducted on a large number of participants and a diverse range of skin pigmentation. Thus far, there is a lack of rPPG studies that would meet the diversity requirements proposed by the FDA in terms of distribution and range of skin pigmentation ([Center for Devices and Radiological Health, 2023](#)).

In this work, we present, for the first time, a smartphone-based, deep learning system that enables passive measurements of HR and daily RHR in the background during normal phone use (collectively referred to as passive heart rate monitoring; PHRM). Compared to previous work, our system provides several advances. First, we validated its performance in a prospective study on the largest and most diverse set of videos (> 185k) to date, collected in laboratory conditions as well as in free-living, real-world conditions using participants' personal phones. Second, we demonstrate how our system provides equitable and accurate HR and daily RHR readings across all skin pigmentation groups. Finally, we demonstrate that PHRM-derived daily RHR is associated with well-established cardiovascular health metrics and risk factors.

## 2. Results

**Overview of System** We designed and developed the PHRM with two major components Fig. 1. First, we constructed an end-to-end HR estimation module that takes as input a short (8-second) video clip of the user's face, performs video stabilization, pre-processing (by face cropping, resizing, interpolating and computing frame differences) and predicts HR along with a measure of confidence using an ensemble ([Ganaie et al., 2022](#)) of computationally-efficient temporal shift convolutional neural networks (TS-CNNs) ([Liu et al., 2020](#)). Next, we designed an algorithm to derive daily RHR by aggregating the HR predictions throughout the day using the confidence of predictions and a Kalman filter. The PHRM was designed to run passively in the background and automatically initiate video capture via the front-facing camera upon a screen unlock event.

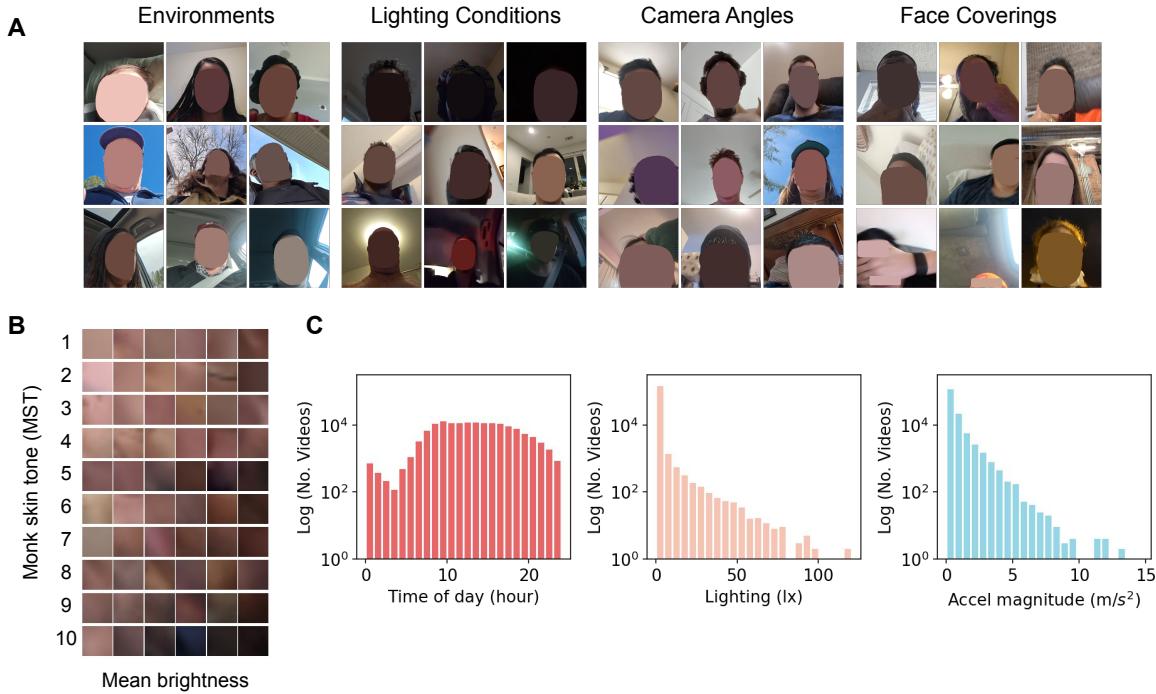
## 2.1. Study Populations

To develop and validate the PHRM, we conducted a series of studies to acquire datasets comprising face videos and HR ground truth (Table 1). In all our studies, we recruited for diversity across age, sex and skin tone groups. We used the electrocardiogram (ECG) as the reference HR ground truth for both the laboratory-based (in-lab) and free-living validation studies. In total, we collected 225,773 videos from 495 participants for PHRM development, and 185,970 videos from 205 participants for PHRM validation.

First, we obtained data to train and tune the PHRM from four separate studies performed in controlled laboratory settings ( $n=28,484$  videos from 365 participants). This data comprises a variety of lighting conditions and physiologic states including at rest, during various exercises, and post-exercise (details in Table S 1). To provide an external test set for model validation, we conducted a fifth, prospective laboratory study that enrolled 104 participants ( $n=1,750$  videos) and captured videos under five different lighting conditions and both at-rest and post-exercise physiologic states. The mean age in this external test set was  $51.3 \pm 14.8$  years; 71 (68.3%) participants were female. We divided participants into three groups of skin pigmentation (Fitzpatrick I-III, Fitzpatrick IV-V, Fitzpatrick VI) based on converting their objective individual topology angle ( $^{\circ}$ ITA) - as measured by a spectroradiometer at the cheeks and forehead - Fitzpatrick skin tones (Del Bino and Bernerd, 2013). We specified these skin tone groups to intentionally overrepresent participants of the darkest skin tones and ensure development of models that perform accurately for this group, a decision that aligned with the three skin pigmentation cohorts subsequently proposed by the FDA (Center for Devices and Radiological Health, 2023). ITA values ranged from  $-73.48^{\circ}$  to  $88.81^{\circ}$  with 44 (42.3%), 25 (24.0%), and 35 (33.7%) participants in skin pigmentation group 1 (lightest), 2 (medium) and 3 (darkest), respectively.

Next, we conducted a prospective free-living study designed to passively record face videos during normal phone use over an 8-day period. The detailed video recording protocol is provided in Appendix A. We applied stratified sampling based on age, sex, body mass index (BMI), and Monk skin tone (MST) to split the free-living data at the participant level: data from 50% of the participants ( $n=197,289$  videos from 130 participants) were set aside for model development (30% for training and 20% for tuning), and data from the remaining 50% of participants ( $n=184,220$  videos from 101 participants) were set aside as the test split for validation. We switched to using the MST in the prospective free-living study since it was designed to be more inclusive of the spectrum of skin tones we see in our society (the laboratory studies were conducted before the introduction of MST and used Fitzpatrick skin tone, the de-facto industry standard at that time). The 101 participants in the test split of the free-living study excludes six individuals who did not meet the minimum adherence criteria, i.e. at least 3 days with more than 40 video clips per day (Fig. S 3). The mean age was  $38.1 \pm 11.4$  years; 58 (53.7%) participants were female. Following FDA's proposal, the entire range of skin pigmentation based on the self-reported MST was represented with at least one participant for each MST value of 1-10. We divided participants into three MST cohorts, yielding 40 (37.0%), 29 (26.9%), and 39 (36.1%) participants in MST 1-4, MST 5-7 and MST 8-10 cohorts, respectively. This distribution also fulfilled the FDA recommendation to have  $\geq 40\%$  of each sex and  $\geq 25\%$  of participants in each of the 3 MST cohorts.

Participants uploaded  $230.7 \pm 172.2$  face videos per day. These videos were recorded passively throughout the day during normal personal phone use subsequent to a screen unlock event. As expected, the unconstrained nature of free-living use and passive recordings yielded videos with a diversity of environments, lighting conditions, camera angles and face coverings (Fig. 2A). These videos spanned all hours of the day, and a wide range of lux and motion levels as measured by the smartphone ambient light sensor and accelerometer, respectively (Fig. 2C). We randomly sampled

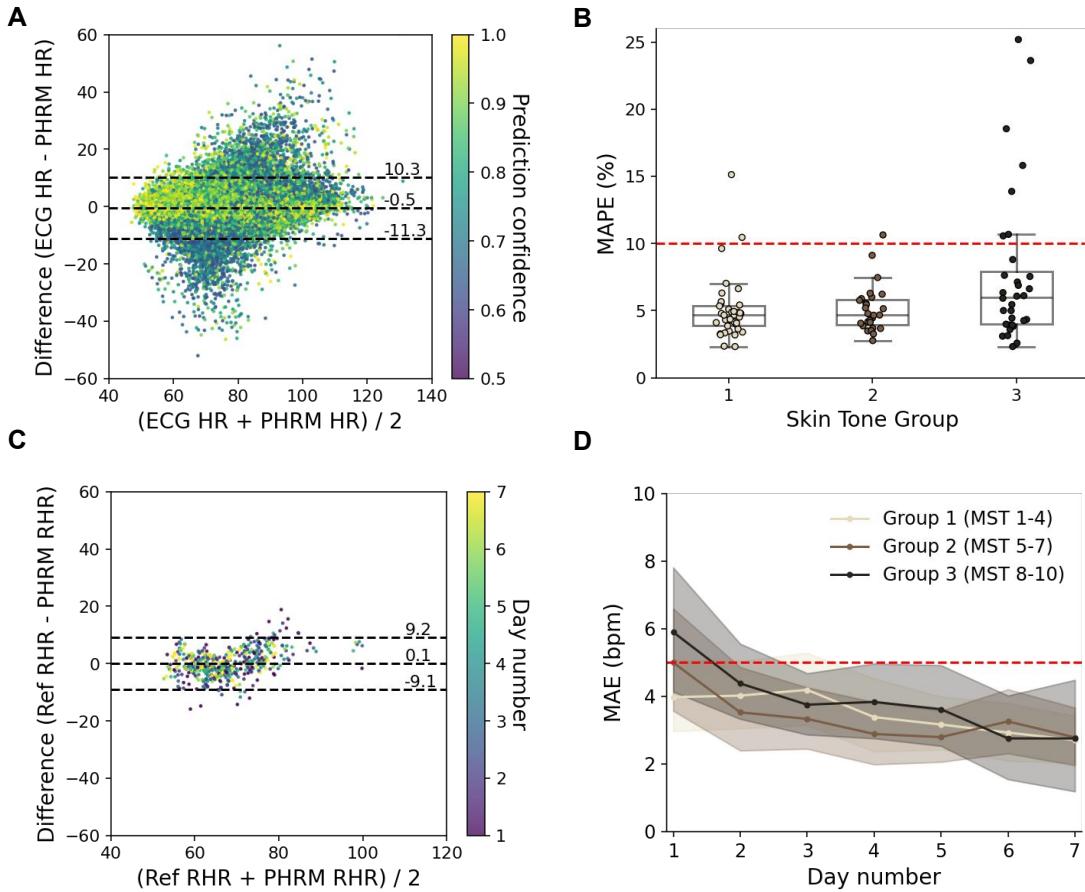


**Figure 2 | Representative examples of the diversity of free-living data used to validate the PHRM.** (A) Illustrative examples of the variety of environments, lighting conditions, front-facing camera angles, and face obstructions for videos captured in the free-living conditions. (B) Examples of facial skin patches randomly sampled from video frames of the cheeks of participants across the full range of Monk skin tones (MST). Videos are sorted by mean brightness across columns and MST across rows (C) From left to right: histograms of the number of 8-sec video clips by the hour of day, illuminance measured by the smartphone ambient light sensor, and the average magnitude of linear acceleration of the smartphone during the videos.

skin patches from video frame crops of participant's cheeks to visualize the range of skin pigmentation under various lighting conditions across the MST range (Fig. 2B).

