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Vital Signs Measurement Using a Smartphone Camera and a Designated Application at the Hospital-at-Home Setting. A Clinical Validation Study

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Abstract

Background.

Hospital-at-Home (HaH) has become a viable alternative to in-hospital stay, worldwide. Reliable vital signs measurement in this setting is of utmost importance. The validity of vital signs acquisition through the use of cellular applications has not been previously explored.

Methods.

This was a prospective, controlled clinical trial in the HaH setting. We compared vital signs of HaH patients, sequentially appreciated by a cellular application measurements (CAM) and by conventional measurement (CM) performed by a nurse, in the patients' homes.

Results.

Vital signs were compared for 91HaH patients (median age 65 years (IQR 22), with 47.3% females), 77.3% patients were classified as bright/white skin tone. CAM heart rate (HR) was median 75 bpm (IQR 21) vs. 77 bpm (IQR 20) by CM, ($p = 0.053$); CAM of systolic blood pressure (SBP) was 124 mmHg (IQR 24.5) vs. 116 mmHg (IQR 20) by CM, ($p = 0.018$); CAM of diastolic blood pressure (DBP) was 75.0 mmHg (IQR 16) vs. 76.0 mmHg (IQR 15) by CM, ($p = 0.599$); CAM respiratory rate (RR) was 18 breaths/min (IQR 6) vs. 16 breaths/min (IQR 5.75) by CM, ($p = 0.003$); CAM oxygen blood saturation was 97.0% (IQR 3) vs. 98.0% (IQR 1) by CM, ($p = 0.002$). Agreement between methods measured by Interrater reliability (ICC) was moderate for HR (ICC = 0.71), lower for RR (ICC = 0.37) and poor for SBP measurement (ICC = 0.21). ICC values for DBP and SpO_2 were − 0.03 and 0.06 respectively. In a multivariable analysis, darker skin categories were associated with substantial bias in diastolic blood pressure estimation.

Conclusions.

Our findings indicate that CAM technology can estimate some physiological parameters, particularly heart rate, but other measurements show limited agreement with standard monitoring. While promising for remote care such as HaH when conventional measurement is unavailable, broader validation, algorithm improvement, and rigorous clinical evaluation are essential before routine, widespread clinical use.

Introduction

Importance of vital signs' measurements in acutely ill patients.

Vital signs are fundamental physiological parameters that provide essential information about the clinical status of patients with acute illness. Measurements such as heart rate (HR), respiratory rate (RR), blood pressure (BP), and oxygen saturation (SpO_2) serve as core indicators used to assess acute illness, guide clinical decision-making, and monitor patient trajectories during hospitalization. Beyond their role in identifying early signs of clinical deterioration, vital signs also provide objective measures of patient recovery and response to treatment, allow longitudinal monitoring of physiological stability, and serve as baseline physiological indices that guide clinical documentation and communication among healthcare providers. Because of their central role in clinical assessment, accurate and reliable measurement of vital signs remains a cornerstone of modern medical care (1).

Changes in vital signs frequently precede adverse clinical outcomes, including in-hospital mortality. A systematic review evaluating the predictive value of vital sign trends in acutely ill patients demonstrated that alterations in physiological parameters, particularly respiratory rate, are strongly associated with pending patient deterioration (2). Studies included in the review showed that respiratory rate alone can predict clinical deterioration with moderate accuracy, and that incorporating measured variability in respiratory rate over time further improves predictive performance (3). Similarly, changes in early warning scores derived from vital signs have been shown to correlate with mortality risk, with respiratory rate contributing substantially to risk stratification (4). These findings highlight the importance of vigilant monitoring of vital sign trends, as easily recordable in-hospital physiological changes often precede clinically apparent deterioration.

Challenges and pitfalls in vital signs' measurements.

Despite their clinical importance, vital signs monitoring in hospital settings remains imperfect. In many institutions measurements are obtained intermittently, and inaccuracies in recording or delayed clinical responses to abnormal values have been widely reported: some due to technical problems and others due to inappropriate measurement techniques (5, 6). Furthermore, patients who initially present with normal vital signs may still experience significant clinical deterioration shortly after admission. Observational studies of patients admitted with initially stable measurements have demonstrated that nearly one-third deteriorate within the first 24 hours of hospitalization (7). These findings underscore the need for more effective and reliable methods of monitoring physiological parameters throughout the course of illness.

Advances and innovations in the realm of vital signs' measurements.

