

ACCEPTED MANUSCRIPT • OPEN ACCESS

A Portable System for Non-Invasive Cardiovascular Monitoring in Older Adults: Design and Validation

To cite this article before publication: Chiara Bencivenga *et al* 2026 *Biomed. Phys. Eng. Express* in press <https://doi.org/10.1088/2057-1976/ae3e9d>

Manuscript version: Accepted Manuscript

Accepted Manuscript is “the version of the article accepted for publication including all changes made as a result of the peer review process, and which may also include the addition to the article by IOP Publishing of a header, an article ID, a cover sheet and/or an ‘Accepted Manuscript’ watermark, but excluding any other editing, typesetting or other changes made by IOP Publishing and/or its licensors”

This Accepted Manuscript is © 2026 The Author(s). Published by IOP Publishing Ltd.



As the Version of Record of this article is going to be / has been published on a gold open access basis under a CC BY 4.0 licence, this Accepted Manuscript is available for reuse under a CC BY 4.0 licence immediately.

Everyone is permitted to use all or part of the original content in this article, provided that they adhere to all the terms of the licence <https://creativecommons.org/licenses/by/4.0>

Although reasonable endeavours have been taken to obtain all necessary permissions from third parties to include their copyrighted content within this article, their full citation and copyright line may not be present in this Accepted Manuscript version. Before using any content from this article, please refer to the Version of Record on IOPscience once published for full citation and copyright details, as permissions may be required. All third party content is fully copyright protected and is not published on a gold open access basis under a CC BY licence, unless that is specifically stated in the figure caption in the Version of Record.

View the [article online](#) for updates and enhancements.

A Portable System for Non-Invasive Cardiovascular Monitoring in Older Adults: Design and Validation

Chiara Bencivenga¹, Roberto Cangemi², Stefania Basili², Antonella Polimeni³, Livio D’Alvia^{1,4} and Zaccaria Del Prete¹

¹ Dept. of Mechanical and Aerospace Engineering, Sapienza University of Rome, Rome, Italy
² Dept. of Translational and Precision Medicine, Sapienza University of Rome, Rome, Italy
³ Dept. of Odontostomatology and Maxillofacial Sciences, Sapienza University of Rome, Rome, Italy
⁴ Dept. of Well-being, Health and Environmental Sustainability, Sapienza Università di Roma, Rieti, Italy
E-mail: chiara.bencivenga@uniroma1.it

Received xxxxxx
Accepted for publication xxxxxx
Published xxxxxx

Abstract

The healthcare system is experiencing profound change, driven by two key factors: the progressive aging of the population and the growing pressure from the increased demand for care. In this context, portable devices play a crucial role in enabling remote monitoring, particularly for older adults. Many portable devices have already been proposed in the literature and introduced to the market. Unfortunately, they all have shortcomings: either they require multiple devices and complex configurations, or they lack clear visual or auditory feedback. This paper, therefore, presents an innovative, non-invasive, user-friendly technological solution for monitoring cardiovascular health. In particular, the device integrates high-sensitivity sensors that allow simultaneous acquisition of photoplethysmographic (PPG) and electrocardiographic (ECG) signals through direct finger contact for 30 seconds, allowing the extraction of fundamental electrocardiographic parameters (PR, QRS, QT, RR, HR), oxygen saturation (SpO₂) and second derivative photoplethysmography indices SDPTG (b/a, c/a, d/a, e/a, SDPTG-AI). The system was validated on an initial cohort of 40 participants (22 women and 18 men; age: 62 ± 11.62 years) by comparing its performance with that of standard medical-grade instrumentation. The system showed good agreement with reference measurements for QRS duration, RR interval, and heart rate, but the PR interval showed greater variability, likely due to difficulties in detecting the P wave. The results concerning SpO₂ were also consistent with those obtained using the standard reference instrumentation. Moreover, the analysis of SDPTG indices suggests that the device could also serve as a screening tool for vascular health. Future work will aim to enhance real-time connectivity, improve P-wave detection accuracy, and validate the device in a larger population.

Keywords: ECG measurement, PPG measurement, cardiovascular monitoring, portable health devices, telemedicine, vital sign monitoring, signal accuracy.

1. Introduction

The healthcare sector is undergoing a profound transformation, driven by rising demand for personalized services and the aging global population. These dynamics are redefining research priorities in both the scientific and technological domains.

According to the World Social Report 2023, the number of people aged 65 and older is projected to double by 2050, reaching 1.6 billion—over 16% of the global population (Luchsinger and United Nations. Department of Economic and Social Affairs n.d.). While increased life expectancy is a positive achievement, it also leads to a higher prevalence of chronic diseases, more hospitalizations, and a greater need for long-term care. These challenges place significant strain on healthcare systems, both financially and organizationally.

Simultaneously, healthcare spending has reached historic highs. An Organization for Economic and Social Affairs (OECD) study of 30 countries shows that health expenditure as a percentage of GDP is at its peak (OECD 2023), driven by both rising costs and a general economic slowdown. Considering these trends, the healthcare system must be restructured to better address growing demand and resource constraints.

For this reason, new technologies are key tools that provide concrete means to optimize care delivery, improve patient monitoring, and enhance prevention. Hence, the healthcare services become more efficient, accessible and personalized.

Technological innovation is emerging as a key enabler in this transformation. Solutions such as telemedicine, big data, artificial intelligence, and wearable sensors can help optimize care delivery, improve remote patient monitoring, and support preventive strategies. Among these, telemedicine—especially when enabled by wearable monitoring devices—plays a crucial role in addressing the needs of the older population (Alsadoon et al 2024).

The COVID-19 pandemic accelerated the adoption of digital tools in healthcare, not only to manage the emergency but also to ensure continuity of care. As a result, people have become more health-conscious, and the industry has responded by developing consumer-grade health monitoring tools like smartwatches and pulse oximeters (Yebda et al 2019) (World Health Organization 2022).

Wearable devices are particularly promising for older adults, allowing for early detection of clinical deterioration, promoting autonomy, and reducing hospital visits. These systems use non-invasive sensors to capture physiological signals such as electrocardiogram (ECG), photoplethysmography (PPG), and electromyography (EMG), from which vital signs like heart rate (HR), oxygen saturation

(SpO₂), and blood pressure (BP) can be derived (Seçkin et al 2023, Deng et al 2023, Stefana et al 2021).

In addition, micro-electro-mechanical systems (MEMS), based on miniature motion sensors such as accelerometers, gyroscopes, and magnetic field sensors, are widely used to monitor the risk of falling, particularly common among older people (Majumder et al 2017) (Ebrahim Nemati n.d.).

In most cases, the data collected by these sensors is transmitted to a central unit via wired or wireless connections (Serhani et al 2020). This means that the data can be forwarded directly to someone's doctor, who can then adjust treatment plans, schedule follow-up visits, and monitor the patient remotely, eliminating the need for them to attend the clinic or the hospital (Pantelopoulous and Bourbakis 2010). These technological solutions help to provide independence in old age, contributing to the individual's physical and mental well-being.

Most systems also include an alarm to alert the physician when values fall outside the physiological range.

Although the patients need continuous monitoring of acute cardiovascular diseases, prolonged use of wearable devices or Holter systems is not always compatible with their needs (Krishnaswami et al 2020). It is therefore necessary to develop alternative, complementary solutions that are easy to use and enable brief measurements in older patients who are not hospitalized. In this way, these tools support conventional approaches by offering early diagnoses and ensuring timely and targeted interventions (Cowie and Lam 2021). In addition to these clinical and organizational challenges, technological issues must also be addressed.

In fact, despite their potential, many commercial devices suffer from issues such as poor usability, limited accuracy, lack of integration across multiple physiological signals, and discomfort, especially for older users, as described by Peek et al. (Peek et al 2014). Almost all systems require multiple devices, cables, or chest straps, which can be inconvenient and discourage consistent use without the help of qualified personnel.

To address these limitations, this work presents the design and validation of a portable cardiovascular monitoring device specifically tailored for older users. The system simultaneously acquires ECG and PPG signals through a simple finger-based interface, eliminating the need for chest straps or external wiring. The device has been designed to be compact, intuitive and easy to use.

