IntelliProve

INTELLIPROVE PROCESSING ENGINE

Accuracy and precision report

BlueHealth Innovation Center supported by Microsoft

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IntelliProve processing engine – accuracy and precision report

Introduction

IntelliProve, a Belgian healthtech company, developed an optical software solution to measure physiological and mental health parameters from a face in less than a minute. Specifically, the underlying processing engine analyzes a 20-second video to compute important physiological parameters such as heart rate (HR), respiratory rate (RR), and heart-rate variability (HRV) and different mental health biomarkers. The optical technology is a combination of years of targeted R&D and valuable partnerships with (international) healthcare organizations, and rely on clinically-validated research (see reference list in attachment). The software algorithms, trained on more than 1,000,000 unique data points, are developed with the ambition to extract deep, meaningful health insights from an accessible phone/tablet/PC camera.

The aim of this report is to provide a high-level overview of the current accuracy and precision levels of the different key parameters used in the algorithms of IntelliProve. The biomarker algorithms (and the underlying assessments) are the result of benchmarking studies with standard reference topical sensors or questionnaires. Data samples collected during these studies are different from the training dataset and are only used to independently validate the models.

Definitions and abbreviations

MAE: Mean Absolute Error
SD: Standard Deviation
SDNN: Standard Deviation of NN intervals
ms: Milliseconds
HRV: Heart Rate Variability
r: Pearson correlation
PPG: Photoplethysmography

HR: Heart Rate

NN-interval: time between two peaks (ms)

ANS: Autonomic Nervous System

RR: Respiration Rate

PNS: Parasympathetic Nervous System

SNS: Sympathetic Nervous System

ECG: Electrocardiogram

Material and methods

Data collection

In this study, a total of 1904 different comparative measurements (from 399 unique subjects, see supplementary table 1 for population characteristics) were performed to assess the general performance of the IntelliProve algorithms. Video recording was performed using a standard RGB camera. A complete list of the used devices can be found in supplementary table 2. In all cases, videos of 20 seconds to 1 minute were recorded using a variety of devices. The resolution of the videos ranges from 480p to 1080p, with frame rates from 30 to 60 frames per second.

Measurement setup

Each participant is instructed to sit still (minimal movements) in front of a camera with appropriate lighting, with the camera positioned within a range of 0.4±0.2m. The video frame should capture the individual's face and upper body. The lighting source is varied between natural, artificial or a combination, to simulate typical daily scenarios. Each data point was standardized to a duration of 30 seconds, and if a recording exceeded this duration, it was automatically split into 30-second chunks. This study only includes participants under informed consent, with no pre-knowledge of any heart rhythm disorder.

Prior to every measurement, measurement conditions are automatically assessed by in-house quality check algorithms developed by IntelliProve. This quality check ensures that the video is captured according to the instructions, in relation to illumination, position of the subject (participant-camera distance) and the general visibility of the skin.

Reference devices

Different devices were used during the study: Pulse oximeter (Contec CMS50E and BeurerPO80) and chest belt heart rate sensor (Polar H7/H10 and Garmin HRM-Dual).

IntelliProve test version

The IntelliProve 23.20 version was used during the execution of this study. The software was accessed through the IntelliProve mobile application.

Data analysis

The results for each parameter, such as heart rate, respiratory rate, and heart-rate variability, are reported in a clear and concise manner, including the mean absolute error (MAE) and standard deviation (SD) of the measurements, as well as the Pearson correlation (r). In the last step the signal morphology is compared with the ground truth PPG signal.

Results

The IntelliProve processing engine uses advanced remote PPG-based heart rate variability (HRV) measurement techniques and facial keypoints for mental well-being and health assessment.

- **Remote PPG-based HRV**

  IntelliProve makes use of photoplethysmography (PPG), an optical method to measure cardiac-synchronous blood volume change in body extremities such as the face, finger and earlobe. As the heart pumps blood, the volume of blood in the arteries and capillaries changes by a small amount in sync with the cardiac cycle. This change in blood volume in the arteries and capillaries underneath the skin leads to small changes in the skin color (visible in the Red/Green/Blue spectrum), from which a PPG waveform is estimated.

  The PPG signal is typically collected using a device (e.g. pulse oximeter) that emits light and measures the amount of light that is absorbed or reflected by the tissue. In the case of IntelliProve, ambient light from the environment (the light

source) and the camera from a smart device (the sensor) is used to collect the 'remote'-PPG. The region of interest is the face because of the 'thin' tissue and optimum blood perfusion. IntelliProve performs mental well-being identification based on the relationship between mental well-being and the variation in time between each heartbeat.

- **Facial keypoints**
  Relying on modern computer vision technology, it is possible to detect and extract facial dynamics and microexpression patterns, reflecting the hemifacial asymmetry in emotion expressions. This makes it possible to objectively detect and predict mental disorders. Typical patterns are raised eyebrows, leaden gazes, swollen faces and hang-dog mouth expressions.