## 2.2. HR Measurements

**In-Laboratory Test Performance.** We first explored how well smartphones measure HR in controlled conditions by comparing PHRM predictions with HR measured by the reference ECG. In the prospective laboratory study comprising 103 participants, we successfully obtained a valid HR measurement (by gating on the confidence scores associated with the PHRM predictions, see details in Methods) in 1360 out of 1750 face videos (77.7%). The one participant we did not obtain any valid HR measurements from was seated far from the camera, resulting in a high failure rate (62.5%) of detecting facial landmarks needed to perform video stabilization. Compared to the reference ECG HR, the PHRM achieved a mean absolute error (MAE) of 4.09 (95%CI: 3.03, 5.33) and a mean absolute percentage error (MAPE) of 5.65% (95%CI: 4.25, 7.29) at the participant level in the overall study population (Table S 1). The MAPE values for all five lighting conditions, and both at-rest and post-exercise conditions were significantly lower than the pre-specified study target of 10% ( $p < 0.001$ ), indicating robustness across lighting and physiologic conditions. The PHRM measurement success rate while participants were at-rest was 78.4% (95%CI: 76.3, 82.5), which was higher than the 62.1% (95%CI: 56.6, 67.6) success rate post-exercise (Table S 2).



**Figure 3 | Accuracy of passive HR and RHR measurements by the PHRM in free-living conditions.** (A) Bland Altman plot showing the agreement between PHRM-estimated HR values and the reference ECG measurements. Colors indicate the confidence level of PHRM predictions. Dashed lines show the bias, lower, and upper limits of agreement adjusted for repeated measurements with unequal numbers of replicates. (B) Boxplots showing the distribution of mean absolute percentage error (MAPE) values for individual participants, grouped by skin pigmentation. The red dashed line indicates the pre-specified accuracy target of  $\text{MAPE} < 10\%$ . (C) Bland Altman plot showing the agreement between PHRM-estimated daily RHR values and the reference wearable HR tracker measurements. Colors indicate the day number since the start of RHR predictions. Dashed lines show the bias, lower, and upper limits of agreement adjusted for repeated measurements with unequal numbers of replicates. (D) Mean absolute error (MAE) of PHRM-estimated RHR as a function of day number since the start of RHR predictions, grouped by skin pigmentation. Shaded areas indicate the 95% confidence intervals. The red dashed line indicates the pre-specified accuracy target of  $\text{MAE} < 5 \text{ bpm}$ .

The Bland-Altman plot showed minimal bias (-0.7) and 95% limits of agreement (LoAs), adjusted for multiple measurements per participant, between -12.9 and 11.5 bpm (Fig. 2). The participant-level MAPE by skin tone groups was 3.81% (95%CI: 2.43, 5.94) for Group 1, 4.43% (95%CI: 3.12, 6.06) for Group 2, and 8.93% (95%CI: 5.60, 12.60) for Group 3; all were significantly  $< 10\%$  ( $p < 0.025$ ). The MAPE was highest for Group 3 under incandescent lighting.

**Free-living Test Performance.** Next, we evaluated the accuracy of passive HR measurements during smartphone use in real-world conditions. In the free-living test set comprising 101 participants, we

**Table 2 | Accuracy of passive heart rate (HR) and daily resting HR (RHR) measurements by the PHRM in free-living conditions across skin pigmentation groups.**

Group	Video-level / Day-level Performance			Participant-level Performance		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE
HR	Total (n=101)	3.59 (3.33-3.88)	5.53 (5.10-6.03)	4.83† (4.41-5.29)	4.58 (4.15-5.06)	7.28 (6.53-8.06)
	Group 1 (n=37; MST 1-4)	3.31 (2.99-3.64)	4.97 (4.48-5.47)	4.55†* (3.99-5.12)	3.66 (3.29-4.11)	5.76 (5.05-6.49)
	Group 2 (n=27; MST 5-7)	3.58 (3.22-4.06)	5.44 (4.74-6.28)	4.56†* (4.14-5.05)	4.14 (3.61-4.75)	6.50 (5.49-7.49)
	Group 3 (n=37; MST 8-10)	4.52 (3.81-5.62)	7.16 (5.98-8.81)	6.12†* (4.87-7.84)	5.81 (4.89-6.86)	7.84†* (7.58-10.43)
	Total (n=101)	3.62† (3.13-4.10)	4.65 (4.07-5.19)	5.35 (4.65-5.90)	4.39† (3.47-5.16)	5.92 (4.49-6.98)
	Group 1 (n=37; MST 1-4)	3.44† (2.67-4.34)	4.38 (3.44-5.31)	5.31 (4.24-6.43)	3.72† (2.91-4.65)	4.69 (3.80-5.56)
RHR	Group 2 (n=27; MST 5-7)	3.47† (2.88-4.06)	4.40 (3.64-5.16)	5.05 (4.14-5.84)	3.56† (2.61-4.72)	4.82 (3.45-6.39)
	Group 3 (n=37; MST 8-10)	4.06† (3.33-4.92)	5.27 (4.29-6.23)	5.74 (4.77-6.77)	5.86 (4.17-7.48)	7.76 (5.38-9.55)
	Total (n=101)	3.62† (3.13-4.10)	4.65 (4.07-5.19)	5.35 (4.65-5.90)	4.39† (3.47-5.16)	5.92 (4.49-6.98)
	Group 1 (n=37; MST 1-4)	3.44† (2.67-4.34)	4.38 (3.44-5.31)	5.31 (4.24-6.43)	3.72† (2.91-4.65)	4.69 (3.80-5.56)
	Group 2 (n=27; MST 5-7)	3.47† (2.88-4.06)	4.40 (3.64-5.16)	5.05 (4.14-5.84)	3.56† (2.61-4.72)	4.82 (3.45-6.39)
	Group 3 (n=37; MST 8-10)	4.06† (3.33-4.92)	5.27 (4.29-6.23)	5.74 (4.77-6.77)	5.86 (4.17-7.48)	7.76 (5.38-9.55)

Errors at the video/day level refers to the average error from all paired measurements. Errors at the participant level refers to the average of the mean error of individual participants. Errors in parentheses indicate 95% confidence intervals. MAE, mean absolute error. MAPE, mean absolute percentage error. MST, Monk skin tone. RMSE, root mean squared error.

†Met pre-specified targets: MAPE for HR < 10%, MAE for RHR < 5 bpm ( $p < 0.05$ )

\*Met pre-specified non-inferiority HR target of < 5 percentage points versus other skin tone groups

observed a lower HR measurement success rate of 43.1% (68,307 valid measurements out of the 158,471 face videos) compared to the laboratory study, as expected given the measurements were in uncontrolled conditions without participants being told to stay still during the duration of the measurement. The measurement success rate decreased by skin tone group, ranging from 58% in group 1, 45% in group 2, to 25% in group 3. These videos were captured using 26 different smartphone models. Compared to the reference ECG HR, the PHRM achieved a video-level MAE of 3.59 (95%CI: 3.33, 3.88) and MAPE of 4.83% (95%CI: 4.39, 5.28); participant-level MAE was 4.58 (95%CI: 4.14, 5.06) and MAPE was 6.09% (95%CI: 5.35, 6.87). Both video- and participant-level MAPEs were significantly < 10% ( $p < 0.001$ ), indicating that the PHRM provided accurate passive HR measurements (Table 2).

The participant-level MAPE by skin tone groups was 5.04% (95%CI: 4.36, 5.89) for Group 1, 5.12% (95%CI: 4.51, 5.80) for Group 2, and 7.84% (95%CI: 6.25, 9.71) for Group 3; all were significantly < 10% ( $p < 0.001$ ). The MAPE values for all three skin tone groups were significantly < 10% at both video and participant level ( $p < 0.001$  for all comparisons), demonstrating that the PHRM provided accurate passive HR measurements for all skin pigmentation groups. The difference in participant-level MAPE between skin pigmentation group 1 versus others, groups 2 versus others, and group 3 versus others was -1.64 percentage points (95%CI: -2.96, -0.37), -1.31 points (95%CI: -2.51, -0.17), and 2.75 points (95%CI: 1.04, 4.70), respectively. This met the prespecified target of non-inferiority of < 5 percentage points, indicating that the PHRM provided equitable HR measurements for all skin pigmentation groups. The Bland-Altman plot showed minimal bias (0.64) and 95% LoAs, adjusted for multiple measurements per participant, between -11.3 and 10.3 bpm (Fig. 3A). Importantly, videos with lower errors tended to have higher confidence scores, illustrating the effectiveness of the confidence-based gating algorithm. Overall, our results indicate that PHRM was robust to diverse lighting, physiologic and real-world conditions, and provided accurate and equitable HR measurements across skin pigmentation groups.

### 2.3. Daily RHR Measurements

As our findings indicated that smartphones could measure HR passively in free-living conditions, we tested our hypothesis that RHR could be estimated on a daily basis using these intermittent HR measurements by comparing PHRM predictions with daily RHR measured by the reference wearable HR tracker. Out of the 101 participants, 90 participants (89.1%) had at least one or more days with  $\geq 20$  valid HR measurements, which was the minimum number of measurements needed to compute a valid daily RHR (Fig. S 3). Among these participants, a valid daily RHR measurement was obtained in 504 out of 685 (73.6%) participant days. Compared to the reference wearable HR tracker, the PHRM achieved a day-level and participant-level MAE of 3.62 bpm (95%CI: 3.18, 4.09) and 4.39 (95%CI: 3.67, 5.17) for RHR measurements, respectively, in the overall study population. Both MAE values were significantly lower than the pre-specified study target of 5 bpm ( $p < 0.001$ ), indicating that the PHRM provided accurate daily RHR measurements passively, during ordinary phone use. The Bland-Altman plot showed minimal bias (0.1) and adjusted 95% limits of agreement were between -9.1 and 9.2 bpm.

The PHRM-derived daily RHR was very highly correlated with daily RHR from the wearable HR tracker ( $r=0.87$ ,  $p < 0.001$ ); correlation with traditional methods of measuring RHR using ECG in a supine ( $r=0.73$ ,  $p < 0.001$ ) and sitting position ( $r=0.74$ ,  $p < 0.001$ ) was also high (Fig. S 4). The intra-person standard deviation for supine and sitting RHR was 5.08 bpm (95%CI: 4.44, 5.78) and 4.52 bpm (95%CI: 3.95, 5.11), respectively. The coefficient of variation (CV) for supine and sitting RHR was 7.85% (95%CI: 6.84, 9.01) and 6.68% (95%CI: 5.81, 7.64), respectively. We observed that reproducibility of PHRM-derived RHR was higher compared to traditional methods with a significantly lower intra-person standard deviation of 1.20 bpm (95%CI: 1.06, 1.35) and coefficient of variation (CV) of 1.77% (95%CI: 1.56, 1.99).

At the day level, MAE of daily RHR measurements by skin tone groups was 3.44 (95%CI: 2.75, 4.62) for Group 1, 3.47 (95%CI: 2.77, 4.25) for Group 2, and 4.06 (95%CI: 3.23, 5.13) for Group 3; all were significantly  $< 5$  bpm ( $p < 0.001$ ). The participant-level MAE by skin tone groups was 3.72 (95%CI: 2.94, 4.57) for Group 1, 3.56 (95%CI: 2.60, 4.77) for Group 2, and 5.86 (95%CI: 4.18, 7.70) for Group 3; MAEs were significantly  $< 5$  bpm for Group 1 ( $p < 0.005$ ) and 2 ( $p < 0.001$ ) but did not reach significance for Group 3 ( $p=0.32$ ). However, we found that the MAE across all skin tone groups decreased over time as the Kalman filter converged. From the third day onwards, the MAE for Group 3 was significantly  $< 5$  bpm. Visually, we observed that the PHRM-derived RHR was able to capture similar trends as the wearable HR tracker (Fig. S 5).

