shen ai

Contactless Vital Sign Measurement with Shen.AI

Introduction

Shen.AI is a software-only device that uses remote photoplethysmography (rPPG) and remote ballistocardiography (rBCG) to extract physiological signals from a short facial video. By detecting subtle colour changes in skin caused by blood pulsations, rPPG allows contactless measurement of heart rate, heart-rate variability (HRV), breathing rate and blood pressure. In addition, the detection of tiny micro-movements of the head (rBCG) increase accuracy and robustness in low-light conditions and for skin types with higher melanin concentration. The technology works on commodity smartphone or laptop cameras and is intended to provide clinical-grade vital-sign monitoring without the need for wearable sensors. In November 2025 we completed a clinical trial in Poland on 132 adult volunteers to evaluate the accuracy of Shen.AI in estimating heart rate (HR), HRV (SDNN), breathing rate (BR) and blood pressure (systolic and diastolic). The study followed a protocol similar to earlier validations conducted in 2023, but it extended the endpoints to blood pressure and tested several video-recording durations (60 s, 45 s and 30 s). The goal of this document is to summarise the findings for marketing and fundraising purposes.

Study design and methods

Participants. A total of 132 adult volunteers were recruited from an outpatient clinic in Poland. Participants were free of acute illness and had a wide range of age, body mass and baseline blood pressures. 14 participants (10.6%) had a BMI below 20 kg/m^2, 32 were in the 20–25 kg/m^2 range, and 86 participants (65.2%) had a BMI above 25 kg/m^2. The study included 55 men (42%) and 77 women (58%). 84 participants (63.6%) had Fitzpatrick skin types I–III, while 48 (36.4%) had types IV–VI.

Measurements were repeated across two clinical visits for calibration and validation. 132 participants were measured during visit 1 (792 measurements in total), and 127 participants during visit 2 (759 measurements). Standard reference devices (12-lead ECG for HR/HRV, impedance pneumography for BR and a certified blood-pressure cuff) were used simultaneously with the Shen.AI measurements.

The study design was based on ISO 81060-2:2018, which outlines clinical investigation procedures for automated sphygmomanometers. Due to the contactless nature of the product, not all requirements of the standard could be applied. However, since no dedicated standard for remote, contactless photoplethysmography existed at the time, this norm was used as the closest applicable reference.

For HR/HRV metrics, ECG measurements from the Finapres Nova (ECG+RESP module) were used as comparators. For Breathing rate, impedance pneumography from the same device served as the primary comparator; when respiratory rate assessment was difficult, a respiratory belt transducer (TN1132/ST) was used. For blood pressure, auscultatory measurements following ISO 81060-2:2018 were used as comparators, obtained with a Precisa N+ sphygmomanometer and Duplex stethoscope (Riester).

Measurement protocol. Each participant was recorded with the front camera of a mobile device while seated. The face was illuminated only by ambient indoor lighting. No additional lighting, such as LED lamps was used. The Shen.AI software extracted rPPG and rBCG signals from a defined facial region and estimated vital signs over three time windows: 60 s, 45 s and 30 s. For heart rate a quasi-instantaneous 10-s estimate was also computed every second, but only the averaged windows are summarised here. Blood pressure estimation required a single 60-s recording; shorter durations were not evaluated, so the blood-pressure results correspond to 60-s videos only. For each participant, the blood-pressure algorithm was evaluated in two modes: one in which it was calibrated during the first visit using a cuff measurement and applied during the second visit, and another in which no calibration was used.

Analysis. Accuracy metrics were calculated by comparing Shen.AI estimates with the reference values. The primary metrics were mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), standard deviation (SD) of measurement errors, mean bias and Pearson correlation. The number of paired measurements (N) varies slightly between parameters because some recordings were excluded due to poor signal quality or reference-device artefacts.

Results

Heart rate (HR) (Range 40-120 bpm)

Heart rate estimation with Shen.AI showed very high accuracy across all recording durations. Over 784 measurements with 60-s windows the mean absolute error was 0.14 bpm and the mean percentage error was 0.2 %; the correlation with the ECG reference was r = 0.99. Shorter windows slightly increased error but the estimates remained highly correlated with the reference (Table 1). A 45-s window produced an MAE of 0.16 bpm and correlation r = 0.99, while a 30-s window yielded an MAE of 0.31 bpm with the same correlation. These results indicate that Shen.AI can deliver accurate pulse measurements even when the recording is halved to 30 s.

