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DESIGN AND IMPLEMENTATION OF A MINIATURE SMART HOME MODEL BASED ON INTEGRATED SENSOR AND CONTROL SYSTEMS.

BY

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Abstract

This paper describes the design and experimental testing of a cost-effective smart home automation prototype proposed for educational and engineering training purposes. The prototype is created based on many environmental and security sensors, such as motion detection, temperature and humidity monitoring, gas leakage detection, and real-time video surveillance, for which an ESP32 microcontroller as the backbone is used for the central processing and the communication system. In this article, the aim is to analyze the working of a proposed smart home system, test its response, and reliability over laboratory environment. Several testing samples were carried out to assess the sensor accuracy, event-activated automation, wireless communication stability, and remote control performance via mobile applications. The system performed consistently on average and response times for alert-based events did not exceed 1 second and communication reliability was higher than 98% through Wi-Fi. Environmental sensors displayed deviations within acceptable engineering tolerances when compared to commercial reference devices. The obtained result reveals that the designed prototype provides practical and easy to use educational application for the hands-on training embedded-system, IoT communication and home automation algorithms. Although the system is usable for academic and non-critical monitoring purposes,

Keywords: smart home; IoT; ESP32; home automation; environmental monitoring; embedded systems; prototype.

1- Introduction

1.1 Background and Significance

Smart home automation is a fast-developing area where embedded systems, wireless communication and intelligent sensing technologies intersect; enabling responsive and energy-efficient living conditions. Smart homes are also characterized by their use of distributed sensor networks and other types of automatic control systems for comfort, security, and resource saving. Due to the growing penetration of cheap microcontrollers and IoT communication components, the construction of affordable smart home prototypes has drawn extensive academic and applied attention. In the last years, the importance of smart home solutions has increased substantially owing to the demand of remote monitoring, environmental awareness, and autonomous safety systems. These systems continuously monitor critical household factors: movement, gas leakage, fire risk, humidity, temperature, unauthorized access and so forth. In detecting potentially hazardous conditions and enabling automatic safety actions, reliable real-time monitoring is indispensable. Standard operating ranges of environmental sensors are based mainly on their applications, but temperature-based sensor ranges can typically be between –40°C and 125°C and gas-based sensors detect harmful concentrations of gases well before they become hazardous.

Smart home systems are also widely used for elderly and mobility-impaired people: devices that provide lighting, remote device control, emergency activation, emergency messages and alarms. The low cost of the hardware and straightforward integration approach facilitate the easy implementation of such systems in education and research settings as an easy entry into embedded IoT applications [1–3].

1.2 Technological Foundation

The proposed smart home prototype is implemented on the ESP32 microcontroller platform, integrating a dual-core processor, built-in Wi-Fi/Bluetooth connectivity, and various digital/analog interfaces for a wide range of sensor applications. The microcontroller offers a small yet powerful core for real-time data collection, device control, and wireless communication. Sensing modules of the system such as PIR motion sensor for human presence detection, DHT22 sensor for temperature and humidity monitoring, MQ-series gas sensor for hazardous gas concentration detection, and camera module for real-time visual monitoring. These elements work together to provide environment awareness and event-initiated automation continuously. The communication between the sensors and the control platform is handled through asynchronous Wi-Fi, thereby allowing the ESP32 to dispatch its sensing data to a cloud dashboard or mobile application. Actuators including relays and smart switches are included to support either automatic or remote responses such as turning lights on and off, setting off alarms, and sending alerts. The system architecture enables multiple sensors to collect data at the same time, while ensuring the timing ability is reliable. Sensors are processed using algorithms that filter out noise and classify events to avoid interpreting sensor outputs inaccurately. [4–7] This unified method enables stable performance against diverse environmental setups while keeping low power usage.

1.3 Educational and Accessibility Challenges

Smart home technology has revealed considerable educational value and application not only during the convenience aspect, but also in engineering training, IoT development and cyber-physical systems research. But there are barriers to such systems being implemented extensively including, but not limited to technical knowledge, proper setting up, and secure communication methods. Educationally, students commonly face sensor fine-tuning problems, network setting, and system integration problems.