Below, we discuss the different biomarkers calculated by the processing engine.

Heart rate

Heart rate (HR) frequency is a measure of the number of times the heart beats per minute. It is a useful metric for monitoring user fitness level and overall health. Generally, a lower heart rate at rest implies more efficient heart function and better cardiovascular fitness. For example, a well-trained athlete might have a normal resting heart rate closer to 40 beats per minute.

As mentioned earlier, the IntelliProve algorithm detects subtle changes in skin color on the face to extract the blood volume pulse. Heart rate can be estimated by counting the systolic peaks per minute in this pulse signal. In figure 1, a comparative analysis between a pulse signal acquired from a PPG sensor versus the face (using the IntelliProve software) is illustrated. A consistent overlap of the systolic peaks can be observed.

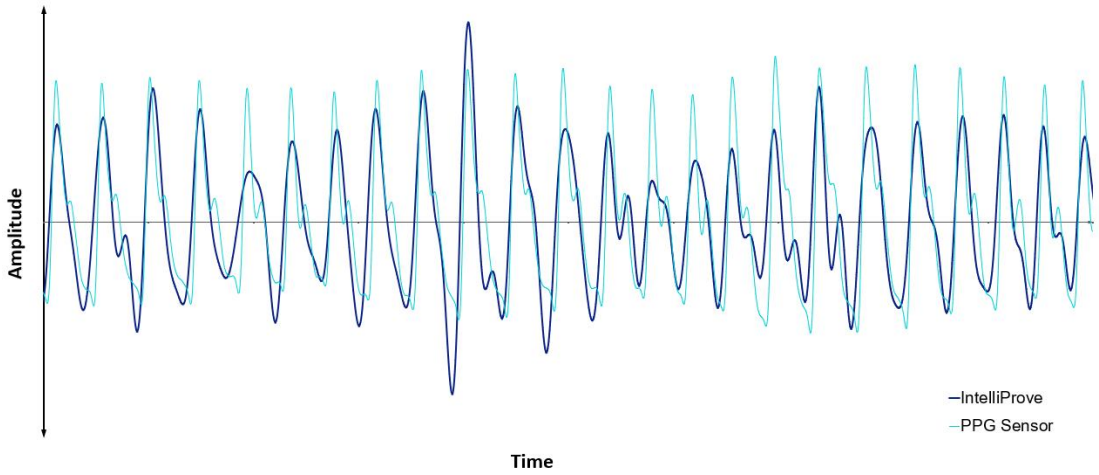

Figure 1: Comparative analysis between a pulse signal acquired from a PPG sensor versus a video of the face using the IntelliProve software.

Comparative analyses between heart rate sensors and IntelliProve revealed a mean absolute error of 2.10 ± 2.36 beats per minute for HR estimation through IntelliProve. A correlation of r=0.982 (p<0,00001) is observed between the two measurement methods, as can be seen in figure 2.

Statistical metric	Pearson correlation (r)	MAE (bpm)	SD (bpm)	AE < 5bpm
Value	0.98	2.10	2.36	92%

Table 1: Accuracy and precision levels of the HR measurement performed by the IntelliProve algorithms in comparison to reference devices.

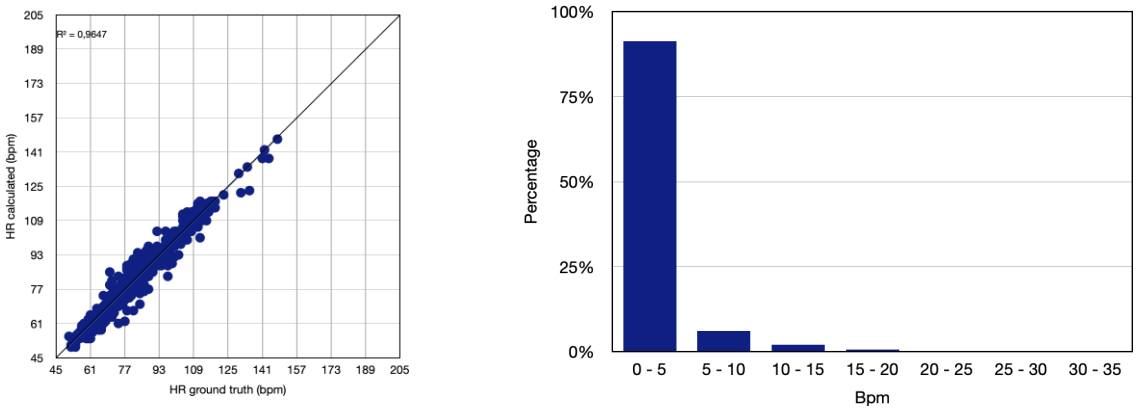

Figure 2: Correlation analysis (left) and error distribution plot (right) of the HR measurement performed by the IntelliProve algorithms in comparison to reference devices.

