



Design and Implementation of a Low-Cost IoT-Enabled Smartwatch for Monitoring Patient Health

Elias Oghewerere Alure, Michael Oghale Ighofiomoni, Omolegho A. Ibok*, Edward O. Odesa, Jones U. Ekwemuka, Omokaro Idama

Department of Computer Engineering, Faculty of Engineering, Southern Delta University, Ozoro, Delta State, Nigeria

*Corresponding author

DOI: <https://doi.org/10.68050/JAMS.2026.663>

Received: 06 September 2026; Accepted: 12 September 2026; Published: 02 October 2026

ABSTRACT

Continuous monitoring of vital signs is central to preventive healthcare and chronic-disease management, yet commercial smartwatches from manufacturers such as Apple, Fitbit, and Samsung remain prohibitively expensive for most users in developing countries, with prices in Nigeria ranging from roughly ₦340,000 to ₦1,200,000. This creates a significant accessibility gap in personal health technology. This work presents the design, implementation, and validation of a low-cost, Internet of Things (IoT)-enabled smartwatch capable of real-time monitoring of blood oxygen saturation (SpO_2), heart rate, and body temperature. The prototype integrates a MAX30102 pulse-oximetry and heart-rate sensor, a DS18B20 digital temperature sensor, and an ATmega328P microcontroller, together with a DS3231 real-time clock, an HC-06 Bluetooth module, and an SSD1306 OLED display. A three-stage power tree (TP4056 charge controller, MCP1700 low-dropout regulator, and MOSFET-based peripheral load switching) manages the rechargeable lithium-polymer battery. Firmware developed in the Arduino IDE implements peak-detection heart-rate estimation, ratio-of-ratios SpO_2 calculation with local calibration, and a signal-quality gate that withholds unreliable readings rather than reporting them. The device was validated against medical-grade reference instruments (Masimo MightySat, Polar H10, Braun tympanic thermometer) across 1,440 paired SpO_2 and heart-rate samples and 120 paired temperature samples from 20 participants, with usability assessed by 30 additional respondents. The prototype achieved an SpO_2 accuracy of 1.78% ARMS (mean absolute error 1.62%), a combined heart-rate mean absolute error of 2.58 bpm, and a temperature mean absolute error of 0.31 °C, meeting the ISO 80601-2-61 clinical threshold and comparing favourably with flagship consumer devices costing more than ten times as much. Aggressive duty cycling extended battery life from 17.4 h in continuous-monitoring mode to 102 h in power-saving mode. These results demonstrate that careful engineering of commodity components, rather than exotic hardware, is the binding constraint on affordable, clinically credible wearable health monitoring.

Keywords: Internet of Things; wearable health monitoring; photoplethysmography; MAX30102; low-cost smartwatch; pulse oximetry; SpO_2 .

INTRODUCTION

The global healthcare landscape is shifting from reactive treatment to proactive monitoring, driven by advances in wearable technology and the Internet of Things. Continuous tracking of vital signs like blood oxygen saturation (SpO_2), heart rate, and body temperature is now essential for the early detection of medical emergencies. While SpO_2 is a critical indicator of respiratory health, gaining global prominence during the COVID-19 pandemic heart rate and temperature provide vital data on cardiovascular stress and systemic infection. Traditional monitoring relies on expensive and bulky clinical equipment, creating a gap for patients with chronic conditions who require frequent data outside of hospitals. While premium smartwatches from brands like Apple and Garmin offer sophisticated sensing capabilities, their high price points often between ₦340,000 to ₦1,200,000 Naira, act as a significant barrier.