Advances in medical technology have introduced new opportunities for continuous and remote monitoring of vital signs. Wearable monitoring devices, for example, have been investigated as tools for improving detection of clinical deterioration. In studies comparing continuous monitoring devices with routine nursing observations, continuous monitoring identified numerous episodes of physiological instability that occurred between standard intermittent assessments (8, 9). Larger systematic reviews have similarly demonstrated that both continuous and enhanced intermittent monitoring strategies can

improve the detection of patient deterioration and increase rapid-response team activations, although their effects on major outcomes such as Intensive Care Unit (ICU) admission remain uncertain (10).

Among vital signs, BP measurement plays a particularly important role in both acute and chronic disease management. Hypertension is one of the most significant modifiable risk factors for cardiovascular disease, chronic kidney disease, and premature mortality worldwide (11, 12). Accurate measurement of BP is therefore essential not only for the acute assessment of hospitalized patients but also for long-term disease prevention and management. Traditional cuff-based sphygmomanometer remains the standard method for BP measurement; however, out-of-office monitoring methods, including ambulatory and home BP measurements have become increasingly important for improving diagnostic accuracy and guiding treatment decisions (13–15).

Importance of vital signs' monitoring in the HaH setting.

In parallel with developments in physiological monitoring technologies, telemedicine-based models of care have expanded rapidly in recent years. Hospital-at-Home (HaH) programs allow selected patients with acute medical conditions to receive hospital-level care while remaining in their homes, supported by remote monitoring and clinical oversight. Several studies have demonstrated the feasibility and safety of this approach. Remote monitoring technologies have been successfully used to manage conditions such as electrolyte disturbances and cardiac rhythm abnormalities in HaH settings, enabling clinicians to maintain continuous physiological surveillance without requiring traditional hospital admission (16, 17). These advancements play a key role in expanding access to care while preserving patient safety in remote environments.

Optical, Camera-based technologies for vital signs' measurement.

Alongside aforementioned developments, optical camera-based technologies have emerged as a novel approach for measuring physiological signals without physical contact with the patient. Remote photoplethysmography (rPPG) enables estimation of cardiovascular and respiratory parameters by analyzing subtle color changes in facial skin captured by digital cameras. Reviews of this technology have highlighted its potential for telemedicine applications while emphasizing the need for robust clinical validation studies (18). Although several smartphone-based approaches to BP estimation have been proposed, substantial variability exists in methodology and validation standards across studies (19).

Recent investigations have demonstrated promising results under controlled experimental conditions. Machine-learning–based optical imaging systems have been shown to estimate BP from facial blood-flow signals with measurement accuracy approaching clinically acceptable thresholds (20). Smartphone-based applications utilizing optical and sensor-derived physiological signals have also demonstrated acceptable agreement with conventional cuff-based measurements in validation studies (21). Similarly, rPPG systems have shown strong concordance with standard monitoring methods for parameters such as heart rate and respiratory rate in clinical environments (22). However, systematic reviews emphasize

that important challenges remain, particularly regarding performance in real-world clinical settings where motion artifacts, lighting conditions, and patient characteristics may affect measurement accuracy (23).

Given the rapid development of remote monitoring technologies and the growing adoption of HaH care models, rigorous validation of camera-based physiological measurement systems is essential. Reliable smartphone-based monitoring tools could significantly enhance the feasibility of remote patient monitoring by enabling patients to measure vital signs without specialized equipment or direct clinician supervision.

Study Objective

The aim of the present study was to evaluate the accuracy and reliability of smartphone camera–based optical measurement of vital signs using the FaceHeart Vitals™ application in an HaH setting. Specifically, the study compared vital signs obtained using conventional measurement methods with those obtained through the FaceHeart Vitals™ smartphone-based system in acutely ill patients in the HaH settings. By assessing agreement between conventional and camera-based measurements, this study seeks to determine whether smartphone-based optical technologies, and specifically the FaceHeart application, can provide clinically reliable physiological monitoring in remote care environments.

Results

A total of 98 patients were initially recruited into the study. Seven patients were excluded due to missing laboratory values at the time of admission and/or at the time of vital signs measurements. The final study cohort therefore consisted of 91 patients (92.9% of the initially recruited participants), who were included in the final analysis. Missing values were handled as missing observations and were not imputed. Accordingly, the sample size for each analysis reflects the number of available observations for the variables included in that specific analysis.