We kindly refer to supplementary figures 1 and 2 to see the impact of skin tone and age categories on heart rate measurement accuracy. For both age and skin color it can be concluded that no significant impact can be observed in signal quality: for each group this margin of heart rate error remains nicely below the threshold of 5bpm (=clinical acceptability criteria).

Respiratory rate

Respiration Rate, or breathing rate, is the number of breaths per minute while at rest. Breathing rates may increase with fever, illness and other medical conditions.

IntelliProve software accurately calculates the respiration rate by detecting the subtle movements of the chest. This is achieved through the use of an in-house software algorithm, which enables the processing engine to identify the correct motion associated with breathing. A respiration signal is created (as can be seen in figure 3) and its frequency is measured. This frequency corresponds with the number of breaths a person takes in one minute (breaths per minute or bpm).

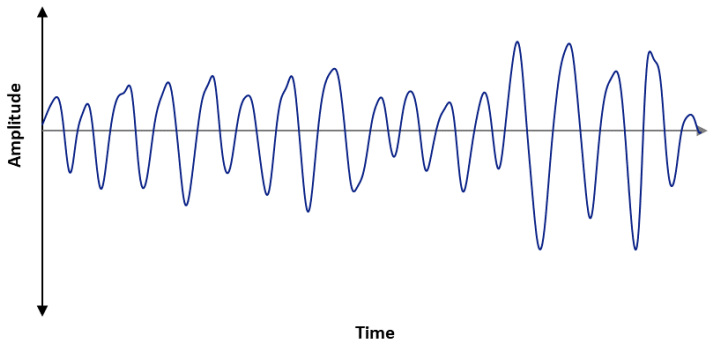

Figure 3: Illustrative example of a respiratory signal acquired from a video of the face using the IntelliProve software.

The current mean absolute error of the RR measurement is 2.02±2.71 breaths per minute. A good correlation ($r=0.825$; $p<0.00001$) between video-based RR measurement and ground truth RR values can be observed, as can be seen in figure 4.

Statistical metric	Pearson correlation (r)	MAE (bpm)	SD (bpm)	AE < 5bpm
Value	0.83	2.02	2.71	91%

Table 2: Accuracy and precision levels of the RR measurement performed by the IntelliProve algorithms in comparison to reference devices

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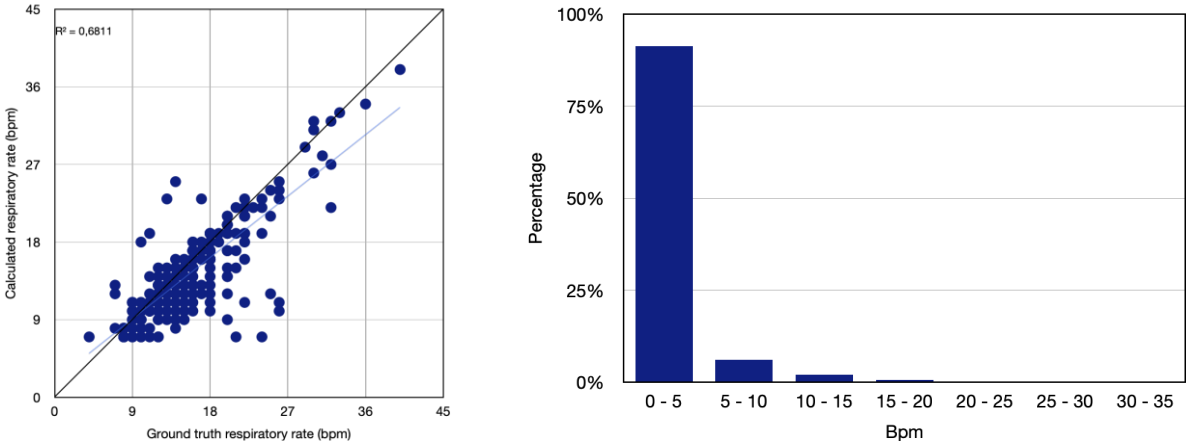


Figure 4: Correlation analysis (left) and error distribution plot (right) of the RR measurement performed by the IntelliProve algorithms in comparison to reference devices.

Heart rate variability

Heart Rate Variability, or HRV for short, is a non-invasive measure of your autonomic nervous system, which is the body's main control center. It is widely considered as one of the best objective metrics for physical fitness and determining your body's readiness to perform. HRV is literally the variance in time between the beats (NN interval) of your heart.

A commonly used statistical metric for representing short-time HRV (over a time duration of the order of 10s to 1 min) is the Standard Deviation of NN intervals (SDNN). NN intervals (or RR intervals) are extracted from the signal's morphology by measuring the distance between systolic peaks.