A dual-signal acquisition strategy was adopted in this study, as simultaneous ECG and PPG recording allows the integration of cardiac and peripheral vascular information within the same temporal window (Karimi et al 2025). This improves measurement consistency and has been shown in

previous works to increase the robustness of cardiovascular monitoring systems (Bassiouni et al 2021)

It should be noted that the proposed device is not intended to replace continuous monitoring systems (e.g., Holter monitors or long-term wearables). Rather, it is designed to provide simple, short (30-seconds), and repeated measurements suitable for home-based follow-up.

To further improve system accessibility, a user interface with visual and auditory feedback is also planned. However, these aspects are beyond the scope of this study, which focuses on the hardware and software validation of the prototype. Furthermore, since aging strongly affects vascular dynamics, age-related waveform variations were intentionally included in the study design.

This paper is structured as follows: Section II reviews the state of the art in wearable cardiovascular monitoring; Section III describes the materials, methods, and the proposed prototype; Section IV presents the validation results against clinical-grade instruments; and Section V discusses conclusions and future work.

2. State of the art

The field of wearable healthcare technologies has evolved significantly in recent years, especially for cardiovascular monitoring. A wide range of systems—both wearable and non-wearable—have been developed to support early diagnosis and remote tracking of vital signs.

In cardiology, the combined acquisition of ECG and PPG signals has demonstrated high diagnostic value, particularly for conditions such as atrial fibrillation, bradycardia, and sleep apnea, which are prevalent in older adults. A recent systematic review by Babar et al. demonstrated that dual-signal systems improve both sensitivity and specificity in rhythm abnormality detection (Babar et al 2023).

As described by Cosoli et al. (Cosoli et al 2021), the solutions present in the literature have, in fact, explored different configurations, including chest straps, ear probes and even rings (van Steijn et al 2025, Adams et al 2022) (Guo et al 2008). In this context, Zhang et al. propose a chest strap ECG monitoring system that integrates the automatic analysis of signal features (Zhang et al 2025). A similar design was proposed more recently by H. Shan et al. (Shan and Jin 2025), which combines a chest strap for ECG signal acquisition with a forehead strap for photoplethysmography signal acquisition.

In addition, Pantelopoulos et al. (Pantelopoulos and Bourbakis 2010) have reported that sensors for measuring physiological parameters have been integrated into smart fabrics in the form of wearable T-shirts or waistcoats. In a recent study, Angelucci et al. (Angelucci et al 2021) described and analyzed the textile technologies currently in use,

providing an overview of the main garments available on the market.

However, many of these systems are still in prototype stages or entail significant trade-offs in comfort, usability, or signal quality.

For example, Hexoskin is a Canadian company specializing in the non-invasive acquisition of various physiological parameters. In particular, the system integrates textile electrodes into a sensorized t-shirt to collect single-lead ECG signals and uses chest bands to monitor thoracic respiration. The technology lacks PPG-signal acquisition sensors, so no oxygen saturation information is provided. Furthermore, comfort is not always guaranteed due to the need to wear the t-shirt for a long time, which can cause skin irritations(Montes et al 2018). Moreover, the device remains pending FDA approval.

The Apple Watch wristband has already received FDA clearance and is CE marked. The device has demonstrated a strong correlation between the 1-lead ECG it acquires and the standard 12-lead ECG. However, since the PPG signal acquired on the wrist is more subject to motion artifacts, the derived oxygen saturation is less accurate than that taken from the finger (Zhang et al 2019). Although this device demonstrates high sensitivity and specificity in detecting atrial fibrillation episodes, it does not provide a more in-depth analysis of the entire electrocardiographic tracing (Shahid et al 2025).

AliveCore, by KardiaMobile (FDA and CE marked), is another mobile compact ECG solution, clinically validated on the market (Klier et al 2023). The technology enables acquisition of both a single-lead (in the standard version) and a 6-lead (in the KardiaMobile 6L version) ECG by simply touching the two electrodes with fingers for approximately 30-60 seconds. However, the device is limited to heart rhythm classification and does not identify the main diagnostic intervals that provide a more detailed analysis of the user's health status.

From this perspective, the literature proposes a series of devices that acquire vital signs non-invasively and explores different configurations. These include portable systems, such as pens and palm-sized devices, as well as wearable devices, such as chest straps and patches (Daniëls et al 2024, Himmelreich et al 2019, Zaprutko et al 2020).

For example, (D'Abbondanza et al 2021), the authors propose a sensitized T-shirt for remote monitoring of cardiovascular health, integrating a single-lead ECG, a finger PPG sensor for SpO₂, a temperature sensor and a triaxial accelerometer. Despite the feasibility of this solution, the system has critical issues in terms of usability and comfort, especially for our target audience.

Another configuration has been proposed by De Capua et al. in (De Capua et al 2010), where the authors propose a device for acquiring 3-lead electrocardiographic signals by applying electrodes to the chest. The implemented algorithm not only classifies the main cardiovascular pathologies but also automatically extracts diagnostic intervals, which are compared with each patient's physiological values to generate alarms in the event of a mismatch. However, the system has limitations, such as the absence of a PPG sensor, which restricts analysis to the ECG signal. Furthermore, the hardware architecture relies on external PDAs for signal processing.

In (Alimbayeva et al 2024), the authors propose a wearable system based on chest electrodes integrated with a MEMS (Micro-Electro-Mechanical Systems) accelerometer for fall detection. The system combines automatic signal processing and transmission to an external unit.

In (Fanucci et al 2013), the authors present a device for the acquisition of multiple vital signals. Specifically, the ECG-SpO₂ module uses a four-ended trunk cable for the ECG signal and a standard fingertip device to acquire photoplethysmography signals. This device also employs threshold-based signal processing to estimate the amplitude of the QRS complex and the RR interval. Although the device represents a valid integrated system for monitoring vital parameters, its significant dimensions make it difficult to be portable or wearable.

Even configurations such as the auricular one have been explored for non-invasive monitoring of vital parameters, as reported in (Da He et al 2015). Using the acoustic pavilion reduces artifacts caused by finger or chest movements during measurement. The device allows the acquisition of three signals: electrocardiographic, photoplethysmographic and ballistocardiograph. The main limitation of this system is the sensor's positioning. In fact, only R peaks can be extracted from the ECG signal because positioning away from the chest significantly reduces signal amplitude.

Despite all these efforts, several key limitations persist:

- Many systems require multiple devices or a complex setup.
- PPG signals acquired at non-optimal sites (e.g., wrist or ear) suffer from poor signal-to-noise ratios.
- ECG interval analysis is often absent or limited to R-R detection.
- Devices may lack clear visual/auditory feedback, which is critical for usability in older adults (World Health Organization (WHO) 2015).

- User interfaces are often not designed with age-related sensory or cognitive impairments in mind (Hood C 2023).

These gaps underscore the need for a new generation of devices that are:

- Integrated (ECG + PPG in one system),
- Non-invasive and cable-free,
- User-friendly, especially for older populations,
- Capable of extracting both basic and advanced physiological metrics.

In response to these challenges, this work introduces a portable monitoring device that simultaneously acquires ECG and PPG signals with a simple finger placement. The system is compact and optimized for ease of use, enabling short-term home monitoring without professional assistance. Unlike many existing devices, it provides a more comprehensive physiological analysis while maintaining comfort and ease of use.

3. Materials and Methods

3.1 System Architecture

The system developed in this work is a compact, wireless, and non-invasive device designed for short-term cardiovascular monitoring. It enables the simultaneous acquisition of electrocardiogram (ECG) and photoplethysmography (PPG) signals through direct finger contact, without requiring external cables, chest straps, or wearable garments.

The system core is based on an ESP32 microcontroller, which manages signal acquisition from two sensors: the MAX30003 for ECG and the MAX30102 for PPG. The collected signals are transmitted to an external computer via USB (during this prototype phase) for real-time visualization and data storage.

All components are enclosed in a custom-designed 3D-printed case that ensures compactness, ergonomic finger positioning, and ease of use.

3.2 Sensors

3.2.1 ECG Sensor – MAX30003

The MAX30003 (Analog Devices) is a medical-grade analog front-end (AFE) dedicated to biopotential acquisition. It features ultra-low power consumption (~85 μ A active, ~1 μ A standby), high common-mode rejection ratio (CMRR), programmable gain, and a high-resolution ADC—making it suitable for wearable applications (Maxim Integrated 2021), (Cinotti et al 2024, Jain et al 2022, Lucas Bonek; Stephen

Fenech; Nicholas Sapoznik; Anthony J. Hanson; Simin Masihi; Dinesh Maddipatla; Masoud Panahi; Massood Z. Atashbar 2020).

