PERFORMANCE EVALUATION OF COMMERCIAL MLX90614 AND MAX30102 SENSORS FOR PORTABLE VITAL SIGN MONITORING DEVICE

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ABSTRACT: Portable vital-sign monitoring is increasingly important for supporting early detection of physiological conditions. This study aims to evaluate the accuracy of a portable sensor in measuring body temperature, heart rate, and oxygen saturation (SpO_2) compared with clinical reference instruments (thermogun and oximeter). A total of 26 healthy adult participants were included. Data were analyzed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), the Shapiro–Wilk normality test, and the Bland–Altman method to assess measurement agreement, including the Limits of Agreement (LoA). The results showed that body temperature had a mean difference of −0.62 °C with an MAE of 0.68 °C and an RMSE of 0.79 °C. For SpO_2, the mean difference was +0.69%, with an MAE of 1.23% and an RMSE of 1.90%. Both parameters indicated small bias and narrow LoA, demonstrating sufficient accuracy for daily monitoring. For heart rate, the mean difference was +1.46 beats per minute (BPM), with an MAE of 5.31 BPM and an RMSE of 6.71 BPM, indicating higher variability caused by movement and individual physiological factors. Overall, the portable sensor can be considered reliable for body temperature and SpO_2 measurement, while heart rate monitoring requires further development to improve stability and accuracy.

KEYWORDS: *Bland–Altman analysis, infrared thermometer, portable sensor, pulse oximeter sensor, vital signs monitoring*

1.0 INTRODUCTION

Monitoring vital signs is a crucial aspect of healthcare, as abnormal physiological changes serve as early indicators of serious conditions such as cardiac arrest and respiratory arrest [1]. Periodic manual monitoring systems are limited by their low recording frequency, which increases the risk of delayed detection [2]. The emergence of portable devices and wearable technologies, supported by wireless data transmission, enables continuous monitoring of vital signs not only in hospitalized patients but also in healthy populations and outpatients [3].

The Medical information regarding body temperature, heart rate (BPM), and oxygen saturation (SpO_2) represents key indicators of an individual's physiological status. In clinical contexts, maintaining a normal heart rhythm and stable oxygen saturation is essential to ensure adequate oxygen supply to body tissues. Disruptions in heart rhythm, such as arrhythmias, may impair cardiac function and potentially lead to heart failure if not promptly addressed [4,5].

Heart rate beats per minute (BPM) and oxygen saturation (SpO_2) are two key physiological parameters commonly measured using a pulse oximeter. In healthy individuals, the normal range of SpO_2 is typically between 95–100%, while resting heart rate ranges from 60–100 bpm. Although these indicators are measured separately, they are closely interconnected physiologically [6]. Red blood cells with an optimal capacity to bind and transport oxygen (high SpO_2) tend to support heart rate stability, whereas excessively rapid (tachycardia) or abnormally slow rhythms (bradycardia) may impair oxygen distribution to body tissues [7].

An SpO_2 value below 95% is generally considered abnormal, and a further decline below 90% is defined as hypoxemia, which requires immediate medical attention [8-11]. Similarly, a heart rate exceeding 100 bpm at rest or dropping below 40 bpm is often regarded as an indicator of significant health disturbances, necessitating further

clinical evaluation by healthcare professionals. Routine monitoring of vital signs is therefore highly important, both for the general population and for groups with higher levels of physical activity [12].

Calibration is a fundamental step to ensure that wearable healthcare devices provide reliable and accurate measurements. Without proper calibration, sensor outputs may deviate from reference standards, leading to biased or clinically irrelevant data [5].

This study developed a device for measuring vital signs using the MAX30102 sensor for heart rate and oxygen saturation (SpO_2) and the MLX90614 sensor for body temperature measurement. Although both sensors are widely used commercial components, their accuracy and measurement consistency may change when integrated into an embedded system, particularly within an ESP32-based portable device. Integration with a microcontroller can affect sensor performance due to technical factors such as electrical noise, power supply stability, inter-module interference, the quality of I^2C communication lines, and differences in signal processing algorithms compared to manufacturer test conditions. Devices using commercial sensors still require system-level calibration and validation, rather than relying solely on individual sensor specifications. This step is essential to ensure that the portable device produces accurate, stable, and reliable data for daily health monitoring [6].

Previous studies have developed portable devices for vital sign monitoring by utilizing heart rate sensors, infrared temperature sensors, and pulse oximeters. Suryani et al. designed a heart rate monitoring device based on the MAX30102 sensor [11], while Wijaya et al. [7] integrated the MLX90614 temperature sensor with a pulse oximeter for outpatient monitoring. However, most of these studies primarily focused on general patients or clinical applications, without providing clear methods for calibration. Consequently, the aspects of calibration and validation of such devices against standard medical instruments have not been extensively explored. This situation creates

a knowledge gap regarding the reliability of portable devices in producing accurate and trustworthy data to support healthcare decision-making [9].

