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IoT-Based Health Monitoring System for Obese Children

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Abstract

Childhood obesity continues to be a serious global health issue with far-reaching effects on people's lives and societies. The research novelty is the development, deployment, and evaluation of OBISENSE, a low cost Internet of Things (IoT) alternative to expensive body analyzers, which is an innovative solution created to address the challenges associated with handling children obesity. OBISENSE is an IoT-based health monitoring system. It combines health science and IoT technology to deliver precise and immediate measures of height, weight, and heart rate parameters, which the OBISENSE system uses to calculate Body Mass Index (BMI) and assess obesity status in real time, making it an essential tool for evaluating and controlling childhood obesity. The OBISENSE system provides a simple-to-use mobile application that encourages users to take an active role in their journey towards better health. Individuals may easily track their health measurements with the app, access previous data, and get personalized guidance for leading a healthy lifestyle. The system's design prioritizes usability, accessibility, and compatibility with current technological platforms to ensure a better user experience. The OBISENSE system was put through extensive testing to confirm its functionality. This project assesses the system's accuracy and dependability through a variety of scenarios, including height, weight, and heart rate measurements, along with subsequent BMI estimations. The findings show that the OBISENSE system reliably delivers accurate and trustworthy health data, enabling efficient monitoring of pediatric obesity. The OBISENSE system is aware of its limitations, including changes in sensor accuracy and potential ambient influences on measurements.

1. Introduction

Childhood obesity has emerged as a critical global health concern, exerting substantial and far-reaching impacts on both individuals and societies. According to the World Health Organization (WHO), those aged between 5 to 19 years old have increased from 32 million in 1990 to more than 160 million in 2022. WHO stated that in 2023 alone, 1–5 children were overweight or obese. There remains a lack of comprehensive research in this area. This research aims to address the critical gap through the following objectives: to design and develop OBISENSE, an IoT-based health monitoring system; to calculate Body Mass Index (BMI); to implement a mobile application; and to test and validate the OBISENSE system in managing childhood obesity. OBISENSE plays a significant role in improving childhood obesity monitoring. OBISENSE records and processes automatically in real time using IoT sensors, stores and analyzes health data, provides BMI calculations and obesity classification, includes a mobile application, and supports health management. The OBISENSE system combines advancements in health science and IoT technology to offer accurate and immediate measurements of vital health metrics, including height, weight, and heart rate.

By leveraging these parameters, the OBISENSE system calculates the Body Mass Index (BMI) and assesses obesity status, thereby establishing a crucial tool for the comprehensive evaluation and management of childhood obesity. In response to the escalating need for effective and user-friendly health management tools, the OBISENSE system features a user-centric mobile application that empowers individuals to proactively engage in their pursuit of improved well-being. This application facilitates the seamless tracking of health measurements, provides access to historical data, and delivers personalized recommendations to promote healthy lifestyle choices. With a strong emphasis on user experience, the OBISENSE system has been meticulously designed for enhanced usability, accessibility, and compatibility across a spectrum of contemporary technological platforms.

Extensive testing and validation processes were employed to rigorously assess the performance of the OBISENSE system. The researchers meticulously evaluated the accuracy and reliability of the system through diverse experimental scenarios that included height, weight, and heart rate measurements, followed by BMI computations. The results of these evaluations affirm that the OBISENSE system consistently delivers precise and trustworthy health data, thereby enabling efficient monitoring and management of pediatric obesity. However, it is important to acknowledge the inherent limitations of the OBISENSE system, which include potential fluctuations in sensor accuracy and susceptibility to ambient influences that could impact measurement outcomes. Considering these limitations, ongoing efforts are essential to refine and optimize the system's performance, ensuring its continued effectiveness in the dynamic landscape of childhood obesity management.