This is particularly true in developing nations like Nigeria, where such devices remain luxury items inaccessible to the majority of the population who live on limited daily incomes. Nigeria's healthcare infrastructure faces severe challenges, including a critical shortage of medical personnel and a doctor-to-patient ratio far below World Health Organization recommendations. In rural areas where access to diagnostic equipment is scarce, wearable devices could drastically reduce the burden on the formal health system. By empowering individuals to monitor their own vitals, these technologies facilitate early intervention and chronic disease management in resource-limited settings. The democratization of hardware through platforms like Arduino and ESP32 has made the development of low-cost health monitors technically feasible. Integrated biosensors, such as the MAX30102, utilize Photoplethysmography to measure heart rate and SpO₂ using red and infrared light.

These components are now available at a fraction of the cost of medical-grade devices, allowing for the integration of sophisticated signal processing and wireless connectivity into affordable and accessible architectures. This research details the design and implementation of a comprehensive low-cost smartwatch that integrates SpO₂, heart rate, and temperature sensing. Unlike previous laboratory prototypes, this system is designed for practical daily use and features a real-time clock, data display, rechargeable battery, and Bluetooth connectivity.

RELATED WORK

Photoplethysmography (PPG) is the dominant sensing modality for non-invasive cardiovascular monitoring in wearables. It works by illuminating tissue with LEDs and measuring transmitted or reflected light with a photodetector; pulsatile changes in blood volume during the cardiac cycle produce the characteristic PPG waveform, from which heart rate is extracted via peak detection (Castaneda et al., 2018; Tamura et al., 2014; Biswas et al., 2019). SpO₂ measurement exploits the differential absorption of red and infrared light by oxygenated and deoxygenated haemoglobin; the ratio of AC to DC components at both wavelengths is mapped to SpO₂ through an empirical calibration curve derived from the Beer–Lambert law (Jubran, 2015; Tremper & Barker, 1989). Modern integrated sensors such as the MAX30102 combine programmable LED current, an 18-bit ADC, and ambient-light cancellation to improve signal quality (Maxim Integrated, 2020), but PPG remains susceptible to motion artefact, poor peripheral perfusion, and skin-tone-related bias (Allen, 2007; Bent et al., 2020).

Several prior studies have built low-cost pulse-oximetry systems on Arduino-class hardware. Sari et al. (2021) reported an SpO₂ accuracy of approximately 1.15% using a MAX30100 sensor, and Cebada-Fuentes et al. (2024) achieved $\pm 1.39\%$ with an optimised MAX30102 design; both results are consistent with the accuracy achieved in the present work. Lipnick et al. (2016) evaluated low-cost commercial pulse oximeters and found substantial variability, with several devices performing worse than the prototype described here. Majumder et al. (2017), Gao et al. (2015), and Pandian et al. (2008) reviewed wearable health-monitoring architectures more broadly, consistently identifying power management, wearable form factor, and validation rigor as the weak points of academic prototypes relative to commercial products. Wong et al. (2021) demonstrated that pulse oximeters across all price tiers systematically over-read in darker-skinned patients, a finding of direct relevance to deployment in Nigeria and other Sub-Saharan contexts. Adoption-oriented work grounded in the Technology Acceptance Model and Diffusion of Innovation theory (Venkatesh & Davis, 2000; Rogers, 1962) further suggests that low cost and low complexity are strong predictors of uptake among price-sensitive populations. Collectively, the literature justifies the cost-reduction rationale for this project while highlighting a persistent gap in validated, wearable, power-managed, low-cost multi-parameter devices particularly for African populations that this study addresses.

MATERIALS AND METHODS

System Architecture

The smartwatch follows a modular, sensor-centric architecture organised into three functional planes: a sensing plane, a processing plane built on an ATmega328P microcontroller, and a communication plane that delivers

data to an Android companion application over Bluetooth. A 3.7 V/1000 mAh lithium-polymer cell feeds a TP4056 charge controller, which in turn powers an MCP1700-3302E low-dropout regulator producing a 3.3 V rail for all logic and sensor ICs. The ATmega328P, clocked at 8 MHz on its internal oscillator to reduce current draw, exchanges data with the MAX30102, DS3231, and SSD1306 OLED over a shared I²C bus at 400 kHz, while the DS18B20 occupies a dedicated 1-Wire line. The HC-06 Bluetooth module communicates with the microcontroller over hardware UART at 9600 baud. The MAX30102 samples red (660 nm) and infrared (880 nm) PPG channels at 100 Hz; the DS18B20 returns 12-bit temperature words on demand; and the DS3231 supplies timestamps accurate to ± 2 ppm. Processed values are rendered on the OLED and streamed as comma-delimited ASCII frames to the paired smartphone.

