Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 11, No. 1, February, Pp. 19-40

Design of real-time user feedback to mitigate spurious SpO_2 readings in pulse oximetry for outpatient monitoring

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Article Info
Keywords:
Pulse Oximetry, SpO_2 Monitoring, Real-time Feedback, Error Mitigation, Outpatient Monitoring, Internet of Things, MAX30100, MQ-7

Article history:
Received: June 21, 2025
Accepted: October 07, 2025
Published: February 01, 2026

Cite:
H. Mukhtar, D. Rahmawati, S. Setiyadi, Istiqomah, and R. A. Madani, "Design of Real-Time User Feedback for Mitigate Spurious SpO_2 Readings in Pulse Oximetry for Outpatient Monitoring", *KINETIK*, vol. 11, no. 1, Feb. 2026.
https://doi.org/10.22219/kinetik.v11i1.2371

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Abstract
Spurious SpO_2 readings—arising from motion artifacts, environmental interference, or device variability—remain a major limitation in wearable pulse oximetry, potentially triggering false alarms or missing hypoxemia during outpatient monitoring. Conventional devices often lack real-time mechanisms to detect and mitigate such errors, with previous reports indicating measurement biases of 11.2 - 24.5% across different models, underscoring the need for improved accuracy and user guidance. To address this gap, we present the design of an IoT-enabled wearable pulse oximeter with real-time user feedback, delivered through a mobile application. The system integrates a pulse oximetry and heart rate sensor (MAX30100) with a carbon monoxide gas sensor (MQ-7) and provides targeted notifications to guide corrective actions such as repositioning the probe, removing nail polish, or moving to fresh air. Validation involved controlled scenario testing (undetected SpO_2, CO >40 ppm, nail polish, and loose contact) and user trials with 15 healthy volunteers from varied academic backgrounds. The prototype demonstrated high accuracy, with low relative errors—0.92% (HR), 0.93% (SpO_2), and 0.015% (CO)—and strong usability, achieving 93.3% compliance with corrective prompts, an average response time of 4.0±0.7 seconds, and a satisfaction score of 4.3/5. Compared with commercial oximeters, the proposed system improved reliability by reducing measurement errors by at least 87% through real-time corrective feedback. Future work will focus on energy-efficient power management and large-scale community-based trials to further validate performance across diverse patient populations.

1. Introduction

Continuous monitoring of heart rate (HR) and oxygen saturation (SpO_2) plays a crucial role in the early detection of respiratory or cardiovascular deterioration, particularly in outpatient and home care settings [1][2]. For instance, SpO_2 levels below a critical threshold indicate respiratory distress or hypoxemia, which—if left undetected—may lead to severe complications such as respiratory failure. Pulse oximetry provides a non-invasive and continuous method for estimating arterial oxygen saturation, enabling healthcare providers and patients to identify hypoxemia before clinical symptoms become apparent [3][4].

The relevance of pulse oximetry increased substantially during the COVID-19 pandemic, when home-based SpO_2 monitoring helped identify patients who required hospitalization and reduced unnecessary emergency visits by approximately 30–38% [5][6][7]. This approach effectively alleviated the burden on emergency departments and inpatient wards during the peak period of healthcare demand [8]. An SpO_2 threshold of 92% was frequently used to triage patients for hospital admission. Collectively, these findings highlight the increasing importance of reliable wearable devices for continuous oxygen monitoring, particularly in unsupervised or home settings.

Despite its widespread adoption, the accuracy of pulse oximetry is still influenced by several confounding factors. Carbon monoxide (CO) exposure, variations in skin pigmentation, motion artifacts, ambient light interference [9][10], [11][12], and cosmetic factors such as nail polish can distort optical signals, leading to a 4–6% overestimation of oxygen saturation [13]–[15][16][17]. Moreover, clinical studies have shown that conventional pulse oximeters often overestimate oxygenation levels in individuals with darker skin tones and are unreliable at detecting hypoxemia when SpO_2 falls below 80% [18]. Device-to-device variability further contributes to inconsistent readings, with reported measurement biases of up to 24% across commercial models [19][20]. Even home-monitoring alerts are occasionally artifact-induced [21]. These limitations underscore the need to enhance sensor design and develop adaptive signal-processing algorithms to ensure accurate and consistent readings across diverse users and environmental conditions.

1.1 Problem Identification

Although pulse oximetry has been widely adopted, most commercial devices still lack mechanisms to detect and correct spurious readings. Conventional oximeters cannot distinguish oxyhaemoglobin (O_2Hb) from carboxyhaemoglobin (COHb), as both absorb light at nearly identical wavelengths, potentially yielding falsely normal saturation values even in the presence of oxygen deficiency [22]. While newer portable oximeters have demonstrated improved accuracy in detecting hypoxemia, they typically do not provide real-time feedback on the quality of their measurements. Users are not actively alerted when inaccuracies arise due to poor perfusion, improper sensor placement, or external interferences such as motion and ambient light [23].

These limitations can lead to delayed clinical responses in outpatient or self-monitoring contexts, undermine user confidence, and generate false alarms that strain telehealth systems [24][25][2]. Consequently, a critical research gap remains in developing intelligent pulse oximetry systems capable of real-time anomaly detection and providing actionable feedback to ensure accurate and reliable SpO_2 measurements across diverse conditions [26]–[29].

1.2 Research Gap and Motivation

Existing research on pulse oximetry has focused on hardware, algorithmic correction, optimization [28][30][31], and integrated alert systems [32][33]. Although these efforts have improved hypoxemia detection [26][34], current technologies still struggle to maintain accuracy in real-world conditions. Common interfering factors—such as motion artifacts, skin pigmentation, nail polish, and carbon monoxide (CO) exposure—remain insufficiently addressed [23]. Advanced oximeters, such as those from Masimo, demonstrate superior robustness (performance index ≈94%, within 7% deviation of control values), outperforming older systems like the *Criticare 5040* (28%) [35]. However, persistent inaccuracies below 90% SpO_2 continue to be reported across populations with varied skin tones and respiratory diseases [36][37][38][39]. These findings reveal a critical research gap: the absence of intelligent pulse oximetry systems capable of detecting anomalies in real time and providing immediate corrective feedback to users.

This limitation is particularly consequential for patients self-monitoring at home—such as those with COPD, cardiovascular conditions, or post-COVID recovery—where missed hypoxemia events or falsely regular readings can compromise safety and clinical response. Yet, few studies have proposed interactive mechanisms involving users in measurement correction.

To address these challenges, this study introduces an IoT-enabled, interactive wearable pulse oximeter that integrates physiological (SpO_2 and HR via MAX30100) and environmental (CO via MQ-7) sensing. The system employs an anomaly-detection algorithm targeting three primary error sources: (1) nail-polish interference, (2) sensor misplacement or poor perfusion, and (3) CO exposure above 40 ppm. Upon detection, the mobile application issues real-time prompts (e.g., "Please tighten the finger adaptor," "Remove nail polish," "Move to fresh air") while annotating CO-affected readings without modifying raw data.

The proposed design aims to reduce spurious SpO_2 errors by 90% or more, achieve 85% or higher user compliance with corrective actions, and enhance patient safety, healthcare efficiency, and clinical trust. Validation includes bench calibration, interference scenario testing, and user trials involving 15 healthy volunteers from diverse backgrounds.

2. Research Method

This section describes the theoretical foundations of pulse oximetry, the design of the proposed wearable system, and the algorithm for detecting and mitigating SpO_2 measurement errors. It also outlines validation protocols and ethical considerations.

2.1 Basic Principles and Measurement Errors in Pulse Oximetry

Pulse oximetry (PO) is a non-invasive medical technique that estimates blood oxygen saturation (SpO_2) by analyzing light absorption at red (660 nm) and infrared (940 nm) wavelengths (see Figure 2a). This technique relies on photoplethysmography (PPG), which detects volumetric changes in microvascular tissue or the skin [40]. The PO device operates in two primary measurement modes (Figure 1): transmissive and reflective. The reflective mode (e.g., forehead or chest) is prone to errors due to variations in tissue density and was therefore excluded from this study [41]. The system used in this study operates in transmissive mode, where light passes through translucent tissues (e.g., the fingertip). To detect SpO_2 levels, this model is superior in penetrating tissue through translucent or thin body parts such as the earlobe or fingertip [42]. It also offers higher accuracy due to consistent tissue thickness and minimal external interference [30][43].

The Beer-Lambert law governs light absorption (A), as shown in Equation 1, which models the absorbance in blood vessel. The parameter c represents Hb concentration, ϵ denotes the absorption coefficient of haemoglobin at a specific wavelength, and l is the path length of the emitted light within a blood vessel. Blood volume fluctuations alter light absorption, reflection, and scattering, forming the PPG signal for SpO_2 estimation [44]. The modulation ratio R in Equation 2 and Equation 3 calculates SpO_2 by comparing pulsatile (AC) and non-pulsatile (DC) components of the absorbed light (see Figure 2b). These absorption variations are crucial to the accuracy of SpO_2 measurements. $A_{red,AC}$ and $A_{IR,AC}$ are the alternating current or pulsatile (AC) components of light absorption in arterial blood. $A_{red,DC}$ and $A_{IR,DC}$ are the direct current or non-pulsatile (DC) components that represent constant tissue absorption from veins, skin, and bone. Based on the Beer-Lambert law [4], these ratios are converted using a calibrated saturation curve ranging from 100% to approximately 70% (see Figure 2c).

$$A = c \in l \tag{1}$$

$$R = \frac{\left(A_{red,AC}/A_{red,DC}\right)}{\left(A_{IR,AC}/A_{IR,DC}\right)} \tag{2}$$

$$\frac{A_{red,AC}/A_{red,DC}}{A_{IR,AC}/A_{IR,DC}} = R \left| R \begin{cases} higher\ R, if\ A_{red,AC} > A_{IR,AC} \\ lower\ R, if\ A_{IR,AC} > A_{red,AC} \end{cases} \right. \tag{3}$$

Despite its clinical utility, pulse oximetry is prone to measurement errors that can yield false-positive or false-negative SpO_2 readings, potentially compromising clinical decisions and patient care. These errors arise from multiple sources, as summarized in Table 1.