Childhood obesity has escalated into a pervasive and alarming global health concern, exerting profound and far-reaching consequences on both individual health and societal well-being. Despite substantial efforts and interventions aimed at mitigating this issue, the prevalence of childhood obesity continues to rise unabated. A notable gap in current healthcare solutions is the absence of a comprehensive, accurate, and user-friendly health monitoring system tailored to address the unique challenges of pediatric obesity management. Existing methods for assessing and managing childhood obesity often lack precision, immediate feedback, and integration of vital health metrics, hindering effective preventive and therapeutic measures. Thus, the research novelty centers on the urgent need for a low cost IoT alternative to expensive body analyzers towards an innovative health monitoring system that offers real-time and accurate measurements of height, weight, heart rate, and subsequent BMI calculation, accompanied by obesity status assessment and guidance. Addressing this research problem is pivotal in facilitating timely and informed decision-making for healthcare practitioners, caregivers, and individuals, fostering a proactive approach to managing childhood obesity and promoting healthier lifestyles.

2. Literature Review

Machorro-Cano et al. [1] proposed PISIoT, a machine learning and IoT-based smart health platform for overweight and obesity control. Their system encompasses data acquisition, processing, and analysis modules, employing K-means clustering and decision trees to predict obesity risk in children with high accuracy. Real-time monitoring and alerts enhance user engagement, yet the platform's reliance on complex algorithms and expensive hardware poses potential limitations. Alsareii et al. [2] devised an IoT framework for obesity extrapolation, spanning data collection, preprocessing, feature extraction, model training, and decision-making layers. Their utilization of logistic regression and random forest algorithms to predict obesity risk based on demographic and lifestyle factors demonstrates the potential for widespread obesity prevention. Nonetheless, data requirements and applicability to rare conditions may limit its versatility. Lam et al. [3] conducted a systematic review of IoT-enabled technologies for childhood obesity intervention. Despite positive outcomes in improving physical activity and diet quality, limitations in sample sizes and long-term follow-up challenge the efficacy of these interventions, emphasizing the importance of inclusive user-centric designs. Mae et al. [4] proposed an IoT-based system for tracking body weight, allowing remote monitoring through a mobile app. The system's affordability and ease of use cater to developing countries, yet its focus on body weight alone and potential inaccuracies for diverse body types warrant further consideration. Abdulmalek et al. [5] reviewed IoT-based healthcare monitoring systems, highlighting potential benefits in enhancing patient quality of life. While comprehensive, the study's lack of focus on obesity-specific issues and potential device suitability limitations may impact its broad applicability.

Bhuvaneswari et al. [6] introduced a remote health monitoring system with machine learning prioritization, leveraging IoT devices to assess various health parameters. The system's early detection capabilities demonstrate promise, yet technical complexity and accessibility barriers necessitate careful implementation. Bhansali and Hiran [7] explored IoT-enabled heart rate monitoring, contributing insights into machine learning-driven health prioritization. Privacy concerns and device suitability underscore the need for tailored approaches, while the study's methodology informs the development of comprehensive health monitoring systems. Mark et al. [8] proposed an IoT-based BMI prediction model utilizing machine learning, enabling accurate BMI estimates for early obesity detection. System accuracy, external factors, and potential cost considerations influence its potential for obesity monitoring. Contardi et al. [9] presented an IoT-enabled system for monitoring oxygen saturation and heart rate. While offering valuable continuous monitoring capabilities, potential external factors and privacy concerns necessitate careful implementation. Celine et al. [10] developed an IoT-based health monitoring system, allowing remote monitoring and analysis.

System accuracy, data reliability, and suitability for varying medical conditions warrant further exploration. Timur et al. [11] introduced an IoT-based smart health monitoring system, emphasizing real-time remote monitoring. While promising, device accuracy and privacy considerations require thorough evaluation. Erinle et al. [12] addressed the accuracy of conventional height and weight measurement methods through a parametric design approach. Despite potential limitations in accessibility and cost, the study highlights enhanced precision in measurement techniques. Faradisa et al. [13] proposed an IoT-based BMI and body fat percentage calculation using fuzzy logic, offering promising accuracy. Device construction costs and broader applicability require further examination. Hasan et al. [14] devised a wireless health monitoring system for chronic conditions, demonstrating cost-effective patient management. While providing a solution for rural areas, specific chronic conditions and technology accessibility considerations warrant additional investigation. Alam et al. [15] introduced an intelligent height measurement system using Bluetooth and image processing, offering accurate and accessible alternatives. Application across diverse environments and lighting conditions remains a potential challenge.