3.2.2 ELECTRODES

Dry Ag/AgCl electrodes were selected to ensure comfort and ease of use. After testing various materials, Ag/AgCl proved superior at rejecting artifacts. The chosen electrodes (EB Neuro) have a 10 mm concave design to ensure firm skin contact during acquisition, reducing motion artifacts.

3.2.3 PPG Sensor – MAX30102

The MAX30102 by Analog Devices is a medical-grade module for non-invasive measurement of hemoglobin saturation and heart rate. The core of the system consists of two high-performance light-emitting diodes (LEDs), each emitting light at a wavelength optimized for physiological measurements: one at 660 nm (red) and the other at 880 nm (infrared). These LEDs are integrated with a photodiode that receives reflected light from the tissue and a digital signal processor with noise-filtering capabilities. Variations in the intensity of the received light, caused by changes in blood volume during the cardiac cycle, are used to generate the photoplethysmography (PPG) signal, which a digital signal processor with noise-filtering capabilities then processes. It also includes a proximity function to conserve power and reduce visible-light emission when the user's finger is not on the sensor. The module can be switched off by software. In standby mode, power consumption is almost zero (0.7 μ A) (Maxim Integrated n.d.).

3.3 Microcontroller Unit (MCU)

Both devices were controlled by a custom-programmed ESP32 microcontroller from Espressif Systems, designed for versatility and power. It is widely used in electronics and the Internet of Things (IoT) and is characterized by high performance, low power consumption, and advanced features. A particular strength of the ESP32 is its integrated connectivity, which includes both Wi-Fi and Bluetooth, making it particularly suitable for applications requiring wireless communication, such as smart home devices, wearables and remote monitoring systems (Espress If 2021).

3.4 Case Design

The device casing was designed in SolidWorks® and fabricated via 3D printing (Bambu Lab X1-Carbon®, PLA). The final design (Fig. 1) is compact (120 × 70 × 43 mm), ensuring portability and ease of use.

The case consists of two interlocking parts (base and lid). The lid includes a rectangular window (51 × 23 mm) for an LCD that displays heart rate and SpO₂ in real time. The base

features custom recesses for finger positioning, ensuring stable contact with the ECG electrodes and the PPG sensor.

3.5 Clinical Validation Protocol

Initially, 40 participants were recruited for the study: 22 women and 18 men (age: 62 ± 11.62 years). Seven subjects were excluded from the final analysis due to insufficient signal quality, primarily caused by unstable finger contact, motion artifacts, or incomplete reference measurements. As a result, the comparative study was performed on the remaining 33 participants: 19 women and 14 men (age: 64 ± 10.48 years). Excluded subjects were not included in any statistical comparison.

Participants were selected based on the absence of known cardiovascular disease and their membership in the target age group. No additional inclusion criteria were applied, as the cohort was intended to be representative of the target population. The study was conducted in accordance with ethical standards for human-subject research and IRB regulations; informed consent was obtained from all participants. The measurements took place in a real clinical context at the II Medical Clinic of the Policlinico Umberto I.

To evaluate the validity of our device, we compared the acquired PPG and ECG signals with those obtained using certified clinical instrumentation, which served as the reference.

For the ECG signal, we used a certified 12-lead electrocardiograph, CARDIOLINE 100-L, and for the SpO₂ value, we used a certified Yimi Life finger pulse oximeter.

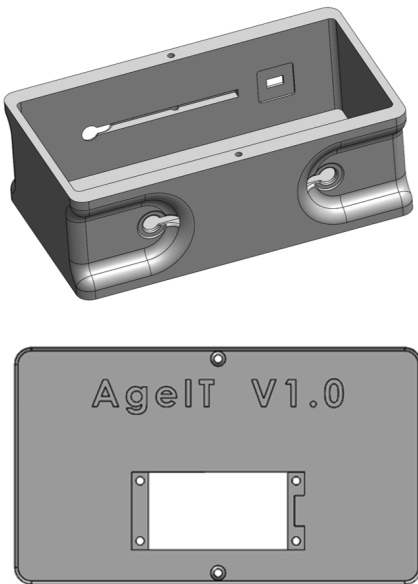


Fig. 1 CAD model of the case made in SolidWorks. On the top, a cross-section view highlights the housing dedicated to the sensors. On the bottom, the CAD model of the lid.

The experiments consist of parallel acquisitions between our prototype and the reference instruments for each subject.

In the standard electrocardiogram, the electrical activity of the heart is recorded by placing 10 electrodes: 6 on the chest and 4 on the limbs. In this way, the 12 standard leads of the electrocardiogram are obtained according to the conventional Einthoven system. The acquisition generally occurs in automatic mode, lasts about 10 seconds, and the result is provided as a static trace, printed or exported as a PDF. The device does not provide raw data; therefore, as explained in the following paragraphs, it was not possible to perform a cycle-by-cycle or beat-by-beat alignment, but only to estimate average values.

The device proposed in this work enables recording of the ECG signal via direct finger contact with the integrated electrodes for conds. In particular, the left thumb and index finger covered the left-side electrodes on the device, while the right thumb was positioned on the device's third and final electrode. This configuration corresponds to lead I (DI), in which the RA (right arm) and LA (left arm) electrodes are positioned on the right and left thumbs, respectively, while the left index finger serves as the reference, taking the role of the LL (left leg) electrode. Finally, the PPG sensor is placed under the index finger of the right hand. Fig. 2 shows a schematic of both configurations: the standard configuration and the configuration proposed in this work.

Before taking the measurement, the correct finger positioning on the sensors was verified, ensuring the

conductive surface was fully covered, and contact was maintained.

The participants were also informed that it was necessary to remain as still as possible throughout the test, avoid hand movements, and remain silent.

Fig. 3 shows the correct finger positioning to be maintained during acquisition.

3.6 Signal Acquisition and Processing

Raw signals from both ECG and PPG sensors were acquired in MATLAB (R2020 b) at sampling rates of 250 Hz for ECG and 50 Hz for PPG. Data were saved in CSV format and processed in Python (v3.9), using the open-source library NeuroKit2 (Le H. Nguyen 2021, Plagwitz *et al* 2024).

3.6.1 ECG Signal Processing

Following the acquisition, ECG traces underwent several post-processing steps to improve signal quality and extract physiological parameters.

(a) Preprocessing

An initial visual inspection was performed to exclude recordings that were excessively noisy. The first and last segments of each signal were trimmed to remove transient artifacts, and the tracings were normalized in amplitude. For this reason, ECG amplitudes are reported in arbitrary units (a.u.). Two filters were then applied:

- A 50 Hz notch filter to remove power line interference.
- A 3rd-order Butterworth band-pass filter (0.3–30 Hz) to isolate the physiological frequency band.

(b) Feature Extraction and Delineation

R-peaks were detected using NeuroKit2's internal `ecg_peaks()` function. The ECG signal was then delineated using `ecg_delineate()` with the Discrete Wavelet Transform (DWT) method, enabling identification of key fiducial points for each cardiac cycle: P waves (P_{onsets}), the beginning and the

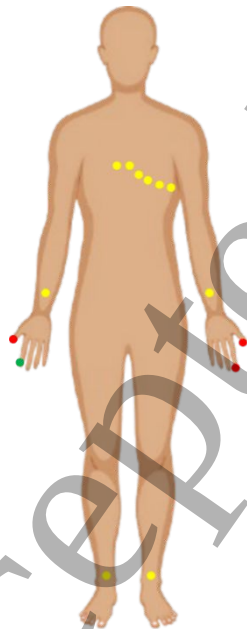


Fig. 2. Comparison of signal acquisition rentals: in yellow, the acquisition points of the CARDIOLINE 100-L (12 Lead); in red, the points where the ECG signal is acquired with our prototype (Single lead); in green, the point where the PPG signal is acquired.

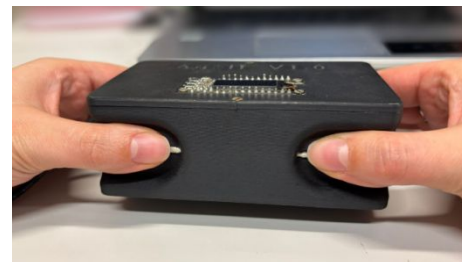


Fig.3 Correct positioning of the thumbs on the acquisition electrodes. This configuration ensures direct and stable contact between the skin and the sensors.

end of the QRS complex (QRS_{onsets} and $QRS_{offsets}$) and the end of the T wave ($T_{offsets}$).