**RHR Association with Health Factors** Finally, we examined if the daily RHR estimated from smartphone use was associated with well-established risk factors. We found that participants with a higher PHRM-derived RHR, after adjusting for chronological age, sex and day of measurement, were more likely to exhibit markers of poorer health, namely obesity and poor cardiovascular fitness (Table 3). In a generalized least square model of PHRM-derived RHR, both higher BMI and lower cardiovascular fitness were independent predictors ( $\beta=1.92 \pm 0.57$  bpm,  $p < 0.001$ ; and  $\beta=-1.90 \pm 0.27$  bpm,  $p < 0.001$  per 1SD increase of BMI and VO<sub>2</sub>max, respectively). Taken together, these results demonstrate that the PHRM produced daily RHR estimates that were accurate and associated with markers of health status.

## 3. Discussion

To our knowledge, this is the first demonstration that smartphones can be used to passively monitor both HR and RHR during normal phone usage in the real-world. It is also the largest and most diverse

**Table 3 | Generalized least squares (GLS) model of PHRM-estimated daily resting heart rate (RHR).**

Covariate	GLS model fit Beta (bpm) per 1 SD increase	ANOVA test	
		X2	p
BMI	1.92 ± 0.57	11.4	0.0007
VO2max	-1.90 ± 0.27	48.0	<0.0001

BMI, body mass index. SD, standard deviation. VO2max, maximal oxygen consumption.

prospective validation study of rPPG to date. Importantly, smartphones were able to produce accurate HR measurements that meet the American National Standards Institute (ANSI) and Consumer Technology Association (CTA) standards for consumer HR monitors ( $MAPE \leq 10\%$ ) ([Consumer Technology Association, 2018](#)) across all skin pigmentation groups. We demonstrated that smartphone-based rPPG meets the pre-specified non-inferiority target for performance across skin-tone groups, which is critical for equitable measurement. We also found that smartphones were able to produce accurate estimates of daily RHR; smartphone-derived RHR was associated with known risk factors for cardiovascular disease.

In this study, we performed validation on 185,970 videos from 205 participants across in-lab and free-living conditions. These participants spanned the entire MST and captured race and ethnicity diversity in skin pigmentation relevant to the US population according to the guidelines proposed by the FDA ([Center for Devices and Radiological Health, 2023](#)). Existing rPPG datasets are much smaller in volume and were almost exclusively collected in controlled (in-lab) settings, many capturing videos using digital single-lens reflex (DSLR) cameras or devices from specialist imaging companies; the largest of these studies include BP4D+ ([Zhang et al., 2016](#)) (1,400 videos from 140 participants), VIPL-HR ([Niu et al., 2019](#)) (2,378 videos from 107 participants), UCLA-rPPG ([Wang et al., 2022](#)) (503 videos from 104 participants), and MMPD ([Tang et al., 2023](#)) (660 videos from 33 participants). Moreover, none of the rPPG datasets or prior studies meet the diversity requirements proposed by the FDA in terms of distribution and range of skin tones.

A recent study ([Savur et al., 2023](#)) showed promising feasibility of rPPG to provide background measurements of HR using tablets provided to participants, achieving 95% LoAs of between -12.4 and 14.6 bpm for HR accuracy at a measurement success rate of 20%. However, tablet usage was low and occurred under very limited conditions, primarily while watching videos at home, which the authors attributed to the fact that the tablet was a new device introduced to the participants. In contrast, our study leveraged personal smartphones already in use by the participants to passively capture measurements in an entirely free-living manner whenever they were naturally interacting with their phones. Encouragingly, our PHRM system achieved better 95% LoAs between -11.3 and 10.3 bpm and a higher measurement success rate of 43% despite the more challenging environments. These results suggest that smartphones could provide passive monitoring of HR throughout the day, providing within-day temporal resolution that may be useful for tracking HR fluctuations due to physical or mental stressors.

Previous state-of-the-art (SotA) rPPG methods have performed poorly for people with darker skin pigmentation. For example, work evaluating prior SotA rPPG methods on a geographically diverse population that included darker skin tones found that the mean error was low (around 1 bpm) but the standard deviation was high (11 bpm) ([Dasari et al., 2021](#)). Previous meta-analysis of existing rPPG datasets and methods reported that HR accuracy was significantly impacted for the darkest skin pigmentation with the MAE increasing from around 3.4 bpm for Fitzpatrick skin types I-V to 13.6 bpm in skin type VI ([Nowara et al., 2020](#)). This highlights the importance of evaluating HR performance on the darkest skin pigmentation (Type VI) separately, and not in combination with

Type V which is common practice in the rPPG field. To address the previous SotA underperformance on darker skin tones, we deliberately devoted approximately one third of our study population to participants of the darkest skin pigmentations (Fitzpatrick Type VI or MST 8-10) during recruitment. This enabled us to train rPPG models that were less susceptible to skin pigmentation bias. In this work, the PHRM system achieved an MAE of 5.2 and 5.81 bpm in the darkest skin pigmentations (Fitzpatrick Type VI or MST 8-10) in controlled and free-living environments, respectively. Our findings indicate that smartphone-based rPPG can provide accurate and equitable HR measurements across all skin pigmentation groups.

Another important finding of this work is that smartphones can passively estimate RHR, which has not been previously demonstrated. Notably, we found that PHRM-based RHR had a lower intra-person standard deviation and CV compared to traditional methods, indicating it was more consistent and reproducible. Presumably, this is because many observations of HR throughout the day capture more consistent RHR values than a single measurement in the supine or sitting position (Dunn et al., 2021). Smartphone-based RHR was significantly associated with known risk factors for cardiovascular health that influence clinic-based RHR, including obesity (Itagi et al., 2020; Martins et al., 2003; Rogowski et al., 2009), and low VO<sub>2</sub>max (Nauman et al., 2011). The results of our system on this study population demonstrate its potential clinical significance and suggest the possibility of using it to ambiently monitor elements of health status via the indicator of RHR. This opens up the possibility of automatically collecting longitudinal RHR data across weeks, months, seasons, and years that may provide valuable health information.

Our work has some limitations. There were a few participants with high MAPEs. From visual inspection of the videos from these participants, we observed frequent head motion and talking. The measurement success rate was lower in the darkest skin pigmentation group after automated confidence-based gating. This is likely related to the signal-to-noise (SNR) of the pulse signal captured in the videos, which has been reported to decrease with darker skin pigmentation (de Haan and Jeanne, 2013; Wang et al., 2014). Lower SNR has been attributed to the increased melanin content in darker skin pigmentation that limits the amount of light entering the deeper skin layers with pulsatile blood vessels and absorbs a portion of diffuse reflections carrying pulsatile information, while the specular reflections are not reduced (de Haan and Jeanne, 2013; Wang et al., 2014). Additionally, we cannot rule out other factors that may differ between the skin tone groups, such as participant physical activity levels, phone device hardware, and environment or lighting conditions. A potential broader mitigation would be to increase the number of measurement attempts when low SNR is encountered. Relatedly, under controlled conditions, we also observed that the MAPEs were highest for the darkest skin tone group under incandescent lighting. This could be due to the fact that incandescent lighting contains much less spectral power in the green wavelengths (Abdel-Rahman et al., 2017), which is optimal for blood absorption and hence SNR of the pulse signal. One approach is to investigate optimizing the camera exposure settings to boost the SNR, which might improve both measurement success rate and accuracy under such lighting. Globally, incandescent lighting is increasingly uncommon as there are ongoing efforts in multiple countries to phase out incandescent lightbulbs to promote energy efficiency (Edge and McKeen-Edwards, 2008).

In this research study, we did not account for constraints on battery consumption in favor of collecting more data and thus opportunistically collected videos any time the phone was unlocked. To minimize smartphone power use, future work is needed to identify the most opportune conditions likely to yield an accurate HR measurement before activating the camera. This would also increase the measurement success rate. Further improvements to the smartphone-based RHR algorithm might also be possible, for example, by considering the time of each HR measurement to account for circadian rhythms, or by using the accelerometer data to identify HR measurements taken after a sufficiently long rest period.

There are important privacy concerns to be considered for respectful use of this technology. Smartphone users should be asked to grant explicit informed consent before enabling passive video-based HR measurement. In our studies, videos were taken of consented participants and first saved locally on their device. The participants then reviewed the videos and manually authorized upload for research use. They were instructed not to upload any videos containing sensitive content or faces other than their own. The PHRM system was designed such that it could be run locally on a smartphone's processors, which enables the videos to be processed on-device. Such a system could be implemented within a protected on-device environment isolated from unauthorized access, such as Android's Trusted Execution Environment, to ensure the video images remain secure during execution. In addition, implementation of such a system could make HR measurement contingent on successful face authentication, mitigating measurements of other individuals and incorrect HR data attribution.

In conclusion, we developed and validated a system for passive measurement of HR and daily RHR during normal phone use that performs accurately across all skin pigmentation groups. This advancement in the state-of-the-art for rPPG methods presents a promising approach to improve equitable access to the benefits of heart health tracking by widening its availability to everyone who has a smartphone.

## 4. Methods

### 4.1. Studies

Between October 2020 to March 2024, we conducted five independent, prospective laboratory studies and a prospective free-living study to obtain datasets to develop and validate the PHRM. All study protocols were approved by an Institutional Review Board (Quorum now known as Advarra, Advarra, Columbia MD and WCG, Puyallup WA). We obtained informed consent from all participants, and the study was conducted in accordance with the principles of the Declaration of Helsinki.

In the laboratory validation studies, we objectively measured skin tone from each participant by using a RM200QC spectrophotometer (Pantone LLC, Carlstadt NJ) to image the skin of the cheeks and forehead. For the free-living study, since it was entirely remote with no in-person component, we provided participants with a visual representation of the Monk skin tone (MST) ([Monk, 2019](#)) to self-assess their skin tone.

**Reference Measurements** To validate HR measurements of the PHRM in laboratory settings, we used ECG recorded by the BIOPAC MP160 system (BIOPAC, Inc., Santa Barbara, CA) as the reference ground truth. We used a custom LabVIEW (National Instruments, Woburn, MA) application to record 3-lead ECG signals from electrodes placed on study participants' upper chests (or upper arms) and lower abdomens.

For validating HR measurements of the PHRM in real-world, free-living conditions, we used the Polar H10 ECG chest strap (Polar, Kempele Finland). The Polar H10 has been validated to provide accurate HR measurements during physical activity ([Gilgen-Amman et al., 2019](#); [Pasadyn et al., 2019](#)). Participants were instructed to put the chest strap on every morning and to wear it for at least 7 hours each day, except during showers or sleep.

Since aggregating multiple watch HR measurements provides more consistent RHR values than spot measurements in a supine or sitting position ([Dunn et al., 2021](#)), we chose to use the daily RHR from the Fitbit Charge 6 (Google, Mountain View, CA) as our primary reference for RHR. Daily RHR produced by Fitbit devices is computed by combining multiple HR measurements across "at rest" periods throughout the day, where the on-device accelerometer has determined that the person

is at rest, and has not recently been moving. If available, sleeping HR is also used to improve the daily RHR estimate. The Fitbit Daily RHR has been shown to be closest to RHR measurements taken lying down immediately upon wake (Russell et al., 2019). In addition, participants were instructed to perform two traditional RHR measurements first thing in the morning, before eating, drinking, exercising, or showering. After putting on the ECG chest strap, they laid in a supine position for 6 minutes. Next, they sat still for another 6 minutes. Supine and sitting RHR measurements were computed as the minimum HR from the ECG recordings and served as secondary references. HR has been found to stabilize in most subjects after 4 minutes of inactivity (Speed et al., 2023).