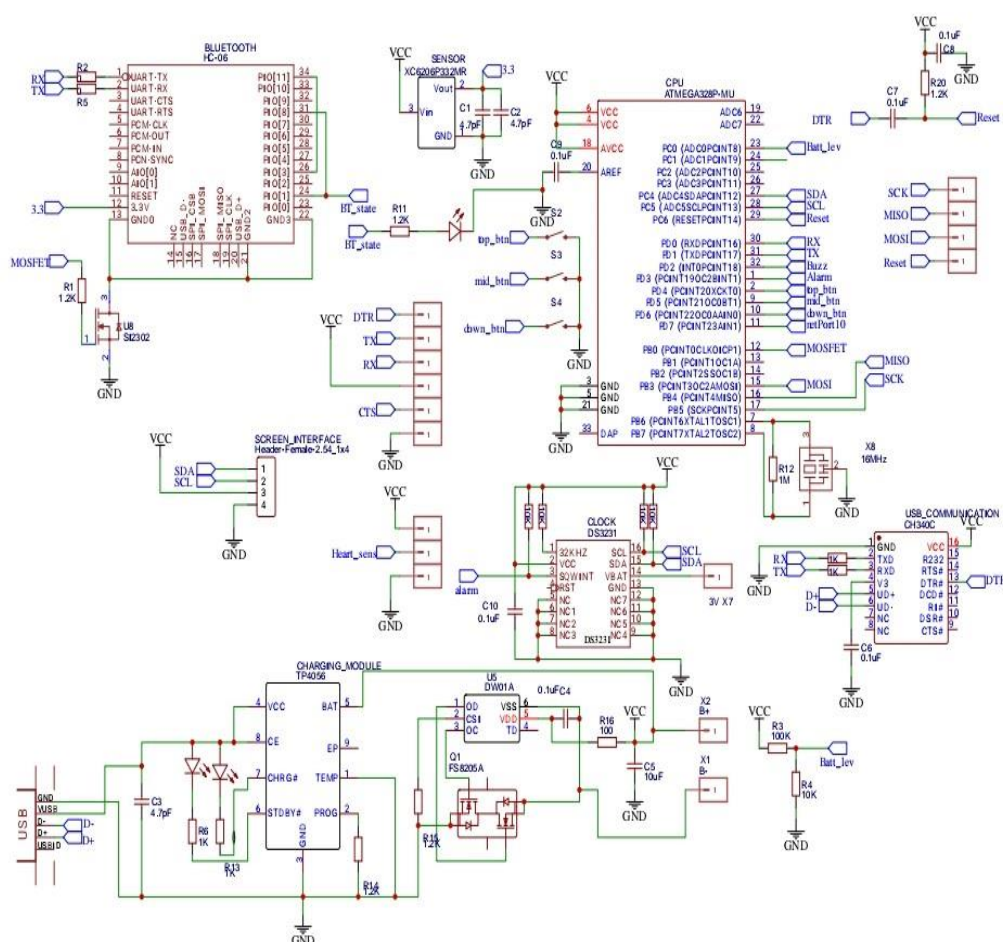


Figure 1: Block diagram and signal flow

MAX30102 Integrated Pulse Oximetry and Heart Rate Sensor

The MAX30102 from Maxim Integrated (Analog Devices) provides the core biosensing capability for SpO₂ and heart rate measurement through integrated optical components and signal processing.