1. Signal acquisition errors, which may be caused by low perfusion, venous pulsation, poor probe positioning or contact.
2. Optical interference errors, originating from skin pigmentation, nail polish, and ambient light.
3. Blood composition-related errors, such as the presence of Carboxyhaemoglobin (COHb) due to Carbon Monoxide (CO) poisoning.
4. Motion artifacts, commonly occuring during patient tremors, movements, or exercise.
5. Algorithmic and device calibration errors, such as limited low-SpO_2 data (<80%) in empirical curves.
6. Different pulse oximeter brands or models exhibiting measurement bias, with false-positive and false-negative rates ranging from 11.2% to 24.5%.

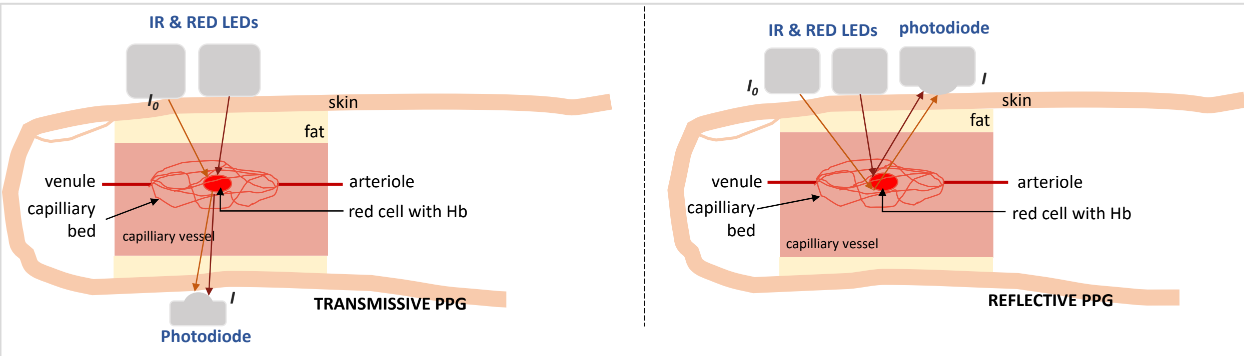

Figure 1. Transmissive and Reflective Modes of the PPG Measurement Method

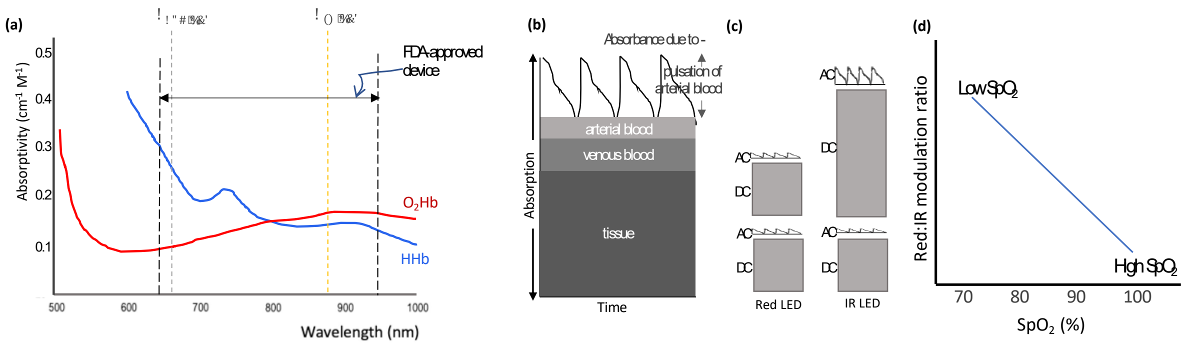

Figure 2. (a) The Optical Absorbance in Medium to the Wavelength of Red and IR LEDs [32], [25]; (b) The Fluctuation in Absorbed Red and IR light in Systole and Diastole of the Cardiac Cycle; (c) The Formed Signal Components of AC and DC Compartments; (d) The Determined Oxygen Saturation from Modulation Ratio of Red:IR Absorbance Amplitudes

Table 1. Classification of Unreliable SpO_2 Readings Due to the Root Cause [11]

No	Error Type	Possibly Causes
1	Incapable reading or No signal	Poor blood perfusion or poor probe positioning
2	Falsely high/elevated SpO_2	Carbon monoxide exposure
3	Falsely low SpO_2	Venous pulsation, excessive movement, or the presence of fingernail polish
4	Falsely low or high SpO_2	Poor probe positioning

Table 2. Carbon Monoxide (CO) Risk Stratification

Range (ppm)	Exposure classification [45][46]	Clinical impact [47][48]	Pathophysiological Mechanism	PO device Protocol
0 - 5	Normal (ambient)	No adverse effects	-	The system flags real-time data on the website with the label 'CO' when both of the following conditions are satisfied: 1) CO level exceeds 4 ppm in scheduled measurements conducted every 30 minutes; and 2) SpO_2 readings appear falsely normal or elevated while the concurrent CO measurement also exceeds 4 ppm. See Table 3 and Figure 3 for the complete protocol.
6 – 9	Low risk/low exposure	Increased cardiovascular risk over 8+ hours	Competitive binding to hemoglobin (COHb formation)	
10 – 24	Hazardous exposure	Headache, nausea within 2–6 hours	Tissue hypoxia due to 10–20% COHb saturation	
25 – 49	Acute Toxicity	Dizziness, cognitive impairment (COHb 20–40%)	Impaired oxygen delivery to brain	
≥50	Fatal	Unconsciousness, death (COHb >50%)	Mitochondrial cytochrome inhibition	

As described in error source number 3 in Table 1, carboxyhaemoglobin (COHb) is a compound formed when carbon monoxide (CO) binds irreversibly to haemoglobin, displacing oxygen (O_2) from its binding site. CO has a much higher affinity for haemoglobin than oxygen, which significantly impairs the oxygen-carrying capacity of the blood. Standard pulse oximeters cannot differentiate between oxyhaemoglobin (O_2Hb) and carboxyhaemoglobin (COHb), as both absorb red and infrared light at similar wavelengths. Consequently, pulse oximeters may display falsely elevated or normal SpO_2 readings, even in cases of oxygen deficiency. For instance, at a COHb level of 10%, an oximeter may report an SpO_2 value of 98% despite the actual oxygen saturation being closer to 88%. When COHb levels exceed 20%, clinical symptoms of hypoxia—such as headache and dizziness—can emerge without any corresponding decrease in the displayed SpO_2 value, presenting a serious diagnostic challenge.

To mitigate this issue, the system proposed in this study incorporates a CO sensor (MQ-7) to monitor ambient CO concentrations. When CO levels exceed 6 ppm and SpO_2 readings are above 98%, the system flags the condition as a “CO” risk (see Table 2), indicating a potential overestimation of oxygen saturation due to COHb presence. This feature serves as an early warning mechanism, prompting clinicians or users to consider the possibility of CO exposure even when SpO_2 values appear within a normal range. To further address these challenges, this study implements real-time error detection (e.g., motion artifact), user guidance protocols (e.g., probe repositioning prompts for poor signal quality), and sensor placement validation to minimize inaccuracies [43][44].

2.2 Proposed System Design

The wearable pulse oximeter system proposed in this study is described in a structured manner by presenting the system architecture and operational workflow. The system architecture presents the integration of hardware and software layers, while the operational workflow describes the processes involved in data acquisition, signal processing, error handling, and data display and storage. As overview, the prototype was developed and validated through three stages: (i) bench calibration of MAX30100 (HR, SpO_2) and MQ-7 (CO) against commercial references; (ii) scenario simulations under controlled interference conditions (probe misplacement/loose contact, nail polish, and CO exposure); and (iii) user trials (n=15) evaluating compliance, response time, and usability. HR and SpO_2 are computed from two consecutive 30-s windows within each 1-min epoch, while MQ-7 warms up for 60 s on activation. Under routine operation, CO is sampled every 30 min; this interval is overridden for immediate sampling when SpO_2 anomalies are detected. Data are displayed on the OLED and streamed to the mobile application and Firebase dashboard for real-time feedback and storage.

2.2.1 System Architecture

The proposed wearable pulse oximeter system integrates hardware and software layers to enhance SpO_2 measurement reliability through real-time anomaly detection, adaptive user feedback, and cloud-based data synchronisation. The general system architecture, shown in Figure 3, is designed to mitigate errors arising from possible causes such as motion artifacts, sensor misplacement, and carbon monoxide exposure. The wearable PO device, integrated with a CO sensor, transmits oxygen saturation (SpO_2), heart rate, and carbon monoxide data to the OLED display. Subsequently, the data was sent to a mobile application using a Bluetooth Low-Energy (BLE) connection. Once stored in the local repository of the mobile application, the data are sent to the dashboard web via Firebase with Wi-Fi connectivity. The mobile application incorporates a data-handling algorithm to enhance measurement reliability.

The wearable PO device hardware or electronic system is presented in Figure 4. It comprises a PPG sensor, a CO sensor, a microcontroller, a display, and a battery. The integrated heart rate and SpO_2 module, featuring the MAX30100 sensor's 16-bit ADC and 100Hz sampling, operates on a 3.3V supply. This sensor consists of a red LED with a typical peak wavelength of 660 nm, an infrared LED with a typical peak wavelength of 880 nm, a photodetector, optimized optics with ambient light cancellation (ALC), a 16-bits sigma-delta ADC, and a proprietary discrete-time filter (DTF) to reject 50/60 Hz interference from cables or other systems, as well as low-frequency residual ambient noise. The MQ-7 CO sensor detects and measures carbon monoxide exposure, with a sensitivity range of gas concentrations from 4 ppm to 100 ppm. The CO sensor utilizes a 5V PWM heater to preheat the MOS sensing element for 60 seconds before taking a measurement, a standard operating procedure that ensures accuracy and reliability. An ESP32 microcontroller (dual-core at 240 MHz, 12-bit ADC) processes and displays the sensor signals on a 0.96-inch OLED with an SSD1306, I^2C interface. This OLED has 128x64 pixels and operates at 3.3V. The system is powered by a Li-ion battery supported by a 134N3P power bank module. Li-ion batteries can store high energy per unit volume, with a total capacity of 2200mAh, a voltage of 3.7V, and a TPS61200 boost converter (5V output).

2.2.2 Operational Workflow

This subsection discusses the software implementation of the operational workflow, which includes data acquisition, signal processing, error handling, and data display/storage. Figure 5 illustrates the proposed system's data flow architecture, while Figure 6 presents the operational workflow of the wearable pulse oximeter, including real-time user feedback for mitigating spurious SpO_2 readings.