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_i - \overline{RR})^2}$$

The current mean absolute error of the SDNN measurement through the IntelliProve algorithms is 13 ± 15 ms (milliseconds). Currently, we observe a good correlation (r=0.89; p<0.00001) between our video-based HRV measurement and ground truth HRV values (measured by using ECG signals acquired from a chest belt sensor). The correlation analysis and distribution plot of the errors can be found in Figure 5.

Statistical metric	Pearson correlation (r)	MAE (ms)	SD (ms)	AE < 40ms
Value	0.89	13	15	96.5%

Table 3: Accuracy and precision levels of the HRV measurement performed by the IntelliProve algorithms in comparison to reference devices.

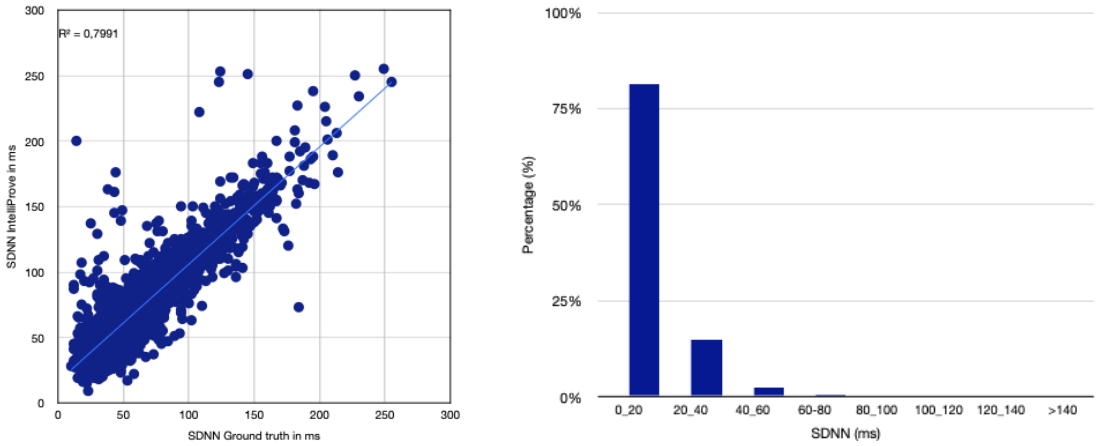


Figure 5: Correlation analysis (left) and error distribution plot (right) of the HRV measurement performed by the IntelliProve algorithms in comparison to reference devices.

ANS balance

Heart Rate Variability (HRV) reflects the functioning and balance of the autonomic nervous system (ANS). The ANS Balance indicates the relative balance between the Parasympathetic Nervous System (PNS) and the Sympathetic Nervous System (SNS), indicating the balance between recovery and physiological stress (both physical and mental).

To validate the accuracy of the ANS balance calculation through the IntelliProve algorithm, a benchmarking study was performed to compare the video-derived ANS balance score from the simultaneous calculated PPG signal-derived ANS balance. A test was conducted to determine the capability of the IntelliProve algorithm in detecting stressful situations and the subsequent imbalance towards SNS activity. All subjects were asked to complete a mathematical exercise during measurement to increase their SNS activity. A clear shift towards SNS activity can be observed, which was also picked up by the IntelliProve algorithms (see figure 6). In 96% of the cases where an increased SNS activity was observed through the use of a contact PPG signal, the IntelliProve algorithms also correctly indicated a shift towards SNS activity (see table 4).

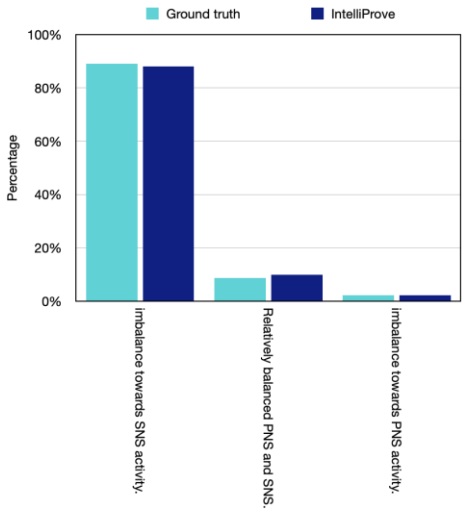


Figure 6: ANS balance distribution plot from subjects performing a mathematical exercise.

		PPG sensor (ANS balance)	
		Imbalance towards SNS activity	***Relatively balanced PNS and SNS***
IntelliProve algorithms (ANS balance)	*Imbalance towards SNS activity*	96%	36%
	Relatively balanced PNS and SNS	4%	64%

Table 4: Accuracies of the IntelliProve algorithms to detect activity within the SNS and PNS.

Acute mental stress score and mental health risk

When a human is coping with a stressful event, his body transmits involuntary responses, all controlled by the part of the ANS called the Sympathetic Nervous System (SNS). Along with the SNS, the Parasympathetic Nervous System (PNS) works on balancing and regulating physiological signals. Heart rate variations, high blood pressure, sweating, are all examples of physiological reactions to stress.