The present study aims to perform calibration and validation of a portable device for vital sign monitoring, including body temperature, heart rate (BPM), and oxygen saturation (SpO_2), using standard medical instruments as reference. Calibration is conducted to ensure that the device generates consistent outputs under various measurement conditions, including variations in the distance of the temperature sensor. Meanwhile, validation seeks to assess the accuracy and agreement of the device's measurements compared to clinical thermoguns and pulse oximeters.

2.0 METHODOLOGY

2.1 Materials

The primary device in this study is a portable vital sign monitoring system designed using the ESP32-WROOM-32 microcontroller, which features a dual-core Tensilica LX6 processor operating at 240 MHz, integrated Wi-Fi and an I^2C communication interface for sensor integration. The hardware configuration of the portable monitoring device was implemented on a compact PCB prototype that integrates all sensors, the ESP32 microcontroller, and the TFT display into a unified system. Each module is connected through dedicated I^2C or SPI communication lines, while a shared 3.3 V supply and a common ground ensure electrical stability across components. To minimize noise—particularly during optical signal acquisition—additional 0.1 μF capacitors were placed on the supply lines of the MLX90614 and MAX30102 sensors. Table 1 summarizes the complete wiring configuration used in the prototype.

Table 1: ESP32 Sensor Module Pinout

Component	Module Pin	ESP32 Pin
MAX30102	GND	GND
	VCC	3.3 V
	SDA	GPIO 21
	SCL	GPIO 22
MLX90614	GND	GND
	VCC	3.3 V
	SDA	GPIO 25
	SCL	GPIO 26
TFT ST7789	GND	GND
	VCC	3.3 V
	MOSI	GPIO 23
	SCK	GPIO 18
	DC	GPIO 5
	RST	GPIO 4

Power delivery is stabilized using the ESP32's internal LDO combined with 100 μF and 10 μF capacitors to reduce electrical noise. Circuit diagrams and prototype photographs are presented in Figure 1 and Figure 2.

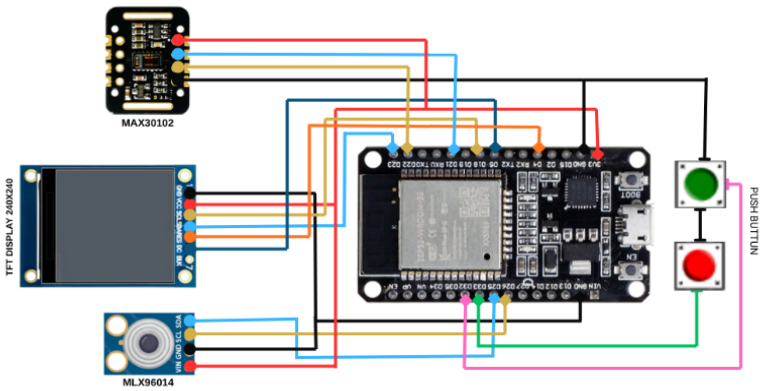

Figure 1: Circuit Schematic of The Portable Vital Sign Monitoring Device

Figure 1 shows the electrical connections between the ESP32 microcontroller, the MLX90614 infrared temperature sensor, the MAX30102 optical heart-rate and SpO_2 sensor, and the ST7789 TFT display.

Figure 2: Physical prototype of the portable vital sign monitoring device

2.2 Sensor Calibration Process

The MLX90614 sensor was calibrated by measuring body temperature at distances between 1 and 10cm and comparing the results with a clinical infrared thermometer. This procedure aimed to determine the optimal measurement distance and ensure consistent sensor performance when integrated into an ESP32-based portable device. The calibrated parameters included:

- Temperature offset compensation
- Signal noise filtering
- Stability of the 3.3 V power supply

The calibration results were used to identify the ideal measurement distance and to assess the reliability of the sensor under practical testing conditions [17].

The MAX30102 sensor required a more detailed calibration process because the quality of the photoplethysmography (PPG) signal is influenced by several physiological and technical factors, including finger pressure, finger placement, blood perfusion, ambient light, and electrical noise produced by the ESP32. The calibration procedure consisted of the following stages:

a. LED Current and Pulse-Width Configuration

The LED drive parameters were configured to ensure adequate tissue penetration while minimizing noise and saturation. The final operating parameters were:

- IR LED current: 7.6 mA
- Red LED current: 7.6 mA
- Pulse width: 118 μs

These settings provided a stable PPG waveform suitable for both heart-rate and oxygen saturation extraction. To optimize PPG temporal resolution and reduce quantization artifacts, the following configurations were applied Sampling rate100 Hz and ADC resolution 16-bit. This configuration allowed the sensor to capture rapid variations in blood volume while maintaining an adequate signal-to-noise ratio.