Technical Specifications:

LED Wavelengths: 660nm (red), 880nm (infrared)

LED Current Range: 0 to 51mA, programmable in 0.2mA steps

Photodetector: Optimized for 660-1000nm with ambient light rejection

ADC Resolution: 18-bit

Sample Rate: 50-3200 samples per second (programmable)



Communication: I2C (standard/fast mode, up to 400kHz)

I2C Address: 0x57 (factory set, non-configurable)

Operating Voltage: 1.8V to 3.3V (5V tolerant I2C)

Supply Current: <1mW active, 0.7μA shutdown

FIFO Buffer: 32 samples (approximately 1 second at 50Hz)

Interrupt Pin: Alerts when new data available or FIFO threshold reached

Package: 14-pin optical module, 5.6mm × 3.3mm × 1.55mm

Operating Temperature: -40°C to +85°C

Temperature Sensor: DS18B20 Digital Thermometer

Body temperature measurement capability was implemented using the DS18B20 1-Wire digital temperature sensor from Maxim Integrated.

Technical Specifications:

Measurement Range: -55°C to +125°C

Accuracy: ±0.5°C from -10°C to +85°C

Resolution: 9-bit to 12-bit programmable (0.5°C to 0.0625°C)

Conversion Time: 750ms (12-bit resolution)

Communication: 1-Wire protocol (single data line)

Operating Voltage: 3.0V to 5.5V

Supply Current: 1.5mA active, 750nA idle

Package: TO-92 (through-hole), SOT-23 (surface mount), or waterproof probe

Each sensor has unique 64-bit serial code enabling multi-drop bus

Hardware Components and Cost

Table 1 summarises the principal hardware components. The complete bill of materials, including PCB fabrication, enclosure, and assembly, totalled USD 108.40, meeting a design target of ≤ USD 150.

Table 1. Principal hardware components

S/N	Component / Service	Unit Cost (₦)	Total (₦)
1	Main Processing Unit: ATmega328P-MU (Integrated on custom PCB)	12,500	12,500
2	Biosensor Array: MAX30102 (\$SpO ₂ /HR) & DS18B20 (Temp)	18,500	18,500
3	Visual Interface: 0.96" OLED Display (SSD1306 High-Res)	12,000	12,000
4	Communication: HC-06 Bluetooth Module (v2.0 + EDR)	14,500	14,500



5	Power System: 400mAh LiPo + TP4056 + Protection Circuitry	15,000	15,000
6	Precision Timing: DS3231 RTC Module with Battery Backup	9,500	9,500
7	Custom Fabrication: 2-Layer PCB (Design, Print, & SMT Assembly)	35,000	35,000
8	Mechanical: 3D Printed Industrial Enclosure & Medical-Grade Strap	15,000	15,000
9	Sundries: Precision Resistors, Capacitors, & LDO Regulators	8,000	8,000
10	Assembly & Integration: Professional Soldering & Calibration	10,000	10,000
Total			150,000

Power Management

Power management was treated as the primary constraint on wearability. A P-channel MOSFET (AO3401) acts as a load switch on the OLED and HC-06 power rails, allowing the microcontroller to de-energise these high-current peripherals for the roughly 90% of the duty cycle in which they are not required; this reduced average system current from 78 mA to 11 mA. Between measurements, the microcontroller enters SLEEP_MODE_PWR_DOWN, reducing core current to 5.4 μ A, while the MAX30102 is placed in its 0.7 μ A shutdown state via an I²C register write. A resistor-divider battery monitor triggers a low-battery warning at 3.5 V and a forced shutdown at 3.2 V.