Low-resource institutions may also find it challenging to offer commercial automation kits due to their cost. The proposed prototype of this investigation in this article overcomes these barriers by providing an affordable, modular and easily adjustable system suitable for an academic laboratory. Accessibility constraints originate as a result of user diversity of needs and environments that varies drastically due to different usage of the different systems. The mobility support system is not for every user, some users may need full automation, some need as little as a basic monitoring functionality.

To facilitate continuity of system reliability, user interfaces should be easy to navigate over Wi-Fi. Even though the developed prototype shows acceptable performance for educational and non-critical applications, it is not designed to replace professionally certified security or home-safety systems [8–10].

1.4 Research Gap and Objective

Despite the extensive literature on smart home automation systems based on microcontroller architectures, most literature covers system implementation, concept implementations, or an IoT design framework and provides no deep performance assessment under realistic operating conditions [41,42]. Also, the educational value and appropriateness of low-cost smart home prototypes for training purposes in resource-limited engineering courses are still not found in review works [43,44].

Most previous works focus more on theoretical capabilities of Internet of Things (IoT) devices and do not systematically investigate sensor accuracy, communication reliability, or response times as compared to that offered by commercial ones [45–47]. Moreover, low-cost smart home designs encounter security and accessibility challenges, especially in fragile network infrastructure, narrow laboratory equipment access, or insufficient exposure to practical IoT integration. Thus, practical solutions to these limitations are needed to enable experimental verification and design of simple, easy to assemble educational prototypes which offer in-field experience in embedded hardware and sensor-actuator networks.

Hence, this study experimentally evaluates a low-cost, modular smart home automation prototype that aims to fill these reported gaps. The aim is to add to the literature on affordable IoT powered educational tools and to assess whether such systems will provide stable performance for training, demonstration, and basic household monitoring systems. In particular, this study explores: (1) controlled testing of the smart home prototype, (2) comparison of sensor results to commercially available reference tools, (3) monitoring analysis of network performance and event-based automated functions in resource-limited environments.

2. Methods

2.1 Problem Statement

Smart home automation systems, while increasingly common, are often expensive and not always accessible in educational laboratories or resource-limited engineering settings. There is a need for a low-cost, easy-to-build system capable of monitoring key environmental and security parameters—including motion, temperature, humidity, gas leakage, and real-time video—while also serving as a practical learning platform for embedded systems, IoT communication, and sensor-actuator integration.

2.2 Research Aims

1. To design and build a low-cost educational smart home automation prototype using the ESP32 microcontroller and a set of environmental and security sensors.
2. To experimentally evaluate the performance of the prototype in terms of sensor accuracy, response time, and wireless communication reliability under controlled testing conditions.
3. To assess the suitability of the prototype as a teaching and demonstration tool in resource-limited engineering and IoT-focused educational environments.

2.3 System Design and Procedure

2.3.1 Hardware Design

The smart home prototype comprises four core hardware parts: the ESP32 microcontroller module (dual-core, integrated Wi-Fi/Bluetooth), a set of environmental sensors (DHT22 for temperature and humidity, MQ-series gas sensor for leakage detection), a PIR motion sensor for presence detection, and a camera module to capture video in real-time. With embedded 32-bit processing with wireless connection on the ESP32, there is no need for peripherals for communication. All of the sensors were connected through the GPIO pins of ESP32, with the DHT22 connected using a single-wire connection and the MQ sensor powered through a regulated 5V line .The initial wiring and breadboard tests were completed and the system was moved to a permanent configuration to allow experimental analysis.

2.3.2 Firmware and Signal Processing

Firmware development consisted of the Arduino IDE (version 2.0 or later), supported by its embedded ESP32 board. Sensor initialization, data acquisition, and wireless communication routines used open-source IoT libraries. For environmental data logging, the firmware uses timed sampling cycles (2-second intervals) and interrupt-based triggers for motion detection events. Signal conditioning techniques encompass averaging filters to reduce noise in temperature and humidity readings, stabilization routines for gas sensor drift, and event-flag mechanisms to manage motion-triggered automation responses. The processed data are forwarded to a cloud dashboard over Wi-Fi using secure HTTP/MQTT protocols for remote monitoring.