3. Materials and Method

The architecture of the OBISENSE health monitoring system is as shown in Fig. 1. All personal data was anonymized prior to analysis, ensuring that participants could not be identified based on the information collected. The system comprises three main components: the OBISENSE App, the Firebase Database, and the ESP8266MOD Board. The OBISENSE App serves as the user interface for the system, allowing users to interact with the health monitoring features. The user interface component enables users to access health metrics, view historical data, set personal health goals, and receive health tips and recommendations. The App communicates with the Firebase Database to store and retrieve health metrics data.

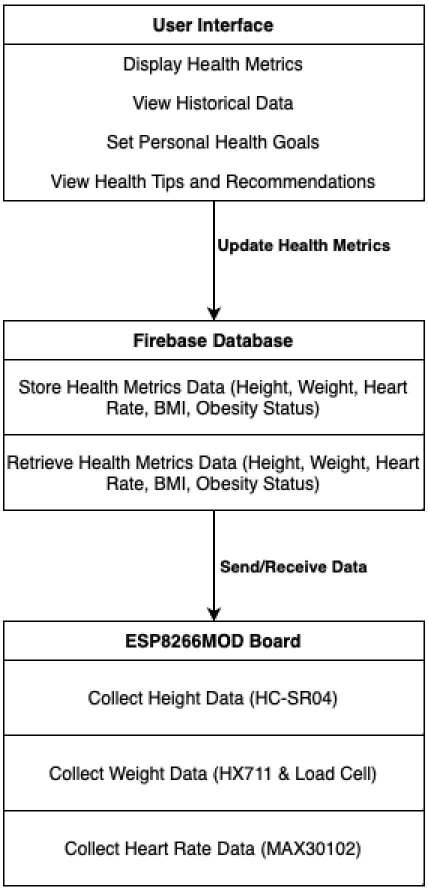


Fig. 1 *Architecture of the OBISENSE health monitoring system showing sensor integration and communication protocols*

The Firebase Database was responsible for securely storing the collected health metrics data. It consists of two primary functionalities: storing health metrics data (e.g., height, weight, heart rate, BMI, and obesity status) and retrieving stored data for display and analysis within the OBISENSE App. The ESP8266MOD Board plays a vital role in collecting health metrics data through various sensors, which are low cost and suitable for IoT health systems. It interfaces with the ultrasonic sensor HC-SR04 to measure height, which is child friendly, the load cell, HX711 amplifier, which has high precision and stability to measure weight, and the MAX30102 sensor to monitor heart rate. Power supply for ESP8266 and sensors prevent data noise and sensor malfunction. The collected data was then transmitted to the Firebase Database for storage and further processing.