**Time Synchronization** To synchronize the clocks across all the study devices during the free-living study, participants performed a daily routine comprising a series of three jumps. We instructed participants to stand still with their hands placed in front of the chest. They held their smartphone enrolled in the study in their dominant hand; the wearable HR tracker was placed on the off-hand. To perform the series of jumps, we asked participants to start a timer, and complete the following sequence: standing still for one minute, three jumps spaced by 10 seconds, followed by standing still for another 10 seconds. We aligned the timestamps of the smartphone and ECG chest strap by maximizing the cross correlation between their respective accelerometer signals after resampling the signals to 60 Hz.

#### 4.2. PHRM-HR Module

The PHRM-HR module is the component of our algorithm that predicts a HR measurement. The PHRM-HR module processes an 8-second video input to predict HR. In this section, we describe the preprocessing pipeline applied to raw video, the deep network used for HR extraction, and the confidence-gating algorithm.

**Developmental Metric.** To assess and optimize each sub-component of the PHRM-HR module, we used the tuning dataset and computed the root mean square error (RMSE) after excluding the bottom 20% of videos with the lowest confidence scores. This approach was chosen to improve robustness against outliers and maintain sensitivity to extreme HR predictions.

**Video Preprocessing** The video preprocessing pipeline consists of five key steps to prepare the video data for HR extraction. Each step is briefly outlined in the following paragraphs, with further details provided in Appendix D.1.

- **Stabilization.** Video stabilization ensures consistent facial alignment across frames. To achieve this, facial landmarks were first detected using the Android face-based augmented reality AR model (Unk, 2024), and their positions were averaged to compute a centroid point. Then, an affine transformation was applied based on this centroid to stabilize each frame.
- **Linear interpolation.** Due to mobile I/O constraints, videos were stored at varying frame rates. All videos were standardized to 15 FPS for consistency. For videos not recorded at 15 FPS, each pixel value across the temporal dimension was interpolated linearly to achieve the target frame rate.
- **Face cropping.** To reduce background noise, the Android face-based AR model was used to detect the bounding box of the face in each frame. Then, we calculated the minimal bounding box covering the face across all frames, with an additional 20% margin in each dimension to include the ears and neck.
- **Resizing.** To ensure mobile compatibility with respect to limited computation, all video frames were resized to 32x32 pixels. In our experiments, we found this resolution was the smallest resolution

that still retained HR information and anti-aliased resampling with area interpolation proved to be the most effective method for preserving HR data at this resolution.

- **Frame differencing.** To highlight pixel value changes associated with physiological signals, we computed the difference between consecutive frames, similar to calculating the first derivative of a physiological signal.

**PHRM-HR Network** We trained a deep learning model to extract HR from video data that was preprocessed as described above. Specifically, the network takes 8-second videos at 15 FPS (a total of 120 frames) as input and outputs a continuous HR value between 40 and 180 BPM. In this section, we describe the network architecture and training process of our model. Ablation experiments were conducted to evaluate each component, with further details provided in Appendix D.2.

- **Network backbone.** We used a temporal shift (TS) convolutional network (Liu et al., 2020) to process each frame, generating a pseudo-PPG signal along the temporal axis. The network consists of five TS blocks, with each block consisting of a 2D convolution layer, ReLU activation, temporal channel shifting, and layer normalization across the channel dimension. The number of channels per block was set to 4, 16, 32, 64, and 128, respectively, with a fixed kernel size of 3. After passing through the TS blocks, average pooling was applied across all channels for each frame, followed by a temporally shared linear layer to produce the pseudo-PPG signal.
- **HR output head.** To extract HR from the pseudo-PPG, we first applied a Fast Fourier Transform to convert the signal into the frequency domain. The frequencies were then bucketized into 1 Hz bins, with the corresponding magnitudes treated as categorical logits. A softmax function was used to convert these logits into HR probabilities. In evaluation, the predicted HR was computed as a weighted sum of the probabilities.
- **Loss function.** We reformulated the HR regression problem as a classification task (Lathuiliere et al., 2020). The ground truth HR value was bucketized into a one-hot vector, corresponding to the relevant HR bins, with a bin size of 1 Hz. Focal loss (Lathuiliere et al., 2020; Ross and Dollár, 2017) was then applied to the HR probabilities and the bucketized HR values, with  $\alpha=5$  and  $\gamma=6$  tuned during training to optimize network performance.
- **Optimization.** We trained the model using the Adam optimizer (Gotmare et al., 2018; Kingma and Ba, 2014; Ross and Dollár, 2017) with a learning rate warm-up and a cosine decay scheduler48–51. Specifically, the model was trained for 20,000 steps, with 3,000 steps allocated for warm-up. Cosine decay was applied for 5,000 steps with a decay rate of 0.95. The learning rate and batch size were determined through a hyper-parameter search on the tuning dataset.
- **Data augmentation.** We applied two sets of augmentations to enhance model generalization. The first set consisted of spatial augmentations (Liu et al., 2024), including up/down and left/right flipping, rotation, and cropping and resizing, applied in a consistent manner across the temporal dimension. The second set introduced temporal noise through speed augmentation (Yang et al., 2022), where video playback was randomly adjusted by a factor between 0.8 and 1.2. Speed augmentation was implemented using the same linear interpolation method described in Video Preprocessing. Each augmentation was applied independently, with probabilities and parameters optimized through hyper-parameter search.
- **Hyper-parameter search.** Given the extensive hyper-parameter search space (learning rate, batch size, augmentation probabilities, etc.), we used a Gaussian process-based search tool to find the optimal parameter combination (Golovin et al., 2017). We set the search to 400 runs, using the post-confidence gated RMSE on validation as the evaluation metric, and the searched hyper-parameters are presented in Table S 6.
- **Ensembling.** We selected the top five models from the hyper-parameter search based on their validation performance and averaged the per-model HR prediction to generate the final HR prediction.

**Confidence Gating** Due to the unconstrained environment of normal phone use in real-world settings, it was necessary to apply a gating criterion to discard face videos that were too noisy for reliable HR estimation, such as those with no face present, face coverings or excessive movement. We found that the deep learning model’s confidence of a HR prediction was an effective metric for this purpose and derived an optimal threshold using the tuning dataset. Specifically, we use the negative entropy of the HR probabilities generated by the PHRM-HR module, where a higher negative entropy indicates a higher confidence. In the Supplementary Materials, we compared two alternatives, including pseudo-PPG SNR and the maximum HR probability, and found negative entropy to be the most effective for determining valid HR measurements.

Another key aspect of gating is determining the cutoff, which defines the threshold below which videos are filtered. To ensure this cutoff is accurate and equitable across different skin tones, we applied two rules when searching for the cutoff in the free-living tune dataset. First, the overall MAPE for each skin tone group had to be  $< 8\%$ . Second, the MAPE gap between any two skin tone groups had to be  $< 3\%$ . The search process is detailed in Appendix D.3.

#### 4.3. PHRM-RHR Model

For the daily RHR algorithm, we maintained simplicity to enhance its generalization. First, we aggregated the valid HR measurements across a single day by computing the 10th percentile value and applying a bias correction factor (which is a constant across all participants). We performed a grid search for the optimal percentile and bias correction values using the tune dataset. Next, we applied a Kalman filter to refine the RHR prediction from noisy estimates. Using the tune dataset, we also identified the minimum number of valid HR measurements needed in a day to provide a valid RHR estimate.

#### 4.4. Statistical Analysis

For HR measurements, we established a pre-determined accuracy target of mean absolute percentage error (MAPE)  $< 10\%$  in accordance with the ANSI/CTA standards for consumer HR monitors (Consumer Technology Association, 2018), which is based on the ANSI/AAMI standard for HR accuracy for ECG monitors (Association for the Advancement of Medical Instrumentation (AAMI), 2002). Measurements were paired observations: PHRM-estimated HR and reference HR from ECG. A paired measurement was dropped if the PHRM did not produce a valid HR measurement, i.e. the confidence of PHRM predictions was lower than the gating cutoff. Each participant contributed multiple 8-second videos for HR measurements. We computed MAPE at the video level as the mean value for all absolute percent error values from each paired measurement and used bootstrapping at the participant level to obtain the 95% confidence intervals (CI). Since each participant contributed a different number of videos, we also computed MAPE at the participant level as the mean value for the MAPEs of individual participants, which we visualized using boxplots. Since the errors were not normally distributed based on a Shapiro-Wilk test, we determined if the participant-level MAPE values were significantly  $< 10\%$  if  $p < 0.05$  using the Wilcoxon sign-rank test. We determined non-inferiority if the upper limit of the 95% CI around the difference in MAPE across participants in any of the three skin pigmentation groups compared to that across participants in the other two skin pigmentation groups was less than a pre-specified 5 percentage points. Bland–Altman plots were used to visualize the agreement between the estimated values and the reference measurements; limits of agreement were adjusted for repeated measurements with unequal numbers of replicates (Bland and Altman, 1999).

For daily RHR measurements, we adopted a pre-specified accuracy target of mean absolute error  $< 5 \text{ bpm}$ , which provided a stricter requirement than MAPE  $< 10\%$ . Similar to above, measurements

were paired observations: PHRM-estimated daily RHR and reference daily RHR from the wearable HR tracker. For the PHRM to yield a valid daily RHR estimate, a minimum of 20 valid HR measurements on that day was needed. Each participant contributed multiple days for RHR measurements. We computed MAE at the day level as the mean value for all absolute error values from each paired measurement and used cluster bootstrapping to obtain the 95% confidence intervals (CI). To account for multiple observations, we also computed MAE at the participant level as the mean value for the MAEs of individual participants, which we visualized using boxplots. Since the Kalman filter in the PHRM-RHR module takes time to converge, we also computed MAE for each day since the start of PHRM-RHR predictions to evaluate the MAE over time. We determined if MAE values were significantly  $< 5$  bpm if  $p < 0.05$  using the Wilcoxon sign-rank test. Bland–Altman plots were used to visualize the agreement between the estimated values and the reference measurements; limits of agreement were adjusted for repeated measurements with unequal numbers of replicates (Bland and Altman, 1999).

Associations between PHRM-estimated daily RHR and known risk factors were evaluated using a generalized least square model accounting for the correlation structure present across the serial estimates of RHR while also adjusting for the clusters within participants (Harrell, 2015). Ground truth measurements and associated estimates of RHR were collected daily for each participant over the course of the study. Therefore, statistical models of RHR have to: 1) account for the serial correlation existing among repeated measurements and 2) adjust for the presence of clusters within subjects. Given its flexibility, we decided to follow a generalized least squares (GLS) modeling approach (Strategies, 2001). First, we evaluated several possible forms for the correlation structure across days of measurement given a subject cluster, and ultimately selected the “spherical correlation” form, as it was most suited to our data in terms of Akaike Information Criterion. We then fitted a GLS model of the PHRM-estimated RHR using BMI and VO<sub>2max</sub> as covariates and adjusting for age, sex, age\*sex and day of measurement. The analyses were conducted in R v4.4.1 leveraging the rms v6.8 and nlme v3.1 packages.