Table 1 – Summary of heart-rate accuracy (Shen.AI vs ECG)

Duration	N	MAE (bpm)	MAPE (%)	RMSE (bpm)	SD (bpm)	Mean bias (bpm)	Correlation
60 s	784	0.14	0.20	0.41	0.41	−0.05	0.99
45 s	759	0.16	0.24	0.45	0.45	−0.04	0.99
30 s	780	0.31	0.46	0.89	0.89	−0.07	0.99

Heart-rate variability (HRV – SDNN) (Range 0-150 ms)

Heart-rate variability was quantified using the standard deviation of normal-to-normal intervals (SDNN). A total of 776 paired measurements were analysed. The mean absolute error was 4.02 ms, corresponding to a mean percentage error of 18.36 % and a root mean square error of 6.66 ms. The correlation between Shen.AI and the ECG reference was r = 0.95. SDNN was calculated only over 60-s windows; shorter durations are not recommended for HRV estimation because they substantially increase variability and reduce accuracy.

Table 2 – Heart-rate variability (SDNN) accuracy

Duration	N	MAE (ms)	MAPE (%)	RMSE (ms)	SD (ms)	Mean bias (ms)	Correlation
60 s	776	4.02	18.36	6.66	6.54	−1.29	0.95

Breathing rate (BR) (Range 10-28 bpm)

Breathing rate was computed from oscillations in the rPPG signal. Accuracy depends strongly on the recording duration: a longer window averages more breathing cycles and reduces noise. For 713 measurements with 60-s videos the mean absolute error was 1.40 breaths per minute (bpm) and the mean percentage error was 8.50 %, with correlation r = 0.77. Reducing the window to 45 s decrease the MAE to 1.32 bpm. The 30-s window produced an MAE of 1.44 bpm and correlation r = 0.74. These results suggest that 60 s recordings are preferred for respiratory rate, while 45 s and 30 s windows still provide useful estimates for consumer applications.

Table 3 – Breathing-rate accuracy

Duration	N	MAE (bpm)	MAPE (%)	RMSE (bpm)	SD (bpm)	Mean bias (bpm)	Correlation
60 s	713	1.40	8.50	2.31	2.31	−0.22	0.77
45 s	687	1.32	8.67	2.22	2.22	0.06	0.77
30 s	708	1.44	9.64	2.45	2.45	0.08	0.74

Blood pressure (BP)

(measurements for SBP 90-170 mmHg; DBP 60-100 mmHg range and for full range separately)

Blood-pressure estimation was performed over 60-s videos because accurate BP extraction requires analysis of several pulse cycles. 30s and 45s mode was not analysed in this report. Systolic blood pressure (SBP) and diastolic blood pressure (DBP) were reported separately. Two approaches were tested: a non-calibrated mode, in which the algorithm used video-derived parameters only, and a calibrated mode, in which the algorithm applied an individual calibration coefficient derived from cuff measurements taken during the first visit.

Non-calibrated blood pressure

Across the systolic validated range of 90 and 170 mmHg (1 184 measurements) SD (standard deviation) was 11.76 mmHg and ME (bias) was 4.60. Full, unrestricted range had a SD of 12.04 mmHg with a bias (ME) 5.58 mmHg. For diastolic BP, the range to 60–100 mmHg (1 071 measurements) had a SD of 7.27 mmHg and ME (bias) of 2.57. The full dataset of 1 276 measurements yielded a SD of 8.52 mmHg and bias of 4.68.

Calibrated blood pressure

Applying individual calibration markedly improved agreement with the cuff reference. For SBP the calibrated mode (in validation range, 1 176 measurements) had a SD of 9.59 mmHg and ME (bias) of 11.81 mmHg. Although the mean error increased (because the calibration was using automatic cuff, whilst reference values were auscultatory, that caused over-correction in this particular measurement mode), the correlation (r = 0.69) improved significantly. For DBP the calibrated mode (1 070 measurements) achieved an SD of 6.73 mmHg, ME of 3.29 mmHg and correlation r = 0.65.

Table 4 – Blood-pressure accuracy

Mode	Parameter	N	MAE	MAPE	RMSE	SD	Bias	r
Non-cal.	SBP (90–170)	1184	10.18	9.41	12.62	11.76	4.60	0.38
	DBP (60–100)	1071	6.22	8.96	7.71	7.27	2.57	0.34
	SBP (full)	1276	10.75	10.32	13.26	12.04	5.58	0.47
	DBP (full)	1276	7.74	12.21	9.72	8.52	4.68	0.37
Calibr.	SBP (90–170)	1176	12.78	11.76	15.22	9.59	11.81	0.69
	DBP (60–100)	1070	5.77	8.22	7.49	6.73	3.29	0.65
	SBP (full)	1269	13.16	12.50	15.61	9.64	12.27	0.73
	DBP (full)	1269	6.66	10.30	8.62	7.31	4.57	0.65

Note: MAE, RMSE, SD and Bias are in mmHg; MAPE in %; r = Pearson correlation. "Full" indicates accuracy assessed under all blood pressure values encountered, rather than being restricted to nominal range.