Patients’ demographics and medical history

Baseline characteristics are summarized in Table 1. The median age was 65 years (IQR 22), with 47.3% females. Median BMI was 25.32 kg/m² (IQR 6.73), and the cohort included a majority of 77.3% patients with bright/white skin tone. Most patients (63.6%) did not have a documented history of hypertension. Majority of patients were admitted to the HaH service from the hospital ward (82.4%). The most common comorbidity included malignancy (42.9%), followed by cardiovascular disease (34.1%), respiratory disease (25.3%), diabetes mellitus (24.2%), and chronic kidney disease (25.3%). The most common chronic medication was for hypertension (39.6%), followed by immune suppressants (25.3%), diabetes mellitus (23.1%), and cholesterol lowering agents (22%). The median HaH length of stay (LOS) was 4 days (IQR 3), and a minority of patients (5.5%) deteriorated and were transferred to the hospital from home care. No patient died during this study.

Vital sign measurements

Median CM HR was 75 bpm (IQR 21) compared to CAM 77 bpm (IQR 20), CM SBP was 124 mmHg (IQR 24.5) compared to CAM 116 mmHg (IQR 20), CM DBP was 75.0 mmHg (IQR 16) compared to CAM 76.0 mmHg (IQR15), CM RR was 18 breaths/min (IQR 6) compared to CAM 16 breaths/min (IQR 5.75), SpO_2 was 97.0% (IQR 3) compared to CAM 98.0% (IQR 1).

Pairwise comparison

Paired comparisons are shown in Table 2. For pulse, the mean difference between CAM and CM was −2.01 bpm (95% CI -4.04 to 0.02), which did not reach statistical significance (p = 0.053). In contrast, CAM measured significantly lower SBP than the CM, with a mean difference of -4.84 mmHg (95% CI -8.83 to -0.84, p = 0.018). For DBP, the mean difference was 0.75 mmHg (95% CI -2.06 to 3.56, p = 0.60), indicating no significant average difference between methods. CAM also measured significantly lower respiratory rate, with a mean difference of -1.59 breaths/min (95% CI -2.62 to -0.55, p = 0.0032). For oxygen saturation, CAM measured significantly higher values, with a mean difference of 0.90% (95% CI 0.33 to 1.47, p = 0.002).

Agreement, reliability, and accuracy

Agreement between CAM and CM varied substantially by parameter and is summarized in Table 3. HR showed the strongest agreement, with an ICC of 0.71, indicating moderate agreement, as well as a mean bias of -2.01 bpm with limits of agreement from − 21.15 to 17.13 bpm. RR demonstrated lower agreement (ICC 0.37) with a mean bias of -1.59 breaths/min, and limits of agreement from − 10.85 to 7.67 breaths/min. Finally, SBP agreement was poor (ICC 0.21) with a mean bias of -4.84 mmHg, and wide limits of agreement from − 42.40 to 32.73 mmHg. DBP and oxygen saturation showed essentially no meaningful agreement, with ICC values of -0.03 and 0.06, respectively. DBP showed a mean bias of 0.75 mmHg, with limits of agreement from − 25.72 to 27.21 mmHg. Oxygen saturation showed a mean bias of 0.90%, with limits of agreement from − 4.49 to 6.30%. Overall, HR was the best-performing parameter, whereas BP and SpO_2 demonstrated limited agreement with conventional monitoring. Moreover, these analyses indicate that, despite relatively small average bias for some parameters, the individual-level agreement between methods was often wide, particularly for blood pressure.

Accuracy metrics further supported these findings. CAM pulse measurements had a MAE of 5.92 bpm, and an RMSE of 9.92 bpm. For SBP, MAE was 14.46 mmHg and RMSE 19.66 mmHg; for DBP, MAE was 10.70 mmHg and RMSE 13.45 mmHg. Respiratory rate showed an MAE of 3.73 breaths/min and an RMSE of 4.96 breaths/min. SpO_2 showed an MAE of 2.13% and an RMSE of 2.88%. Taking together, these accuracy metrics indicate that HR was the most accurate parameter measured by CAM, while blood pressure measurements were associated with substantially larger errors.

Clinical classification agreement

Clinical classification agreement was also limited for most parameters and is summarized in Table 4. For BP classification using AHA categories, agreement was poor, with Cohen's weighted kappa 0.186. For pulse classification into bradycardia, normal, and tachycardia, agreement was higher, with Cohen's weighted kappa 0.569, representing the best categorical agreement among all studied parameters. RR classification showed low agreement, with Cohen's weighted kappa = 0.295. For classification into normal versus hypoxemia, agreement was absent, with Cohen's kappa equal to 0. This is explained, as all CAM oxygen saturation measurements fell in the normal category, whereas CM identified 12 hypoxemic patients.