From these, the following intervals were computed:

$$PR_{INTERVALS} [ms] = (t_{QRS_{onset}} - t_{P_{onset}}) * \frac{1000}{fs}$$

$$QRS_{DURATIONS} [ms] = (t_{QRS_{offset}} - t_{QRS_{onset}}) * \frac{1000}{fs}$$

$$QT_{INTERVALS} [ms] = (t_{T_{onset}} - t_{QRS_{onset}}) * \frac{1000}{fs}$$

$$RR_{INTERVALS} [ms] = (t_{R+1} - t_R) * \frac{1000}{fs}$$

The heart rate (HR) in beats per minute (bpm) was then calculated as:

$$HR [bpm] = \frac{60.000}{RR [ms]}$$

(c) Post-filtering of Parameters

To exclude physiologically implausible values, extracted parameters outside the following ranges were discarded:

$$PR_{INTERVALS} [ms] < 0; PR_{INTERVALS} [ms] > 300$$

$$QRS_{DURATIONS} [ms] < 0; QRS_{DURATIONS} [ms] > 150$$

$$QT_{INTERVALS} [ms] < 0; QT_{INTERVALS} [ms] > 600;$$

$$RR_{INTERVALS} [ms] < 300; RR_{INTERVALS} [ms] > 2000$$

Mean values were computed across valid cardiac cycles and compared to reference values obtained from the 12-lead

3.6.2 PPG Signal Processing

In the preliminary phase of the PPG signal study, a qualitative analysis of signals acquired from both channels was conducted to inform subsequent processing.

The IR channel was selected for signal analysis because it yielded higher signal quality and a cleaner trace than the RED channel. For this reason, filtering and segmentation were applied to the IR signal.

(a) Preprocessing and Channel Selection

PPG signals were acquired from both the RED and IR channels; however, the IR channel was selected for further processing due to superior signal quality.

The signal was cleaned using the `ppg_clean()` function in NeuroKit2, which applies a 3rd-order Butterworth band-pass filter (0.5–8 Hz) to isolate the pulsatile component while suppressing noise.

(b) Cycle Segmentation

Systolic peaks were detected using `ppg_findpeaks()`, and each cardiac cycle was defined as the interval between two consecutive peaks.

(c) SpO₂ Estimation

For each cycle, the AC and DC components of both RED and IR signals were calculated:

$$AC_{\lambda} = \max(signal_{\lambda}) - \min(signal_{\lambda})$$

$$DC_{\lambda} = \min(signal_{\lambda})$$

Then, the AC/DC ratio was calculated separately for both the RED and IR:

$$\frac{AC}{DC}_{\lambda} = \frac{\max(signal_{\lambda}) - \min(signal_{\lambda})}{\min(signal_{\lambda})}$$

The R-ratio was then derived as:

$$R = \text{mean} \frac{(AC/DC)_{RED}}{(AC/DC)_{IR}}$$

This parameter is proportional to the ratio of red to infrared light absorption and serves as the basis for estimating oxygen saturation.

Using a linear empirical formula from literature, oxygen saturation (SpO₂) was estimated as:

$$SpO_2 = A - (B * R)$$

where A and B are calibration constants derived from studies present in the literature (D'Alvia et al 2024).

(d) Second Derivative and SDPTG Analysis

The first and second derivatives of the filtered PPG signal were computed. The second derivative of the PPG (SDPTG) was used to extract vascular aging indices. Each subject's SDPTG signal was averaged across cycles. Five key nodal points were identified: Local maxima: a, c, e, and Local minima: b, d.

From these, the following indices were computed: four SDPTG indexes: b/a, c/a, d/a and e/a, and SDPTG-AI index (Aging Index), defined as (b-c-d-e)/a,

These indices have been shown to correlate with age and vascular stiffness (Lee et al 2011, Takazawa et al 1998).

3.7 Accuracy Evaluation

We evaluated the accuracy of the physiological parameters acquired by our device using two metrics: Mean Absolute Percentage Error (MAPE) and the Bland–Altman plot.

Both metrics were calculated for each extracted signal value: PR intervals, QRS durations, QT intervals, RR intervals, heart rate HR, and SpO₂.

The analysis was designed to assess the agreement between physiological parameters estimated by the prototype and those obtained from clinically validated reference instruments.

3.7.1 MAPE

The MAPE is a metric used to assess the accuracy of forecasting methods by expressing forecast errors as a percentage of the actual value.

For each parameter, we computed as follows:

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left(\left| \frac{X_{b,i} - X_{p,i}}{X_{b,i}} \right| \right) \times 100$$

where $X_{b,i}$ represents the value measured by the standard electrocardiograph, $X_{p,i}$ the value measured by our portable device, and N is the total number of measurements.

3.7.2 BLAND-ALTMAN ANALYSIS

The Bland-Altman analysis enables estimation of agreement between two measurement methods, in this case between values obtained from our prototype and those obtained with the clinical reference instruments.

In general, the analysis plots the difference between the two measurements against their average, helping to assess agreement and identify any systematic bias or random error.

For each parameter, we computed as follows:

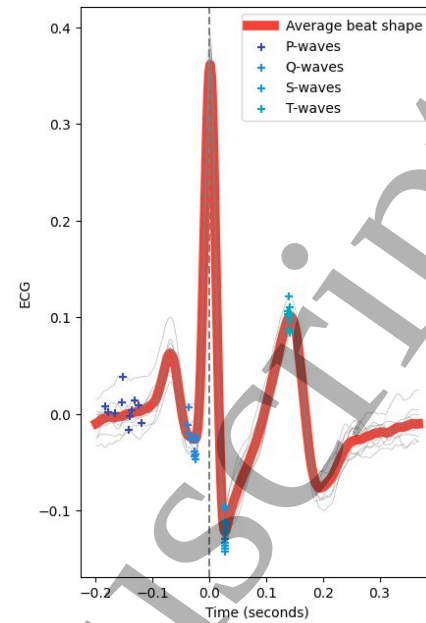


Fig. 5 Average cardiac cycle obtained using the automatic Neurokit2 function (Bencivenga et al 2025)

$$X_{diff} = X_{p,i} - X_{b,i}$$

$$X_{mean} = \frac{X_{p,i} + X_{b,i}}{2}$$

Where $X_{b,i}$ represents the value measured by the standard electrocardiograph, $X_{p,i}$ the value measured by our portable device, and N is the total number of measurements.

We performed a Bland-Altman analysis with a 95% confidence interval.

4. Results

4.1 Case Study: Single-Subject Analysis

To illustrate the signal acquisition and processing pipeline, we first present results from a single participant.

4.1.1 ECG results

The raw ECG signal acquired with the prototype (Fig. 4a) shows clearly identifiable R peaks but was affected by baseline drift and noise. After applying a 50 Hz notch filter and a band-pass filter (0.3–30 Hz), signal quality improved with a more stable baseline and reduced artifacts. Figure 4b, report ECG trace extracted from the Cardioline 100L printend report.

Using NeuroKit2, an average cardiac cycle was computed by aligning each beat to the R peak (Fig. 5). This visualization showed a consistent beat-to-beat morphology. Automatic

delineation (Fig. 6) identified the PR, QRS, QT, and RR intervals.

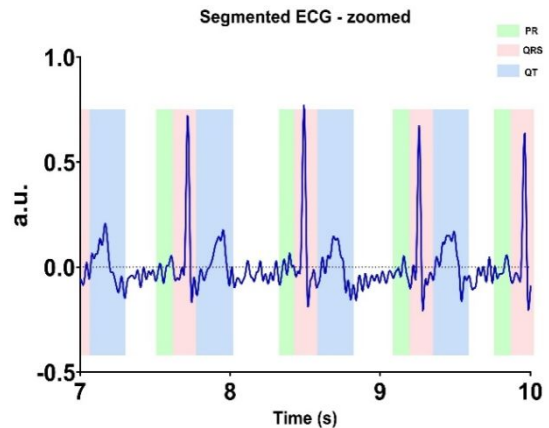


Fig. 6. Segmentation of the filtered ECG signal with the main physiological intervals highlighted: the QRS complex in pink, the PR interval in green and the QT interval in blue. A temporal zoom is shown [7-10s]

Table 1 compares the parameters estimated by the proposed algorithm with their corresponding reference values (REF), along with the absolute error for each parameter.