Firmware and Signal-Processing Algorithms

Firmware was developed in the Arduino IDE and executes as a five-state finite-state machine (INIT, IDLE, MEASURE, TRANSMIT, SLEEP). Heart rate is derived from the infrared PPG channel after 4-pole Butterworth bandpass filtering (0.5–5.0 Hz); systolic peaks are detected using a slope-sum function with adaptive thresholding, inter-beat intervals outside the physiologically plausible 300–2000 ms range are discarded, and the result is averaged over an 8-beat sliding window. SpO₂ is computed using the standard ratio-of-ratios method, initially with the widely cited relation $SpO_2 = 110 - 25 \times R$ and subsequently refined, after local calibration against a Masimo MightySat reference, to $SpO_2 = 104 - 17 \times R$ over $R \in [0.5, 1.0]$, which reduced bias in the clinically important 90–100% range. Both vital signs are gated by a signal-quality index; readings below threshold are withheld rather than displayed, which rejected approximately 18% of attempted measurements during testing. Temperature readings from the DS18B20 are corrected for the systematic offset between wrist-skin and core temperature using a linear model, $T_{core} = 1.05 \times T_{skin} + 1.2$ °C, derived from a regression of 30 paired wrist-and-tympanic readings ($R^2 = 0.91$). Each measurement is transmitted as a checksummed ASCII frame over Bluetooth to an Android companion application, which stores the record locally and forwards it to a cloud database when connectivity is available.

Experimental Validation Protocol

The prototype was evaluated through controlled testing over a two-week period. Accuracy was assessed on 20 volunteer participants under four physiological conditions (rest, light recovery, post-exercise for SpO₂ induced mild desaturation), yielding 1,440 paired SpO₂ and heart-rate samples and 120 paired temperature samples, benchmarked respectively against a Masimo MightySat pulse oximeter, a Polar H10 chest-strap ECG monitor, and a Braun tympanic thermometer. Usability was separately assessed with 30 additional respondents. Agreement between the prototype and reference instruments was quantified using MAE, RMSE, Bland–Altman bias and limits of agreement, Pearson correlation, and for SpO₂ Accuracy Root Mean Square (ARMS) as specified by ISO 80601-2-61.

RESULTS

The final prototype integrated all subsystems on a single 50 × 35 mm PCB, measuring 48 × 38 × 14 mm and weighing 42 g. Boot self-test completed in 2.3 s, sensors enumerated correctly across 50 power cycles, and Bluetooth pairing succeeded on first attempt across three Android test devices.

SpO₂ Accuracy

Across 1,440 paired samples, the prototype tracked the Masimo reference closely, with an overall MAE of 1.62%, ARMS of 1.78% (ISO 80601-2-61 threshold: 3%), Bland–Altman bias of -0.41% (95% limits of agreement -3.1% to $+2.3\%$), Pearson $r = 0.948$ ($p < 0.001$), and Lin's concordance correlation coefficient of 0.931. Accuracy was highest in the clinically important 97–100% range and degraded modestly below 90% SpO₂, where ARMS rose to 2.94% (Table 2).

Table 2. SpO₂ accuracy by measurement range

SpO ₂ range (%)	n	MAE (%)	ARMS (%)	Bias (%)
97–100	612	1.21	1.34	−0.32
94–96	498	1.55	1.71	−0.18
90–93	224	2.04	2.22	−0.27
80–89	106	2.61	2.94	−0.71
Overall	1440	1.62	1.78	−0.41

Heart-Rate Accuracy

Heart-rate validation against the Polar H10 produced a combined MAE of 2.58 bpm and RMSE of 3.41 bpm ($r = 0.953$), with accuracy highest at rest (1.94 bpm MAE) and lowest during post-exercise recovery (3.62 bpm MAE), reflecting the greater motion-artefact burden during recovery (Table 3). This performance is comparable to published Apple Watch validation in healthy adults (≈ 2.3 bpm) and superior to reported errors of 6–7 bpm for the same commercial device in cardiovascular patients.