During initialization, the PPG signal typically exhibits fluctuations due to sensor warm-up and unstable finger contact. The first 5–10 secondsof recorded data were discarded to eliminate transient instability and obtain a consistent baseline before feature extraction.

b. Filtering and Noise Reduction

To suppress optical, electrical, and motion-induced noise, a multistage filtering pipeline was implemented:

- Moving average filter: window size = 5
- Low-pass filter: cutoff frequency = 5 Hz
- Additional 100 μF decoupling capacitor on the sensor supply line to reduce electrical interference from the ESP32

These filtering steps significantly improved the clarity of the PPG waveform and the accuracy of peak detection for heart-rate estimation [18]. Measurements from the MAX30102 were compared with a clinical-grade pulse oximeter. The evaluation metrics included Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These metrics were used to quantify the deviation between the portable device and the clinical reference, serving as the basis for accuracy assessment in the Results section.

2.3 Research Subjects

The study involved a total of 26 university students aged 17–22 years, consisting of 13 male and 13 female participants. All individuals were informed about the objectives, procedures, and potential risks of the study, and each participant provided written informed consent prior to data collection. Only individuals who were physically healthy, had no history of cardiovascular or respiratory disorders, and were not taking medication that could influence heart rate or oxygen saturation were included. Participants presenting with acute illness, poor peripheral perfusion, or skin abnormalities at the measurement site were excluded to maintain consistency and ensure measurement reliability.

The research procedures followed the ethical principles outlined in the Declaration of Helsinki, emphasizing participant rights, comfort, privacy, and safety. Participation was entirely voluntary and free from any form of coercion or academic pressure. All participants retained the right to withdraw at any point without penalty. Before data collection, each individual received a clear explanation of the study's purpose, workflow, estimated duration, and any minimal discomfort that might arise from sensor placement or finger contact.

A sample size of 26 was deemed appropriate for the preliminary validation of a medical device prototype, particularly since the focus of this study was on assessing device accuracy rather than making broader population-level inferences. The use of healthy young adults provided a homogeneous physiological baseline, which was suitable for evaluating the technical performance of the sensor system under controlled conditions.

The homogeneity of the sample also introduced specific limitations. The findings cannot be generalized to children, older adults, or individuals with clinical conditions such as anemia, arrhythmia, vascular disorders, or impaired peripheral perfusion. These groups may exhibit different physiological characteristics that can affect optical and thermal sensor outputs. Broader validation across multiple age groups and clinical populations is required in future research to establish wider applicability and clinical robustness of the monitoring system.

2.4 Research Design

This study employed a quantitative, cross-sectional approach. This design was selected because data were collected within a single measurement period without long-term intervention, allowing the results to accurately reflect the subjects' physiological conditions at the time of the study [10]. Validation was performed by comparing the results of the portable device with certified medical instruments,

namely the Thermogun Infrared Thermometer DT-8826 for body temperature and the FamilyDr Pulse Oximeter for heart rate (BPM) and oxygen saturation (SpO_2) [12].

Data analysis included descriptive statistical calculations, the Shapiro–Wilk normality test, and error assessment using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Additionally, Bland–Altman plots were utilized to evaluate the agreement between the portable device and reference instruments.

2.5 Research Procedures

The research was conducted through several main stages, as follows

1. Equipment Preparation and Initial Calibration

All devices used, including the portable vital sign monitoring system, clinical thermogun, and clinical pulse oximeter, were checked for proper functioning prior to data collection. Initial calibration was performed to ensure that the reference instruments operated according to the manufacturer's standards.

2. Preparation of Subjects

A total of 26 healthy students were instructed to remain in a resting state for at least five minutes before measurements. Data collection was conducted in a temperature-controlled room (22–25 °C) to minimize environmental influences on the measurements.

3. Data Acquisition

Participants were asked to sit calmly while body temperature was measured using a non-contact infrared sensor on the forehead. Heart rate (BPM) and oxygen saturation (SpO_2) were measured using the optical sensor on the index finger of the portable device. The measurements were then compared with a clinical standard pulse oximeter and an infrared thermogun as reference instruments.

4. Data Recording and Storage

All measurements from the portable device were recorded via the PlatformIO interface connected to the Serial Monitor and TFT display. The data were subsequently exported in CSV format for further analysis.