Participants were asked to fill in a combination of questionnaires to assess the mental health status of the individual in terms of physiological stress and anxiety (e.g. PHQ-9, GAD-7, CSAI-2). Based on the outcome of these questionnaires, every participant was classified according to a certain mental health risk profile (low, medium or high). Using this approach, a validation of the acute mental stress score and underlying trend-based mental health risk was performed.

The classification accuracies of the IntelliProve algorithms for the different mental health risks can be found in table 5. It can be concluded that in 100% of the cases participants with a high mental health risk will also be labeled as 'high risk' through the IntelliProve processing engine (true positive cases). Although the discriminative power of IntelliProve between medium and low risk profiles is substantially lower, it can be concluded from table 6 that 89.1% of the combined medium/low cases will also be labeled as medium/low through IntelliProve.

		Questionnaires (Mental health risk)		
		High	***Medium***	***Low***
IntelliProve algorithms (Mental health risk)	*High*	100.0%	13.3%	0.0%
	Medium	0.0%	48.0%	70.6%
	Low	0.0%	38.7%	29.4%

Table 5: Accuracies of the IntelliProve algorithms to classify high, medium and low mental health risk profiles, defined through reference questionnaires.

		Questionnaires (Mental health risk)	
		High	***Medium/Low***
IntelliProve algorithms (Mental health risk)	*High*	100.0%	10.9%
	Medium/Low	0.0%	89.1%

Table 6: Accuracies of the IntelliProve algorithms to classify high and combined medium/low mental health risk profiles, defined through reference questionnaires.

Resonant breathing score

To assess the performance of the Resonant breathing score, a specific measurement set-up was created. Participants were first instructed to perform an irregular breathing, which simulates a non-resonant breathing state (see first 60 seconds in the figure below). Subsequently, participants were asked to follow a breathing pace of 6 bpm (5s

in-, 5s outhale) to induce resonant breathing over time (see seconds 60-120 in the figure below). The recordings were divided into 3 segments ('non resonant breathing', 'partial resonant breathing' and 'resonant breathing').

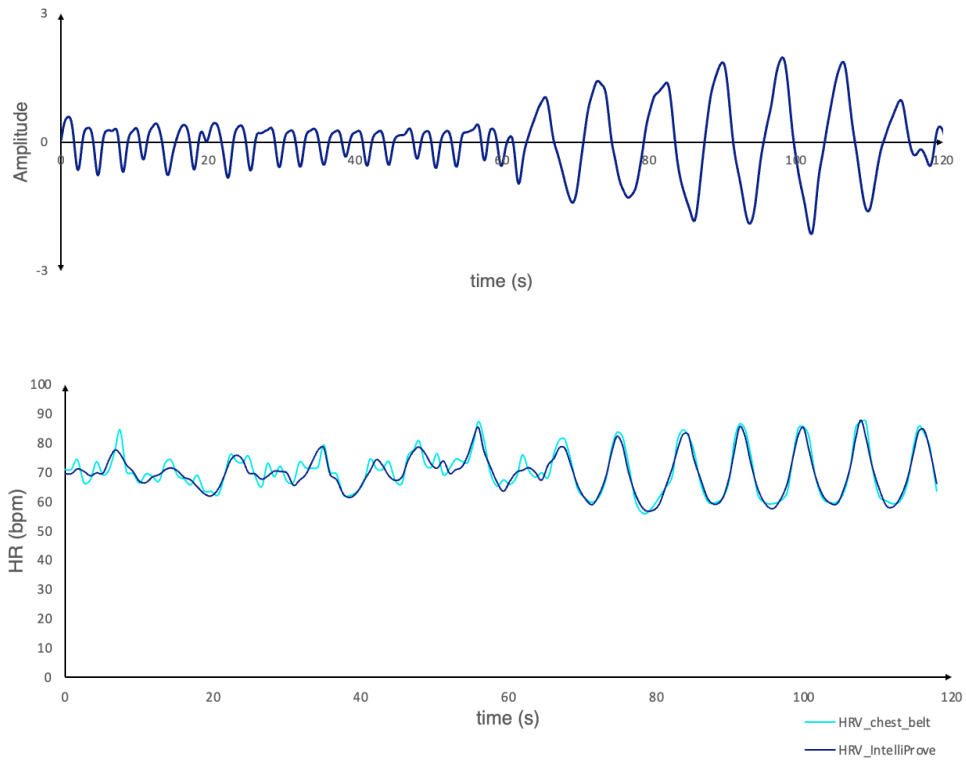


Figure 7: Upper: respiratory signal acquired from a video of the face using the IntelliProve software during non-resonant (0-60sec) and resonant breathing state (60-120sec). Lower: comparative analysis between the heart rate fluctuations measured by HRV sensor and measured by a video of the face using the IntelliProve software.