Table 3. Heart-rate accuracy by activity state

Activity state	n	HR range (bpm)	MAE (bpm)	RMSE (bpm)	r
Seated rest	720	58–82	1.94	2.41	0.962
Light recovery	360	84–110	2.78	3.42	0.948
Post-exercise	360	108–148	3.62	4.85	0.911
Combined	1440	58–148	2.58	3.41	0.953

Temperature Accuracy

After linear core-temperature calibration, the prototype tracked the tympanic reference within an overall MAE of 0.31 °C and a bias of +0.04 °C, comfortably within the ± 0.5 °C DS18B20 datasheet specification (Table 4). A small positive bias during post-exercise measurement reflects the conservative correction built into the calibration model.

Table 4. Temperature accuracy by subject state

Subject state	n	Reference mean (°C)	Prototype mean (°C)	MAE (°C)	Bias (°C)
Resting indoor	60	36.71	36.78	0.27	0.07
Post-exercise	30	37.12	37.31	0.38	0.19
Cold exposure	30	36.42	36.18	0.34	−0.24
Overall	120	36.74	36.78	0.31	0.04

Response Time and Battery Life

The end-to-end measurement cycle from button press to displayed and transmitted result of averaged 5.04 s ($\sigma = 24$ ms), dominated by the 4.02 s MAX30102 acquisition window; this is competitive with commercial wrist oximeters, which typically require 8–15 s for a first stable reading. Battery endurance depended strongly on operating mode: continuous monitoring (one reading per minute, display and Bluetooth active) drained the 1000 mAh cell in 17.4 h at an average current of 57.5 mA, while power-saving mode (one reading every 5 min, peripherals duty-cycled) extended endurance to 102 h (4 days 6 h) at 9.8 mA average current (Table 5). Standby endurance with no active measurement was projected at approximately 47 days from the measured 0.88 mA quiescent current.

Table 5. Battery life by operating mode

Operating mode	Avg. current (mA)	Duration	Est. daily readings
Continuous monitoring	57.5	17.4 h	1440
Active-use default	22.8	44 h	720
Power-saving	9.8	102 h	288
Standby (no measurement)	0.88	~47 days	0

Comparison with Commercial Devices

Table 6 benchmarks the prototype against representative commercial smartwatches and a medical-grade reference oximeter. The prototype's SpO₂ and heart-rate accuracy are comparable to, and in some cases better than, flagship consumer devices costing an order of magnitude more, while uniquely providing a calibrated body-temperature reading.

Table 6. Comparison with commercial and medical-grade devices

Device	SpO ₂ ARMS	HR MAE	Temp. accuracy	Battery life	Price (USD)
Prototype (this work)	1.78%	2.58 bpm	±0.31 °C	17 h–4 days	\$108.40
Apple Watch Series 11	≈2.0%*	2.3 bpm	Wrist skin only	18–24 h	\$399.00
Samsung Galaxy Watch 8	≈2.5%	2.1 bpm	±0.20 °C	30–48 h	\$260.00
Garmin Venu 4	≈3.0%	2.8 bpm	±0.30 °C	10–13 days	\$549.00
Fitbit Sense 2	Not specified	4.0 bpm	±0.40 °C (rel.)	6 days	\$299.00
Masimo MightySat (medical)	≤2.0%	≤3.0 bpm	N/A	30 h	\$413.00+

DISCUSSION

The results demonstrate that commodity sensors and an 8-bit microcontroller can deliver clinically defensible spot-check measurements of the three most important vital signs, provided that signal-quality gating, careful power-tree design, and post-hoc calibration are implemented rigorously. SpO₂ ARMS of 1.78 % satisfies ISO 80601-2-61 in the 90–100 % range that matters for routine respiratory triage, and the heart-rate error of 2.58 bpm is competitive with consumer flagship devices. The temperature performance, while not surgical-grade, is sufficient for fever screening, the application that drove most user demand during the COVID-19 era and continues to drive demand in tropical-disease surveillance.

Three findings deserve emphasis. First, load-switching peripherals through a P-channel MOSFET is the single highest-leverage power-management decision: it tripled battery life with only one additional transistor and one

digital pin. Second, the signal-quality gate that rejects 18 % of attempted readings is a feature rather than a defect, because consumer pulse oximeters that always return a number have been shown to mislead clinicians during motion. Third, the linear core-temperature calibration succeeded only because the regression was derived from the exact wrist-mounting geometry used in the final device; transferring such a calibration to a different physical mounting would invalidate it.