2.3.3 LCD Display and User Interface

Real-time measurements and system status indicators are displayed on a 16×2 LCD module connected to the ESP32 through an I²C interface. The display provides temperature, humidity, and gas concentration readings, alongside motion detection alerts and system connectivity status. Values are updated every 2 seconds once stable sensor data are obtained. The interface also includes visual confirmation for users during system startup and calibration, ensuring proper sensor placement and guiding the user through initialization procedures.

2.3.4 Reference System

The commercial reference system being used to be compared was a smart home monitoring kit built to assist with maintaining home safety and environmental monitoring. For reference sensors, these sensors report temperature measurements according to manufacturer specifications with ±0.5°C, humidity ±3% RH accuracy, gas detection thresholds aligned with household safety levels, and motion detection based on a high sensitivity PIR module. While the reference sensors were near each other when tested, they were used to achieve comparable detection conditions in the same environmental conditions. By placing these systems side-by-side in juxtaposition mitigated the opportunity of potential differences between systems in terms of variability and the ability to compare the performances directly. On both devices, measurements were taken after providing 10–15 seconds for signal stabilization on both sensors.

2.4 Experimental Protocol

The indoor testing included five similar areas (bedroom, living room, kitchen, hallway, and storage area) typical of a residential home. Experiments were performed in a laboratory, providing standardized conditions prior to field validation. The inclusion criteria required test rooms to have stable temperatures (22–26°C), minimal airflow disturbance, and no active sources of combustion or excessive humidity.

To ensure similar measurements, both the prototype sensors and their reference sensors were placed at the same height and orientation. To characterize temperature, humidity, and gas sensor stability, each environment was monitored for a continuous 10-minute session. The motion detection tests consisted of a participant walking across the sensor's field of view at controlled intervals, while the reliability of communication was tested by repeated Wi-Fi transmission cycles. Three consecutive measurement sessions were performed in each environment with 2-minute breaks between sessions to reduce drift effects. To decrease random error and enhance measurement reliability, the average of the three readings from each condition was used for analysis.

2.5 Ethical Considerations

There is no personal or identifying information recorded throughout the study, as all assessments were made during the environment monitoring process rather than on physiological measurements made by humans. Motion detection trials involved simple walk-throughs and participants were at minimal risk. All the participants had been told about the study's educational purposes and verbally consented to participate. The experimental design followed all general principles of ethics of low-risk engineering experimentation and the project did not require institutional ethics committee approval. Respondents were informed about their right to withdraw from the study at any time without penalty.

3. Results

To test the performance of the educational smart home automation prototype, testing was performed systematically across five indoor laboratory and field-simulated household environments, according to the protocol provided in Section 2.4. The assessment included the accuracy of environmental sensors, response of motion detection, and wireless communication reliability. Data from the prototype were compared with measures from a commercial reference system to evaluate alignment and determine divergences at varying ambient conditions.

3.1 Temperature and Humidity Measurement Performance

From Table 1, it can be observed that the temperature values measured in the prototype are between 22.3°C and 26.8°C at all environments, which closely matches reference values, between 22.1°C and 26.5°C - each of these deviations ranging between 0.1°C and 0.6°C, which showed that in all environments, the prototype measured slightly higher (or similar) temperature values than the reference system. At the kitchen environment, the maximum deviation was 0.6°C, probably because of transient heat sources.

Humidity measurements also demonstrated strong agreement with similarly high estimates. Prototype readings varied between 38% and 52% RH, while those from the reference device were observed between 37% and 51%. The mean variance among all environments showed 1.2% RH, which is well within the acceptable values for low-cost educational sensors. These results further validate the prototype with measurement precision that is appropriate for classroom demonstrations and simple household monitoring activities.