## References

- Augmented faces introduction. <https://developers.google.com/ar/develop/augmented-faces>, Aug. 2024. Accessed: 2024-10-4.
- F. Abdel-Rahman, B. Okeremgbo, F. Alhamadah, S. Jamadar, K. Anthony, and M. A. Saleh. Caenorhabditis elegans as a model to study the impact of exposure to light emitting diode (LED) domestic lighting. *J. Environ. Sci. Health A Tox. Hazard. Subst. Environ. Eng.*, 52(5):433–439, Apr. 2017.
- J. Alexander, M. Sovakova, and G. Rena. Factors affecting resting heart rate in free-living healthy humans. *Digit Health*, 8:20552076221129075, Oct. 2022.
- L. Alhalabi, M. J. Singleton, A. O. Oseni, A. J. Shah, Z.-M. Zhang, and E. Z. Soliman. Relation of higher resting heart rate to risk of cardiovascular versus noncardiovascular death. *Am. J. Cardiol.*, 119(7):1003–1007, Apr. 2017.
- Association for the Advancement of Medical Instrumentation (AAMI). ANSI/AAMI EC13:2002: Cardiac monitors, heart rate meters, and alarms, 2002.
- J. M. Bland and D. G. Altman. Measuring agreement in method comparison studies. *Stat. Methods Med. Res.*, 8(2):135–160, June 1999.
- C. Ceconi, G. Guardigli, P. Rizzo, G. Francolini, and R. Ferrari. The heart rate story. *Eur. Heart J. Suppl.*, 13(suppl\_C):C4–C13, Sept. 2011.

Center for Devices and Radiological Health. Approach for improving the performance evaluation of pulse oximeter devices taking into consideration skin pigmentation, race and ethnicity: Discussion paper and request for feedback. Technical report, US Food & Drug Administration, Nov. 2023.

Consumer Technology Association. *Physical Activity Monitoring for Heart Rate*. 2018.

A. Dasari, S. K. A. Prakash, L. A. Jeni, and C. S. Tucker. Evaluation of biases in remote photoplethysmography methods. *NPJ Digit Med*, 4(1):91, June 2021.

G. de Haan and V. Jeanne. Robust pulse rate from chrominance-based rPPG. *IEEE Trans. Biomed. Eng.*, 60(10):2878–2886, Oct. 2013.

S. Del Bino and F. Bernerd. Variations in skin colour and the biological consequences of ultraviolet radiation exposure. *British Journal of Dermatology*, 169(s3):33–40, 2013.

Department of Health and Social Care. Equity in medical devices. [gov.uk/government/publications/equity-in-medical-devices-independent-review-final-report](https://gov.uk/government/publications/equity-in-medical-devices-independent-review-final-report), Mar. 2024. Accessed: 2024-6-5.

L. S. Dhingra, A. Aminorroaya, E. K. Oikonomou, A. A. Nargesi, F. P. Wilson, H. M. Krumholz, and R. Khera. Use of wearable devices in individuals with or at risk for cardiovascular disease in the US, 2019 to 2020. *JAMA Netw Open*, 6(6):e2316634, June 2023.

J. Dunn, L. Kidzinski, R. Runge, D. Witt, J. L. Hicks, S. M. Schüssler-Fiorenza Rose, X. Li, A. Bahmani, S. L. Delp, T. Hastie, and M. P. Snyder. Wearable sensors enable personalized predictions of clinical laboratory measurements. *Nat. Med.*, 27(6):1105–1112, June 2021.

J. Edge and H. McKeen-Edwards. Light bulbs and bright ideas? the global diffusion of a ban on incandescent light bulbs. In *80th annual conference of the Canadian political science association. University of British Columbia*, 2008.

M. A. Ganaie, M. Hu, A. K. Malik, M. Tanveer, and P. N. Suganthan. Ensemble deep learning: A review. *Engineering Applications of Artificial Intelligence*, 115:105151, 2022.

R. Gelles-Watnick. Americans' use of mobile technology and home broadband, Jan. 2024.

R. Gilgen-Ammann, T. Schweizer, and T. Wyss. RR interval signal quality of a heart rate monitor and an ECG holter at rest and during exercise. *Eur. J. Appl. Physiol.*, 119(7):1525–1532, July 2019.

D. Golovin, B. Solnik, S. Moitra, G. Kochanski, J. Karro, and D. Sculley. Google vizier. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, New York, NY, USA, Aug. 2017. ACM.

A. Gotmare, N. S. Keskar, C. Xiong, and R. Socher. A closer look at deep learning heuristics: Learning rate restarts, warmup and distillation. Oct. 2018.

T. W. Hansen, M. Kikuya, L. Thijs, K. Björklund-Bodegård, T. Kuznetsova, T. Ohkubo, T. Richart, C. Torp-Pedersen, L. Lind, J. Jeppesen, H. Ibsen, Y. Imai, J. A. Staessen, and IDACO Investigators. Prognostic superiority of daytime ambulatory over conventional blood pressure in four populations: a meta-analysis of 7,030 individuals. *J. Hypertens.*, 25(8):1554–1564, Aug. 2007.

F. E. Harrell. *Regression modeling strategies: With applications to linear models, logistic and ordinal regression, and survival analysis*. Springer series in statistics. Springer International Publishing, Cham, Switzerland, 2 edition, Aug. 2015.

- A. B. H. Itagi, M. K. Jayalakshmi, and G. Y. Yunus. Effect of obesity on cardiovascular responses to submaximal treadmill exercise in adult males. *J Family Med Prim Care*, 9(9):4673–4679, Sept. 2020.
- C. D. Johansen, R. H. Olsen, L. R. Pedersen, P. Kumarathurai, M. R. Mouridsen, Z. Binici, T. Intzilakis, L. Køber, and A. Sajadieh. Resting, night-time, and 24 h heart rate as markers of cardiovascular risk in middle-aged and elderly men and women with no apparent heart disease. *Eur. Heart J.*, 34 (23):1732–1739, June 2013.
- W. B. Kannel, C. Kannel, R. S. Paffenbarger, Jr, and L. A. Cupples. Heart rate and cardiovascular mortality: the framingham study. *Am. Heart J.*, 113(6):1489–1494, June 1987.
- A. Kerai. Cell phone usage statistics: Mornings are for notifications. <https://www.reviews.org/mobile/cell-phone-addiction/>, July 2023. Accessed: 2024-9-3.
- D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. Dec. 2014.
- M. Korshøj, M. Lidegaard, F. Kittel, K. Van Herck, G. De Backer, D. De Bacquer, A. Holtermann, and E. Clays. The relation of ambulatory heart rate with all-cause mortality among middle-aged men: a prospective cohort study. *PLoS One*, 10(3):e0121729, Mar. 2015.
- S. Lathuiliere, P. Mesejo, X. Alameda-Pineda, and R. Horaud. A comprehensive analysis of deep regression. *IEEE Trans. Pattern Anal. Mach. Intell.*, 42(9):2065–2081, Sept. 2020.
- X. Liu, J. Fromm, S. Patel, and D. McDuff. Multi-Task temporal shift attention networks for On-Device contactless vitals measurement. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 19400–19411. Curran Associates, Inc., 2020.
- X. Liu, G. Narayanswamy, A. Paruchuri, X. Zhang, J. Tang, Y. Zhang, R. Sengupta, S. Patel, Y. Wang, and D. McDuff. rppg-toolbox: Deep remote ppg toolbox. *Advances in Neural Information Processing Systems*, 36, 2024.
- D. Martins, N. Tareen, D. Pan, and K. Norris. The relationship between body mass index, blood pressure and pulse rate among normotensive and hypertensive participants in the third national health and nutrition examination survey (NHANES). *Cell. Mol. Biol. (Noisy-le-grand)*, 49(8):1305–1309, Dec. 2003.
- T. Mishra, M. Wang, A. A. Metwally, G. K. Bogu, A. W. Brooks, A. Bahmani, A. Alavi, A. Celli, E. Higgs, O. Dagan-Rosenfeld, B. Fay, S. Kirkpatrick, R. Kellogg, M. Gibson, T. Wang, E. M. Hunting, P. Mamic, A. B. Ganz, B. Rolnik, X. Li, and M. P. Snyder. Pre-symptomatic detection of COVID-19 from smartwatch data. *Nat Biomed Eng*, 4(12):1208–1220, Dec. 2020.
- E. Monk. The monk skin tone scale. 2019.
- J. Nauman, I. Janszky, L. J. Vatten, and U. Wisløff. Temporal changes in resting heart rate and deaths from ischemic heart disease. *JAMA*, 306(23):2579–2587, Dec. 2011.
- X. Niu, S. Shan, H. Han, and X. Chen. RhythmNet: End-to-end heart rate estimation from face via spatial-temporal representation. *IEEE Trans. Image Process.*, 29:2409–2423, Oct. 2019.
- E. M. Nowara, D. McDuff, and A. Veeraraghavan. A meta-analysis of the impact of skin type and gender on non-contact photoplethysmography measurements. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*. IEEE, June 2020.

- P. Palatini, M. Winnicki, M. Santonastaso, G. De Venuto, G. Zanata, O. Bertolo, G. Frigo, and A. C. Pessina. Reproducibility of heart rate measured in the clinic and with 24-hour intermittent recorders. *Am. J. Hypertens.*, 13(1 Pt 1):92–98, Jan. 2000.
- S. R. Pasadyn, M. Soudan, M. Gillinov, P. Houghtaling, D. Phelan, N. Gillinov, B. Bittel, and M. Y. Desai. Accuracy of commercially available heart rate monitors in athletes: a prospective study. *Cardiovasc Diagn Ther*, 9(4):379–385, Aug. 2019.
- M.-Z. Poh and Y. C. Poh. Validation of a standalone smartphone application for measuring heart rate using imaging photoplethysmography. *Telemedicine and e-Health*, 23(8):678–683, 2017.
- D. Qiao, A. H. Ayesha, F. Zulkernine, N. Jaffar, and R. Masroor. ReViSe: Remote vital signs measurement using smartphone camera. *IEEE Access*, 10:131656–131670, 2022.
- G. Quer, P. Gouda, M. Galarnyk, E. J. Topol, and S. R. Steinhubl. Inter- and intraindividual variability in daily resting heart rate and its associations with age, sex, sleep, BMI, and time of year: Retrospective, longitudinal cohort study of 92,457 adults. *PLoS One*, 15(2):e0227709, Feb. 2020.
- Z. Raisi-Estabragh, J. Cooper, R. Judge, M. Y. Khanji, P. B. Munroe, C. Cooper, N. C. Harvey, and S. E. Petersen. Age, sex and disease-specific associations between resting heart rate and cardiovascular mortality in the UK BIOBANK. *PLoS One*, 15(5):e0233898, May 2020.
- O. Rogowski, A. Steinvil, S. Berliner, M. Cohen, N. Saar, O. K. Ben-Bassat, and I. Shapira. Elevated resting heart rate is associated with the metabolic syndrome. *Cardiovasc. Diabetol.*, 8:55, Oct. 2009.
- T.-Y. Ross and G. Dollár. Focal loss for dense object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2980–2988, 2017.
- A. Russell, C. Heneghan, and S. Venkatraman. Investigation of an estimate of daily resting heart rate using a consumer wearable device. Oct. 2019.
- C. Savur, R. Dautov, K. Bukum, X. Xia, J.-P. Couderc, and G. R. Tsouri. Monitoring pulse rate in the background using front facing cameras of mobile devices. *IEEE J Biomed Health Inform*, 27(5):2208–2218, May 2023.
- M. Seviiri, B. M. Lynch, A. M. Hodge, Y. Yang, D. Liew, D. R. English, G. G. Giles, R. L. Milne, and P.-A. Dugué. Resting heart rate, temporal changes in resting heart rate, and overall and cause-specific mortality. *Heart*, 104(13):1076–1085, July 2018.
- C. Speed, T. ArNeil, R. Harle, A. Wilson, A. Karthikesalingam, M. McConnell, and J. Phillips. Measure by measure: Resting heart rate across the 24-hour cycle. *PLOS Digit Health*, 2(4):e0000236, Apr. 2023.
- R. M. Strategies. With applications to linear models. *Logistic Regression, and Survival Analysis.* [Google Scholar], 2001.
- Y. Sun and N. Thakor. Photoplethysmography revisited: From contact to noncontact, from point to imaging. *IEEE Trans. Biomed. Eng.*, 63(3):463–477, Mar. 2016.
- J. Tang, K. Chen, Y. Wang, Y. Shi, S. Patel, D. McDuff, and X. Liu. Mmpd: multi-domain mobile video physiology dataset. In *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 1–5. IEEE, 2023.