In figure 8, Resonant Breathing scores during the different segments can be seen. During the non-resonant breathing phase, a low mean Resonant Breathing score is observed due to the presence of irregular breathing patterns (33.6 ± 19.9 %). A higher mean Resonant Breathing score is obtained during the partial resonant breathing state (62.1 ± 14.9 %). Finally, in the phase where the coherence between breathing and heart rate variability is manifested, the highest Resonant Breathing scores were obtained (76.0 ± 7.3 %).

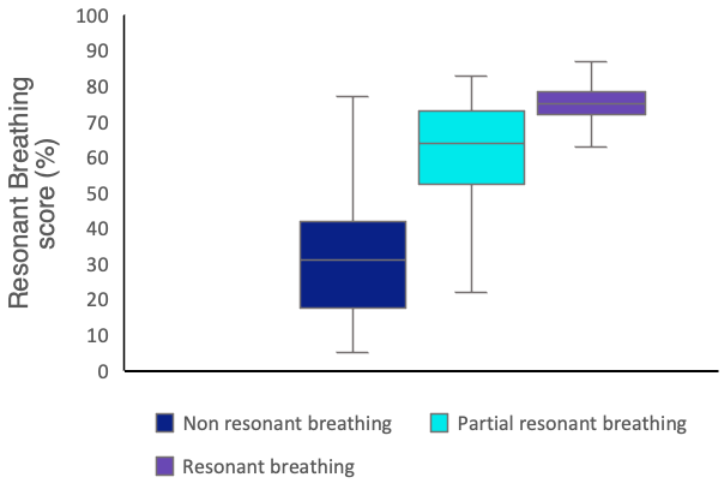


Figure 8: Box plot representation of the Resonant breathing scores over the different phases.

In the table below, the performance results of the IntelliProve algorithms are presented.

		Resonant breathing exercise		
		NO	***PARTIAL***	***YES***
IntelliProve Resonant breathing score	*NO (<40%)*	66%	9%	0%
	PARTIAL (40-70%)	25%	64%	12%
	YES (>70%)	9%	27%	88%

Table 7: Accuracies of the IntelliProve algorithms to classify resonant and non-resonant breathing states.

Conclusion

In this report, the performance of the IntelliProve processing engine was validated. Based on a total of 1904 different comparative measurements from 399 subjects, accuracy and precision levels were described for every biomarker measured by IntelliProve from a video of the face. Below, an overview of the performance metrics of the different biomarkers can be found.

	HR (AE<5bpm)	RR (AE< 5bpm)	HRV-SDNN (AE< 40ms)	ANS balance (detection SNS activity)	Mental health risk (high)	Mental health risk (medium / low)	Resonant breathing state detection
IntelliProve algorithms (%)	92	91	96.5	96	100	89.1	88

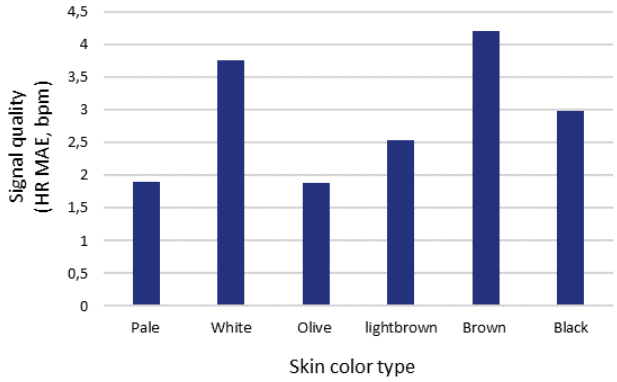
Annex

n	**Age** (4-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79) (%)	**Sex** (m, v) (%)	**Skin type** (type 1, 2, 3, 4, 5, 6) (%)	**Ethnicity** (White, Black or African American, American Indian or Alaska Native, Asian, Native Hawaiian or other Pacific Islander) (%)
399	(13, 20, 8, 16, 17, 15, 11)	(58, 42)	(11, 16, 23, 21, 15, 14)	(63, 14, 18, 5, 0)

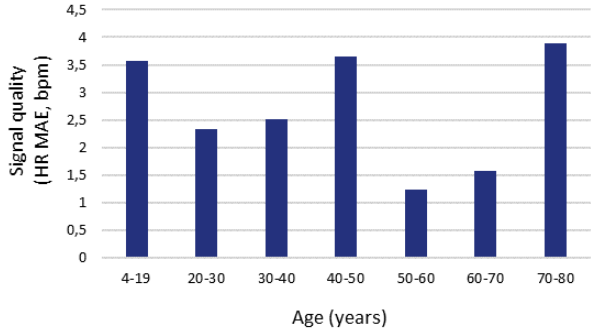
Supplementary table 1: Overview of the subject characteristics included in this validation study. Skin type: 1: Pale white, 2: White, 3: Darker white, 4: Light brown, 5: Brown, 6: Dark brown or black.