4.1.2 PPG Signal

The raw infrared-channel PPG signal (Fig. 7 in light red) was filtered and normalized to remove motion artifacts (Fig. 7 in black) enabling SpO₂ estimation. For this subject, the measured SpO₂ was 95%, compared to 97% measured by the reference pulse oximeter.

The second derivative of the signal was used to identify the nodal points a–e (Fig. 8), allowing computation of SDPTG indices. The SDPTG values for this subject are presented in Table 2.

4.2 Aggregate Results – Full Cohort (n = 33)

Table 1. Estimated values of PR, QRS, QT, RR intervals and heart rate (HR) obtained by the prototype, compared to reference values. The absolute error for each parameter is also reported.

Parameter	Prototype	Reference	Absolute Error
PR (ms)	96.6	136.0	39.4
QRS (ms)	90.3	94.0	3.7
QT (ms)	352.0	380.0	28.0
RR (ms)	732.6	977.0	244.4
HR (bpm)	81.9	61.0	20.9

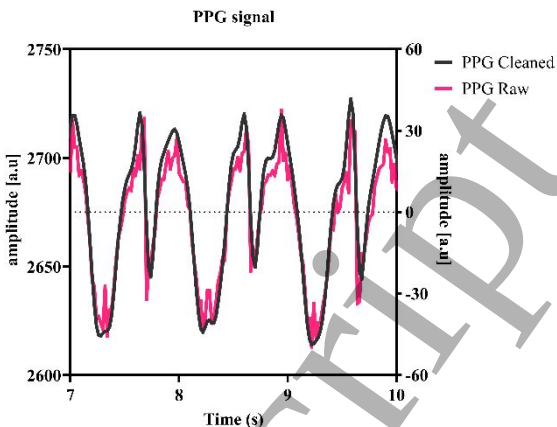


Fig.7 Comparison between the raw acquired PPG signal (light red) and the filtered one (black), relating to the same time interval [7–10 s].

Following the case study, we extended our analysis to the full cohort of 33 subjects.

4.2.1 ECG-Derived Parameters

ECG signals were successfully acquired in all included participants. Automatic extraction of cardiac intervals (PR, QRS, QT, RR) and heart rate was completed for each subject.

Table 3 summarizes the number extracted, discarded and included values, for each ECG-derived parameter.

Comparison with the 12-lead clinical ECG system revealed different error magnitudes across parameters. The QRS duration, RR interval, and heart rate exhibit mean absolute percentage errors (MAPE), of 11.7%, 14.2%, and 18.2%, respectively. In contrast, the PR and QT intervals exhibited higher MAPE values (24.8% and 19.7%, respectively).

Bland–Altman analysis was performed to assess the agreement between the prototype and the reference system for each parameter (Figs 9 a–e). The PR interval showed the largest dispersion in the Bland–Altman analysis (Fig. 9a),

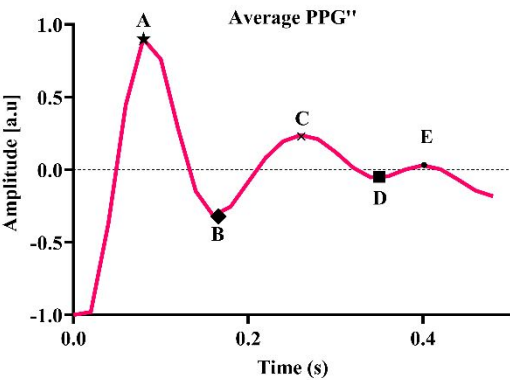


Fig.8 Cycle-averaged second derivative PPG with the relative nodal points A, B, C, D and E highlighted

Table 2. Values of the SDPTG indices (b/a, c/a, d/a, e/a) and the SDPTG Aging Index (AI) calculated from the second derivative of the signal

SDPTG Index	Value
b/a	-0.351
c/a	0.265
d/a	-0.057
e/a	0.034
SDPTG-AI	-0.593

while QRS duration and RR interval had narrower limits of agreement and minimal bias (Fig. 9c and 9d).

Both PR and QT intervals were underestimated by the prototype (Fig. 9a and 9b). Scatter plots and correlation coefficients (R^2) for all parameters are shown in (Figs 9 f-j), with values of 0.962 for PR, 0.982 for QRS, RR and HR, and 0.994 for QT intervals.

Table 3 Number of values extracted, discarded (with percentage) and included in the final analysis for each ECG-derived parameter

Parameter	Extracted Values	Discarded Values (%)	Included Values
PR	627	42 (6.7%)	585
QRS	627	66 (10.5%)	561
QT	627	8 (1.3%)	619
RR	633	7 (1.1%)	626

4.2.2 Photoplethysmographic Signal and Oxygen Saturation

The photoplethysmographic (PPG) signal acquired via the IR channel of the MAX30102 was filtered to remove artifacts and was suitable for SpO₂ estimation in all subjects.

The oxygen saturation (SpO₂) values estimated from the PPG data were compared with those obtained from a commercial finger pulse oximeter. revealed a MAPE of 2%.

Bland-Altman analysis showed a mean bias of 1% with limits of agreement of ± 1.96 SD. A small systematic bias was observed, as SpO₂ values from the prototype device were generally lower than the reference values Fig. 10a, , indicating

a slight underestimation. A scatter plot of SpO₂ values is shown in Fig. 10b.

4.2.3 SDPTG Indexes and Age-Related Trends

For each subject, we extracted the five characteristic points (a, b, c, d, and e) from the second derivative of the PPG waveform (SDPTG) and computed the corresponding indices: (b/a, c/a, d/a, e/a), and the aging index (AI).

To investigate age-related differences, the sample was divided into two groups: subjects under 65 and those aged 65 or older. In the older group, the b/a and d/a ratios were higher, whereas the c/a and e/a ratios and the overall systolic wave amplitude were lower (Fig. 11 a-d). The SDPTG-AI index showed higher values in the older group (Fig. 11e). Table 4 summarizes the SDPTG indices for subjects aged under and over 65.

4.2.4 Sex-Related Differences

Sex-related differences in SDPTG indices were also evaluated. Women showed higher b/a, c/a, and e/a ratios, whereas men exhibited higher d/a ratios. These differences were not statistically tested in this preliminary analysis and are reported in Fig. 12

5 Discussion

The present study evaluated a portable, fingertip-based system for the acquisition of ECG and PPG signals using a short, non-invasive measurement protocol. Despite the limited acquisition time (30 s), the system enabled extraction of multiple physiological parameters, allowing an assessment of its performance relative to clinically validated reference instruments. Taken together, these findings indicate the potential feasibility of a home-based cardiovascular monitoring configuration, particularly in contexts where ease of use is a primary requirement.