- A. Vazir, B. Claggett, S. Cheng, H. Skali, A. Shah, D. Agulair, C. M. Ballantyne, O. Vardeny, and S. D. Solomon. Association of resting heart rate and temporal changes in heart rate with outcomes in participants of the atherosclerosis risk in communities study. *JAMA Cardiol*, 3(3):200–206, Mar. 2018.
- W. Wang, S. Stuijk, and G. De Haan. Exploiting spatial redundancy of image sensor for motion robust rppg. *IEEE transactions on Biomedical Engineering*, 62(2):415–425, 2014.
- W. Wang, A. C. Den Brinker, S. Stuijk, and G. De Haan. Algorithmic principles of remote ppg. *IEEE Transactions on Biomedical Engineering*, 64(7):1479–1491, 2016.
- Z. Wang, Y. Ba, P. Chari, O. D. Bozkurt, G. Brown, P. Patwa, N. Vaddi, L. Jalilian, and A. Kadambi. Synthetic generation of face videos with plethysmograph physiology. In *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, June 2022.
- B. P. Yan, C. K. Chan, C. K. Li, O. T. To, W. H. Lai, G. Tse, Y. C. Poh, and M.-Z. Poh. Resting and postexercise heart rate detection from fingertip and facial photoplethysmography using a smartphone camera: A validation study. *JMIR Mhealth Uhealth*, 5(3):e33, Mar. 2017.
- B. P. Yan, W. H. S. Lai, C. K. Y. Chan, S. C.-H. Chan, L.-H. Chan, K.-M. Lam, H.-W. Lau, C.-M. Ng, L.-Y. Tai, K.-W. Yip, O. T. L. To, B. Freedman, Y. C. Poh, and M.-Z. Poh. Contact-Free screening of atrial fibrillation by a smartphone using facial pulsatile photoplethysmographic signals. *J. Am. Heart Assoc.*, 7(8), Apr. 2018.
- Y. Yang, X. Liu, J. Wu, S. Borac, D. Katabi, M.-Z. Poh, and D. McDuff. SimPer: Simple self-supervised learning of periodic targets. Oct. 2022.
- Z. Zhang, J. M. Girard, Y. Wu, X. Zhang, P. Liu, U. Ciftci, S. Canavan, M. Reale, A. Horowitz, H. Yang, J. F. Cohn, Q. Ji, and L. Yin. Multimodal spontaneous emotion corpus for human behavior analysis. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, June 2016.

## Supplementary Material

### A. Additional Information for Free-Living Protocol

This section details the protocol used for collecting free-living data, aimed at capturing face videos and ground truth measurements in natural, real-world settings. Participants were instructed to follow a specific morning routine, including capturing RHR using a Fitbit and Polar chest strap, as well as aligning accelerometer signals across devices. Throughout the day, video clips were recorded periodically as participants used their phones. To ensure privacy and transparency, several safeguards were implemented, including participant review of video clips, restrictions on recording conditions, and cropping of videos to only show the participant's face. Fig. 1 illustrates the sequence of events during the ambient video recording process.

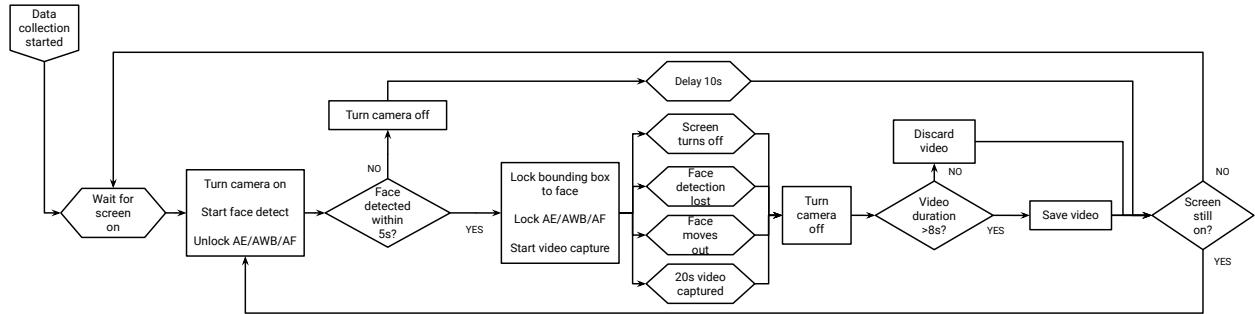
**Participant Instruction** Free-living data collection aimed to collect face videos and ground truth under natural, real-world conditions. Participants were instructed to adhere to the following protocol each morning:

- Immediately after waking up, begin data collection on their phone, Fitbit, and Polar chest strap
- Lie still for 6 minutes, then sit still for 6 minutes to measure resting heart rate on the Fitbit / Polar
- Jump three times while holding the phone and wearing the Fitbit / Polar, thus creating accelerometer signals across all three devices to be used for timestamp alignment

Participants then used their phone throughout the day as they normally would. Brief video clips would be periodically recorded from the front-facing camera when the phone was in use.

**Transparency & privacy** Given the intrusive nature of this data collection, several precautions were implemented to avoid inadvertently collecting sensitive material and to be transparent about the collected data:

- Video data never left the phone until it was manually reviewed and approved by the participant. Participants were instructed to view each video clip and delete clips containing other people or any sensitive subjects.
- Recording could only occur within 10 minutes of the phone being unlocked and only while a face was visible. Recording immediately stopped whenever the phone was locked or if no face was in frame. This was intended to reduce the chance of recording someone other than the participant.
- Videos were cropped automatically (based on the Android AR model) to only the participant's face to avoid recording the background environment.
- On-screen indicators were displayed whenever a video recording was in progress.



**Figure 1 | Sequence of events in an ambient video recording.** Upon screen unlock, the front-facing camera would start at VGA resolution (640x480 px), 15 FPS, and with the phone's default 3A settings (autoexposure, autofocus, auto-white balance) enabled. If a face was detected within five seconds, the camera would lock the current 3A settings and begin recording frames. Recorded frames were cropped to a stationary bounding box set by the initial position of the face, and saved as Motion JPEG (M-JPEG) at maximum quality to avoid inter-frame compression. The recording would automatically end after 20 seconds had elapsed, if the face moved out of the bounding box, or if the screen was turned off. Clips shorter than 8 seconds were discarded. If the screen was still on, this sequence would restart with the camera reset to its initial settings. This sequence could repeat up to 30 times per screen unlock, for a maximum 10 minutes of video.

## B. Additional Results in Laboratory Setting

In this section, we present tables and figures that summarize the performance of the PHRM in laboratory conditions, evaluating its accuracy and success rates under diverse lighting scenarios. Table 1 shows the accuracy of HR measurements, providing detailed results on how well the PHRM matches reference measurements across varying conditions. Meanwhile, Table 2 focuses on the success rate of measurements, indicating how often the PHRM successfully captured valid HR readings. In addition, Fig. 2 visualizes these findings through a Bland-Altman plot and boxplots. The Bland-Altman plot illustrates the agreement between PHRM-estimated HR values and reference ECG measurements, with color coding for prediction confidence levels, while the boxplots highlight the distribution of MAPE and MAE across participants, categorized by skin pigmentation.

**Table 1 | Accuracy of heart rate (HR) measurements by the PHRM in diverse laboratory conditions and lighting.**

	Group	All	Condition	Lighting (at-rest)				Dim LED	Normal LED
			At-Rest	Post-Exercise	Fluorescent	Incandescent	Natural		
MAE	Total (n=103)	4.09 (3.03 - 5.33)	4.28 (3.19 - 5.59)	2.16 (1.71 - 2.70)	3.69 (2.51 - 5.15)	4.06 (2.85 - 5.53)	3.72 (2.41 - 5.39)	3.62 (2.45 - 5.11)	4.24 (2.88 - 5.90)
	Group 1 (n=44)	3.00 (1.74 - 5.09)	3.04 (1.75 - 5.20)	1.85 (1.48 - 2.29)	3.42 (1.73 - 5.88)	2.80 (1.56 - 4.83)	2.87 (1.53 - 5.29)	3.22 (1.69 - 5.75)	3.16 (1.63 - 5.36)
	Group 2 (n=25)	3.16 (2.28 - 4.23)	3.31 (2.37 - 4.43)	1.93 (1.16 - 2.98)	2.62 (1.69 - 3.63)	4.02 (2.46 - 5.95)	3.73 (1.84 - 6.77)	2.40 (1.70 - 3.35)	3.24 (1.87 - 4.98)
	Skintone 3 (n=34)	6.17 (4.03 - 8.62)	6.70 (4.32 - 9.43)	3.09 (1.80 - 4.78)	5.25 (2.74 - 8.33)	7.05 (3.72 - 11.26)	5.96 (3.18 - 9.40)	5.74 (3.03 - 9.17)	7.53 (3.75 - 12.15)
	Total (n=103)	5.65† (4.25 - 7.29)	6.01† (4.43 - 7.75)	2.74† (2.11 - 3.52)	4.95† (3.54 - 6.58)	5.90† (4.08 - 8.06)	4.88† (3.42 - 6.70)	5.15† (3.52 - 7.23)	5.75† (4.02 - 7.81)
	MAPE	Group 1 (n=44)	3.81† (2.43 - 5.94)	3.92† (2.50 - 6.10)	2.20† (1.73 - 2.78)	4.26† (2.46 - 6.85)	3.67† (2.25 - 5.82)	3.71† (2.22 - 6.22)	4.17† (2.45 - 6.86)
MAPE	Group 2 (n=25)	4.43† (3.12 - 6.06)	4.74† (3.31 - 6.49)	2.58† (1.44 - 4.38)	3.95† (2.47 - 5.62)	5.93† (3.44 - 9.28)	5.02† (2.67 - 8.68)	3.53† (2.41 - 4.96)	4.51† (2.74 - 6.58)
	Group 3 (n=34)	8.93† (5.60 - 12.60)	9.83 (6.15 - 14.11)	4.11† (2.37 - 6.46)	7.27† (3.88 - 11.47)	11.07 (5.44 - 18.61)	7.81† (4.56 - 11.65)	8.89 (4.23 - 15.07)	10.57 (5.18 - 17.21)

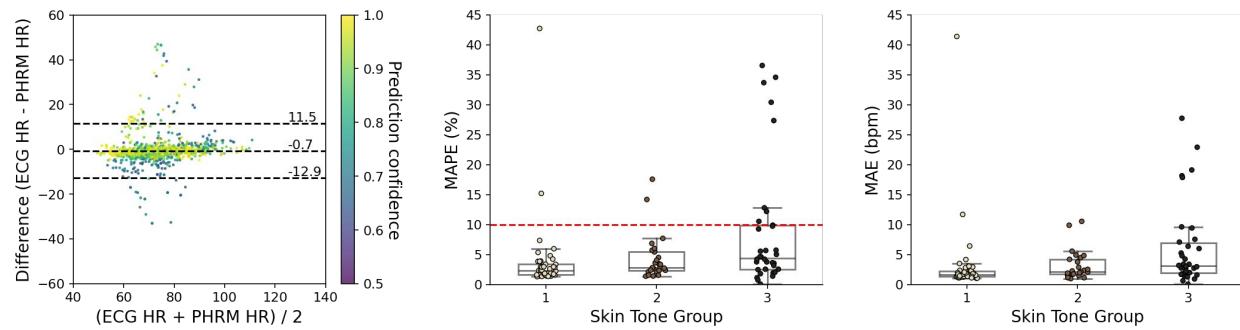
Group 1, 2, 3 correspond to Fitzpatrick skin Types I-III, IV-V, and VI, respectively.