Measurement error

Univariate analyses were performed for both signed measurement error (CAM – CM) and absolute measurement error. Variables associated with an outcome at $p < 0.1$ were entered into multivariable models. Corrected multivariable models identified several independent predictors of measurement error: For pulse signed error, higher hemoglobin remained independently associated with greater positive bias in CAM pulse measurements (β = 1.54 (95% CI 0.35 to 2.74); p = 0.012). For HR absolute error, several independent associations were observed: brown skin tone versus bright/white skin tone was associated with larger absolute pulse error (β = 7.23 (95% CI 3.31 to 11.14); p < 0.001), diabetes mellitus with larger absolute HR error (β = 5.12 (95% CI 1.35 to 8.89); p = 0.008), higher conventional SBP with smaller absolute pulse error (β = -0.107 (95% CI -0.196 to -0.019); p = 0.018), and higher hemoglobin with smaller absolute pulse error (β = -1.13 (95% CI -2.12 to -0.15); p = 0.024). For SBP signed error, malignancy showed borderline significance in the multivariable model (β = -8.16 (95% CI -16.35 to 0.03); p = 0.051), while no independent predictors reached conventional statistical significance for SBP absolute error. For DBP signed error, brown skin tone versus bright/white skin tone was independently associated with more negative DBP bias (β = -11.88 (95% CI -18.43 to -5.32); p < 0.001), higher platelet count was associated with lower DBP signed error (β = -0.035 (95% CI -0.060 to -0.011); p = 0.005), and dementia was associated with markedly higher DBP signed error (β = 26.41 (95% CI 0.88 to 51.94); p = 0.043). No independent predictors were retained for DBP absolute error. For RR signed error, no variable reached statistical significance in multivariable analysis, although higher conventional temperature remained borderline (β = 1.66 (95% CI -0.05 to 3.37); p = 0.056). For RR absolute error, dark skin tone versus bright/white skin tone was associated with greater absolute RR error (β = 4.11 (95% CI 0.34 to 7.88); p = 0.033), higher creatinine with greater absolute RR error (β = 0.99 (95% CI 0.01 to 1.97); p = 0.048), and cholesterol-lowering medication use with lower absolute RR error (β = -1.74 (95% CI -3.48 to -0.01); p = 0.049). For SpO_2 signed error, female sex was independently associated with lower signed SpO_2 error (β = -1.88 (95% CI -3.01 to -0.74); p = 0.002), while higher sodium (β = 0.253 (95% CI 0.072 to 0.433); p = 0.007), higher conventional HR (β = 0.061 (95% CI 0.014 to 0.109); p = 0.012), history of HTN (β = -1.81 (95% CI -3.24 to -0.38); p = 0.014), cholesterol-lowering medication use (β = 1.54 (95% CI 0.20 to 2.87); p = 0.024), and higher neutrophil percentage (β = 0.048 (95% CI 0.003 to 0.093); p = 0.037) were also independently associated with signed error. For SpO_2 absolute error, higher hemoglobin (β = 0.323 (95%

CI 0.078 to 0.568); p = 0.010) and higher conventional temperature (β = 0.736 (95% CI 0.097 to 1.376); p = 0.025) were associated with greater absolute error.

Table 1
Patients' demographics and medical history

Patients' Characteristics	**Total Cohort [N = 91]**
Demographics	
Admitted from Home; [N (%)])	4 (4.4)
Admitted from ER; [N (%)])	12 (13.2)
Admitted from Ward; [N (%)])	75 (82.4)
Age; (Years; Median [IQR])	65 [22]
Gender (Female; [N (%)])	43 (47.25)
Weight (Kg; Median [IQR])	76 [24.38]
Height (Cm; Median [IQR])	170 (13)
BMI; Median [IQR]	25.32 [6.73]
Skin Tone: Bright/White; [N (%)]	68 (77.3)
Skin Tone: Brown; [N (%)]	17 (19.3)
Skin Tone: Dark; [N (%)]	3 (3.4)
Vitals at Admission – CM	
Pulse (BPM; Median [IQR])	75 [21]
SBP (mmHg; Median [IQR])	124 [24.5]
DBP (mmHg; Median [IQR])	75 [16]
RR (Breaths/min; Median [IQR])	18 [6]
SpO_2 (%; Median [IQR])	97 [3]
Vitals at Admission – CAM	
Pulse (BPM; Median [IQR])	77 [20]
SBP (mmHg; Median [IQR])	116 [20]
DBP (mmHg; Median [IQR])	76 [15]
RR (Breaths/min; Median [IQR])	16 [5.75]
SpO_2 (%; Median [IQR])	98 [1]
Laboratory Values at Admission	
CRP (mg/L; Median [IQR])	81.51 [97.45]
WBC/μL; Median [IQR]	8.28 [4.14]