First, Data Acquisition: The MAX30100 sensor captures PPG signals by sampling at a rate of at least 25Hz to determine HR and SpO_2, using two consecutive 30-second averaging windows within a one-minute interval. This approach is consistent with the definition of heart rate in beats per minute and ensure an adequate temporal window for accurate estimation. The 30-second averaging window also aligns with current smartwatch practices, helping to reduce transient noise and stabilize measurement. The MQ-7 sensor requires a 60-second warm-up period upon system activation. Under regular operation, it measures CO levels at standard periodic intervals of 30 minutes, which balances power efficiency with the relatively slow variation of ambient CO concentration. However, this interval is overridden when asynchronous validation is triggered by abnormal SpO_2 (e.g., Case 2 or Case 3, see below), ensuring real-time CO hazard detection during critical events. All acquired data from both sensors are transmitted to the ESP32 microcontroller. Estimates are updated every 30 s and published to the mobile application and web dashboard every 60 s to balance responsiveness and bandwidth usage.

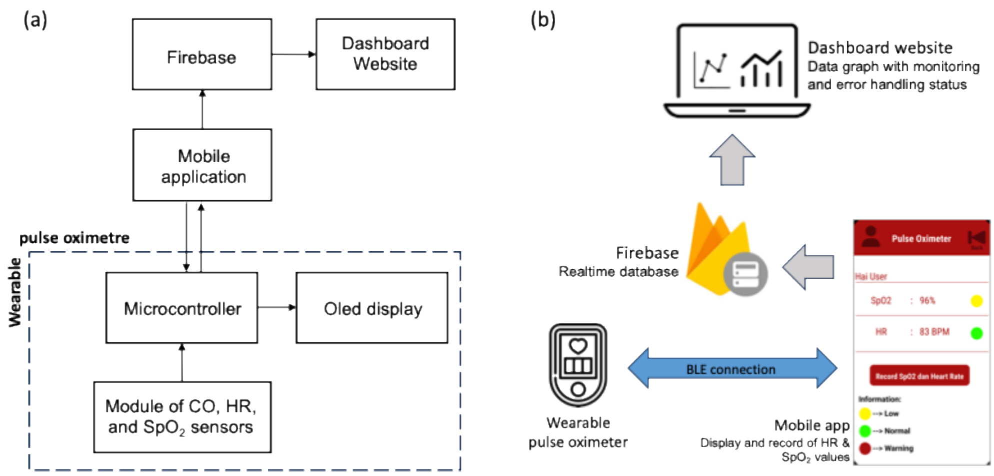

Figure 3. The General System of the Proposed System is Shown in (a) The Diagram Block and (b) The Illustration of the Principal Work

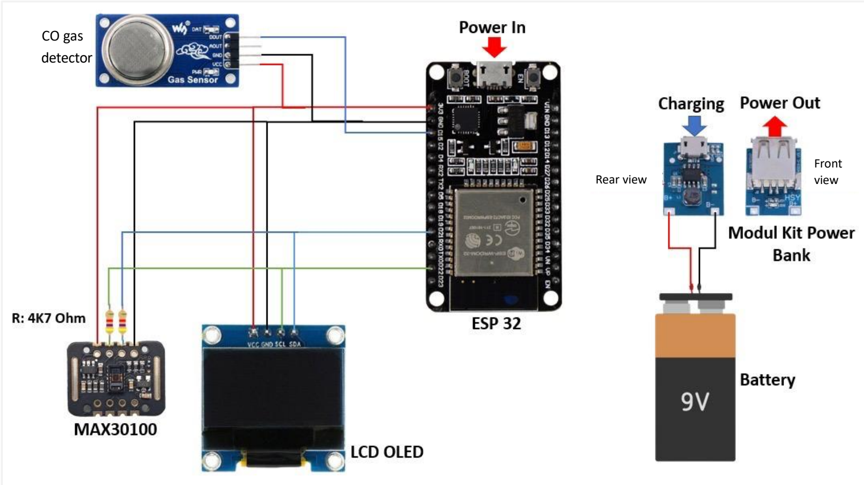

Figure 4. The General System of the Proposed System is Shown in (a) The Diagram Block and (B) The Illustration of the Principle

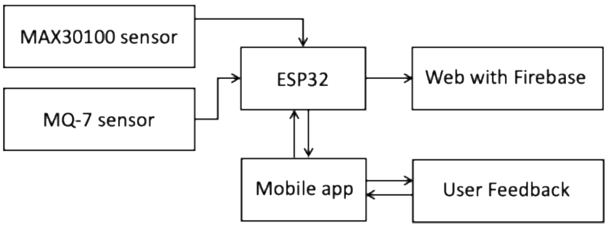

Figure 5. The General System of the Proposed System is Shown in (a) The Diagram Block and (b) The Illustration of the Principle

Table 3. Heart Rate (HR) Interpretation [15], [49]

Range (bpm)	Clinical category	Visual display on mobile app		Visual example on mobile app		
		Display text	Color scheme	Data Example	Realtime	Record
<30	Severe Bradycardia	'critical'	white text on red	HR: 25 bpm		critical
30-50	Mild Bradycardia	'low'	grey text on yellow	HR: 48 bpm		low
50-100	Normal (Resting)	'normal'	white text on green	HR: 90 bpm		normal
100-120	Mild Tachycardia	'warning'	white text on orange	HR: 115 bpm		warning
>120	Severe Tachycardia	'warning'	white text on red	HR: 140 bpm		warning

† AHA (2021) Guidelines for Heart Rate Interpretation

Table 4. Oxygen Saturation (SpO_2) Interpretation

Range (%)	Clinical category	Visual display on mobile application		Visual example on mobile app		
		Display text	Realtime	Data Example	Realtime	Record
<85	Critical hypoxemia	'warning'	white text on red	SpO_2: 81%		warning
85-89	Moderate hypoxemia			SpO_2: 86%		warning
90-94	Mild hypoxemia	'low'	grey text on yellow	SpO_2: 92%		low
95-100	Normoxia	'normal'	white text on green	SpO_2: 98%		normal

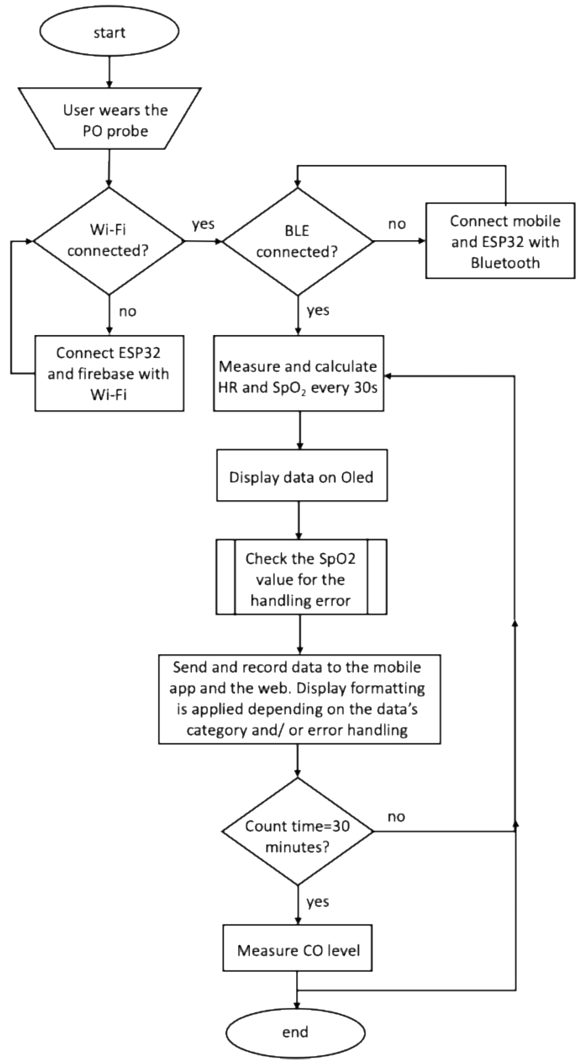

Figure 6. The General System of the Proposed System is Shown in (a) The Diagram Block and (b) The Illustration of the Principle

Second, Signal Processing: The acquired PPG signal, sampled at 25 Hz, is used to calculate HR and SpO_2. Heart rate, expressed in beats per minute (bpm), is derived from the heartbeat period using **Error! Reference source not found.**, which converts the interval into beats per millisecond, then scales it to beats per second and finally to beats per minute. SpO_2 is determined based on the ratio of red to infrared LED light intensities, as expressed in **Error! Reference source not found.**4.

$$HR\ (bpm) = \frac{1}{beatperiod} \times 1000 \times 60 \tag{4}$$

As part of the signal processing stage, the measured heart rate (HR) and oxygen saturation (SpO_2) values are classified based on established thresholds and displayed accordingly. Table 3 provides the classification criteria for HR, while Table 4 presents the interpretation of SpO_2 levels. Colour-coded indicators are applied to each category to enhance clarity during real-time monitoring, enabling users to identify and differentiate the conditions quickly.

Third, Error Handling: According to the flowchart in Figure 6, the SpO_2 value calculated by the microcontroller is continuously evaluated to determine whether it corresponds to any of the cases defined in Table 4. These cases exhibit specific patterns or anomalies that indicate signal distortion, carbon monoxide exposure, or other potential measurement errors. Once a case is identified, the mobile application cross-references the detected event with the user (see

Table 5) to determine the appropriate response. For the CO override rule, as defined in Table 2 and Table 5, if SpO_2 ≥95% and changes by ±3–5% within 30 s, or if SpO_2 is persistently undetected for ≥ 30 s, the controller triggers immediate CO sampling. When CO exceeds 6 ppm and SpO_2 remains ≥95%, the reading is flagged as “CO risk” and annotated in the dashboard; otherwise, the validated SpO_2 is published as usual. This rule ensures real-time detection of potential CO-related overestimation without altering raw SpO_2 values.