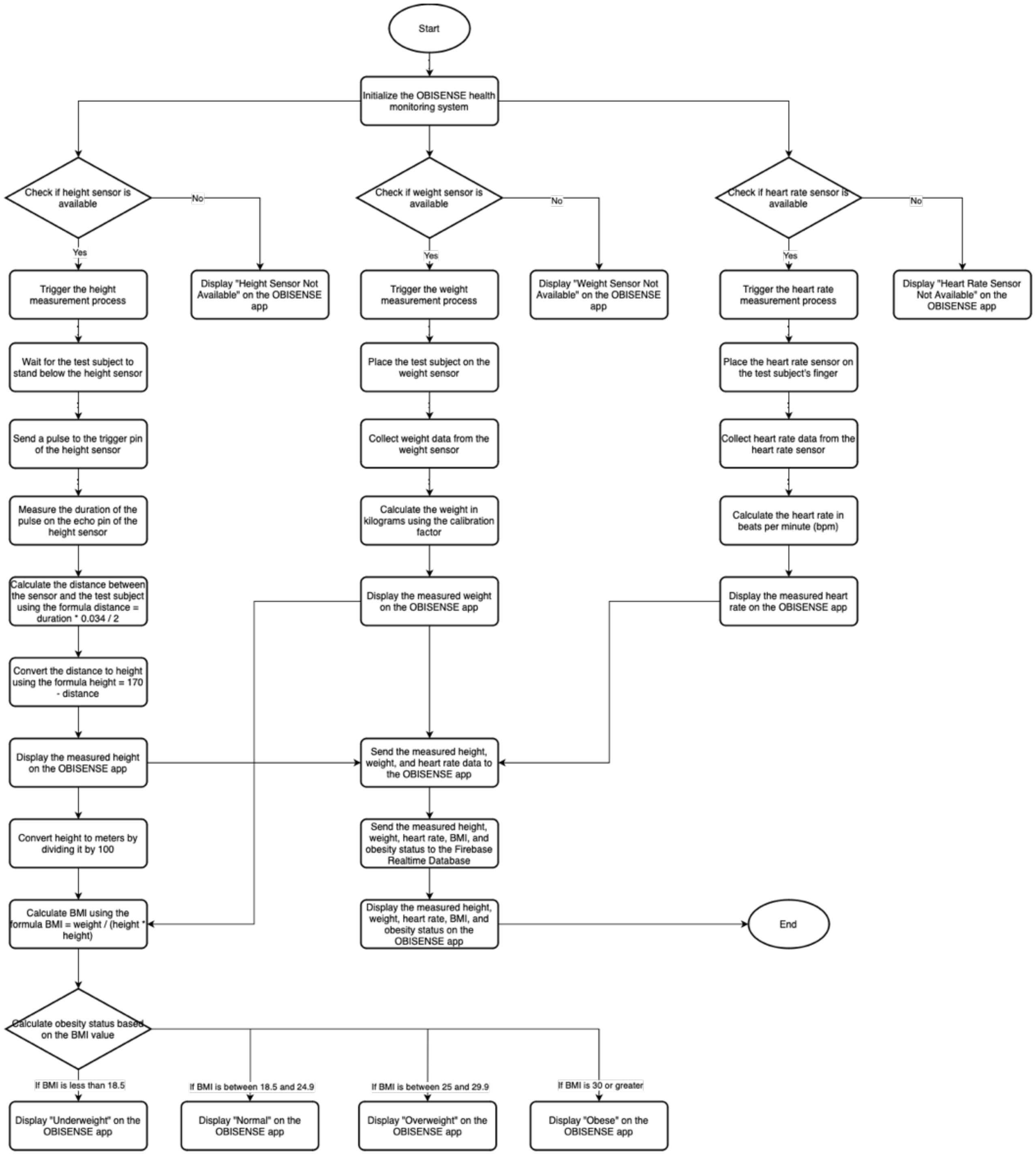
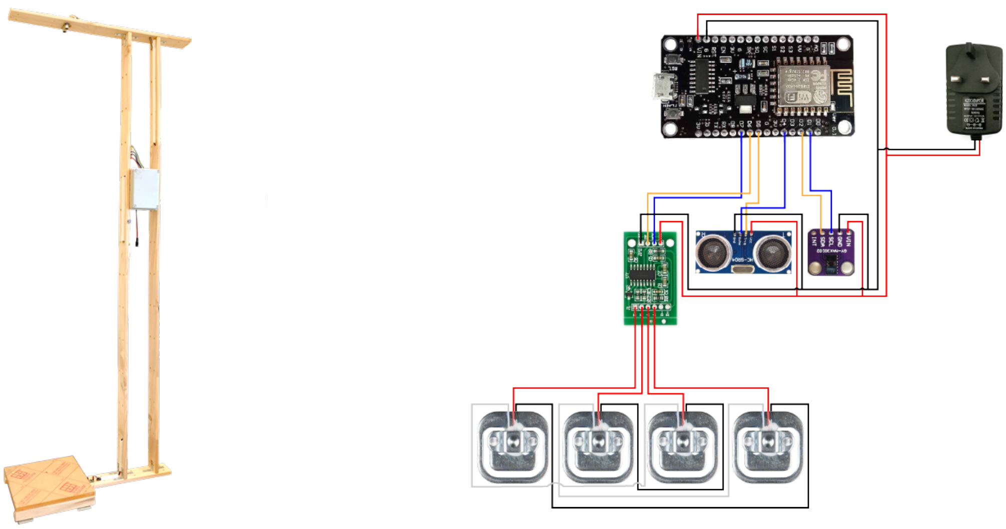