3.0 RESULTS AND DISCUSSION

3.1 Descriptive Statistics of Subjects

This study involved 26 university students as participants, aged between 17 and 22 years. The mean age of the participants was 19.04 ± 1.54 years, indicating that the majority belonged to the 18–20-year age group. The gender distribution was balanced, with 13 males and 13 females, thereby minimizing sex-related physiological variability. All participants were healthy, with no history of cardiovascular or respiratory disorders, and were not taking medications that could affect heart rate or oxygen saturation. Initial measurements from the portable sensor and reference instruments indicated that the participants were relatively homogeneous, resulting in minimal inter-subject biological variability and supporting the consistency of the physiological data obtained. Figure 3 illustrates the age distribution of the participants, showing the percentage of each age group within the sample.

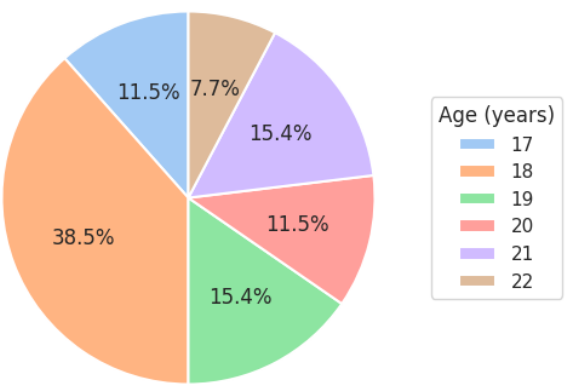

Figure 3: Age Distribution of Participants

Interpretation of Figure 3 suggests that the study sample was predominantly composed of young adults (18–19 years), consistent with the typical university student population, allowing the assessment of sensor accuracy within a relatively homogeneous age group. The percentage of each age group may also provide insight into the potential influence of age on physiological variations such as heart rate and oxygen saturation.

3.2 Temperature Movement Across Distances

The average body temperature values measured by the MLX90614 infrared sensor were recorded at distances ranging from 1 to 10 cm. Each measurement was repeated three times on the forehead to examine the accuracy differences between the sensor and the DT-8826 Thermogun. The data is presented in Table, and a linear regression graph is provided in Figure 4.

Table 2: Temperature Sensor Testing and Calibration

Distance (cm)	Sensor Temperature (Mean ± SD, °C)	Thermogun (°C)	Error (°C)	Calibrated (°C)	Accuracy (%)
1	36.67 ± 0.72	36.7	-0.03	36.671	99.91%
2	36.67 ± 0.21	36.7	-0.03	36.671	99.91%
3	36.53 ± 0.15	36.7	-0.17	36.673	99.82%
4	36.20 ± 0.56	36.7	-0.50	36.676	98.64%
5	36.17 ± 0.31	36.7	-0.53	36.677	98.55%
6	36.10 ± 0.20	36.7	-0.60	36.678	98.37%
7	35.83 ± 0.06	36.7	-0.87	36.681	97.91%
8	35.63 ± 0.06	36.7	-1.07	36.683	97.09%
9	35.40 ± 0.10	36.7	-1.30	36.686	96.46%
10	35.23 ± 0.12	36.7	-1.47	36.688	96.00%

The results indicate that at close distances (1–3 cm), the readings from the sensor closely matched the reference values, with very small errors ranging from −0.03 to −0.17 °C. However, as the distance increased, the sensor tended to record lower temperatures, with a maximum error of −1.47 °C at a distance of 10 cm. This phenomenon is consistent with the operating principle of infrared sensors, in which the infrared energy emitted by the body spreads over a larger area at greater distances, resulting in less energy being received by the sensor.

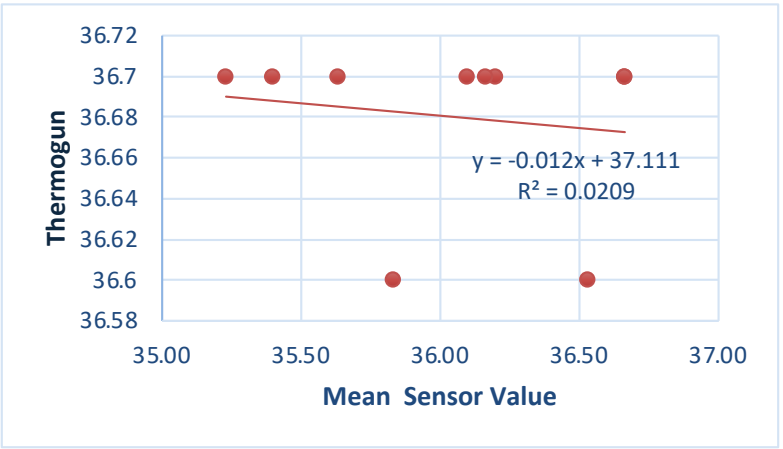

Figure 4: Linear Regression Graph

To correct this discrepancy, linear calibration was performed using the regression equation y = −0.012x + 37.111, where x represents the measurement distance (cm) and y represents the calibrated temperature. Post-calibration measurements presented in Table 2 indicate that the sensor readings were adjusted to closely match the Thermogun values across all distances, achieving an accuracy of 96–99%. The linear regression graph in Figure 4 illustrates the negative relationship between measurement distance and sensor error.