Table 5. Some Checks of the Utilization of Developed Devices are Needed to Avoid Spurious SpO_2 Readings based on SpO_2 Changes or Acquisitions

No	Case Type or Criteria	Following supervising act in microcontroller	Error Handling on Mobile App		Data display and storage	
			Display Text: Guide for user	User Response	Mobile App	Website Data
1	Incapable reading/ No signal SpO_2 = NULL for 30s Possibly caused by improper probe position	- It sends a warning text to mobile app. - Once SpO_2 is detected and the value does not indicate an error condition, the measured SpO_2 is sent to the mobile app and website via Firebase.	Alert “SpO_2 undetected. Please restart your device or put the device sensor on the other fingers”	User follows the instructions manually.	Display and store data with color labels according to level category.	Stores and displays data in graphical form against time.
2	Falsely normal to elevated High Normal SpO_2 (>= 95%) AND suddenly elevated (± 3-5%) Suspected of carbon monoxide poisoning/ exposure	- It directly measures CO level - If CO > 6 ppm, a warning is sent to the mobile app; otherwise, the validated SpO_2 value is sent to both the app and the website via Firebase.	Alert ‘Excessive CO detected”	If this alert is displayed, the user should take immediate action by ventilating the room, evacuating the area, or seeking help if symptoms such as dizziness occur.	Display and store data with color labels according to level category.	The received data is saved. On the data graph, the ‘CO’ label and a dotted line are added to the received SpO_2 value.
3	Falsely low or high SpO_2 << 90% (awfully low) or suddenly high > 98% suspected of poor/loose probe positioning	- It sends a warning text to mobile. - It retries the measurement if the user selects ‘YES’.	Alert “Please tighten the finger adaptor or fix the position. Has it been done?” *Please select one option below:* [YES] [NO]	Users select the answer according to the conditions asked. *If the user answers ’YES’, it means the user has fixed the position of the sensor probe.*	[For answer ‘NO’]: Display and store the data categorized as low (red color)	[For answer ‘NO’]: The received data is saved. On the data graph, the ‘Loose’ label is added to the received SpO_2 value.
		- It resends the warning message to the mobile app if the user selects ‘NO’ or remains idle for 90 seconds.	Alert "Do you have any nail polish on your fingers?"	If the answer is ‘YES’, the user will be suggested to remove it, and	[For answer ‘NO’]: Display and store data with color	[For answer ‘NO’]: The received data is saved. On the data

		- If users answer 'NO' or idle 90s, then it sends the data to both the app and the website.	*Please select one option below:* [YES] [NO]	return to using the PO device.	labels according to level category.	graph, the 'Polish' label is added to the received SpO_2 value.
4	Mild hypoxia < 94% Low SpO_2 suspected presence of fingernail polish	- It sends a warning text to mobile app. - When the user responds with 'NO', it transmits the data to both the app and the website; otherwise, the data is not sent.	Alert "Please tighten the finger adaptor or fix the position. Has it been done?" *Please select one option below:* [YES] [NO]	Users select the answer according to the conditions asked. *If the user answers 'NO', it means the user has fixed the position of the sensor probe.*	[For answer 'NO']: Display and store data with color labels according to level category.	[For answer 'NO']: The received data is saved. On the data graph, the 'Loose' label is added to the received SpO_2 value.

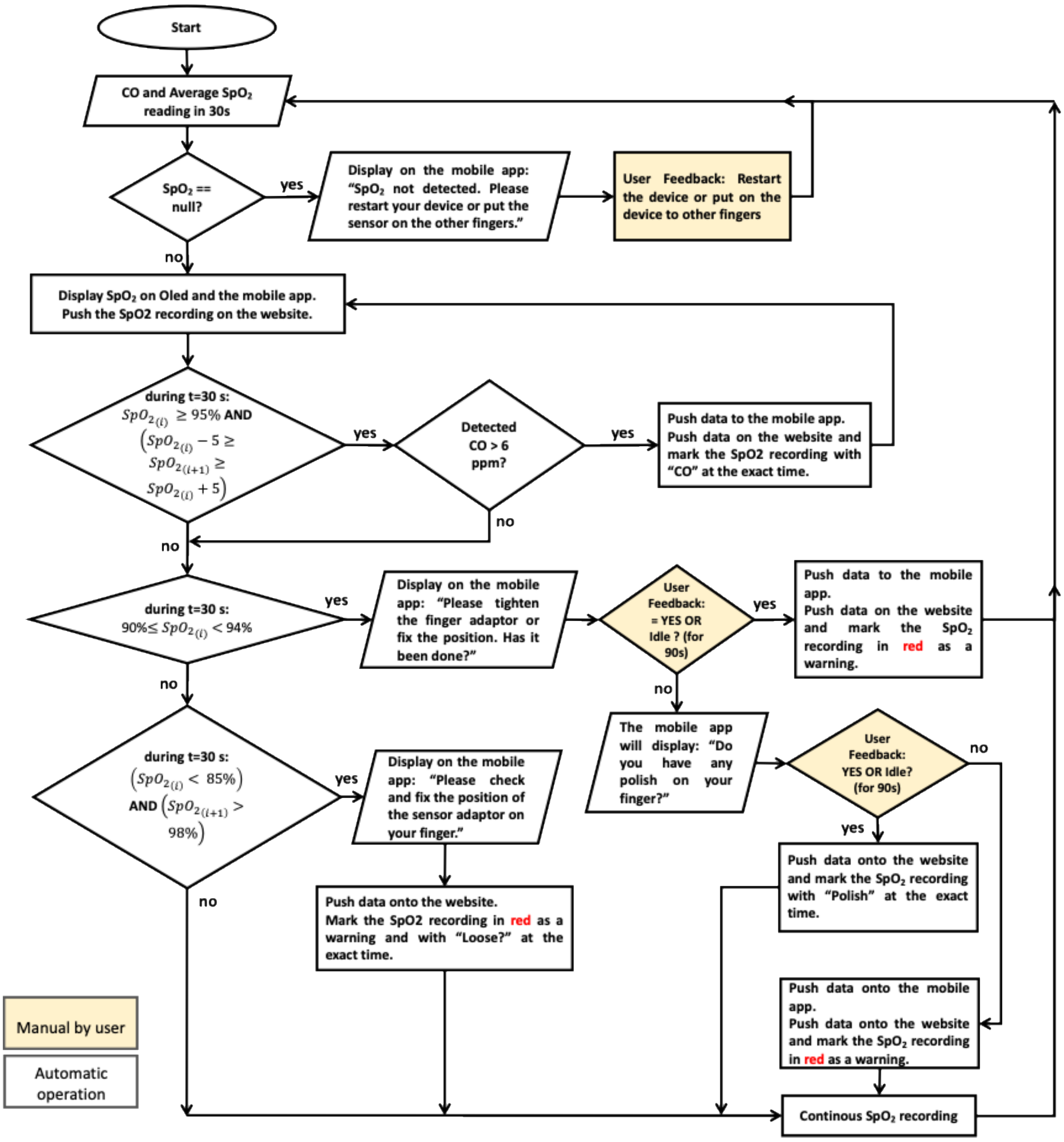

Figure 7. The UML Activity Diagram of the Error-handling Algorithm

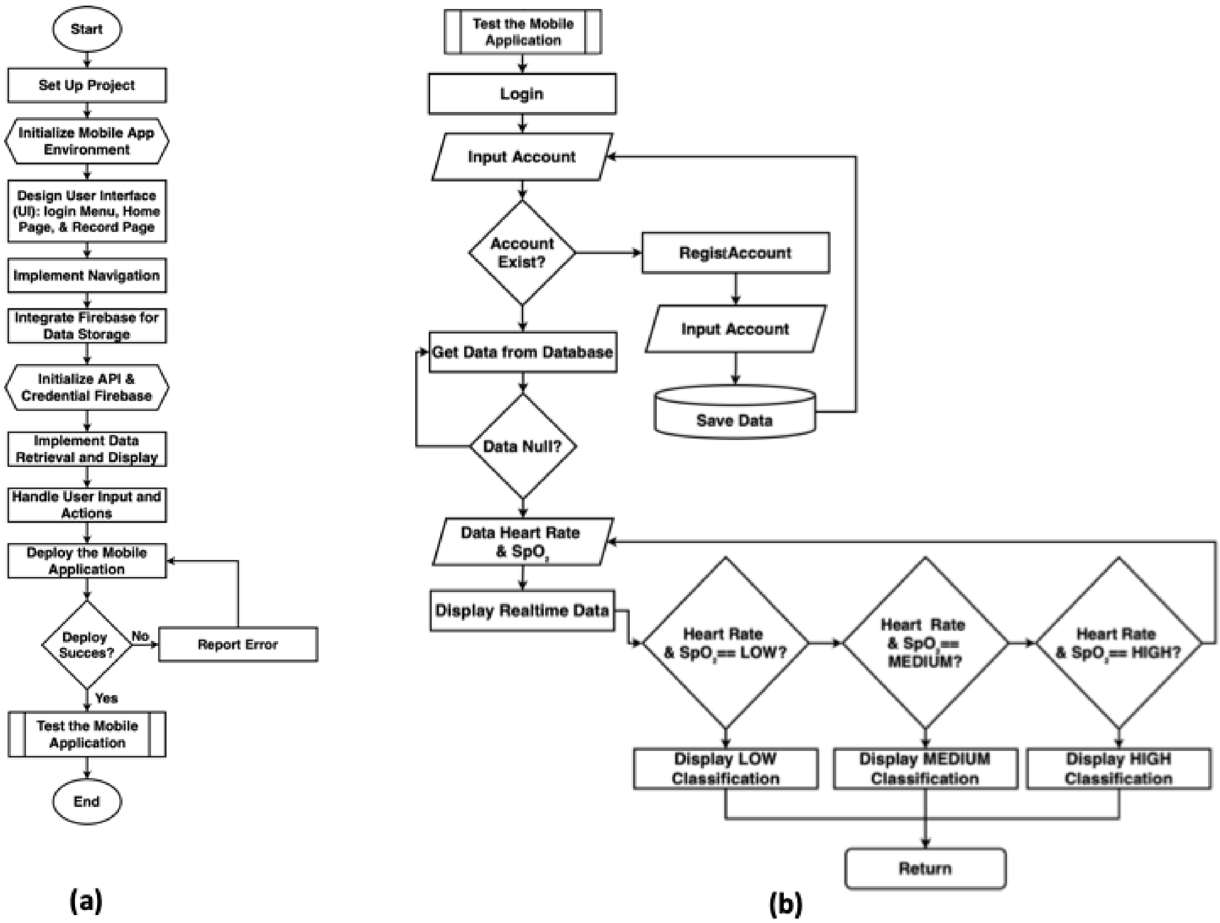

Figure 8. Workflow of the Mobile Application for the Proposed Pulse Oximetry Monitoring System. (a) General Flowchart of App Development, Including Initialization, UI Design, Firebase Integration, and Deployment. (b) Detailed Testing Procedure Illustrating Data Retrieval, Error Handling, and User Interaction Flow

Once discrepancies or abnormal patterns are confirmed, the system initiates corrective actions such as issuing real-time warnings, providing actionable recommendations, or prompting the user for confirmation. This mechanism constitutes part of the system's error-handling strategy, designed to minimise inaccuracies in SpO_2 readings (refer to

Table 5 and Figure 7), which may arise from various error sources outlined in Table 1. This error-handling step is essential to ensure that only valid and reliable SpO_2 readings are processed in subsequent stages.