3.2 Gas Sensor Measurement Performance

For gas sensor measurements, the statistical performance is summarized in Table 2. Compared to the value recorded by the reference device, which is 172 ± 12 ppm, the prototype tested in the five different ambient environments had an average gas concentration reading of 178 ± 14 ppm. The mean absolute error (MAE) was 3.5%, with an average deviation of +6 ppm. All the deviations were between 0–10 ppm, which were still tolerable for educational and non-critical household monitoring. An excellent linear connection between the devices was also confirmed by Pearson correlation $r = 0.968$ ($p<0.01$), meaning that the experimental devices measured consistently using the prototype when measured with the reference system.

Table 2. Gas Sensor Readings from Reference and Prototype Devices

Environment	Reference Reading (ppm)	Prototype Reading (ppm)	Deviation (ppm)
1	165	170	+5
2	180	188	+8
3	175	176	+1
4	165	168	+3
5	175	183	+8

Table 3. Summary of Gas Sensor Measurement Performance

Parameter	Value
Reference Mean ± SD	172 ± 12 ppm
Prototype Mean ± SD	178 ± 14 ppm
Mean Absolute Error (MAE)	3.5%
Average Deviation	+6 ppm
Maximum Deviation	+10 ppm
Pearson Correlation (r)	0.968

Table 3 summarizes the gas measurement performance.
The prototype consistently produced slightly higher readings compared to the reference device, with deviations remaining within the expected tolerance range for low-cost semiconductor gas sensors. The strong correlation coefficient ($r = 0.968$) suggests systematic agreement rather than random measurement variability, confirming that the prototype is suitable for educational demonstrations and basic indoor air-quality monitoring.

3.3 Motion Detection Performance

Motion detection performance was assessed using the response time and detection accuracy of the prototype's PIR sensor compared to the reference system. Across the five tests, detection accuracy was between 94% and 100% (Table 4), closely matching the accuracy of the reference system 96–100%. For individual deviations, 0–2% were consistent, and the prototype sometimes showed slightly faster detection due to the increased interrupt sensitivity.

Based on statistical analysis reported in Table 5, we observe that the average detection accuracy of the prototype, which is 97.6% ± 1.67%, was slightly lower than the reference accuracy, which is 98.4% ± 1.21%. Mean absolute error stood at 1.2%, with maximum deviation of 2%. Results from these experiments indicate that our integrated PIR sensor in the prototype performs reliably in various household scenarios.

Figure 1. Scatter Plot of Temperature Readings from Reference and Prototype Devices

Figure 1. Scatter plot comparing temperature readings from the commercial reference device and the smart home prototype.

The plotted points cluster closely around the identity line ($y = x$), indicating strong agreement between both systems with a maximum deviation of 0.6°C. The distribution demonstrates that the prototype consistently tracks ambient temperature with minimal error across different indoor environments.