3.3 Sensor and Reference Comparison Analysis

Table 3 presents a descriptive statistical analysis of the measurement errors of the sensor compared to the reference instruments. Table 4 shows the evaluation of the sensor using the Mean Absolute Error (MAE), which provides an overview of the average magnitude of error and assesses the general accuracy of the sensor relative to the standard instruments [14 – 16]. The Root Mean Square Error (RMSE) was employed to evaluate the consistency and precision of the measurements, giving greater weight to extreme errors and thereby indicating the stability of the sensor's performance under various measurement conditions. Figures 5, 6, and 7 display visual comparisons of the measurement data, illustrating the agreement between the sensor readings and reference instruments. The Shapiro–Wilk Test was employed to assess whether the distribution of measurement errors from the sensor followed a normal distribution, thereby determining whether subsequent statistical analyses could use parametric or non-parametric methods [16]. The measurements obtained from the sensor were compared with reference instruments, showing varying differences across each physiological variable.

Table 3: Comparison of Sensor and Reference Values

Variable	Sensor (Mean ± SD)	Reference (Mean ± SD)	Difference (Mean ± SD)
Body Temperature (°C)	36.12 ± 0.54	36.74 ± 0.23	-0.62 ± 0.49
BPM	83.85 ± 12.80	82.38 ± 15.69	1.46 ± 6.68
SpO_2 (%)	99.00 ± 1.02	98.31 ± 1.64	0.69 ± 1.81

The mean body temperature recorded by the sensor was 36.12 ± 0.54 °C, whereas the Thermogun reference measured 36.74 ± 0.23 °C. The resulting difference was −0.62 ± 0.49 °C, indicating that the sensor tended to provide slightly lower readings compared to the reference. Nevertheless, this difference remains within an acceptable deviation

range for non-invasive body temperature measurements.

The sensor recorded a mean heart rate of 83.85 ± 12.80 BPM, while the reference oximeter measured 82.38 ± 15.69 BPM, yielding a difference of 1.46 ± 6.68 BPM. This indicates that, despite the relatively high variability (large SD), the mean sensor measurements closely approximated the reference values. The higher variability is likely influenced by individual physiological factors as well as motion artifacts during measurement.

Regarding SpO_2 measurements, the sensor recorded a mean value of 99.00 ± 1.02%, whereas the reference oximeter measured 98.31 ± 1.64%, resulting in a difference of 0.69 ± 1.81%. These results indicate that the sensor demonstrates good accuracy in measuring oxygen saturation, with relatively small deviation. The low error observed for this parameter supports the use of the sensor for real-time oxygenation monitoring in healthy populations.

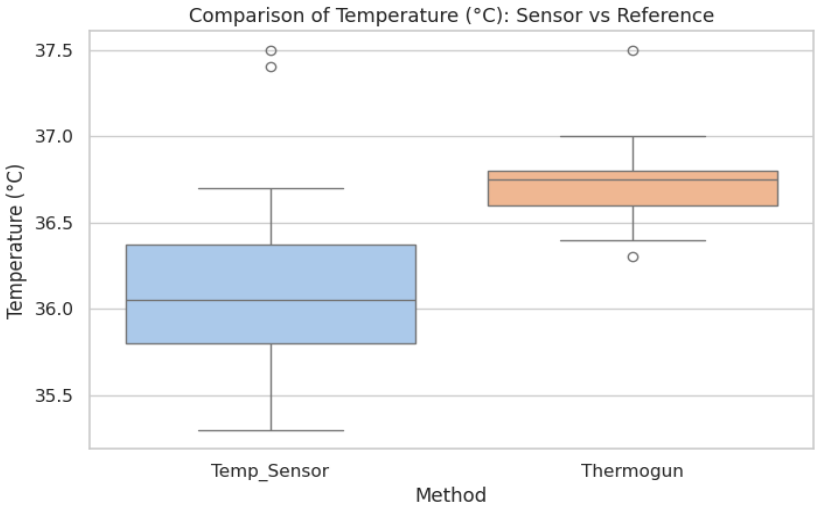

Figure 5: Differences in Body Temperature Measurements Using the MLX90614 Sensor and the Thermogun Infrared Thermometer DT-8826 Reference.