Fourth, Data Storage and Display: After completing signal validation and correction procedures, the system proceeds to the data storage and display stage. Raw data from the initial HR and SpO2 measurements are displayed directly on the OLED screen. Validated physiological parameters—including heart rate (HR), SpO_2, and carbon monoxide (CO) levels—are presented in real-time via the mobile application and web interface. The data are visualized with standardized labels and color-coded indicators based on predefined classification thresholds (see Table 3 and Table 4). This design ensures an intuitive interpretation of physiological status. Simultaneously, the data are stored in a cloud layer that utilizes Firebase Realtime Database for authenticated storage and streaming. The web dashboard renders HR, SpO_2, and CO values with labelled flags (e.g., "CO", "Loose", and "Polish") and provides role-based access. The use of this dashboard is to support historical tracking and classification.

Figure 8 and Figure 9 illustrate the stages in designing the mobile application. Diagrams in Figure 8 show how the app ensures real-time synchronisation of SpO_2 and HR data, providing corrective prompts to the user when abnormal conditions are detected. Figure 8 also presents the step-by-step development workflow of the mobile application for the proposed pulse oximetry monitoring system. The process begins with project initialization and mobile app environment setup. Key steps include designing the user interface (UI) components (e.g., login menu, home page, and record page) and implementing navigation features for seamless user interaction. Firebase is integrated for data storage, ensuring real-time synchronisation of heart rate and SpO_2 data. After initializing the API and Firebase credentials, data retrieval and display mechanisms are implemented, allowing the application to handle user input and interactions effectively.

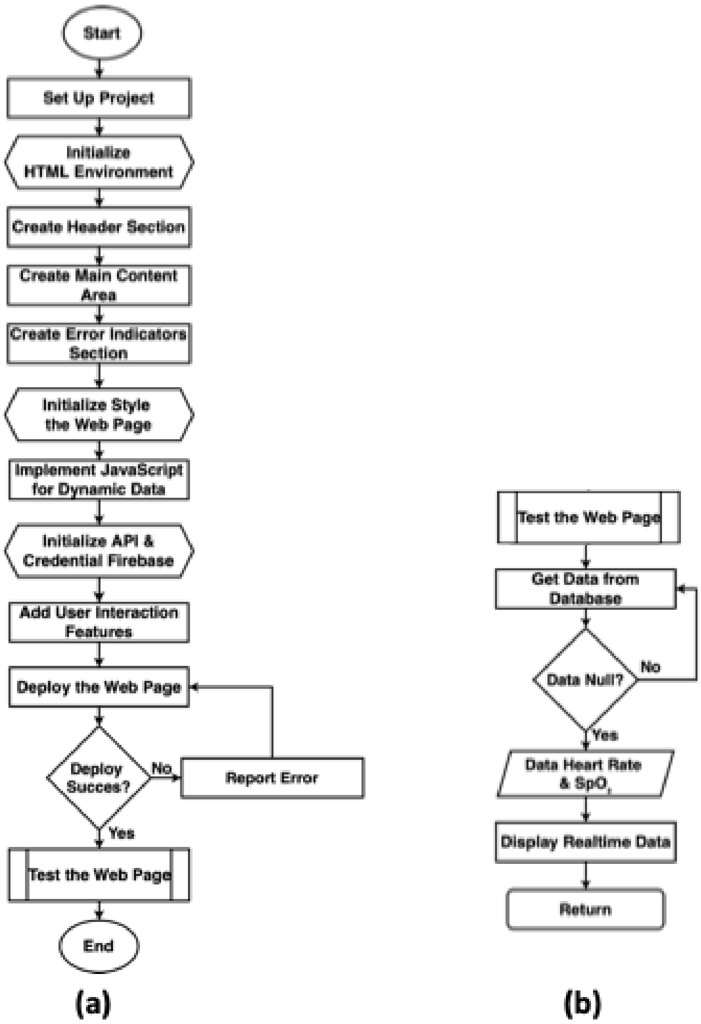

Figure 9. (a) Flowchart of Website with Firebase in General, with (b) The Details of Testing the Web Page

The deployment phase follows, during which the application is tested to ensure successful deployment. It is reported that in the event of an error, prompting further debugging before retesting. Figure 8 details the operational workflow of the mobile application during usage. Upon launching the application, the user is prompted to log in by entering their account credentials. Users can register and save their account data in the Firebase database if the account does not exist. Once logged in, the application retrieves heart rate and SpO_2 data from the database. If no data are available, the system prompts the user to perform new measurements. The retrieved data are displayed in real-time and categorized into three classifications—LOW, MEDIUM, or HIGH—based on predefined threshold parameters for heart rate and SpO_2 levels. The system continuously updates the display with the latest data, ensuring accurate monitoring.

2.2.3 Firebase and Web-Based Dashboard Setup

Data are defined as the values of attribute associated with an entity, while a database is a collection of such entities. A database is an information system designed to store, process, and manage data for various applications. Once the wearable pulse oximeter was worn and the mobile application was accessed, the next step involved configuring Firebase, a web-based platform provided by Google that is accessible for free. The Firebase setup included creating a database using the *Create Database* function and utilizing the Realtime Database feature to store and manage data efficiently.

The web-based dashboard for this project was developed using HTML, CSS, and JavaScript. Hypertext Markup Language (HTML) was employed to structure and display the website content in a browser. Cascading Style Sheets (CSS) define the website's visual appearance, enhancing its design and ensuring an attractive layout. CSS was chosen for its simplicity and robust control over HTML document styling. JavaScript enables client-side interactions and supports dynamic user engagement through the web interface [50].

The dashboard served as a data visualization tool capable of presenting extensive information across multiple pages or a single screen. Although web-based, the dashboard was designed as a private user interface, restricting access to ensure security. The website content, written in HTML format, was accessed via the HTTP protocol using a designated URL, commonly referred to as the homepage. The dashboard was developed using Visual Studio Code, utilizing five files: one .html file, one .css file, one .js file, and two .jpg image files. All files were interconnected, with *dashboard.html* serving as the central file that linked the others to render a cohesive webpage, as depicted in Figure 9. Once the dashboard design was finalized, the output was displayed using the *Open with Live Server* feature in Visual Studio Code. This feature allows the HTML file to be opened as a fully functional website in the default browser application.

2.3 Ethical and Data Considerations

As a preliminary prototype validation (non-clinical testing), this study adhered to the following protocols:

1. Participant Involvement:
   - Healthy volunteers (n=15) tested the device under supervision.
   - No medical diagnosis or decision-making was involved.
2. Data Collection:
   - Only anonymized SpO_2 and HR values were stored locally on the device.
   - Firebase temporarily stored test data (deleted after analysis) with email-based access controls.
3. Consent Process
   - Verbal and formal informed consent was obtained, emphasizing the non-medical nature of the trial.
   - Participants could withdraw anytime without penalty.

Formal ethical review was exempted in accordance with the ethics committee guidelines for low-risk engineering prototypes.

3. Results and Discussion

The results section presents the developed PO device and the sensor validation, including the proposed error-handling algorithm, as well as the mobile application and web-based interface.

3.1 Developed Wearable Device

The wearable pulse oximetry device was designed to focus on ergonomic usability and precise sensor alignment to ensure accurate signal acquisition.

Figure *10* highlights the improved finger holder, incorporating a tension-adjustable strap to optimize sensor-skin contact pressure. While the design demonstrates reliable performance in controlled settings, further studies are needed to evaluate its robustness under high-motion conditions (e.g., walking or manual labour). The adjustable silicone strap also ensures secure contact between the optical sensors (LED and photodetector) and the fingertip, accommodating finger circumferences ranging from 20 to 35 mm. This design minimizes motion artifacts while maintaining user comfort during prolonged use.

3.2 Calibration and Sensor Validation

This subsection outlines three procedures for calibrating each sensor variable: heart rate in beats per minute (bpm), SpO_2 in percentage (%), and carbon monoxide (CO) in parts per million (ppm). All sensor calibrations were conducted by comparing the measured sensor with each variable meter of a manufactured device. Repeated and corrected measurements were performed to validate the MAX30100 sensor by comparing the values of HR and SpO_2 with those from a manufactured pulse oximeter fingertip sensor (model C101A2). The corrected values of HR and SpO_2 were refined using linear Equation 5 and Equation 6, respectively, as shown in Figure 11.

$$HR = (0.974 \times HR_m) + 5.9194 \tag{5}$$

$$SpO_2 = \left(0.1829 \times SpO_{2_m}\right) + 80.451 \tag{6}$$

Where HR is the heart rate measured by the reference device, and HR_m is the heart rate measured by the sensor, SpO_2 is the oxygen saturation level measured by the reference device, and SpO_{2m} is the oxygen saturation level measured by the sensor. These two equations are then used to correct the sensor measurements to obtain the final or corrected value. Figure 11 illustrates the calibration and validation results for HR and SpO_2 before and after correction. The regression plots demonstrate a strong linear relationship between the MAX30100 output and the reference readings, with a significant improvement in proportionality after calibration. The coefficient of determination (R^2) increased from

0.93 to 0.997 for HR and from 0.95 to 0.999 for SpO_2, confirming that the proposed correction effectively reduces measurement deviation and nonlinearity.

Complementing these visual findings, Table 6 presents a quantitative summary of the calibration performance. After applying the correction model, the mean absolute error (MAE) decreased from 11.22 bpm to 0.73 bpm (a 93% reduction) for HR and from 0.73% to 0.06% (a 92% reduction) for SpO_2. The root-mean-square error (RMSE) also decreased by 76% and 72%, respectively. These results demonstrate that the proposed regression-based compensation significantly enhances measurement accuracy while maintaining low computational cost, which is essential for real-time processing in wearable systems.