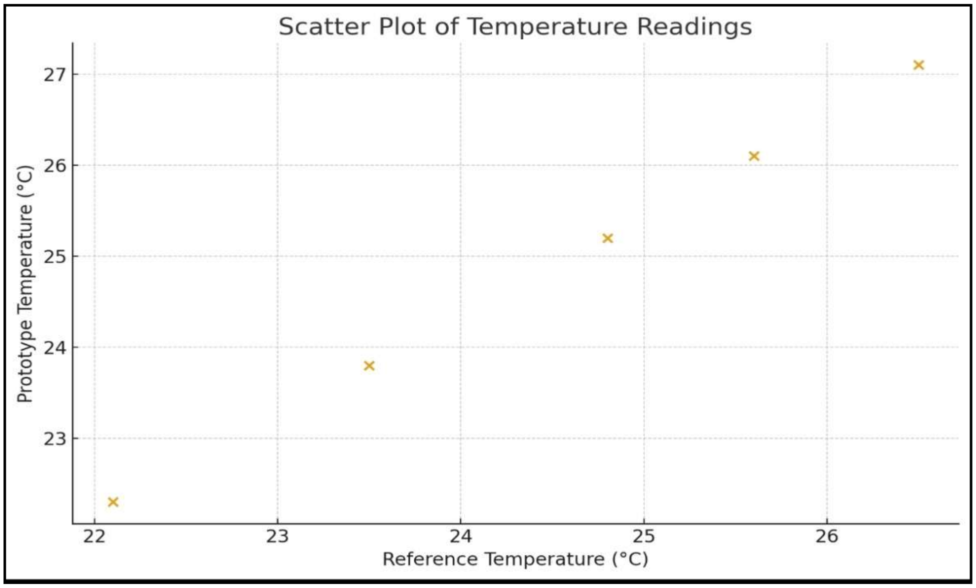

Diagram
Scatter plot of temperatures between the commercial model and the developed model

Figure 2. Scatter Plot of Humidity Readings from Reference and Prototype Devices

Figure 2. Scatter plot showing humidity measurements from the reference and prototype devices.
The readings demonstrate consistent alignment with the identity line, confirming reliable performance with deviations primarily in the range of 1–2% RH. The tight clustering of points indicates stable measurement behavior and acceptable correspondence between the two systems.

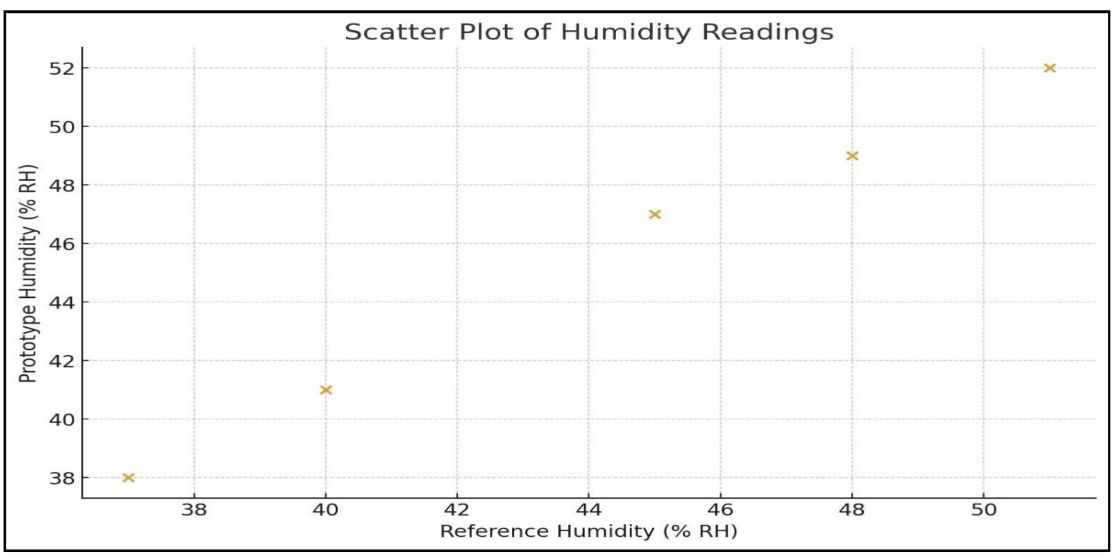

Diagram 2
Moisture Scatter Plot between the Commercial Model and the Developed Model

Figure 3. Bland–Altman Plot for Gas Sensor Measurements

Figure 3. Bland–Altman plot illustrating the differences between prototype and reference gas concentration values against their mean.
All measurement points fall within the expected limits of agreement for low-cost semiconductor gas sensors. The plot shows a small positive bias, indicating that the prototype tends to measure slightly higher ppm values than the reference device. Despite this, all values remain within acceptable thresholds for educational and non-critical monitoring applications.