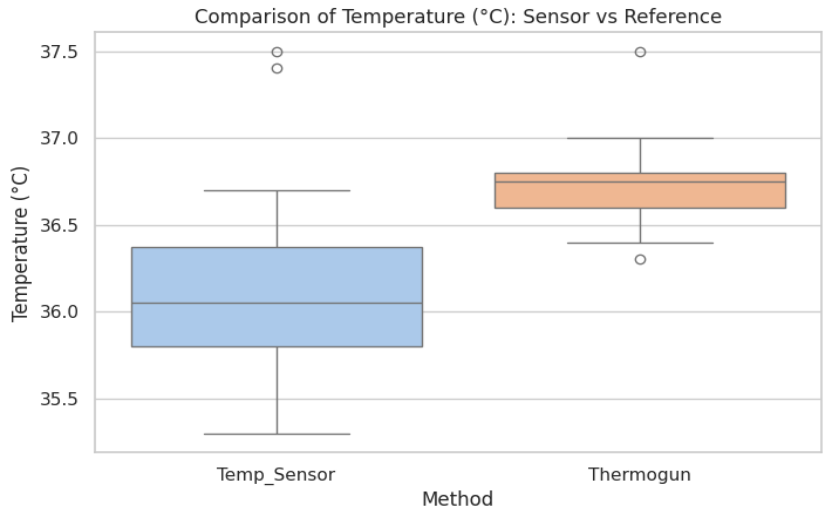

Figure 6: Differences in Heart Rate Measurements Using the MAX30102 Sensor and the FamilyDr Pulse Oximeter Reference.

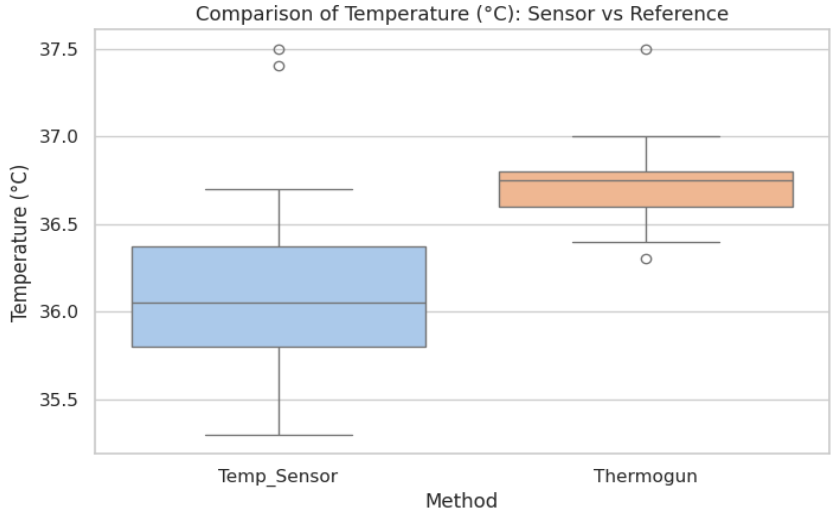

Figure 7: Differences in Oxygen Saturation (SpO_2) Measurements Using the MAX30102 Sensor and the FamilyDr Pulse Oximeter Reference.

This analysis indicates that, although small differences exist between the sensor and reference measurements, the sensor performance remains sufficiently reliable, particularly for body temperature and SpO_2 parameters. However, the higher variability observed in heart

rate measurements warrants attention to improve the precision of the sensor under certain conditions.

Table 4: Sensor Accuracy Evaluation
(MAE, RMSE, and Error Normality Test)

Variable	MAE	RMSE	Shapiro–Wilk
Body Temperature (°C)	0.681	0.786	W=0.980, p=0.873
Heart Rate (BPM)	5.308	6.708	W=0.930, p=0.078
SpO_2 (%)	1.231	1.901	W=0.881, p=0.006

Based on the evaluation results presented in Table 4, the sensor performance compared to the reference instruments demonstrated varying levels of accuracy across different variables. Body temperature measurements showed MAE = 0.681 and RMSE = 0.786, indicating a relatively low level of error. The Shapiro–Wilk normality test (W = 0.980, p = 0.873) confirmed that the error distribution was normal ($p > 0.05$), suggesting that temperature measurements are consistent with the assumption of normal distribution.

Heart rate (BPM) measurements showed MAE = 5.308 and RMSE = 6.708, indicating higher variability in error compared to body temperature. The Shapiro–Wilk test (W = 0.930, p = 0.078) indicated that the error distribution did not significantly deviate from normality ($p > 0.05$). Higher deviations do not compromise the statistical validity of the BPM data.

Heart rate measurements showed a mean difference of 1.46 ± 6.68 BPM. The relatively large variability can be attributed to several factors commonly found in optical pulse sensors, including motion artifacts, inconsistent finger pressure, and variations in finger placement during measurement. These factors may temporarily disrupt the photoplethysmography (PPG) signal and lead to fluctuations in beat-to-beat detection.