Fig. 1 *Operational flowchart of the OBISENSE system, including communication through Wi-Fi/Bluetooth*

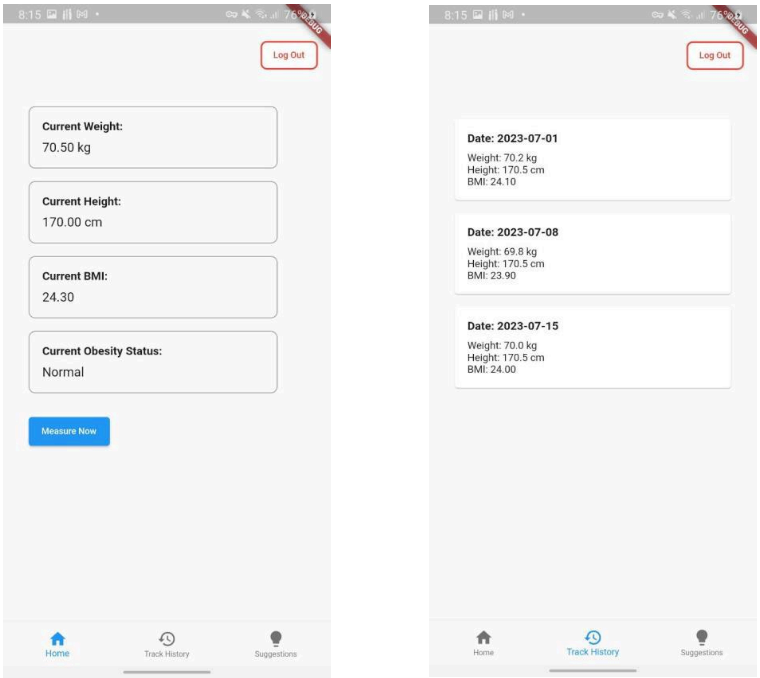
The main process of the system is summarized in Fig. 2, which includes initialization of sensors and microcontroller, acquisition of height, weight, and heart rate data, calculation of BMI and obesity status, and wireless transmission of results to Firebase via Wi-Fi/Bluetooth. The mobile application retrieves and displays the stored data. The system proceeded to trigger the height measurement process. This involved activating the height sensor, prompting the test subject to position themselves beneath it, transmitting a pulse to initiate measurement, gauging the pulse's duration, computing the distance between the sensor and the subject, transforming the distance to height, and displaying the outcome on the OBISENSE app. Similar processes were repeated for the weight sensor. The presence of a heart rate sensor causes the system to initiate heart rate measurement. This encompasses situating the heart rate sensor on the subject's finger, acquiring heart rate data, calculating beats per minute, and conveying the outcome to the OBISENSE app. A corresponding notification was presented on the app if the heart rate sensor was lacking.

Subsequently, the system calculates the BMI by processing height and weight data. Obesity status was then determined based on the BMI value, with distinct classifications displayed on the app. The integration of height, weight, and heart rate data into the OBISENSE app follows, enabling users to access these metrics. The system further updates the Firebase Realtime Database with the accumulated health metrics, including height, weight, heart rate, BMI, and obesity status. Ultimately, the measured metrics were presented on the OBISENSE app for user visualization.



(a) (b)

Fig. 3 *(a) Physical prototype of the OBISENSE system; (b) Circuit diagram of the OBISENSE system*



(a) (b)

Fig. 4 *(a) Home screen of the OBISENSE mobile app; (b) History tracking screen of the OBISENSE app*