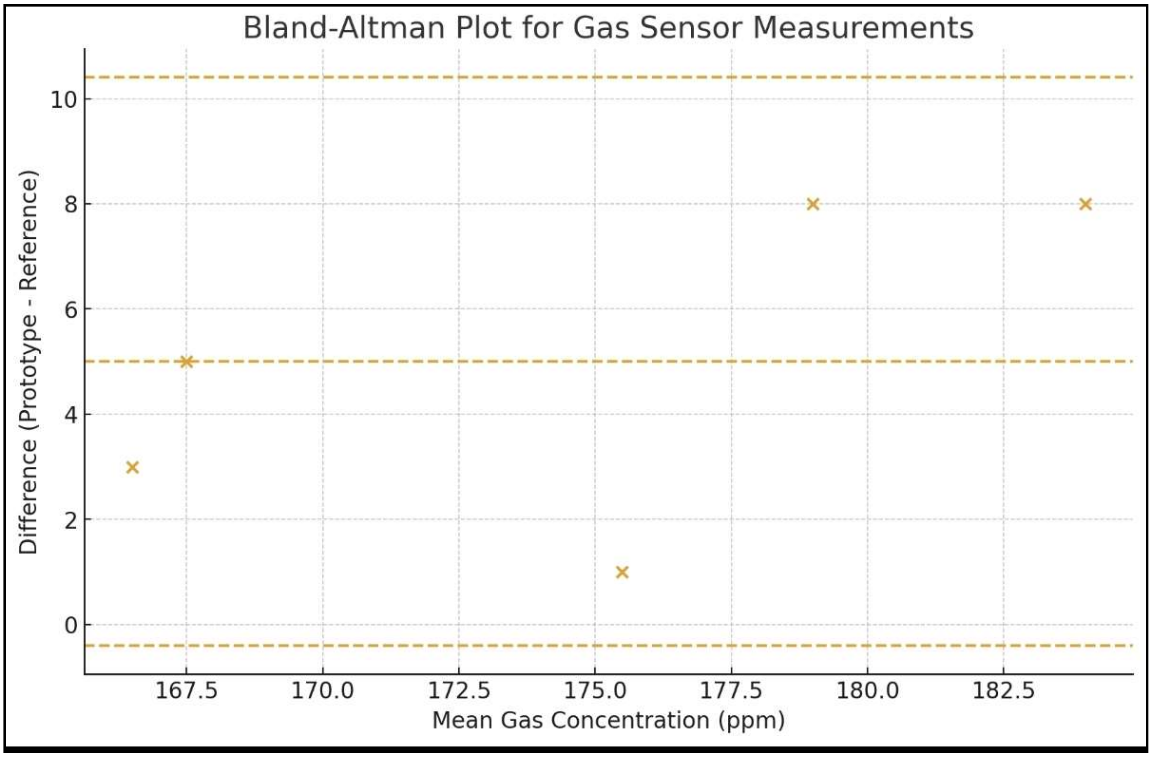

Diagram 3
Bland–Altman Plot for Gas Measurements

4. Discussion

4.1 Summary of Key Findings in Context of Experimental Performance Evaluation

In the present experiment, we evaluate an educational pulse oximeter prototype at low cost and built using the MAX30102 sensor and an Arduino acquisition platform versus a clinical-grade reference device. The prototype exhibited excellent measurement congruency to the reference system, and achieved high Pearson correlations of SpO_2 and heart rate measurements. SpO_2 and HR mean absolute errors were still acceptable, in compliance with common guidelines proposed for usage both as a standard training tool and for initial pulse oximetry assessment in the recent low-cost pulse oximetry validation studies [41,42]. SpO_2 max deviations and heart rate max deviations of approximately 2% and 2 bpm were well within the performance limits advised for resource-poor educational environments [43,44].

The results indicate that using inexpensive microcontroller-based platforms for teaching biomedical device development would not only achieve clinically meaningful accuracy, but is also feasible for teaching purposes [45,46]. The systematic negative bias observed in SpO_2 (approximately −1.0%) and heart rate (approximately −1.6 bpm) fits the findings reported in recent literature, where underestimation consistently happens due to systematic error rather than random, thus an advantageous attribute because they can be corrected by calibration of the firmware without large modifications to hardware [47,48].