SpO_2 measurements showed MAE = 1.231 and RMSE = 1.901, reflecting relatively small errors. The Shapiro–Wilk test yielded W = 0.881, p = 0.006, indicating that the error distribution for SpO_2 does not follow a normal distribution. This suggests the presence of systematic variation in the sensor's oxygenation measurements compared to the reference, which should be considered in further analyses using non-parametric tests or additional calibration. Although the temperature sensor data were validated using a clinical-grade infrared thermometer, this study did not provide validation evidence for SpO_2 and BPM measurements against gold-standard medical devices such as arterial blood gas analysis or ECG-based heart rate monitors. This limitation should be addressed in future research to confirm the accuracy of the optical sensor components beyond descriptive comparison.

The sensor demonstrated satisfactory performance in measuring body temperature and SpO_2 with relatively small errors, while BPM exhibited higher deviations. Only the SpO_2 variable displayed a non-normal error distribution, potentially affecting the interpretation of inferential analyses. The findings of this study align with previous research evaluating the performance of wearable devices and portable sensors in vital sign monitoring. Soon et al. [1] reported that deviations in body temperature measurements between portable sensors and clinical reference instruments generally ranged from ±0.5 to 0.8 °C, which is comparable to the results of this study (−0.62 °C). Heart rate measurements in the study by El-Amrawy & Nounou (2015) indicated that wearable devices showed an average difference of 1–5 BPM compared to medical oximeters, consistent with the findings of this study (+1.47 BPM). Oxygen saturation measurements also demonstrated high sensor accuracy (98.98%), supporting the finding that non-invasive optical sensor-based devices exhibit deviations of less than 2% compared to standard oximeters [12].

3.4 Sensor Agreement Analysis Using the Bland–Altman Method

The Bland–Altman method is a statistical analysis used to assess agreement between two measurement instruments by calculating the bias (mean difference) and Limits of Agreement (LoA) as acceptable bounds of variation. Unlike correlation, which only indicates the directional relationship between variables, the Bland–Altman approach emphasizes the closeness of sensor measurements to the standard instrument, making it more relevant for evaluating whether two methods can be used interchangeably [13 - 16].

The Bland–Altman method was selected in this study because, although sensor accuracy can be assessed using MAE and RMSE, systematic bias often cannot be detected through correlation alone. Body temperature measurements showed a relatively small bias with narrow Limits of Agreement (LoA), indicating that the sensor is sufficiently aligned with the standard. Heart rate (BPM) measurements exhibited a larger bias and wider LoA, reflecting greater variability in the results. Oxygen saturation (SpO_2) measurements showed a small bias but slightly wider LoA, suggesting potential deviations under certain conditions. Narrower LoA indicate better agreement between the sensor and the reference. A summary of the analysis is presented in Table 5, with data visualization provided in the corresponding figures.

Combined analysis using MAE, RMSE, Shapiro–Wilk test, correlation, and Bland–Altman plots provides a comprehensive overview of sensor performance. High agreement results support the sensor's validity for health monitoring, whereas results with wider LoA are more suitable for general monitoring rather than clinical diagnosis.

Table 5: Summary of Bland–Altman Analysis

Variable	Bias (Mean Difference)	LoA (Lower–Upper	Interpretation
Body Temperature (°C)	-0.62	-1.59 - 0.35	Most data within LoA; differences small and acceptable
Heart Rate (BPM)	1.46	-11.54 – 14.46	Wider distribution; still within tolerable limits
SpO_2 (%)	0.69	-2.85-4.23	Nearly all data within LoA; accuracy considered adequate

Bland–Altman analysis presented in Table 5 indicated a bias of −0.62 °C for body temperature measurements, with Limits of Agreement (LoA) ranging from −1.59 to 0.35 °C. The sensor tends to slightly underestimate temperature compared to the reference instrument, while the difference remains within clinically acceptable limits. Heart rate measurements showed a bias of 1.46 BPM with LoA from −11.54 to 14.46 BPM, indicating higher variability and a wider error distribution, yet still relevant for non-invasive physiological monitoring.

Oxygen saturation (SpO_2) measurements exhibited a bias of 0.69% with LoA ranging from −2.85 to 4.23%, reflecting results closely aligned with the reference instrument and demonstrating good agreement. Figures 8, 9, and 10 provide visualizations of the Bland–Altman analysis results. The analysis confirms that the sensor achieves satisfactory agreement with the reference, particularly for body temperature and SpO_2 measurements, whereas heart rate measurements show greater variability.