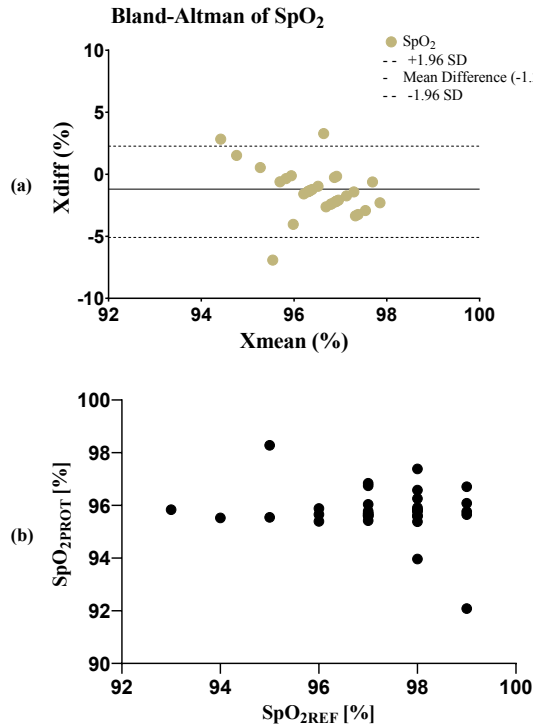
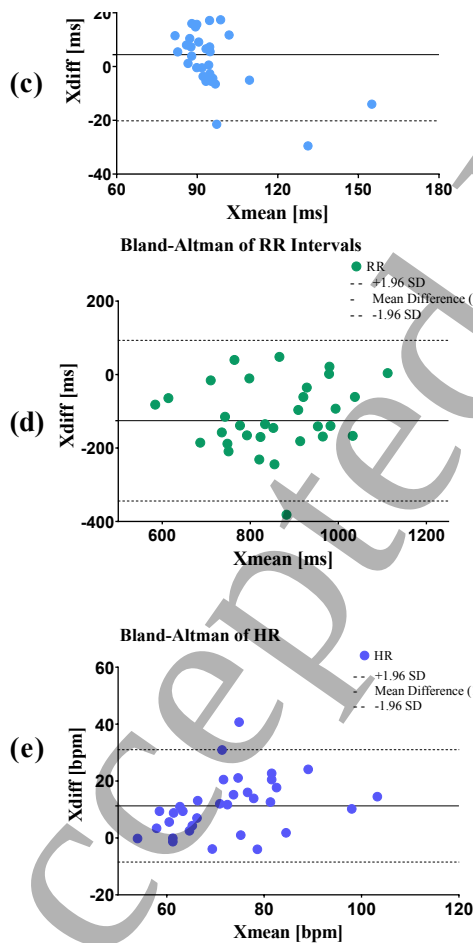
A key outcome of the study is the reliable detection of R peaks across recordings, which enabled stable estimation of rhythm-derived parameters such as RR intervals and heart rate. QRS complex duration also showed good agreement with the clinical reference, suggesting preservation of the main ECG deflections under the fingertip acquisition configuration.

In contrast, PR and QT interval estimation was more challenging. These parameters depend on accurate estimation of P- and T-wave onset and offset, which are characterized by lower amplitude and increased sensitivity to noise and contact variability. The absence of adhesive electrodes and standardized limb placement further limits morphological fidelity in a fingertip-based, single-lead configuration.

Moreover, comparison with a standard 12-lead electrocardiograph is inherently influenced by differences in

lead vector orientation and electrode placement, which affect,
as stated, waveform morphology and interval measurements

Accepted Manuscript

Fig.10 Bland-Altman plot (a) and scatter plot (b) for SpO₂Fig 9. Results of Bland Altman analysis for PR, QT, QRS, RR intervals and HR (a,b, c, d, e), with highlighted the acceptance regions and the bias, scatter plot for each parameters and correlation factor R² is presented in (f, g, h, i and j)

Despite these limitations, the performance observed for several parameters falls within, or is comparable to, values reported in the literature for other wearable or single-lead systems.

For instance, QT interval estimation in this study yielded a mean absolute percentage error (MAPE) of 19.7%, which is higher than the 12.1% reported by Panni et al. for a chest-strap-based device (Panni et al 2025). Conversely, the MAPE observed for QRS duration (11.7%) is lower than that reported in the same study, suggesting that the main high-amplitude ECG deflections are well preserved in the fingertip configuration.

The higher error observed for PR interval estimation (MAPE = 24.8%) reflects the known difficulty of reliably detecting the P wave in single-lead, fingertip-based configurations without stable adhesive or chest-mounted electrodes. This limitation is likely attributable to reduced fidelity in identifying the onset and offset of low-amplitude waveform components and is consistent with prior findings in single-lead wearable research. While chest-strap systems may offer more robust morphological acquisition, they are inherently less convenient and may present usability barriers for older adults, emphasizing the importance of considering intended use when evaluating device performance.

Regarding the overestimation of heart rate values, two main factors should be considered: algorithmic factors, including beat detection accuracy, signal noise, and filtering and averaging effects; device hardware characteristics. In this regard, the proposed single-lead prototype is based on low-cost components (approximately 60 €) and operates at a sampling frequency of 250 Hz, compared with the 12-lead Cardioline 100-L, which acquires data at 500 Hz per channel and represents a higher-end clinical system (approximately 2000 €).

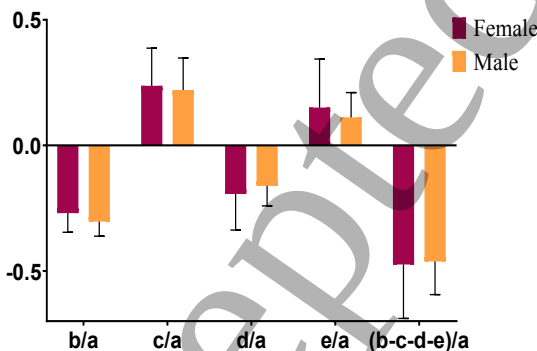


Fig.12 Comparison of SDPTG index values (b/a, c/a, d/a, e/a) in female (purple) and male (orange) subjects.

Despite the presence of a systematic positive bias in heart rate estimation, the scatter plot analysis revealed a strong linear correlation with the reference measurements ($R^2 = 0.98$). This indicates that the prototype is able to reliably track

inter-subject and inter-measurement variability, while producing heart rate estimates that are consistently shifted toward higher values. The low rejection rate observed for RR

Table 4. SDPTG index values in subjects aged <65 years and ≥65 years. The arrows indicate the index trend in the older group compared to the younger group.

Index	<65	≥65	Trend
b/a	-0.290	-0.262	↑
c/a	0.234	0.216	↓
d/a	-0.210	-0.140	↑
e/a	0.157	0.110	↓
SDPTG-AI	-0.473	-0.461	↑

intervals (1.1%, Table 3) suggests that the observed bias is not attributable to extensive beat exclusion or poor signal quality. Instead, it is plausibly due to small systematic deviations in RR interval estimation across accepted beats, which translate into an overestimation of heart rate.

These small deviations may be partly explained by reduced temporal precision in R-peak detection, which propagates to RR interval estimation and, consequently, to heart rate calculation.

MAPE values for QRS, RR, and HR (11.7%, 14.2%, and 18.3%, respectively) and their corresponding standard errors (approximately 1.7%, 1.7%, and 2.7%, respectively) fall within or are comparable to the ranges reported for other fingertip-based or wearable single-lead devices (Dooley et al 2017, Panni et al 2025, Rehman et al 2024).

Prior studies have documented similar performance: the HeartKey Test Watch reported mean HR errors <1 bpm with a beat rejection rate of ~8.5% (Funston et al 2022), smartphone-based fingertip PPG showed RMSE ~1.4% compared to ECG (Yan et al 2017), and finger PPG sensors demonstrated test-retest reliability for RR intervals against ECG (Rogers et al 2025).

Despite the observed limitations in morphological ECG feature extraction, the system demonstrated reliable estimation of rhythm-related parameters, particularly heart rate and RR variability. These parameters are often sufficient for remote monitoring, preliminary screening, and home-based cardiovascular assessment applications.

PPG-derived parameters demonstrated more consistent behaviour, particularly oxygen saturation (SpO_2), which showed a lower MAPE (2%) and narrower Bland-Altman

limits than the reference instrument. According to the ISO standard (ISO - International Organization for Standardization 2017), this level of accuracy (<5%) can be considered generally reliable and clinically acceptable.

However, the scatter plot (fig 10b) reveals an important nuance: the measured SpO₂ values show essentially no correlation with the reference measurements ($R^2 < 0.5$). This indicates that, while the device provides values within an acceptable accuracy range, it does not reliably track the variability of the reference system in this dataset. In other words, the device may provide clinically acceptable SpO₂ readings on average, but its ability to follow moment-to-moment changes is limited.

Beyond traditional parameters, we explored the second derivative of the PPG waveform (SDPTG), providing additional insights into vascular health and aging. For each subject, five characteristic points (a, b, c, d, e) were extracted, and the corresponding SDPTG indices (b/a, c/a, d/a, e/a, and the aging index, AI) were computed. Subjects were divided into two groups: under 65 and 65 or older. In the older group, b/a and d/a ratios moderately increased, consistent with age-related arterial stiffness, while c/a and e/a ratios decreased, along with the overall amplitude of the systolic wave. The SDPTG-AI index also showed a slight increase, further supporting the hypothesis of vascular aging.

A preliminary analysis of sex-related differences revealed slightly higher b/a, c/a, and e/a ratios in women, whereas men showed higher d/a values. Although these differences were modest and not statistically tested, they align with previously reported gender-related variations in vascular compliance and warrant further investigation in larger datasets. These trends are in line with findings from previous literature and validate the potential use of the device not only for basic vital sign monitoring but also for non-invasive vascular assessment.