†Met pre-specified target of MAPE < 10% (p < 0.05)

**Table 2 | Measurement success rate by the PHRM in diverse laboratory conditions and lighting.**

Group	All	Condition At-Rest	Post-Exercise	Lighting Fluorescent	Incandescent	Natural	Dim LED	Normal LED
Total	75.66	78.39	62.07	85.02	75.09	73.96	77.03	80.99
(n=103)	(69.75 - 81.22)	(72.39 - 84.06)	(53.52 - 70.67)	(79.07 - 90.49)	(68.08 - 81.70)	(65.54 - 81.99)	(69.09 - 84.21)	(73.87 - 87.71)
Success Rate								
Skintone 1 (n=44)	93.29 (89.87 - 96.06)	95.88 (93.02 - 98.20)	78.99 (68.60 - 88.14)	97.78 (95.24 - 100.0)	93.70 (88.97 - 97.66)	94.57 (89.92 - 98.41)	94.78 (90.30 - 98.48)	98.47 (96.06 - 100.0)
Skintone 2 (n=25)	80.44 (70.18 - 89.22)	83.33 (72.63 - 92.25)	65.28 (47.83 - 80.77)	87.67 (76.71 - 97.10)	82.05 (70.83 - 91.67)	81.25 (66.23 - 92.86)	82.67 (69.41 - 94.12)	83.33 (69.44 - 95.45)
Skintone 3 (n=34)	44.60 (36.13 - 53.35)	45.85 (36.99 - 55.31)	39.39 (24.24 - 54.90)	60.76 (47.14 - 74.03)	40.48 (27.59 - 52.88)	32.91 (19.74 - 47.44)	44.83 (31.11 - 59.14)	50.62 (35.80 - 65.48)

Group 1, 2, 3 correspond to Fitzpatrick skin Types I-III, IV-V, and VI, respectively.



**Figure 2 | Accuracy of HR measurements by the PHRM in laboratory settings.** (A) Bland Altman plot showing the agreement between PHRM-estimated HR values and the reference ECG measurements. Colors indicate the confidence level of PHRM predictions. Dashed lines show the bias, lower, and upper limits of agreement adjusted for repeated measurements with unequal numbers of replicates. (B) Boxplots showing the distribution of mean absolute percentage error (MAPE) values for individual participants, grouped by skin pigmentation. The red dashed line indicates the pre-specified accuracy target of MAPE < 10%.

## C. Additional Results in Free-Living Setting

In this section, we detail following figures that present results of our analysis in free-living conditions. Fig. 3 presents the flowchart outlining the inclusion criteria applied throughout the study, including quality control measures and filtering steps for valid data. Fig. 4 compares the PHRM's daily RHR measurements with traditional RHR values in free-living conditions, illustrating the agreement with both supine and sitting measurements. Additionally, Fig. 5 highlights the trends in daily RHR measurements over a seven-day period, comparing PHRM results with those from a reference wearable heart rate tracker, offering insight into the variability of participant data.

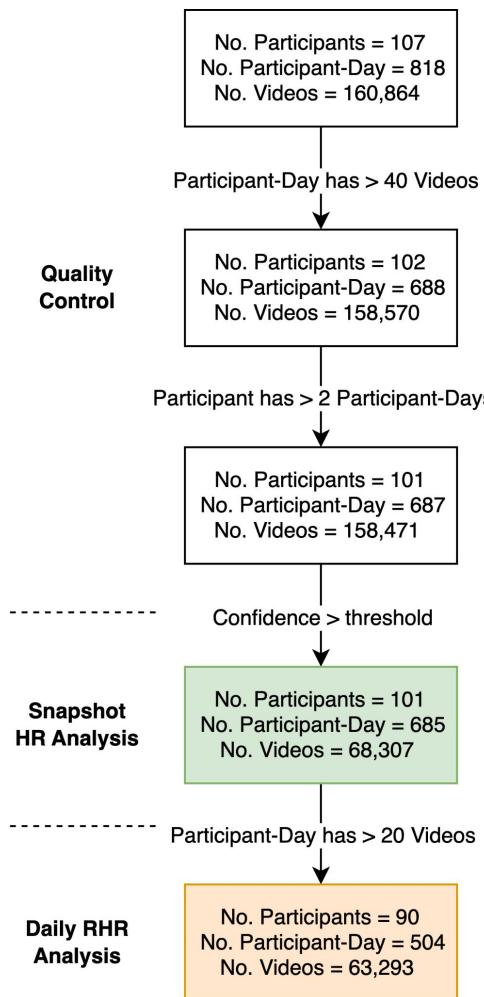
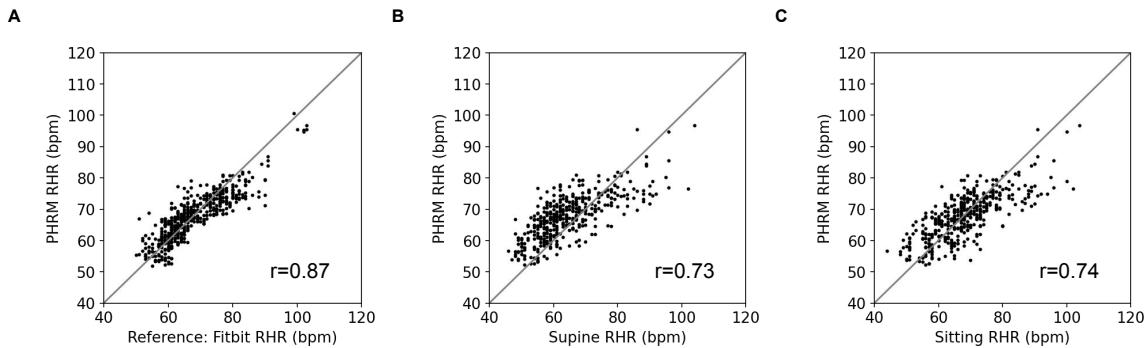
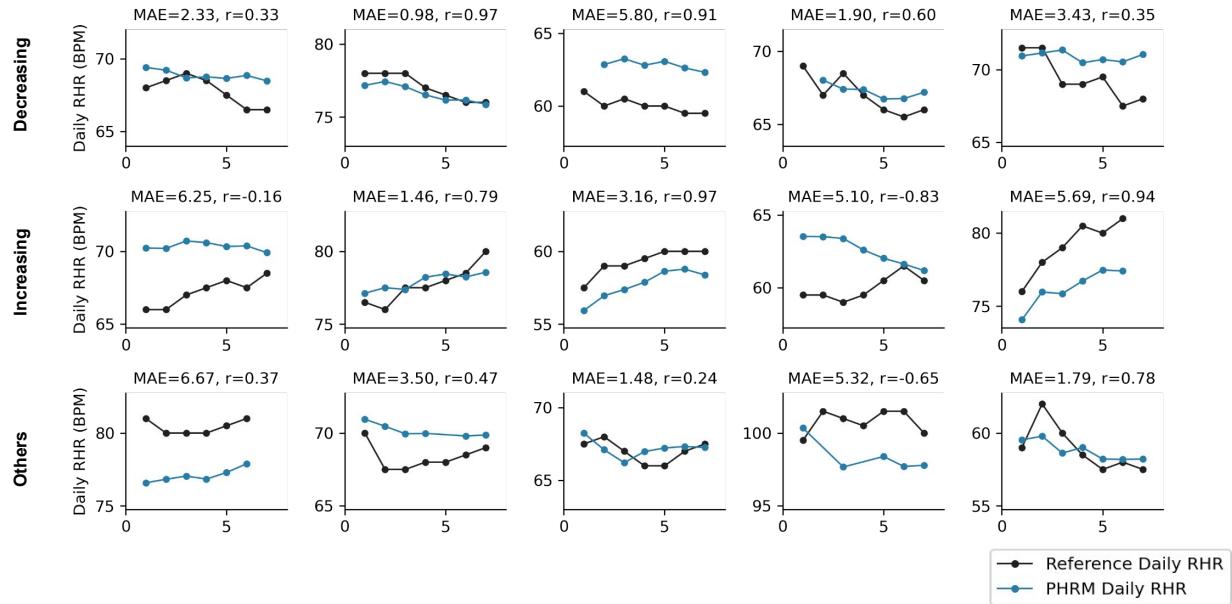


Figure 3 | Flowchart of inclusion criteria for free-living study. We excluded 6 participants who did not meet the minimum adherence criteria of at least 3 days with more than 40 video clips per day. Valid heart rate (HR) measurements determined by gating on the deep learning model's confidence scores associated with the HR predictions.



**Figure 4 | Comparison of daily RHR measurements by the PHRM against reference and traditional RHR measurements in free-living conditions.** Scatter plots showing the agreement between PHRM-estimated daily RHR values and (A) reference RHR from a Fitbit wearable HR tracker, (B) supine RHR measurements from ECG, (C) sitting RHR measurements from ECG, respectively.



**Figure 5 | Trends for daily RHR measurements over the week.** Comparison of daily RHR estimates from the proposed PHRM and a reference wearable RHR tracker over a 7-day period, sampled from participants exhibiting diverse trends. To enhance interpretability, participants were categorized into three groups based on reference wearable RHR trends: decreasing, increasing, and other patterns.

## D. PHRM Ablation Experiments

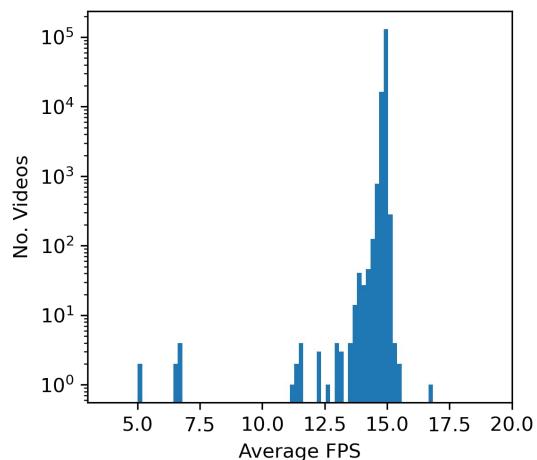
### D.1. Video Preprocessing

In this section, we analyze these preprocessing techniques to address challenges related to video stabilization, frame rate variability, resolution, and temporal consistency, which directly impact the accuracy of HR signals. By evaluating each technique’s contribution (Table 3), we aim to identify the optimal configuration that balances computational efficiency with signal retention, ensuring robust performance across diverse video conditions.