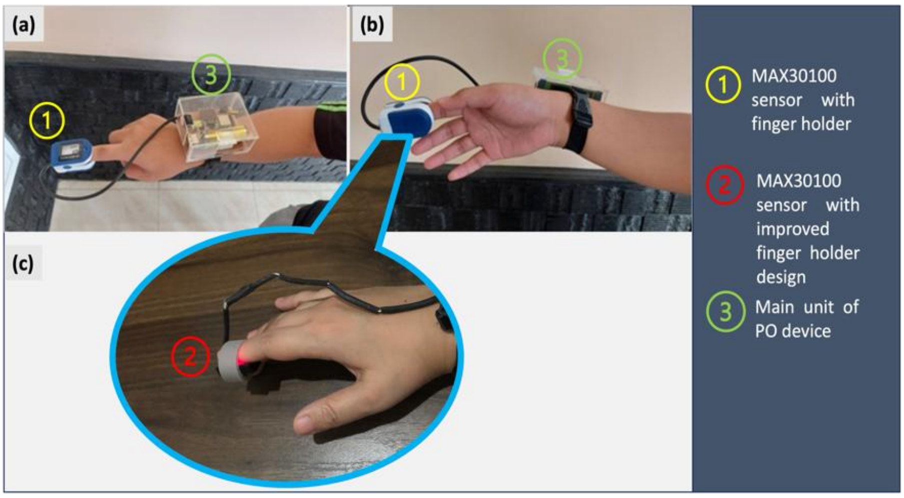

Figure 10. (a). Top-view with MAX30100 Finger Holder, (b) Side-view with MAX30100 Finger Holder. (c). Enhanced Finger Holder Design featuring an Adjustable Strap for Accurate SpO_2 Readings

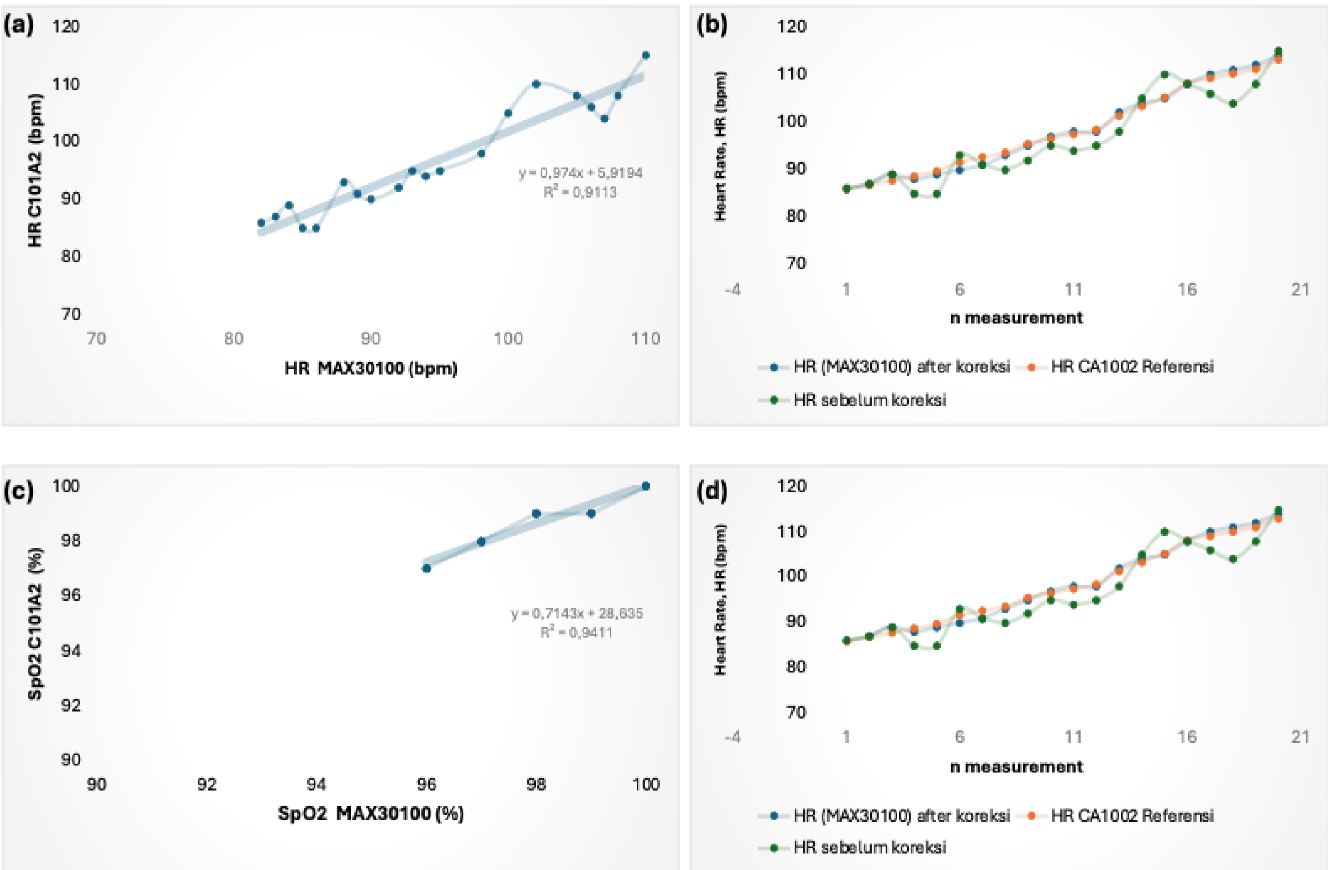

Figure 11. Calibration Results of the MAX30100 Sensor Before and After Correction: (a, b) Heart-rate Regression and Comparison Plots, (c, d) SpO_2 Regression and Comparison Plots, Demonstrating Strong Linearity and Proportionality Improvement After Correction

When compared with existing calibration approaches, the proposed method outperforms adaptive filtering (1.03% error) [31], Chebyshev-based filtering (1.45% error) [28], and uncalibrated photoplethysmography (PPG) systems, which typically report errors of 2–3% [25], [51]. This level of accuracy confirms the effectiveness of the combined hardware–software correction strategy and establishes a reliable foundation for the subsequent feedback and user-interaction experiments described in Section 3.3.

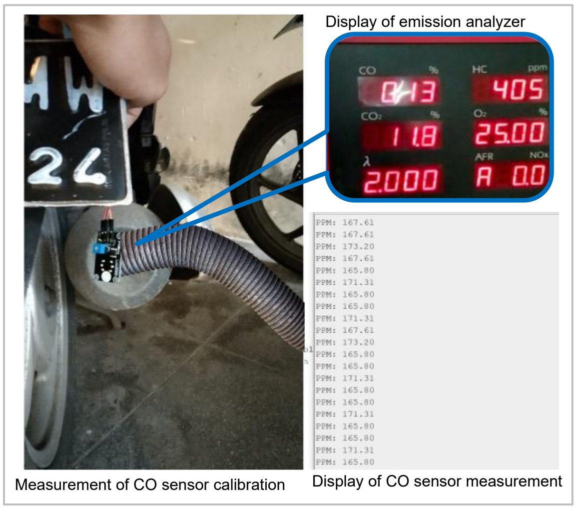

Figure 12. Illustration of Calibrating Carbon Monoxide (MQ-7 sensor) Compared to an Automotive Emission Analyzer (SUKYOUNG SY-GA 40)

Table 6. Quantitative Summary of Calibration Results Presenting the Mean Absolute Error (MAE), Root-Mean-Square Error (RMSE), and the Corresponding Percentage of Error Reduction After Applying the Correction Model

Parameter	Heart Rate, HR (bpm)		Oxygen Level, SpO_2 (%)	
	MAE	RMSE	MAE	RMSE
Before Correction	11.22	3.34	0.73	0.84
After Correction	0.73	0.82	0.06	0.24
Error Reduction	10.49	2.52	0.67	0.60

Table 7. Comparison of Carbon Monoxide Measurement Results Between the MQ-7 CO Sensor and the Emission Analyzer

No	MQ-7 sensor		Corrected MQ-7 sensor	Emission Analyzer
	CO (ppm)	CO (%)	CO (%)	CO (%)
1	165.80	0.16580	0.16677	0.17
2	158.83	0.15883	0.16000	0.16
3	158.83	0.15883	0.16000	0.16
4	164.02	0.16402	0.16505	0.17
5	158.83	0.15883	0,16000	0.16
.	.	.	.	.
.	.	.	.	.
21	193.78	0.19378	0.19396	0.19
22	187.27	0.18727	0.18763	0.19
23	187.27	0.18727	0.18763	0.19
24	177.07	0.17707	0.17772	0.18
25	173.20	0.17320	0.17396	0.18
.	.	.	.	.
.	.	.	.	.
38	149.10	0.14910	0.15055	0.15
39	150.66	0.15066	0.15207	0.15
40	152.25	0.15225	0.15361	0.15

The MQ-7 sensor was used to check for the presence of carbon monoxide (CO) gas. When the SpO_2 sensor reported an abnormally low values, the CO sensor was also evaluated to verify the accuracy of its reading performance. The MQ-7 measurements were validated by comparing it to an automotive emission analyzer (Sukyoung, SY-GA 401). The procedure is described in Figure 12, where the MQ-7 sensor and the hose tip of the gas analyzer are attached to the motorcycle exhaust. The CO sensor and gas analyzer measured the smoke from motorcycle exhaust in ppm units and CO concentration (%). The unit conversion from ppm to $\%$ is given in Equation 7.

$$1\,ppm = (1/10000)\% \tag{7}$$

Table 7 shows the results of calibration and correction. The relative errors of the CO sensor before and after correction range from 0.305% to 3.837% and from 0.002% to 3.449%, respectively. These errors are significantly decreasing because the average error before and after corrections is 1.531% and 0.015%, respectively. The difference in CO measurement obtained using the MQ-7 sensor and emission analyzer is very small, ranging from 2 to 5 ppm.

The results of this study demonstrate higher accuracy compared with previous works using the same MQ-7 sensor. For example, an air quality detector reported differences of 1-27 ppm [51], a developed gas detector exhibited errors of approximately 0.6-6.7% [52], an early warning system reported an error of 1.115% [53], and other studies reported concentration identification errors as high as 11.043% [54]. The low error rate achieved in this study can be attributed significantly to the role of validation testing, which involved comparative analysis using a sophisticated commercial-grade instrument under field conditions. This approach ensured that the data accuracy and reliability against standardized reference device, minimizing discrepancies and enhancing the overall performance of the proposed system.