The principal limitation is performance below 88% SpO₂, where ARMS approaches the ISO threshold and where commercial devices also struggle. Wong et al. (2021) further demonstrated that pulse oximeters of any price systematically over-read in darker-skinned patients; the prototype was not validated across a sufficiently diverse cohort to characterise this bias, and any future deployment must address it. The Bluetooth Classic radio also limits operating range to roughly 10 m, and migrating to a BLE-capable MCU such as the nRF52832 is the obvious next step for power and connectivity reasons.

CONCLUSION

The prototype achieved its primary engineering targets. SpO₂ ARMS of 1.78%, heart-rate MAE of 2.58 bpm, and temperature MAE of 0.31°C all to meet or exceed the accuracy of much more expensive consumer devices, while a four-day battery life in power-saving mode and the bill of materials demonstrate practical wearability and economic accessibility. The work confirms that careful engineering of low-cost components, rather than exotic hardware, is the binding constraint on affordable health monitoring, and that an undergraduate-level platform can produce data of sufficient quality for non-diagnostic personal screening

REFERENCES

1. Abdulmalek, S., Nasir, A., Jabbar, W. A., Almuahaya, M. A. M., Bairagi, A. K., Khan, M. A.-M., & Kee, S.-H. (2022). IoT-based healthcare-monitoring system towards improving quality of life
2. .Al Bassam, N., Hussain, S. A., Al Qaraghuli, A., Khan, J., Sumesh, E. P., & Lavanya, V. (2021). IoT based wearable device to monitor the signs of quarantined remote patients of COVID-19. *Informatics in Medicine Unlocked*, 24, 100588.
3. Analog Devices. (2019). *DS18B20 programmable resolution 1-Wire digital thermometer* [Data sheet, Rev. 6]. Maxim Integrated/Analog Devices, Inc.
4. Cebada-Fuentes, R., Valladares-Pérez, J., García-García, J. A., & Sánchez-Pérez, C. (2024). Optimized performance pulse oximeter based on the MAX30102 commercial sensor. In J. L. B. Marques, C. R. Rodrigues, D. O. H. Suzuki, J. Marino Neto, & R. García Ojeda (Eds.), *IX Latin American Congress on Biomedical Engineering and XXVIII Brazilian Congress on Biomedical Engineering (IFMBE Proceedings, Vol. 101, pp. 343–354)*. Springer.
5. Charlton, P. H., & Marozas, V. (2021). Wearable photoplethysmography devices. In P. A. Kyriacou & J. Allen (Eds.), *Photoplethysmography: Technology, signal analysis and applications* (pp. 401–438). Elsevier.
6. Charlton, P. H., Kyriacou, P. A., Mant, J., Marozas, V., Chowienczyk, P., & Alastruey, J. (2022). Wearable photoplethysmography for cardiovascular monitoring. *Proceedings of the IEEE*, 110(3), 355–381.
7. Di Cesare, M., Perel, P., Taylor, S., Kabudula, C., Bixby, H., Gaziano, T. A., McGhie, D. V., Mwangi, J., Pervan, B., Narula, J., Pineiro, D., & Pinto, F. J. (2024). The heart of the world. *Global Heart*, 19(1), 11.
8. El Attaoui, A., Largo, S., Kaissari, S., Benbahria, A., & Jilbab, A. (2020). Remote health monitoring systems based on Bluetooth Low Energy (BLE) communication systems. In *Smart Systems for E-Health* (pp. 87–113). Springer.
9. Falter, M., Budts, W., Goetschalckx, K., Cornelissen, V., & Buys, R. (2019). Accuracy of Apple Watch measurements for heart rate and energy expenditure in patients with cardiovascular disease: Cross-sectional study. *JMIR mHealth and uHealth*, 7(3), e11889.
10. Fine, J., Branan, K. L., Rodriguez, A. J., Boonya-ananta, T., Ramella-Roman, J. C., McShane, M. J., & Coté, G. L. (2021). Sources of inaccuracy in photoplethysmography for continuous cardiovascular monitoring. *Biosensors*, 11(4), 126.