Used devices
Logitech C920 HD Pro
HUAWEI P9 Frontal
Logitech C310 webcam
EO-23121C RGB Edmund Optics
RealSense F200
Smartphone Gigaget Gs5 48 MP camera
IPhone Xs Front & Rear camera
Samsung Galaxy S9 plus Front & Rear camera
IPhone 6S smartphone Front and Rear camera
IPhone SE 2020 Rear camera
Huawei P10 Lite 12-MP f/2.2
IPad 6GEN Front & Rear camera
Samsung Galaxy S9 PLUS Front
Asus Vivobook
IPhone Xr Front & Rear camera
IPhone Xr Rear camera
IPhone SE Rear camera
Gigaset GS5 Front camera
Macbook Pro Late 2021 14 inch

Supplementary table 2: Overview of the different devices used in this study.



Supplementary figure 1: Heart rate measurement accuracy (i.e. signal quality) in function of skin color categories.



Supplementary figure 2: Heart rate measurement accuracy (i.e. signal quality) in function of age categories.

References

Ref	Study type	N	Patient population / Indication	Study objective	Safety outcome	Performance outcome	Study conclusions
Pinheiro N, Couceiro R, Henriques J, Muehlsteff J, Quintal I, Goncalves L, Carvalho P. Can PPG be used for HRV analysis? Annu Int Conf IEEE Eng Med Biol Soc. 2016 Aug;2016:2945-2949.	Clinical trial	68	Cardio vascular disease	Investigation of the hypothesis of using PPG signal features as surrogates for HRV indexes, in three different contexts: healthy subjects at rest, healthy subjects after physical exercise and subjects with cardiovascular diseases (CVD)	No safety issues reported	The achieved results suggest that PPG signals can be often used as an alternative for HRV analysis in healthy subjects, with significant correlations above 82%, for both time and frequency features. Contrarily, in the post-exercise and CVD subjects, time and (most importantly) frequency domain features shall be used with caution (mean correlations ranging from 68% to 88%).	Results confirm that the majority of PPG signal indexes may be used as surrogates for ECG-based HRV in healthy subjects at rest, as reported in the literature
Nasseri, M., Nurse, E., Glasstetter, M., Boettcher, S., Gregg, N. M., Nandakumar, A. L., Joseph, B., Attia, T. P., Viana, P. F., Bruno, E., Biondi, A., Cook, M., Worrell, G. A., SchulzeBonhage, A., Duempelmann, M., Freestone, D. R., Richardson, M. P. & Brinkmann, B. H. (2020). Signal quality and patient experience with wearable devices for epilepsy management. EPILEPSIA, 61 (S1), pp.S25-S35.	Clinical trial	70	Patients with epilepsy undergoing in-hospital or in-home electroencephalographic (EEG) monitoring, and healthy volunteers.	Investigate the signal quality and patient experience with wearable devices for epilepsy management	No safety issues reported	Current wearable devices can provide high-quality data and are acceptable for routine use.	Continued development is needed to improve data quality, consistency, and management, as well as acceptability to patients.
Nitzan M, Babchenko A, Khanokh B, Landau D. The variability of the photoplethysmographic signal--a potential method for the evaluation of	Clinical trial	33	Healthy volunteers and diabetic patients	Investigate the use of PPG signals for the evaluation of the autonomic nervous system.	No safety issues reported	The curves of the baseline and the amplitude of the PPG signal for the non-diabetic subjects showed high correlation between the left and the right hands. For most of the diabetic patients the right–left correlation coefficients were significantly lower	Our initial results have shown that the variability of the PPG parameters shows promise for the assessment of the function of the autonomic nervous system.