3.3 Demonstration of Utilizing a Wearable PO Device

This subsection elucidates the utilization of the developed PO device in conjunction with the mobile application and webpage. The device is designed for accurate monitoring by positioning the user's index finger on the MAX30100 sensor adapter, a compact and reliable optical sensor commonly used for measuring heart rate and oxygen saturation (SpO_2). After placing the finger on the sensor (see

Figure *10*), the user secures it with an adjustable fabric strap to ensure stability and prevent displacement. Proper finger placement is crucial for accurate readings, and the fabric should be snug but not overly tight, thereby preventing discomfort and restricted blood flow. This design minimizes errors from misalignment or movement, improving the measurement accuracy.

3.3.1 Mobile application

Sign-in and log-in pages were implemented to secure the users' oxygen saturation and heart rate data. The developed pulse oximeter mobile application consists of three pages: 1) the log-in page, 2) the home page, and 3) the record page, as shown in Figure 13. Every user of the PO device is required to create an account to access the recorded measurement data using their user ID by clicking "Register an account." The home page monitors oxygen saturation and heart rate data, guiding users in preventing reading errors. Meanwhile, the record page stores the recorded data. This system also implements guide checks when the application reads low oxygen saturation. If an error occurs while reading, the data are not stored locally. The stored data in local storage are transmitted to the database Firebase and deleted from the local repository.

3.3.2 Demonstration of Real-Time User Feedback for Mitigating Spurious SpO_2 Readings

This subsection demonstrates the algorithm's data handling strategy to prevent SpO_2 reading errors by providing real-time interactive feedback to the users while using the device. As shown in Table 1, the developed device was tested under several conditions, including carbon monoxide (CO) exposure, the presence of nail polish, and scenarios with a variety of SpO_2 levels, to evaluate the device's features and performance. The procedure is illustrated using a Unified Modelling Language (UML) activity flow diagram in Figure 7. Four changes in SpO_2 values are monitored or marked when the patient or user wears the developed device on a finger. These changes are described as follows.

Case-1: When SpO_2 is undetected, the device displays the instruction "*SpO_2 undetected. Please restart your device or put the device sensor on the other fingers*". The user must then turn off the power button and turn it back on or replace the current finger with another one (see Figure 14).

Case-2: If SpO_2 suddenly increases to 95% or higher than the previous SpO_2 value for 30 seconds and fluctuates within the range of ±3-5%, the CO sensor measures ambient air conditions. If CO > 45 ppm, an alert is displayed: "*Detected CO > 40 ppm*" (see Figure 14).

Case-3: If SpO_2 suddenly changes to a value between 90% and 94% for 30 seconds:

(i) If the user answers "*Yes,*" the system displays the warning: "*Please tighten the finger adaptor or fix the position. Has it been done?*" (see Figure 14).

(ii) If the user answers "*No*," the system asks: "*Do you have any polish on the nail*?" (see Figure 14).

- If the user answers "*Yes*", the system displays: "*It is better to remove the nail polish*" (see Figure 14). This system suggests this to the user.
- For user interactions that require a "*Yes*" or "*No*" response, if no response is received within 90 seconds, the system automatically assumes "*Yes,*" and the recording is marked in red as a warning. A red warning for the reading (illustrated next in Figure 15) indicates that this value may be incorrect due to negligence or misuse.
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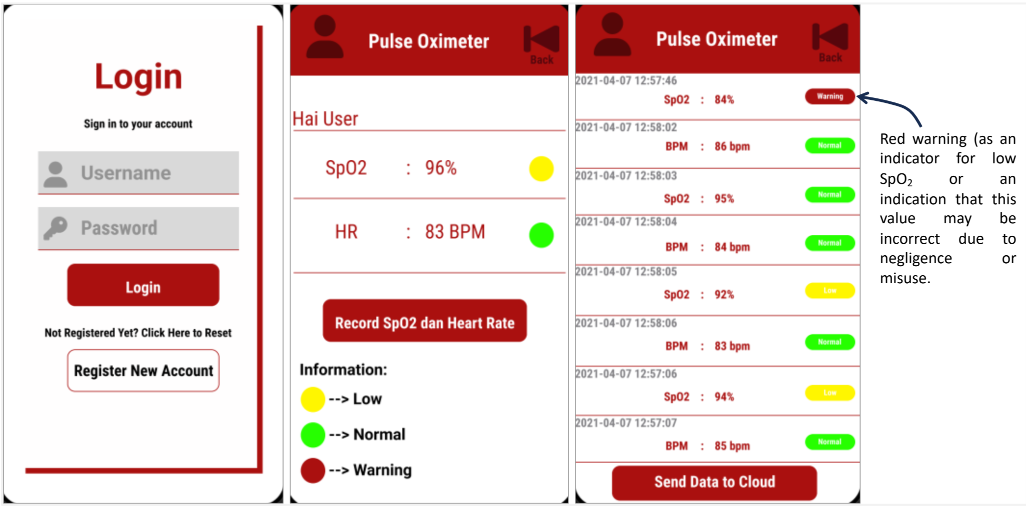

Figure 13. User Interface of the Developed Mobile Application: Login Page for Secure User Access and Account Creation. The Home Page Displays Real-time SpO_2 and HR Data with Colored Indicators, and the Record Page Displays Stored Measurements Linked to the Firebase Database. The Red Indicator Highlights Possible Erroneous Readings (e.g., Due to Poor Contact or Misuse) to Help Users and Clinicians Identify Data Quality Issues

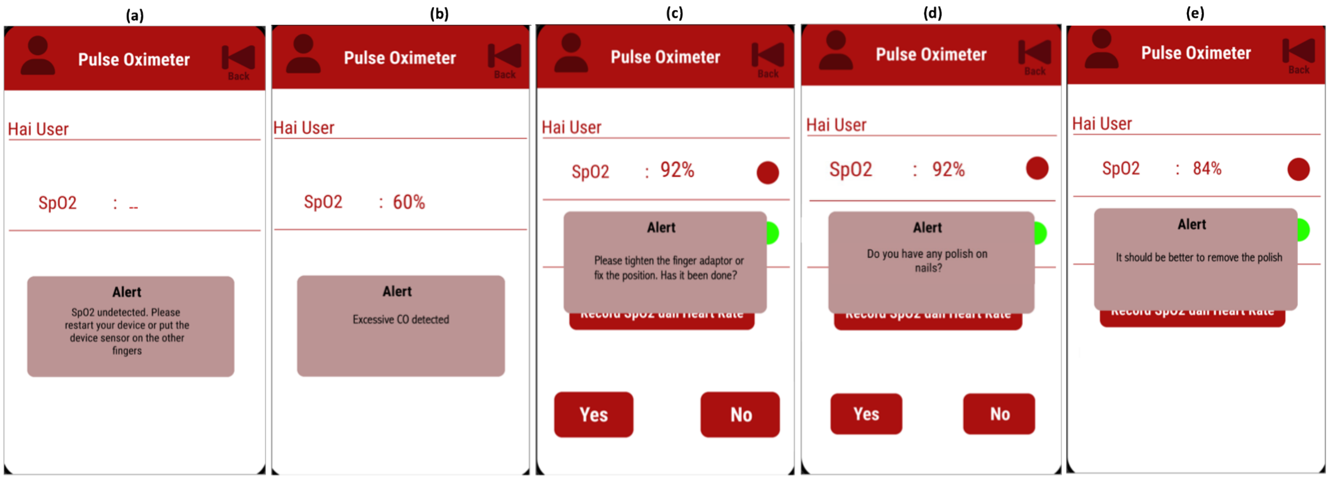

Figure 14. Illustration of Interactive Prompts for Mitigating Possible Spurious SpO_2 Readings: (a) Undetected SpO_2 Reading, (b) Falsely normal/elevated SpO_2 caused by CO Exposure, (c) Falsely Low SpO_2 Due to Loose Sensor or Excessive Movement, (d) and (e) Falsely Abnormal Readings Due to Nail Polish. Each Prompt Guides the User with yes/no Questions or Direct Corrective Instructions (e.g., "Please Tighten the Finger Adaptor") to Ensure Reliable Measurements

Hence, the result of this study provide improved prompt mechanisms for detecting potential errors in SpO_2 readings compared with a previous study that evaluated various skin tones. Despite implementing corrective measures, the earlier study reported that over 90% of readings lacked sufficient accuracy [40]. The study also highlighted that skin tone, IMU sensors, and user-level calibration impact measurement accuracy and should be carefully considered in the future by designing wrist-worn SpO_2 sensors and associated measurement algorithms. Despite the increasing trend of utilizing sensors integrated into Android and iOS smartphones [55][56] to facilitate device accessibility,handheld phones present challenges for continuous monitoring. In contrast, wearable devices such as bracelets or smartwatches [6][41][57] offer a viable alternative for measuring vital signs, and smartwatches can serve as interim devices for continuous vital sign assessment.

3.3.3 Recorded Data in Web Dashboard

This web application was developed as a user interface to provide real-time recording data, displaying heart rate and SpO_2 (see Figure 15. Data are transmitted to the web page via Firebase storage, which is intended to record HR and SpO_2 reading data, along with data handling markers when SpO_2 readings are suspected to be inaccurate. In addition to reducing false SpO_2 readings, the recorded data can serve as user medical records that can be further analyzed by doctors later, if necessary. The red line in Figure 15 indicates the possibility of false SpO_2 readings with "*CO*" markers. Another condition occurs when the SpO_2 reading is suspected to be inaccurate due to loose probe placement, indicated by a "*Loose*" marker. Furthermore, the platform can support future research by incorporating questions about patient awareness of factors such as heart disease and obesity. These questions can be asked at the beginning of the user login process.

In summary, compared with prior wearable pulse oximetry systems that primarily rely on post-processing for motion artifact suppression or hardware-only noise mitigation [28][31][35][51], the proposed user-interactive workflow—combining real-time acquisition prompts (Section 3.3.2) with traceable event flags on the dashboard (“CO”, “Loose”, “Polish”, Figure 15—provides an end-to-end mechanism to detect, attribute, and mitigate spurious readings as they occur. This integrated approach enables faster recovery from erroneous measurement states and improves user adherence (as detailed in Section 3.4), while preserving auditability for clinical review—capabilities that are typically absent in passive oximetry systems.