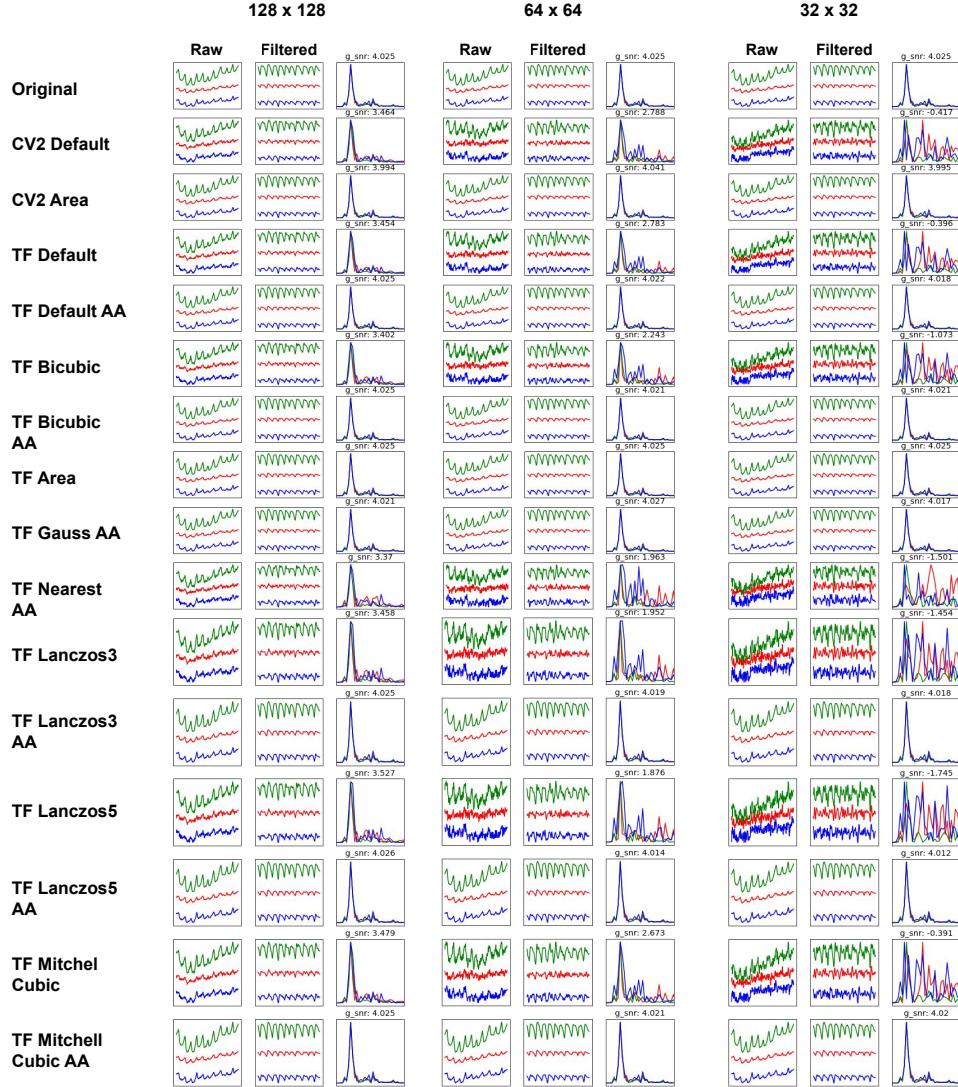
**Table 3 | Ablation Studies of Video Preprocessing.** The baseline is the reported model, trained with video stabilization, a resolution of 32x32, and frame differencing. Gated-RMSE is the Development metric, computed as RMSE after excluding the bottom 20% of videos with the lowest confidence scores. For each row, a separate hyper-parameter search was performed, and the best tune metric is presented.

	Gated RMSE
Baseline	10.37
48x48 Resolution	10.52
16x16 Resolution	NaN
No Video Stabilization	10.77
No Frame Differencing	12.08

- **Video Stabilization.** In Table 3, we compare the performance of models with and without video stabilization on the tune set. Video stabilization improved gated-RMSE by 0.40. However, while it enhanced overall performance, we observed that stabilization failed in some cases and introduced noticeable artifacts in certain videos. This presents an opportunity for further improvements.
- **Resizing.** Video resolution is critical for balancing computational cost and HR signal retention. Our goal was to identify the smallest video resolution that retains HR information and apply it consistently across frames. Fig. 7 compares 15 resizing methods from OpenCV2 and TensorFlow across three resolutions: 128x128, 64x64, and 32x32. In the illustration, the original video has a green channel SNR of 4.025. At higher resolutions (e.g., 128x128), the resizing method has little effect on HR signal retention, with SNR values ranging from 3.37 to 4.025. However, as resolution decreases, the choice of resizing method becomes more significant. At 32x32, TensorFlow’s area resizing method maintained an SNR of 4.025, matching the original video, making it the preferred method. Additionally, Table 3 compares the impact of different resolutions (48x48 and 16x16) on model training. We found that 32x32 was the minimal resolution that did not degrade performance on the tune set.
- **Frame Differencing.** Table 3 shows that removing frame differencing reduces performance on the tune set from 9.55 to 12.08.
- **Linear Interpolation.** Fig. 6 shows the average video frames-per-second (FPS) distribution for the free-living test dataset, with an average FPS of 14.94 and a standard deviation of 0.10. Notably, over 76.4% of videos have an FPS lower than 15, underscoring the need to standardize the frame rate.



**Figure 6 | Video FPS on Freeliving Test Cohort.** This figure shows the distribution of average FPS across videos, with the majority of videos falling within the 12 to 15 FPS range.



**Figure 7 | Different Resizing Methods and Resolutions.** Comparison of raw and processed signals using different resizing methods and resolutions (128x128, 64x64, 32x32). Each row represents a different resizing method, including OpenCV (CV2) and TensorFlow (TF) variants, with and without anti-aliasing (AA). The columns display raw signals, detrended and filtered signals, and the corresponding signal-to-noise ratio (SNR) values. The SNR values highlight the impact of resolution and resizing techniques on signal quality, with higher resolutions generally maintaining stronger signal integrity across different methods.

## D.2. HR Network

We conducted comprehensive ablation experiments to evaluate the effectiveness of each component in the deep model. In each experiment, a single component was modified to assess its impact on performance. The full list of ablation experiments is provided below, with performance on the tune set for each variation shown in Table 4.

**Table 4 | Ablation Studies of rPPG HR Network.** The table presents results on the tune set, showing how modifications to the network backbone, HR output head, loss functions, data augmentation techniques, and ensemble strategies affect the model’s accuracy. Each ablation study isolates a single component to assess its contribution to overall performance.

Gated RMSE		
Baseline (No Ensemble)		10.37
Architecture	Smaller Model	10.91
	Larger Model	10.42
	FFT Head and MAPE Loss	11.02
Output Head and Loss	Dense Head and MAPE Loss	11.63
	Dense Head and Focal Loss	12.75
	No Rotation	10.69
Augmentations	No Cropping and Resizing	10.61
	No Speed Augmentation	10.79
	Top 3	9.96
Ensemble	Top 5	9.92

- **Network Backbone.** We tested both smaller and larger model configurations. Our model outperformed the smaller configuration and matched the performance of the larger one.
  - Smaller model: Channel sizes of 2, 8, 16, 32 and 64.
  - Larger model: Channel sizes of 8, 32, 64, 128 and 256.
- **HR Output Head and Loss Function.** We found the model to be sensitive to the choice of HR output and loss function. As described in the Methods section, the reported approach (FFT head + Focal loss) treats HR extraction as a classification task. We also tested different combinations of output head and loss function:
  - Dense Head + Focal Loss: Replaces the FFT with a traditional dense layer and softmax to map the pseudo-PPG to HR bins, using focal loss.
  - Dense Head + MAPE Loss: Uses a dense layer to directly output a single HR value from the pseudo-PPG.
  - FFT Head + MAPE Loss: Applies a weighted sum of HR probabilities and HR bins, using MAPE loss between predicted and ground truth HR values.
- **Data Augmentation.** We evaluated the impact of removing each augmentation method on tune performance. Each contributed between 0.30 and 0.42 gated-RMSE points.
  - No Rotation: Removes rotation.
  - No Cropping and Resizing: Removes cropping and resizing.
  - No Speed Augmentation: Removes speed augmentation.
- **Ensemble.** Lastly, we compared various ensemble strategies:
  - Top 3 Checkpoints: Ensembles predictions from the top 3 models.
  - Top 5 Checkpoints: Ensembles predictions from the top 5 models.

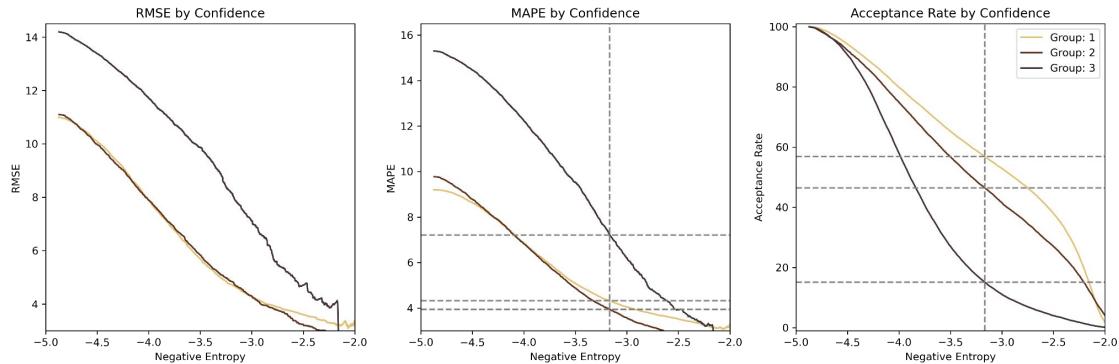
### D.3. Confidence Gating

We evaluated two alternatives for obtaining confidence scores: the maximum of HR probabilities and the pseudo-PPG SNR. Table 5 compares their performance on the tune dataset. When the acceptance rate was set to 80%, negative entropy demonstrated superior performance over both alternatives.

**Table 5 | Confidence Gating Alternatives.** This table presents the performance of two confidence scoring methods—maximum of HR probabilities and pseudo-PPG SNR—on the tune dataset. Negative entropy demonstrated superior results when the acceptance rate was set to 80%.

Gated RMSE		
Baseline		9.92
Alternatives	Maximum of HR Probabilities	10.04
	Pseudo PPG SNR	11.53

Fig. 8 illustrates the process of determining the confidence threshold using the free-living tune dataset. As outlined in the Methods section, the goal was to set a threshold where the MAPE for each skin tone group remains below 8, and the MAPE difference between groups is less than 3. Based on this criterion, we selected a negative entropy threshold of -3.17, highlighted by the gray line in the figure.



**Figure 8 | Confidence Gating Threshold Search.** This figure illustrates the process of determining the optimal confidence threshold using the free-living tune dataset. The negative entropy threshold was set at -3.17 (indicated by the gray line) to ensure that the MAPE for each skin tone group remained below 8 and the MAPE difference between groups was less than 3.

#### D.4. Hyper-Parameters

This subsection details the hyper-parameter choices that were chosen by search algorithm.

**Table 6 | Hyper-parameter Choices.** We presents the hyper-parameters for top 5 runs in Tune dataset, and these runs were chosen automatically by searching algorithm.

random_crop_with_resize		random_flip	random_speed			Optimizer	
probablity	minimal crop size	probablity	min_speed	max_speed	probablity	batch size	learning rate
7.63109	0.577256	0.412314	0.85	1.15	1	32	0.003
7.64416	0.615019	0.406043	0.85	1.154268	1	32	0.003
7.624905	0.752059	0.300096	0.85	1.15	1	32	0.003
7.697844	0.557755	0.445152	0.85	1.15	1	64	0.003
7.655166	0.580071	0.408653	0.849836	1.15	0.999916	32	0.003