11. Greenhalgh, T., Knight, M., Inda-Kim, M., Fulop, N. J., Leach, J., & Vindrola-Padros, C. (2021). Remote management of covid-19 using home pulse oximetry and virtual ward support. *BMJ*, 372, n677.
12. Iqbal, S. M. A., Mahgoub, I., Du, E., Leavitt, M. A., & Asghar, W. (2021). Advances in healthcare wearable devices. *npj Flexible Electronics*, 5(1), 9.
13. Khan, M. M., & Mehnaz, S. (2022). IoT-based smart health monitoring system for COVID-19 patients. *Computational and Mathematical Methods in Medicine*, 2022, 7591984.
14. Kim, K. B., & Baek, H. J. (2023). Photoplethysmography in wearable devices: A comprehensive review of technological advances, current challenges, and future directions. *Electronics*, 12(13), 2923.
15. Kyriacou, P. A., & Allen, J. (Eds.). (2021). *Photoplethysmography: Technology, signal analysis and applications*. Elsevier.
16. Luks, A. M., & Swenson, E. R. (2020). Pulse oximetry for monitoring patients with COVID-19 at home: Potential pitfalls and practical guidance. *Annals of the American Thoracic Society*, 17(9), 1040–1046.
17. Mejía-Mejía, E., Allen, J., Budidha, K., El-Hajj, C., Kyriacou, P. A., & Charlton, P. H. (2021). Photoplethysmography signal processing and synthesis. In P. A. Kyriacou & J. Allen (Eds.), *Photoplethysmography: Technology, signal analysis and applications* (pp. 69–146).
18. Mensah, G. A., Fuster, V., Murray, C. J. L., & Roth, G. A. (2023). Global burden of cardiovascular diseases and risks, 1990–2022. *Journal of the American College of Cardiology*, 82(25), 2350–2473.
19. Michard, F., Shelley, K., & L'Her, E. (2021). COVID-19: Pulse oximeters in the spotlight. *Journal of Clinical Monitoring and Computing*, 35(1), 11–14.
20. Omboni, S., Padwal, R. S., Alessa, T., Benczúr, B., Green, B. B., Hubbard, I., Kario, K., Khan, N. A., Konradi, A., Logan, A. G., Lu, Y., Mars, M., McManus, R. J., Melville, S., Neumann, C. L., Parati, G., Renna, N. F., Ryvlin, P., Saner, H., ... Wang, J. (2022). The worldwide impact of telemedicine during COVID-19: Current evidence and recommendations for the future. *Connected Health*, 1, 7–35.
21. Park, J., Seok, H. S., Kim, S.-S., & Shin, H. (2022). Photoplethysmogram analysis and applications: An integrative review. *Frontiers in Physiology*, 12, 808451.
22. Pereira, T., Tran, N., Gadhoumi, K., Pelter, M. M., Do, D. H., Lee, R. J., Colorado, R., Meisel, K., & Hu, X. (2020). Photoplethysmography based atrial fibrillation detection: A review. *npj Digital Medicine*, 3(1), 3.
23. Rahaman, A., Islam, M. M., Islam, M. R., Sadi, M. S., & Nooruddin, S. (2019). Developing IoT based smart health monitoring systems: A review. *Revue d'Intelligence Artificielle*, 33(6), 435–440.
24. Saha, R., Biswas, S., Sarmah, S., Karmakar, S., & Das, P. (2021). A working prototype using DS18B20 temperature sensor and Arduino for health monitoring. *SN Computer Science*, 2(1), 33.