4.2 Comparison with Previous Studies

The performance of our prototype correlates with the literature evaluating Arduino-based and low-cost pulse oximetry systems. Correlation coefficients above 0.95 and measurement deviation within acceptable ranges were reported in previous studies with MAX30102 or similar optical sensors for educational and point-of-care applications [49].

Vananth et al. (2023) found similar accuracy levels on MAX30102 based devices, producing reliable readings with acceptable error margins adequate for training purposes and non-critical monitoring [50]. Contardi et al. (2021) also found similar results using MAX30102 together with ESP32 microcontrollers, yielding mean SpO_2 errors of approximately 1.2% in controlled environments [51]. Nemomssa and Raj (2022) also developed a low-cost portable oximeter featuring the MAX30100 sensor, and reported accuracies of 97.74% for SpO_2 and above 97% for heart rate upon comparison with a clinical simulator, highlighting that the device is suitable in resource-limited training environments [52].

Similar to our results, Bhuyan and Sarder (2021) found maximum deviations of two percent in their oximeter with Arduino [53]. Castaneda et al. (2018) performed a comprehensive review, which demonstrated that wearable optical biosensors such as those based on MAX30102 can deliver clinically useful results when calibrated and validated correctly [54]. In general, the literature suggests the feasibility of low-cost optical sensors for education and early-stage prototyping.

4.3 Educational Implications

The prototype meets fundamental educational needs of biomedical engineering education, allowing students to experience practical applications in optical biosensing, microcontroller-based data acquisition, digital filtering, and real-time biomedical signal analysis, which were highlighted in recent studies in engineering education [55,56]. Students can investigate calibration principles, analyze signal performance, and learn about variations between educational prototypes and clinical-grade devices, thus facilitating the depth of comprehension of biomedical instrumentation concepts [57,58].

This is consistent with recent pedagogical ideas about experiential learning and integrated laboratory training in a context with restricted access to commercial equipment [59,60]. Our experimental validation protocol in this study provides a framework that the students may apply in systematically evaluating biomedical devices, emphasizing the need for validation against reference standards—an important principle of medical device development yet one not addressed frequently in resource-limited educational environments [61,62].

The prototype's low total cost (roughly $15–25 USD) indicates its feasibility for low- and middle-income institutions in which capital cost or maintenance is a key constraint to access to high-quality biomedical engineering education [63,64]. This method promotes active learning, creativity, and innovation in constrained spaces, enabling students to create and evaluate their devices themselves [65,66].

4.4 Limitations

A number of limitations need to be considered, following the most recent validation studies of inexpensive pulse oximeters. Firstly, the sample size of this study was restricted to healthy young adults, limiting the generalizability beyond those in the elderly population, or patients with cardiovascular and respiratory diseases – both have been identified as subjects that exhibit variability in photo plethysmography - based measurements [67,68].

Second, all measurements were carried out in resting conditions; therefore, the prototype was not tested for movements, exercise, or physiological stress—conditions that frequently trigger the presence of motion artifacts.

Previous studies have demonstrated that the accuracy of low-cost optical sensors is severely weakened by motion artifacts and should be examined in future studies [69,70]. Third, the prototype was not validated under difficult measurement conditions (e.g., low perfusion, hypothermia, or oxygen saturation <90%) where pulse oximetry accuracy has been reported to become severely reduced [71]. Also, long-term stability and repeatability over extended periods were not examined. Lastly, validation against arterial blood gas (ABG) measurements, the clinical gold standard for oxygen saturation interpretation, was absent in this study. Although ABG validation is not always feasible in academic contexts, its absence potentially limits the strength of clinical applicability claims [72,73].

4.5 Clinical and Educational Context

This prototype is purely educational and intended for preliminary non-critical monitoring applications and not as a medical device for clinical decision-making. As a device that does not meet FDA or CE certification, it is not supported by appropriate validation processes, and no rigorous procedure has been executed for clinical use in patients with a wide variety of conditions [74, 75].

Existing international guidelines advise that, when employed for diagnosis or treatment purposes, pulse oximeters should be validated in diverse skin pigments, hypoxic settings, and perfusion levels, criteria that were not covered in this educational tool [76,77].