Overall, age-dependent changes in SDPTG indices—such as increases in b/a and d/a and decreases in c/a and e/a—are consistent with established markers of vascular aging (Choi and Park 2023). While preliminary variability across subjects was observed for some indices, confirming sex- or age-related patterns requires larger, stratified cohorts. While some intersubject variability was observed, the capture of physiologically plausible trends highlights the device's sensitivity to individual differences and its potential for personalized vascular monitoring.

6 Conclusion

This study proposes an accessible, finger-based monitoring solution for healthy aging, developed through collaboration between clinicians and engineers. The device reliably acquires ECG and PPG signals and extracts clinically significant

parameters from a 30-second recording, with satisfactory overall accuracy given its simplicity and portability.

Several limitations were identified. Low-amplitude ECG components, particularly the P wave, are difficult to detect, affecting PR interval estimation. The system is sensitive to finger movements, which may reduce signal quality and measurement repeatability, especially in older adults with tremor. The single-lead ECG configuration (lead I) also limits diagnostic capability compared with standard multi-lead clinical systems. Time-based features capture most diagnostically relevant information, but amplitude-related parameters are not reliably accessible in the current fingertip setup. RR-derived heart rate estimates are influenced by hardware specifications, suggesting that more robust HR estimators could further improve accuracy.

Despite these limitations, the device performs well in estimating blood oxygen saturation (SpO₂) and second-derivative photoplethysmography (SDPTG) analysis. Its non-invasive and portable design represents a clear advantage in terms of usability, particularly for older users, and helps overcome the main barriers to adoption identified in previous studies (Peek et al 2014). Preliminary durability tests indicated stable performance across multiple sessions; although long-term effects of perspiration and environmental conditions will need systematic evaluation.

Future work will focus on several key areas to enhance the device's functionality, usability, and clinical applicability. First, wireless communication will be integrated to enable real-time data transfer for home monitoring and telemedicine, allowing clinicians and caregivers to remotely track ECG and PPG signals. Second, a user-friendly graphical interface (GUI) will be developed to display physiological parameters, provide alerts for abnormal values, and visualize trends over time, improving accessibility for older adults and patients with chronic conditions. Third, signal quality and accuracy will be enhanced by implementing machine learning algorithms for more robust P-wave and T-wave detection, as well as adaptive filters to reduce motion artifacts, particularly in single-lead fingertip ECG recordings. Fourth, the device will be further validated in clinical populations with cardiovascular disease to assess its utility for both screening and diagnostic purposes. Finally, advanced analysis and personalization approaches will be explored, including predictive modelling of vascular and heart rate trends, adaptive parameter estimation based on individual physiology, and integration of SDPTG indices for risk assessment, ultimately supporting more tailored, preventive cardiovascular care.

Funding

This work was supported by the “PNRR Progetto Partenariati Estesi AGE-IT - PE8. Conseguenze e sfide dell'invecchiamento, PE0000015, CUP: B53C22004090006”

Ethical statement

This study was conducted in accordance with the Declaration of Helsinki, as a part of a broader research study approved by the Ethics Committee of Azienda Policlinico Umberto 1 (protocol code 0099/2021).

Data availability statement

The data cannot be made publicly available upon publication because no suitable repository exists for hosting data in this field of study. The data that support the findings of this study are available upon reasonable request from the authors.

References

Adams T, Wagner S, Baldinger M, Zellhuber I, Weber M, Nass D and Surges R 2022 Accurate detection of heart rate using in-ear photoplethysmography in a clinical setting *Front Digit Health* 4

Alimbayeva Z, Alimbayev C, Ozhikenov K, Bayanbay N and Ozhikenova A 2024 Wearable ECG Device and Machine Learning for Heart Monitoring *Sensors* 24

Alsadoon A, Al-Naymat G and Jerew O D 2024 An architectural framework of elderly healthcare monitoring and tracking through wearable sensor technologies *Multimed Tools Appl* 83 67825–70

Angelucci A, Cavicchioli M, Cintorrino I A, Lauricella G, Rossi C, Strati S and Aliverti A 2021 Smart textiles and sensorized garments for physiological monitoring: A review of available solutions and techniques *Sensors (Switzerland)* 21 1–23

Babar F, Cheema A M, Ahmad Z, Sarfraz A, Sarfraz Z, Ashraff H, Tayyab H, Bajwa A M, Ali H, Sarfraz M, Shahzad A and Sabzwari S R A 2023 Sensitivity and Specificity of Wearables for Atrial Fibrillation in Elderly Populations: A Systematic Review *Curr Cardiol Rep* 25 761–79

Bassiouni M M, Hegazy I, Rizk N, El-Dahshan S A and Salem A M 2021 Combination of ECG and PPG Signals for Healthcare Applications: A Survey *Advances in Modelling and Analysis B* 64 63–70

Bencivenga C, D’Alvia L, Cangemi R, Basili S and Del Prete Z 2025 Performance Validation of a Low-Cost Multisensor Device in the Healthy Aging Field *IEEE International Symposium on Medical Measurements and Applications, MeMeA* (Institute of Electrical and Electronics Engineers Inc.)

De Capua C, Meduri A and Morello R 2010 A smart ECG measurement system based on web-service-oriented architecture for telemedicine applications *IEEE Trans Instrum Meas* 59 2530–8

Choi J and Park M G 2023 Variations in the Second Derivative of a Photoplethysmogram with Age in Healthy Korean Adults *Int J Environ Res Public Health* 20

Cinotti E, Centracchio J, Parlato S, Andreozzi E, Esposito D, Muto V, Bifulco P and Riccio M 2024 A Narrowband IoT Personal Sensor for Long-Term Heart Rate Monitoring and Atrial Fibrillation Detection *Sensors* 24

Cosoli G, Spinsante S, Scardulla F, D’Acquisto L and Scalise L 2021 Wireless ECG and cardiac monitoring systems: State of the art, available commercial devices and useful electronic components *Measurement (Lond)* 177

Cowie M R and Lam C S P 2021 Remote monitoring and digital health tools in CVD management *Nat Rev Cardiol* 18 457–8

D’Abbondanza N, Ferrazza M, Lucangeli L, Piuze E and Pallotti A 2021 Sensorized T-Shirt for Cardiological Patients in Telemonitoring † *Engineering Proceedings* 11

D’Alvia L, Mattioli L, Palermo E and Del Prete Z 2024 Development and Validation of an Algorithm for Calibrating Photoplethysmography Integrated Device 2024 *IEEE International Symposium on Medical Measurements and Applications, MeMeA 2024 - Proceedings* (Institute of Electrical and Electronics Engineers Inc.)

Daniëls F, Ramdjan T T T K, Mánfai B, Adiyaman A, Smit J J J, Delnoy P P H M and Elvan A 2024 Detection of atrial fibrillation in persons aged 65 years and above using a mobile electrocardiogram device *Netherlands Heart Journal* 32 160–6

Deng Z, Guo L, Chen X and Wu W 2023 Smart Wearable Systems for Health Monitoring *Sensors* 23

Dooley E E, Golaszewski N M and Bartholomew J B 2017 Estimating accuracy at exercise intensities: A comparative study of self-monitoring heart rate and physical activity wearable devices *JMIR Mhealth Uhealth* 5

Espress If 2021 *ESP32 Series Datasheet Including Online*: <https://www.espressif.com/en/support/download/documents>.