Figure 15. Web Dashboard Showing Real-Time SpO_2 (top) and HR (bottom) Data Integrated from Firebase. Labelled Markers Indicate Suspected Errors: “CO” for Carbon Monoxide, “Nail polish” for Cosmetic Interference, and “Loose”

for Poor Contact. The Interface Helps Users and Healthcare Providers Track History, Spot Anomalies, and Further Review Flagged Events

3.4 User Trial Test Experience

The wearable pulse oximeter (PO) system was evaluated to ensure accurate device responses under various real-world conditions that commonly interfere with SpO_2 measurement. A total of 15 first-year undergraduate students participated in the user trial. All participants received a detailed explanation of the study objectives and device operation, followed by a brief orientation session that demonstrated proper finger placement and provided examples of potential notifications from the mobile application. Each participant signed an informed consent form before the trial, acknowledging their voluntary participation and the right to withdraw at any time.

The participants represented a balanced distribution of backgrounds, with one-third from the Faculty of Economics and Business, one-third from the Faculty of Creative Industries, and the remainder from the Faculty of Engineering. This distribution ensured that the usability of the device and the app notifications could be assessed not only among technically oriented participants but also those from non-engineering backgrounds. To accommodate this diversity, the app notifications were designed with intuitive elements, including short text instructions (e.g., “Please tighten the finger adaptor”), yes/no prompts (e.g., “Do you have nail polish on your finger?”), and color-coded alerts to facilitate quick understanding.

Each participant performed 50 test runs, consisting of five iterations for each of the four test cases (see Table 5), resulting in a total of 20 feedback-related tests per participant. Descriptions and participant responses are summarised in below and illustrated in Figure 16. The average number of successful reactions per case, as reported by all participants, ranged between 4.3 and 5.0. User perceptions and responses were further evaluated, as outlined in below. During the trials, participants from all backgrounds demonstrated high compliance with corrective prompts (93.3%), with an average response time between 4 and 5 seconds and a satisfaction rating above 4 on a 5-point scale. Only the nail polish warning exhibited a relatively slower response (5.2 ± 0.7 seconds) and lower compliance (87%), suggesting that additional user guidance may be necessary in a specific scenario.

In Case 1 of below, a simulation of SpO_2 signal loss lasting ≥30 seconds demonstrated that the device successfully issued an “SpO_2 undetected” alert and prompted the user to replace the finger or restart the device. The signal-recovery success rate reached 98%, validated across five different finger positions. Case 2 evaluated the detection of carbon monoxide (CO) interference. Under conditions where the SpO_2 reading was ≥ 95% with a 3–5% deviation for 30 seconds, the device accurately detected CO concentrations > 40 ppm and displayed a red alert via the mobile application. Participants followed the prompt to move to fresh air, achieving a 100% successful detection rate and demonstrating robustness against environmental interference. In Case 3a, interference due to poor sensor contact was simulated using motion artifacts and intentionally loose or stretched sensor tape. The device issued a yellow alert, instructing users to tighten the sensor, resulting in a correction success rate of 92%. Case 3b examined optical interference caused by nail polish. When SpO_2 readings were between 90% and 94% without motion artifacts, the system prompted users to confirm the presence of nail polish and advised removal if applicable. After user confirmation, the results showed an 87% reduction in reading errors, validated across five different nail-polish colours. Compared with conventional pulse oximeters (PO) operating without guided feedback, the developed PO system reduced measurement errors by at least 87% and achieved an average user compliance rate of 93% when corrective prompts were issued.

Table 8. User Trials Evaluation for Wearable PO Device (n=15)

Test case	Device Response	User Action Required	Average ± uncertainty of successful response	Success Criteria	Remarks
Case 1: Undetected SpO_2	"SpO_2 undetected. Please restart device or change fingers"	1. Power cycle device 2. Switch finger	4.7±0.5	Signal recovery within 60s	Validated with 5 finger positions
Case 2: CO Interference	"Detected CO >40 ppm"	Move to fresh air area	5.0±0.0	CO < 40 ppm within 5 mins	Tested with controlled CO exposure near motorcycle exhaust
Case 3a: Poor Contact	"Tighten finger adaptor" (Yellow warning)	Adjust fabric (probe) tightness	4.7±0.6	Stable reading within 30s	Validated with loose/stretched fabric

Case 3b: Nail Polish	"Do you have nail polish?" → "Remove polish" if yes	Remove polish or confirm	4.3±0.6	Reading stability improvement	Tested with 5 polish colors (red, deep red, blue, magenta, purple)

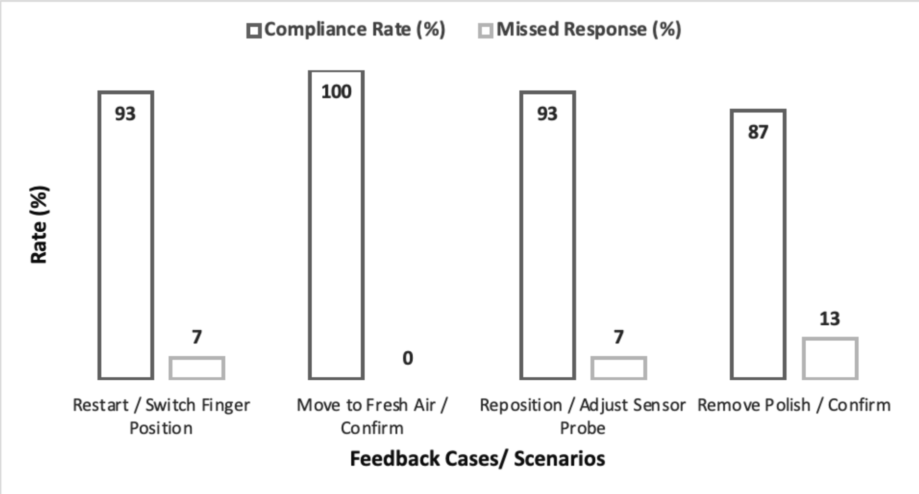

Figure 16. User Compliance Across User Responses on Feedback Scenarios

Table 9. User Feedback Evaluation (n=15)

Prompt Type	User Action Required	Average ± uncertainty of Response Time (s)	Success Rate	User Satisfaction (scale of 1-5)
Undetected SpO_2	Restart/change finger position	4.6±0.5	93%	4.53
CO warning	Move to fresh air	4.2±0.4	100%	4.73
Poor contact warning	Reposition sensor	4.0±0.7	93%	4.66
Nail polish alert	Remove polish or confirm	5.2±0.7	87%	4.13

User perception and response were surveyed for all participants, as summarized in above. Each command type was evaluated based on action success rate, response time (mean and uncertainty response time), and user satisfaction (scale 1–5 or *Very Satisfied–Satisfied –Fair–Dissatisfied–Very Dissatisfied*). Uncertainty response time was calculated using the standard deviation. The "SpO_2 undetected" command achieved a 93% success rate, with a response time of 4.6±0.5 seconds and a satisfaction rating of 4.53. The CO alert received the highest satisfaction rating (4.73), with a response time of 4.2±0.4 seconds and 100% success rate. The nail polish alert exhibited the slowest response time (5.2±0.7 seconds), with an 87% success rate and the lowest satisfaction rating (4.13), indicating a potential need for additional user education. The poor-contact alert achieved 93% compliance, with a rapid response time of 4.0±0.7 seconds and a satisfaction rating of 4.66. These results demonstrate that the developed wearable PO device can accurately detect and respond to disturbances, thereby maintaining user comfort and trust in the interaction.

Beyond technical improvements, these findings have important practical implications. Real-time feedback enables patients to self-correct during home or outpatient monitoring, thereby reducing their reliance on continuous supervision by healthcare professionals. This capability may help lower the workload of medical staff in long-term monitoring programs, particularly for chronic conditions such as COPD or cardiovascular diseases, where continuous SpO_2 assessment is critical. Furthermore, integrating such systems into telehealth platforms could improve early anomaly detection, enhance patient safety, and promote more efficient utilisation of healthcare resources. Future development will focus on optimizing device energy efficiency and conducting larger-scale trials to validate performance across broader populations and real-world environments.

While the current validation was limited to 15 first-year university students from diverse faculties, further evaluation with larger populations is required. Future work will therefore prioritize testing the system in community-based settings that involve diverse age groups and health backgrounds. Such trials will enable assessment of usability, compliance, and accuracy under real-world conditions, where users may have varying levels of technical familiarity and different health risk profiles. Expanding to larger community cohorts will provide more substantial evidence for clinical adoption and integration into public health monitoring programs.

Another significant limitation of the current prototype is its energy efficiency. The device achieves an average of 4–5 hours using a 9V battery, which may limit its long-term use in outpatient settings. Future development will therefore focus on optimized LED activation, implementation of ESP32 deep-sleep modes, and higher-capacity lithium-ion or rechargeable batteries with boost converters.

4. Conclusion

This study successfully designed and developed a wearable pulse oximeter with an interactive system capable of detecting and correcting inaccurate SpO_2 readings in real-time. Experimental validation demonstrated that the device accurately monitored vital signs and provided immediate user feedback to prevent errors in reading. Integrating intelligent algorithms with a responsive user interface improved the reliability and usability of the device in ambulatory settings. The main contributions of this work include: (1) real-time mitigation of oximetry errors, enhancing data integrity compared to passive monitoring systems; (2) a user-centric design approach that promotes active engagement in health monitoring and supports informed clinical decision-making; and (3) potential benefits for clinical and home healthcare, particularly in reducing false alarms and improving care delivery in low-resource settings. Future work will focus on refining the algorithm and validating the system through large-scale clinical trials involving diverse populations. Advancements in sensor technology are also needed to further minimize the impact of external factors on measurement accuracy.

Additionally, the current device provides an average operating time of 4–5 hours using a 9V battery. Future improvements in power management will be required to extend its applicability for continuous outpatient monitoring. Future trials should expand to involve larger community cohorts. This step is essential for evaluating usability and compliance across a more representative population and ensuring the system's readiness for real-world outpatient and community healthcare applications. Overall, this study advances wearable health monitoring technologies and offers promising implications for improving patient care in both clinical and remote environments.

Acknowledgement

We extend our deepest gratitude to the Directorate of Research and Community Service at Telkom University for providing the internal funding and resources that enabled us to conduct this study. We would like to acknowledge the assistance and guidance provided by a technician from BRIN Bandung in measuring the carbon monoxide level. Last, we express our heartfelt gratitude to all participants who generously contributed their time to the experiment.

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