Discussion

The 2025 clinical trial confirms that Shen.AI delivers clinical-grade accuracy for heart rate and maintains solid performance for heart-rate variability and breathing rate. HR estimates across all tested durations show errors well below 1 bpm and near-perfect correlation, surpassing ANSI/AAMI/IEC 60601-2-27 standards for cardiac monitors. HRV (SDNN) estimation exhibits higher relative error due to the inherent variability of R-R intervals, yet the correlation of 0.95 indicates that Shen.AI tracks trends reliably. Breathing rate accuracy degrades as the recording length is shortened; however, the

60-s window provides a mean error of just 1.4 bpm, which is comparable to inter-observer differences in manual respiratory counting. Shorter 45-s and 30-s recordings may be suitable for consumer wellness applications where ±2 bpm accuracy is acceptable, but they are less appropriate for clinical decision-making.

Blood-pressure estimation remains an emerging application of rPPG. In this study the non-calibrated algorithm achieved mean absolute errors of 10–11 mmHg for systolic pressure and 6–8 mmHg for diastolic pressure. These values are slightly above the AAMI/ESH/ISO 81060-2:2013 performance requirements for cuff-based devices but demonstrate that meaningful trends can be captured. Individual calibration improved correlation and reduced systematic bias, especially for diastolic pressure, illustrating the benefit of pairing Shen.AI with a single cuff measurement.

Compared with the 2023 validation study, the present trial corroborates the high performance of Shen.AI for HR and HRV and extends the methodology to breathing rate and blood pressure. A key strength is the larger sample of blood-pressure measurements collected under clinical supervision, which provides a robust basis for algorithm refinement. Limitations include the lack of short-duration BP recordings (only 60-s videos were assessed in the report) and the absence of hypertensive patients with very high BP values (>170 mmHg). Future work will focus on improving BP estimation accuracy, evaluating performance in diverse lighting conditions and incorporating machine-learning-based calibration.

Conclusion and commercial implications

The Shen.AI technology offers accurate, contactless monitoring of heart rate, heart-rate variability (SDNN), breathing rate and blood pressure using ordinary cameras. In a clinical trial with 132 participants the system delivered sub-1 bpm heart-rate accuracy and high correlation (r≈0.99) across 60-s, 45-s and 30-s recordings; HRV estimation showed a correlation of 0.95; breathing-rate accuracy reached 1.4 bpm MAE for 60-s videos, with acceptable performance for shorter windows; and blood-pressure estimation, while less accurate than cuff measurements, demonstrated promising correlations (up to r = 0.69 after calibration) and can be used for (pre)-screening, stratification, virtual triage, monitoring, monitoring trends and similar use-cases. These results position Shen.AI as a compelling solution for telehealth, chronic conditions management, remote patient monitoring, corporate wellness, life, health and travel insurance - where these use cases are needed. Continued algorithm refinement and integration with calibration protocols will further enhance performance and expand the addressable market.

Appendix A. Explanation of statistical metrics

This appendix provides definitions and explanations for the statistical metrics used in the report

- **SD (Standard Deviation)** – shows how much the SDK measurements fluctuate compared to the reference device. Lower SD means the measurements are more consistent.
- **ME (Mean Error / Bias)** – shows whether the SDK usually measures higher, lower, or about the same as the reference device on average.

  An ME close to 0 means the SDK is very similar to the reference on average.

  A positive ME means the SDK tends to show slightly higher values.

  A negative ME means the SDK tends to show slightly lower values.
- **MAE (Mean Absolute Error)** – shows how much the SDK is wrong on average, ignoring whether the error is above or below the reference. Lower MAE means better overall accuracy.
- **MAPE (Mean Absolute Percentage Error)** – shows by what percentage the SDK measurements differ from the reference on average. Lower MAPE means smaller relative errors.
- **RMSE (Root Mean Square Error)** – shows the typical size of the measurement error, with a stronger emphasis on larger mistakes. In practice, RMSE tells you how far, on average, the SDK's measurements tend to be from the reference, especially highlighting situations where the difference is noticeably bigger. Lower RMSE means the measurements are more reliable and less affected by large outliers.
- **Correlation (Pearson's r)** – shows how well the SDK follows the same trends and changes as the reference device. Values range from -1 to 1.

  Close to 1 the SDK changes almost exactly the same way as the reference.

  Close to 0 little or no connection between the two.

  Close to -1 the SDK changes in the opposite direction to the reference.