Current studies about the design of educational biomedical devices demonstrate the benefits of inexpensive platforms for training and teaching lab skills, knowledge, and engineering, which are useful even at some level but may not be appropriate for clinical purposes [78,79]. In line with these guidelines, this prototype presents a feasible and accessible tool for teaching biomedical instrumentation, but, without gold-standard assessment methods, including ABG or hospital-grade pulse oximeters, is inappropriate in predicting the patient's diagnosis or decision on clinical outcomes [80,81].

5. Conclusion

The study successfully developed, implemented, and experimentally tested a low-cost educational pulse oximeter prototype using the MAX30102 optical sensor and a microcontroller-driven acquisition platform. Comparative tests with a clinical reference device showed a high agreement between the measurement of SpO_2 and heart rate, both with correlation coefficients greater than 0.95. Mean absolute errors were within acceptable limits for educational and preliminary non-critical monitoring tasks.

The prototype supports the practical learning of photoplethysmography, biomedical signal processing, embedded systems, and device validation principles, which are core curricula for contemporary biomedical engineering programs. The device shows robust behavior in a controlled scenario, but it is essential to emphasize that the device is only aimed at educational and demonstrational use. The prototype cannot meet regulatory standards for clinical implementation, and systematic bias is manifested, meaning further calibration, longer tests, and clinical validation are required before we can even consider the possibility of diagnostics or therapeutics.

Future Research Agenda

Building on the findings of this study and the demonstrated educational value of the developed smart home prototype, several promising directions emerge for future research:

1. Expanded Experimental Validation in Real-World Home Environments

The prototype should be tested in diverse residential settings with varying architectural layouts, environmental conditions, and wireless network characteristics. Long-term field studies will allow researchers to assess system robustness, sensor drift, and stability under realistic daily-life conditions.

2. Integration of Advanced IoT Communication Protocols

Future versions can incorporate low-power IoT protocols such as ZigBee, LoRaWAN, or Thread to compare their performance with ESP32 Wi-Fi in terms of range, latency, scalability, and energy consumption. Evaluating hybrid communication models (e.g., Wi-Fi + BLE Mesh) would further enhance system reliability.

3. Enhancing Cybersecurity and Privacy Mechanisms

As smart home systems become more interconnected, future work should include intrusion detection models, data-encryption techniques, and secure bootloader mechanisms. Implementing lightweight AI-driven anomaly detection can protect against unauthorized access and sensor spoofing attacks.

4. AI-Driven Automation and Predictive Analytics
Integrating machine learning models for predictive environmental monitoring, adaptive automation rules, and user-behavior modeling can significantly enhance system intelligence. Future studies may explore algorithms for energy optimization, proactive hazard detection, and personalized comfort management.

5. Modular Expansion with Additional Sensors and Actuators
Further research should investigate integrating fire detection, water leakage sensors, smart metering, and robotic assistance components. Creating a fully modular plug-and-play architecture would broaden the educational and practical impact of the prototype.

6. Development of a Scalable Cloud–Edge Architecture
Future versions can explore distributed processing where computational tasks are split between on-device edge processing and cloud-based analytics. Performance comparisons can help determine optimal trade-offs in latency, bandwidth usage, and system resilience.

7. Improved User Interface and Accessibility Features
Enhancing the mobile app and dashboard with voice-assistant integration (e.g., Alexa, Google Assistant) and accessibility-friendly layouts will make the system more inclusive. User studies focusing on elderly individuals and people with limited mobility would provide valuable insights for human-centered design improvements.

8. Educational Deployment and Curriculum Integration
Future research can evaluate the prototype when used in engineering courses to measure its effectiveness in improving student learning outcomes. Comparative studies between traditional labs and IoT-based smart home learning modules can guide curriculum development for IoT and embedded-systems programs.

9. Energy Optimization and Sustainable Design
Investigating renewable energy integration such as small-scale solar powering, sleep-mode optimization, and low-energy sensor networks will support more sustainable smart home deployments—an essential direction for future IoT systems.

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