Patients' Characteristics	Total Cohort [N = 91]
Neutrophils (%; Median [IQR])	73.2 [13.5]
PLT/μL; Median [IQR]	222 [121]
Hemoglobin (g/dL; Median [IQR])	11.89 [2.23]
Creatinine (mg/dL; Median [IQR])	0.83 [0.29]
Urea (mg/dL; Median [IQR])	31 [22]
Sodium (mEq/L; Median [IQR])	140 [4]
Potassium (mEq/L; Median [IQR])	4.10 [0.65]
Background Diagnoses	
Malignancy; [N (%)]	39 (42.9)
Background HTN [N (%)])	15 (17.0)
Cardiovascular disease; [N (%)]	31 (34.1)
Respiratory disease; [N (%)]	23 (25.3)
Diabetes Mellitus; [N (%)]	22 (24.2)
Chronic Kidney Disease; [N (%)]	23 (25.3)
Background medications	
Hypertension; [N (%)]	36 (39.6)
Diabetes Mellitus; [N (%)]	21 (23.1)
Cholesterol; [N (%)]	20 (22)
Immune Suppressants; [N (%)]	23 (25.3)
Clinical outcomes	
Length of Stay (Days; Median [IQR])	4 [3]
Discharged Home; [N (%)])	86 (94.5)
Transferred to Hospital; [N (%)])	5 (5.5)

Table 2
Paired comparisons

Parameter	CM Mean ± SD	CAM Mean ± SD	MAE	RMSE	Mean difference (CAM - CM)	95% CI	P value
HR (bpm)	77.8 ± 13.3	75.8 ± 12.6	5.923	9.918	-2.011	-4.0448, 0.0228	0.0526
SBP (mmHg)	126.2 ± 17.7	121.3 ± 12.5	14.462	19.663	-4.8352	-8.8265, -0.8439	0.0181
DBP (mmHg)	75.4 ± 10.4	76.1 ± 8.3	10.703	13.448	0.7473	-2.0647, 3.5592	0.5988
RR (/min)	18.4 ± 4.4	16.8 ± 4.1	3.732	4.956	-1.5854	-2.6234, -0.5473	0.0032
SpO_2 (%)	96.3 ± 2.4	97.2 ± 1.5	2.132	2.882	0.9011	0.3278, 1.4744	0.0024

Table 3
Level of agreement *LoA, Level of agreement;*

Parameter	ICC	Bias (Mean Error)	SD of differences	Lower LoA	Upper LoA
Pulse (bpm)	0.7092	-2.011	9.7656	-21.1515	17.1295
SBP (mmHg)	0.2105	-4.8352	19.1649	-42.3984	32.7281
DBP (mmHg)	-0.0296	0.7473	13.5019	-25.7165	27.211
RR (/min)	0.3731	-1.5854	4.7244	-10.8452	7.6744
SpO_2 (%)	0.0546	0.9011	2.753	-4.4948	6.297

Table 4
Clinical classification agreement

Clinical classification	Agreement (κ)	Interpretation
Blood Pressure (AHA categories)	0.1859	Slight Agreement
Pulse (bradycardia / normal / tachycardia)	0.5687	Moderate Agreement
Respiratory rate (bradypnea / normal / tachypnea)	0.2948	Fair Agreement
SpO2 (normal / hypoxemia)	0	No Agreement

Discussion

In this validation study, we evaluated the ability of a smartphone application, which uses camera-based PPG technology, to estimate vital signs in patients hospitalized in an HaH setting. Overall, the results demonstrate feasibility for vital signs' measurement in the HaH settings, with variability in performance across physiological parameters, with acceptable performance for heart rate estimation but lower agreement with conventional measurements for blood pressure, respiratory rate, and oxygen saturation.

Across all analytic approaches, pulse rate consistently demonstrated the best performance among the evaluated parameters. Pulse measurements showed moderate agreement with conventional monitoring and the lowest error magnitude among the studied vital signs, with a mean absolute error of approximately 5.9 bpm and a root mean square error of 9.9 bpm. Although this level of error is not negligible, similar performance ranges have been reported in previous studies evaluating camera-based PPG systems for heart rate estimation. Several experimental studies of smartphone-based or camera-based PPG have demonstrated mean absolute heart rate errors typically ranging between 2–8 bpm under controlled conditions, with performance often deteriorating in real-world settings due to motion artifacts, ambient lighting variability, and patient-specific factors (28–30). These findings suggest that heart rate estimation remains the most robust physiological parameter obtainable from camera-based PPG, likely because the pulsatile changes in blood volume underlying heart rate detection generate a relatively strong optical signal compared with more complex physiological parameters. Our findings support the use of CAM for HR follow up in the HaH settings, for the purpose of earlier potential patients' deterioration.