- Fanucci L, Saponara S, Bacchillone T, Donati M, Barba P, Sanchez-Tato I and Carmona C 2013 Sensing devices and sensor signal processing for remote monitoring of vital signs in CHF patients *IEEE Trans Instrum Meas* 62 553–69
- Funston R, Gibbs A, Diven J, Francey J, Easlea H, Murray S, Fitzpatrick M, Condon A and Mitchell A R J 2022 Comparative study of a single lead ECG in a wearable device *J Electrocardiol* 74 88–93
- Guo D G, Tay F E H, Xu L, Yu L M, Nyan M N, Chong F W, Yap K L and Xu B 2008 A long-term wearable vital signs monitoring system using BSN *Proceedings - 11th EUROMICRO Conference on Digital System Design Architectures, Methods and Tools, DSD 2008* pp 825–30
- Le H, Nguyen T H D A Q P A Q L Q H L and A T 2021 Heart Rate Feature Extraction based on Neurokit2 with Python
- Da He D, Winokur E S and Sodini C G 2015 An ear-worn vital signs monitor *IEEE Trans Biomed Eng* 62 2547–52
- Himmelreich J C L, Karregat E P M, Lucassen W A M, van Weert H C P M, de Groot J R, Louis Handoko M, Nijveldt R and Harskamp R E 2019 Diagnostic accuracy of a smartphone-operated, single-lead electrocardiography device for detection of rhythm and conduction abnormalities in primary care *Ann Fam Med* 17 403–11
- Hood C S N V C et al. 2023 *Remote Patient Monitoring* Online: <https://psnet.ahrq.gov/perspective/remote-patient-monitoring>
- ISO - International Organization for Standardization 2017 ISO/CD 80601-2-61: Medical electrical equipment Part 2-61:2017 Particular requirements for basic safety and essential performance of pulse oximeter equipment” Online: <https://www.iso.org/standard/84595.html>
- Jain A, Singh M and Singh B 2022 Real time system on chip based wearable cardiac activity monitoring sensor *Measurement: Sensors* 24
- Karimi S, Nateghi M, Cestero G I, Chitadze L, Deepanshi, Yang Y, Vyas J H, Chen C, Bouzid Z, Yaldiz C O, Harris N, Bull R, Stone B T, Lynn S K, Bracken B K, Inan O T, Bremner J D and Sameni R 2025 Prescreening depression using wearable electrocardiogram and photoplethysmogram data from a psycholinguistic experiment *Physiol Meas* 46
- Klier K, Koch L, Graf L, Schinköthe T and Schmidt A 2023 Diagnostic Accuracy of Single-Lead Electrocardiograms Using the Kardia Mobile App and the Apple Watch 4: Validation Study *JMIR Cardio* 7
- Krishnaswami A, Beavers C, Dorsch M P, Dodson J A, Masterson Creber R, Kitsiou S, Goyal P, Maurer M S, Wenger N K, Croy D S, Alexander K P, Batsis J A, Turakhia M P, Forman D E, Bernacki G M, Kirkpatrick J N, Orr N M, Peterson E D, Rich M W, Freeman A M and Bhavnani S P 2020 Gerontechnology for Older Adults With Cardiovascular Diseases: JACC State-of-the-Art Review *J Am Coll Cardiol* 76 2650–70
- Lee C, Sik Shin H and Lee M 2011 Relations between ac-dc components and optical path length in photoplethysmography *J Biomed Opt* 16 077012
- Lucas Bonek; Stephen Fenech; Nicholas Sapoznik; Anthony J. Hanson; Simin Masihi; Dinesh Maddipatla; Masoud Panahi; Massood Z. Atashbar 2020 Development of a Flexible and Wireless ECG Monitoring Device
- Luchsinger G and United Nations. Department of Economic and Social Affairs *World social report 2023 : leaving no one behind in an ageing world*
- Majumder S, Mondal T and Deen M J 2017 Wearable sensors for remote health monitoring *Sensors (Switzerland)* 17
- Maxim Integrated 2021 *MAX30003 - Ultra-Low Power, Single-Channel Integrated Biopotential (ECG, R-to-R Detection) AFE* Online: www.maximintegrated.com/thermal-tutorial.
- Maxim Integrated *MAX30102--High-Sensitivity Pulse Oximeter and Heart-Rate Sensor for Wearable Health* Online: www.maximintegrated.com
- Montes J, Young J C, Tandy R and Navalta J W 2018 *Reliability and Validation of the Hexoskin Wearable Bio-Collection Device During Walking Conditions* Online: <http://www.intjexersci.com>
- OECD 2023 *Health at a Glance 2023* (OECD)
- Panni L, Cosoli G and Scalise L 2025 *Metrological Evaluation of Wearable ECG Systems: Heart Rate Estimation and PQRST Waveform Analysis*
- Pantelopoulous A and Bourbakis N G 2010 A survey on wearable sensor-based systems for health monitoring and prognosis *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews* 40 1–12

Peek S T M, Wouters E J M, van Hoof J, Luijckx K G, Boeije H R and Vrijhoef H J M 2014 Factors influencing acceptance of technology for aging in place: A systematic review *Int J Med Inform* 83 235–48

Plagwitz L, Bickmann L, Fujarski M, Brenner A, Gobalakrishnan W, Eckardt L, Büscher A and Varghese J 2024 The Rlign Algorithm for Enhanced Electrocardiogram Analysis through R-Peak Alignment for Explainable Classification and Clustering Online: <http://arxiv.org/abs/2407.15555>

Rehman R Z U, Chatterjee M, Manyakov N V., Daans M, Jackson A, O’Brisky A, Telesky T, Smets S, Berghmans P J, Yang D, Reynoso E, Lucas M V., Huo Y, Thirugnanam V T, Mansi T and Morris M 2024 Assessment of Physiological Signals from Photoplethysmography Sensors Compared to an Electrocardiogram Sensor: A Validation Study in Daily Life *Sensors* 24

Rogers D W, Himariotis A T, Sherriff T J, Proulx Q J, Duong M T, Noel S E and Cornell D J 2025 Test–Retest Reliability and Concurrent Validity of Photoplethysmography Finger Sensor to Collect Measures of Heart Rate Variability *Sports* 13

Seçkin A Ç, Ateş B and Seçkin M 2023 Review on Wearable Technology in Sports: Concepts, Challenges and Opportunities *Applied Sciences (Switzerland)* 13

Serhani M A, El Kassabi H T, Ismail H and Navaz A N 2020 ECG monitoring systems: Review, architecture, processes, and key challenges *Sensors (Switzerland)* 20

Shahid S, Iqbal M, Saeed H, Hira S, Batool A, Khalid S and Tahirkheli N K 2025 Diagnostic Accuracy of Apple Watch Electrocardiogram for Atrial Fibrillation: A Systematic Review and Meta-Analysis *JACC: Advances* 4

Shan H and Jin W 2025 A Multi-Sensor-Based System for Cardiovascular Health Monitoring 2025 5th International Conference on Sensors and Information Technology, ICSI 2025 (Institute of Electrical and Electronics Engineers Inc.) pp 442–7

Stefana E, Marciano F, Rossi D, Cocca P and Tomasoni G 2021 Wearable devices for ergonomics: A systematic literature review *Sensors (Switzerland)* 21 1–24

van Steijn N J, Peppinkhuizen S, Postema P G, Knops R E and Winter M M 2025 Ventricular arrhythmia detection with a wearable ring-type photoplethysmography sensor: A feasibility study *Heart Rhythm*

Takazawa K, Tanaka N, Fujita M, Matsuoka O, Saiki T, Aikawa M, Tamura S and Ibukiyama C 1998 *Assessment of Vasoactive Agents and Vascular Aging by the Second Derivative of Photoplethysmogram Waveform* Online: <http://ahajournals.org>

World Health Organization 2022 *Consolidated telemedicine implementation guide*

World Health Organization (WHO) 2015 *Systematic review of needs for medical devices for ageing populations* Online: www.who.int

Yan B P, Chan C K Y, Li C K H, To O T L, Lai W H S, Tse G, Poh Y C and Poh M Z 2017 Resting and postexercise heart rate detection from fingertip and facial photoplethysmography using a smartphone camera: A validation study *JMIR Mhealth Uhealth* 5

Yebda T, Benois-Pineau J, Amieva H and Frolicher B 2019 Multi-sensing of fragile persons for risk situation detection: Devices, methods, challenges *Proceedings - International Workshop on Content-Based Multimedia Indexing* vol 2019-September (IEEE Computer Society)

Zaprutko T, Zaprutko J, Baszko A, Sawicka D, Szalek A, Dymecka M, Telec W, Kopciuch D, Ratajczak P, Michalak M, Rafał D, Szyszka A and Nowakowska E 2020 Feasibility of Atrial Fibrillation Screening With Mobile Health Technologies at Pharmacies *J Cardiovasc Pharmacol Ther* 25 142–51

Zhang X, Zhan Y, Wang X and Yang J 2025 A Chest Strap-Based System for Electrocardiogram Monitoring *Applied Sciences (Switzerland)* 15

Zhang Y, Song S, Vullings R, Biswas D, Simões-Capela N, Van Helleputte N, Van Hoof C and Groenendaal W 2019 Motion artifact reduction for wrist-worn photoplethysmograph sensors based on different wavelengths *Sensors (Switzerland)* 19