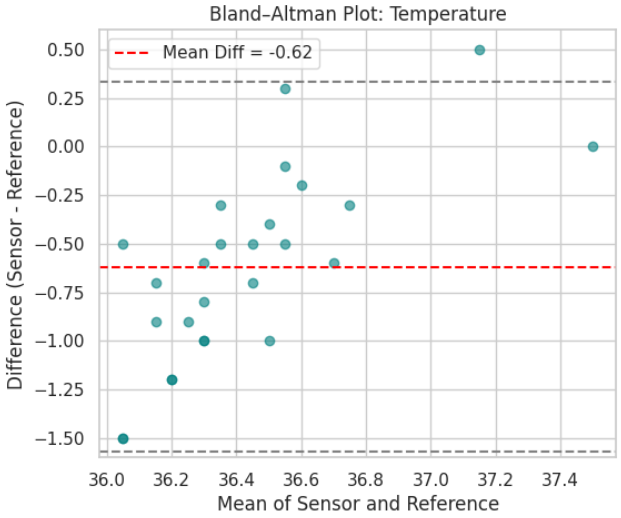

Figure 8: Bland–Altman Analysis Results for Body Temperature

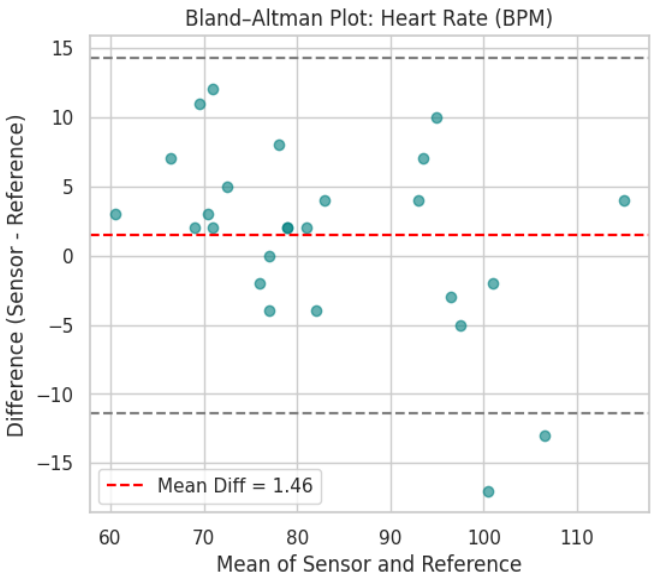

Figure 9: Bland–Altman Analysis Results for Heart Rate (BPM)

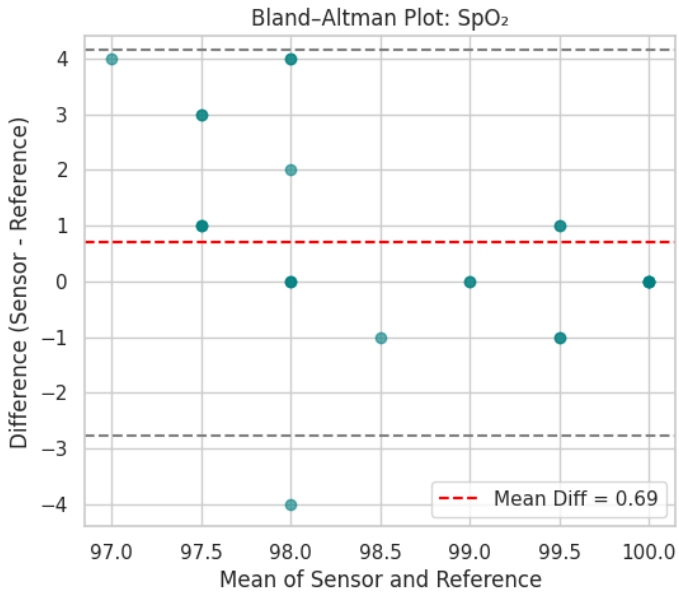

Figure 10: Bland–Altman Analysis Results for Oxygen Saturation (SpO_2)

4.0 CONCLUSION

This study demonstrates that the portable sensor device is capable of measuring body temperature, heart rate, and oxygen saturation with acceptable performance when compared to clinical reference instruments. The body temperature and SpO_2 parameters exhibited low error values, stable error distributions, and narrow bias and Limits of Agreement (LoA) in the Bland–Altman analysis, indicating that the device is suitable for daily health monitoring.

In contrast, heart rate measurements showed higher error variability with wider LoA. This condition reflects the influence of motion artifacts and individual physiological variability that affect the quality of the PPG signal. Therefore, the accuracy of heart rate estimation still requires improvement through optimized signal processing and more adaptive calibration methods.

Future studies are recommended to involve a larger sample size as well as more diverse age groups and clinical conditions. The development of advanced signal processing algorithms, noise-reduction techniques, and intelligent calibration approaches is expected to improve device precision particularly for heart rate estimation and strengthen its potential applicability in broader medical monitoring contexts.

CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare and are in agreement with the contents of the manuscript.

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