In contrast to the above, blood pressure estimation demonstrated lower agreement with conventional measurements. Both systolic and diastolic BP measurements showed low reliability, wide limits of agreement, and substantial measurement error. The mean absolute error exceeded 14 mmHg for systolic blood pressure and 10 mmHg for diastolic blood pressure, with Bland–Altman limits of agreement spanning several tens of millimeters of mercury. These findings indicate that CAM-derived BP values cannot be considered interchangeable with conventional blood pressure measurements in the clinical context evaluated in this study. This limitation is consistent with the well-recognized challenges of estimating blood pressure from optical signals alone. Unlike heart rate detection, which directly reflects pulsatile blood flow, blood pressure estimation requires either oscillometric measurement, calibrated pulse wave analysis, or additional physiological modeling. As a result, attempts to derive blood pressure from single-site optical PPG signals remain an active area of research but have not yet demonstrated sufficient reliability for clinical use in previous publications (31, 32).

Respiratory rate estimation also demonstrated limited reliability. Although the mean absolute error was approximately 3–4 breaths per minute, the agreement with conventional measurements remained modest and Bland–Altman analysis revealed relatively wide limits of agreement. RR estimation using optical PPG signals typically relies on indirect physiological effects, such as respiratory modulation of the pulse waveform or subtle motion-related changes in facial perfusion. Because these signals are weaker and more susceptible to motion artifacts than the primary pulsatile signal used for heart rate detection, variability in respiratory rate estimation is not unexpected (33).

Similarly, oxygen saturation estimation demonstrated limited clinical reliability in this cohort. Although the average measurement error was modest (MAE ≈ 2.1%), categorical analysis revealed a critical limitation: CAM failed to identify any of the hypoxemic cases detected by CM. As a result, categorical agreement for oxygen saturation classification was essentially absent. Because detection of hypoxemia is the principal clinical purpose of pulse oximetry, this finding raises important concerns regarding the clinical safety of relying on camera-based oxygen saturation estimation without further validation.

An additional finding of this study was the association between patient-specific physiological characteristics and measurement accuracy. In the multivariable analysis, hemoglobin concentration was associated with pulse measurement bias and accuracy. Higher hemoglobin levels were associated with increasing positive bias in signed pulse error but with smaller absolute pulse error, suggesting improved measurement stability in patients with higher hemoglobin concentrations. This observation is physiologically plausible, as hemoglobin is the primary chromophore responsible for light absorption in the wavelength ranges typically used for PPG (34). Variations in hemoglobin concentration can therefore influence the amplitude and signal-to-noise ratio of PPG signals, potentially affecting algorithmic performance.

Skin tone was also associated with measurement error for several parameters. In multivariable analysis, darker skin categories were associated with significantly larger absolute HR error and RR error, and with substantial bias in diastolic blood pressure estimation. For example, brown skin tone was associated with an increase of approximately 7 bpm in absolute pulse error, while darker skin categories demonstrated marked shifts in diastolic blood pressure error. These findings are consistent with previously described limitations of optical sensing technologies across different levels of skin pigmentation. Camera-based PPG relies on detecting subtle variations in light absorption and reflection within the dermal microvasculature. Melanin, the principal determinant of skin pigmentation, absorbs light across a broad range of wavelengths and can reduce the amount of light that penetrates to deeper vascular structures and returns to the camera sensor. As a result, higher melanin concentrations may reduce the signal-to-noise ratio of PPG signals and increase measurement variability. Similar effects have been described in other optical monitoring technologies. Studies of pulse oximetry have demonstrated that oxygen saturation measurements may be systematically biased in individuals with darker skin pigmentation, particularly at lower saturation levels (35, 36). Experimental studies of rPPG have also reported reduced signal quality and increased measurement variability in individuals with higher skin pigmentation levels (37). Our findings therefore add to a growing body of literature suggesting that optical monitoring technologies may exhibit differential performance across skin pigmentation levels, underscoring the importance of validating digital health tools across diverse patient populations.

Conclusion

Taken together, the results of this study suggest that while CAM may be capable of estimating certain physiological parameters, most notably heart rate, the observed variability and limited agreement for

other parameters indicate that these measurements cannot currently be considered interchangeable with conventional monitoring methods. Further algorithm refinement and expanded validation across diverse populations, and careful clinical evaluation will be required before such technologies can be reliably integrated into routine, professional clinical practice.