the autonomic nervous system. Physiol Meas. 1998 Feb;19(1):93-102.						than those for the non-diabetic subjects	
Nilsson L, Johansson A, Kalman S. Monitoring of respiratory rate in postoperative care using a new photoplethysmographic technique. J Clin Monit Comput. 2000;16(4):309-15.	Clinical trial	16	Patient with mild systemic disease (ASA 2)	Photoplethysmography (PPG) is a non-invasive optical technique that measures variations in skin blood volume and perfusion. The PPG signal contains components that are synchronous with respiratory and cardiac rhythms. We undertook this study to evaluate PPG for monitoring patients' respiratory rate in the postoperative care unit, using a new prototype device. We compared it with the established technique, transthoracic impedance (TTI).	No safety issues reported	A total of 10,661 breaths were recorded, and the mean +/- SD respiratory rate was 12.3 +/- 3.5 breaths/minute. When compared with TTI, the rates of false positive and false negative breaths detected by PPG (visual procedure) were 4.6 +/- 4.5% and 5.8 +/- 6.5%, respectively. When using the algorithm for breath detection from PPG, the rates of false positive and false negative breaths were 11.1 +/- 9.7% and 3.7 +/- 3.8%, respectively, when compared to TTI. Lower respiratory rates increased the occurrence of false-positive breaths that were detected by the PPG using visual identification ($p < 0.05$). The same tendency was seen with the automated PPG procedure ($p < 0.10$).	Our results indicate that PPG has the potential to be useful for monitoring respiratory rate in the postoperative period.
Lee J, Reyes BA, McManus DD, Mathias O, Chon KH. Atrial fibrillation detection using a smartphone. Annu Int Conf IEEE Eng Med Biol Soc. 2012;2012:1177-80.	Clinical trial	25	Prospective subjects with AF pre- and post-electrical cardioversion	Investigation of the detection of atrial fibrillation (AF) based on the ability to record a pulsatile photoplethysmogram (PPG) signal from a fingertip using the built-in camera lens.	No safety issues reported	It should be recognized that for clinical applications, the most relevant objective is to detect the presence of AF or normal sinus rhythm (NSR) in the data. Using this criterion, we achieved an accuracy of 100% for both detecting the presence of either AF or NSR.	A built-in camera of a smart device can be used to detect atrial fibrillation based on the acquired PPG signal.
Nilsson L, Johansson A, Kalman S. Respiration can be monitored by photoplethysmography with high sensitivity and specificity regardless of anaesthesia and ventilatory mode. Acta Anaesthesiol Scand. 2005 Sep;49(8):1157-62.	Clinical trial	12	Patients scheduled for major abdominal surgery requiring invasive monitoring of the central venous pressure (CVP) and arterial blood pressure (ABP) as well as peripheral venous cannulae for fluid infusion.	Investigation whether respiration can be monitored by photoplethysmography with high sensitivity and specificity regardless of anaesthesia and ventilatory mode	No safety issues reported	PPG sensitivity for breath detection was [mean (SD)] >86(21)% and specificity >96(12)%. Respiratory detection in the macrocirculation (CVP, PVP and ABP) showed a sensitivity >83(29)% and specificity >93(12)%. The coherence between signals was high (0.75-0.99). The three measurement situations did not significantly influence sensitivity, specificity or time shifts between the PPG, PVP, ABP, and the reference CVP signal despite changes in	A respiratory synchronous variation in PPG and all invasive pressure signals was detected. The reflection mode PPGr signal seemed to be a constant phenomenon related to respiration regardless of whether or not the subject was awake, anaesthetized or ventilated, which increases its clinical usefulness in respiratory monitoring.

						physiological data between measurements.	
Addison PS, Jacquel D, Foo DMH, Borg UR. Video-based heart rate monitoring across a range of skin pigmentations during an acute hypoxic challenge. J Clin Monit Comput. 2018 Oct;32(5):871-880.	Clinical trial	10	Healthy volunteers	Investigate the video-based heart rate monitoring (based on PPG signal) across a range of skin pigmentations during an acute hypoxic challenge	No safety issues reported	Agreement between video-based heart rate and that provided by the pulse oximeter was as follows: Bias = – 0.21 bpm, RMSD = 2.15 bpm, least squares fit gradient = 1.00 (Pearson R = 0.99, p < 0.0001), with a 98.78% reporting uptime. Excellent agreement was found between the HRvid and HRp in a study covering the whole range of skin pigmentation types (Fitzpatrick scales I–VI), using standard room lighting and with moderate subject motion.	The results provide a strong indication of the potential to determine heart rate from video image streams of subjects exhibiting a range of skin pigmentations with moderate motion.
Shirbani F, Hui N, Tan I, Butlin M, Avolio AP. Effect of Ambient Lighting and Skin Tone on Estimation of Heart Rate and Pulse Transit Time from Video Plethysmography. Annu Int Conf IEEE Eng Med Biol Soc. 2020 Jul;2020:2642-2645.	Experimental setup	12	Healthy volunteers	Investigate the effect of Ambient Lighting and Skin Tone on Estimation of Heart Rate and Pulse Transit Time from Video Plethysmography	No safety issues reported	The estimated HR error (HR-error) was significantly lower for vPPG from green channels in both ROIs (ROI1 [p<0.001], ROI2 [p<0.05]). The signal from ROI1 demonstrated lower HR-error than ROI2 (p<0.001). HR-error from the darkest lighting conditions (Lumen 1 and 2) were significantly higher than the others (p<0.05). Furthermore, HRerror showed a positive correlation with skin tone scores in every lighting condition. However, at brighter lighting intensity,	HR error was independent of the skin tone score.HR-error and the ratio of vPTT/PAT increase with darker skins and at darker backgrounds. However, at brighter lighting conditions, the skin tone score is not a confounder of vPPG accuracy.

Supplementary table 3: Overview of different scientific research papers describing the clinical validation and use cases of photoplethysmography during health assessment.

IntelliProve

Integrate AI-driven health assessment into your solution

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