The present findings further emphasize the importance of independent validation of digital health technologies prior to extensive clinical implementation. Smartphone-based monitoring tools offer considerable theoretical advantages for remote monitoring and telemedicine, particularly in HaH care models. However, the adoption of such technologies must be guided by rigorous evaluation of measurement accuracy and reliability. Technologies that provide physiologic estimates without adequate validation may introduce clinical risk if their results are used for medical decision-making.

Notwithstanding the above, we find CAM technology useful for vital signs measurement when conventional measurements, performed by professional clinical staff or family members, in the HaH settings are not available. Reliable heart rate measurements may aid in early recognition of physiological stress and other vital signs could be interpreted in accordance with our findings above.

Limitations

Several limitations of this study should be considered when interpreting the results. First, the use the CAM requires the device to be held steadily in front of the patient's face for approximately 30–60 seconds while measurements are acquired. This requirement may present practical challenges, particularly among elderly patients or individuals with reduced mobility, tremor, or cognitive impairment. Because our study population consisted primarily of older adults receiving HaH care, it is possible that motion artifacts or difficulty maintaining a stable position contributed to variability in measurement accuracy. In real-world use, this requirement may limit the practicality of the technology in certain patient populations.

Second, conventional blood pressure measurements were obtained using an inflatable cuff, which is known to induce a transient sympathetic response in some patients. The well-described 'white coat' phenomenon may lead to temporary elevations in blood pressure and heart rate during cuff inflation. Because CAM do not involve cuff inflation, it is possible that some of the observed differences between the two methods, particularly the tendency toward lower CAM blood pressure and pulse readings may partly reflect this physiological effect rather than purely measurement inaccuracy.

Third, the age distribution of the study population may also influence the generalizability of the findings. The cohort consisted primarily of older adults, reflecting the typical demographic profile of HaH programs. Age-related changes in skin physiology, including thinning of the epidermis, altered dermal vascularization, and changes in skin elasticity, may influence optical signal detection. These factors could potentially affect the performance of camera-based PPG algorithms and therefore limit extrapolation of our findings to younger populations.

Fourth, this study evaluated single time-point measurements rather than repeated longitudinal measurements. Physiological parameters such as heart rate, respiratory rate, and blood pressure may vary over time, and repeated measurements could provide additional insights into measurement stability and reproducibility. Future studies incorporating repeated measurements may therefore provide a more comprehensive assessment of algorithm performance.

Finally, while the sample size of this study was sufficient for method comparison analyses, it remains relatively modest for identifying predictors of measurement error in multivariable models. Some of the associations observed between patient characteristics and measurement error should therefore be interpreted cautiously and may require confirmation in larger cohorts.

Methods

Study Design.

This was a prospective, within-patient comparative study conducted in the HaH service of Sheba-BEYOND, the Chaim Sheba Medical Center arm for telemedicine services. The study protocol was approved by the institutional review board of Chaim Sheba Medical Center (IRB approval #SMC-1341-24). Patients admitted to the Sheba-BEYOND HaH program between March 2025 and February 2026 were prospectively screened for participation. The study objectives, procedures, and potential risks were explained to all eligible participants, and written informed consent was obtained prior to enrollment. Eligibility criteria included adults aged ≥ 18 years who were hospitalized in the HaH service due to acute illness, were mentally competent to provide informed consent and physically able to undergo conventional vital sign measurements. Participants were allowed to withdraw from the study at any stage without affecting their medical care.

Following enrollment, demographic and clinical data were extracted from the electronic medical records of participating patients. Extracted information included demographic characteristics, medical history, chronic medications, laboratory values, and clinical outcomes. All patient data were anonymized and stored in accordance with institutional review board regulations.

Each patient had their vital signs measured using both conventional clinical methods by the nurse, during her home visit and the FaceHeart Vitals™ smartphone application. All measurements were performed in the patients' homes by trained medical staff members as part of routine clinical care. Conventional measurements included pulse rate, BP, RR, SpO_2, and body temperature. BP was measured using a standard sphygmomanometer cuff, and oxygen saturation was measured using a pulse oximeter. Conventional measurements served as the reference standard against which FaceHeart measurements were compared. Immediately following the conventional measurements, vital signs were measured using the FaceHeart smartphone application on a designated operational device used by the clinical staff. The application provided measurements of heart rate, BP (both SBP and DBP), RR, and SpO_2 using camera-based optical technology. Both conventional and FaceHeart measurements were

recorded using a standardized data collection form. In addition, the medical staff member performing the measurements recorded each participant's skin tone (categorized as bright/white, brown, or dark.

Statistical Analysis

Continuous variables were evaluated for distribution using graphical inspection, including histograms and Q–Q plots. Normally distributed variables are presented as mean ± standard deviation (SD), while non-normally distributed variables are presented as median and interquartile range (IQR). Categorical variables are presented as counts and percentages.

Paired measurements of physiological parameters obtained using CM and CAM were compared for the following vital signs: pulse rate, systolic blood pressure (SBP), diastolic blood pressure (DBP), RR, and SpO_2. For each parameter, paired t-tests were performed to evaluate whether the mean difference between measurements differed significantly from zero. A statistically significant result indicated systematic bias between the two measurement methods. Agreement between CAM and CM was evaluated using several complementary approaches. Reliability between measurement methods was assessed using the intraclass correlation coefficient (ICC), which quantifies the consistency between paired measurements obtained by two methods. ICC values were interpreted according to commonly accepted thresholds: poor agreement (< 0.5), moderate agreement (0.5–0.75), good agreement (0.75–0.9), and excellent agreement (> 0.9) (24).

Agreement between CAM and CM was further assessed using Bland–Altman analysis (25). For each vital sign, the difference between the two methods was plotted against the mean of the two measurements. Bland–Altman plots were used to visualize systematic bias and the range of expected differences between the two measurement techniques. The following parameters were calculated: mean bias (average difference between methods), standard deviation of the differences, and 95% limits of agreement calculated as bias ± 1.96 X SD.

In addition to continuous measurement agreement, agreement in clinically meaningful categories was evaluated using Cohen's kappa coefficient (26). Vital signs were categorized using established clinical thresholds. BP was categorized using the American Heart Association classification (27): normal (< 120), elevated (120–129), hypertension stage 1 (130–139), hypertension stage 2 (≥ 140). Pulse was categorized as bradycardia (< 60 bpm), normal (60–100 bpm), and tachycardia (> 100 bpm). RR was categorized as bradypnea (< 12 breaths/min), normal (12–20 breaths/min), and tachypnea (> 20 breaths/min). SpO_2 was categorized as normal (≥ 94%), and hypoxemia (< 94%). For ordinal classifications (BP, pulse, and RR), weighted kappa was used to account for the ordered nature of the categories. Kappa values were interpreted as: slight agreement (< 0.2), fair agreement (0.21–0.4), moderate agreement (0.41–0.6), substantial agreement (0.61–0.8), and almost perfect agreement (≥ 0.8).

Accuracy of CAM was summarized using the Mean Error (bias); the average difference between CAM and CM, the Mean Absolute Error (MAE), reflecting the average magnitude of measurement error, and the Root Mean Square Error (RMSE), penalizing larger errors more strongly than MAE and therefore reflecting the presence of occasional large measurement deviations.

To identify factors associated with measurement accuracy, univariate and multivariable linear regression analyses were performed. To this end, two types of outcome variables were analyzed for each physiological parameter: signed measurement error (CAM – CM), representing systematic bias; and absolute measurement error (|CAM - CM|), representing magnitude of measurement inaccuracy. Univariate linear regression analyses were first performed. Variables associated with the outcome at $p < 0.10$ were selected as candidates for multivariable modeling. Separate multivariable linear regression models were constructed for each outcome variable. To avoid mathematical coupling between predictors and outcomes, baseline vital signs corresponding to the same physiological parameter were excluded from the respective models (e.g., conventional pulse was excluded from pulse error models, and both SBP and DBP were excluded from blood pressure error models). Ordinal predictors, including skin tone, history of hypertension, and admission source, were entered into regression models as categorical variables using dummy coding. Regression results are reported as β coefficients with 95% confidence intervals (CI) and p-values. All statistical tests were two-sided, and a p-value < 0.05 was considered statistically significant.

Declarations

Human Ethics and Consent to Participate declaration

The study protocol was approved by the institutional review board of Chaim Sheba Medical Center (IRB approval #SMC-1341-24). All participating patients signed an informed consent form according to the Helsinki declaration.

Author Contribution

O.D, N.M, G.S, H.H, B.F, R.S, D.R, A.E.Z, L.A, G.B participated in the study design; O.D, N.M, G.S, H.H, B.F, R.S, D.R, A.E.Z, L.A, G.B took part of study data mining and analysis; O.D, N.M, G.S, H.H, B.F, R.S, D.R, A.E.Z, L.A, G.B took part of writing the initial manuscript and the final version for submission

Data Availability

All data supporting the findings of this study will be available with the corresponding author under requests compatible with the IRB regulations.

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