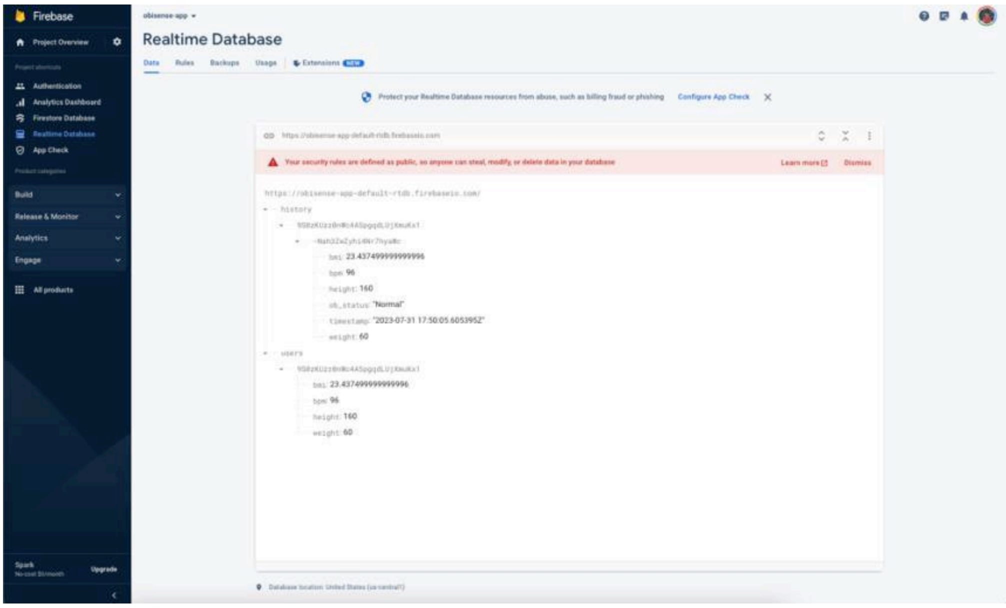


Fig. 5 *Firebase database dashboard for OBISENSE*

During the testing session, an intricately designed experimental setup was employed to evaluate the functionality comprehensively, accuracy, and dependability of the OBISENSE health monitoring system, as shown in Fig. 3. This setup encompassed several key elements and procedures, including the participation of a diverse group of individuals spanning different age groups and body types as test subjects, meticulous calibration of essential sensors such as the ultrasonic sensor for height measurement, load cell for weight measurement, and MAX30102 sensor for heart rate measurement, integration of the OBISENSE App as shown in Fig. 4 with the Firebase Realtime Database on mobile devices for seamless data transmission and display as shown in Fig. 5. Systematic measurement processes involved height, weight, and heart rate assessments, as well as data collection and analysis through the ESP8266MOD Board. This led to the computation of BMI and obesity status, validation of measurements against standard medical instruments, and iterative testing with multiple subjects, ensuring consistency and identification of discrepancies or anomalies for further investigation.

4. Results Analysis

In the testing phase of the OBISENSE project, an evaluation of the functionality and accuracy of the health monitoring system was conducted. OBISENSE measurements were compared with standard clinical instruments; weight was compared to a calibrated digital weighing scale (±0.1 kg), height to a manual stadiometer (±0.5 cm), heart rate to a pulse oximeter, the load cell showed errors between 0.3–1.2 kg and ultrasonic sensor height deviations were between 0.5–2 cm. These errors are higher than those reported in similar studies using laser range sensors or strain-gauge load cells, indicating the influence of calibration limitations and mechanical instability. The height, weight, and heart rate measurement functionalities were rigorously assessed to ensure compliance with accuracy requirements. A total of four test subjects were included in the prototype validation phase. For each subject, measurements were repeated three times to assess reproducibility and sensor behavior. Although the system was functional, the accuracy of the measurements varied across parameters. Controlled experiments were carried out to validate each element's precision. Throughout the testing, data was collected and analyzed to identify discrepancies and issues.

4.1 Height Measurement Test

In the height measurement testing phase, data was gathered for each height measurement, and the sensor-to-test subject distance was calculated using the formula distance = duration * 0.034 / 2. The resulting measured height was then compared to the reference height obtained through measuring tape. Analyzing the disparities between measured and reference heights affirmed the system's accuracy. This testing encompassed three different tests, and the outcomes were graphically depicted, validating the precision of the height measurement system. The first graph, a line graph, displayed the difference between the actual height and the measured height for each test. The graph showed consistent measurements, with the measured height slightly lower than the actual height for all three tests. The second graph demonstrated the accuracy of the height measurement test for each subject. Test #1 had an accuracy of 0% because of the minimum sensor value, which is 103 cm. However, Test #2 achieved an accuracy of 99.03%, and Test #3 achieved an accuracy of 99.40%. The height measurement system is accurate

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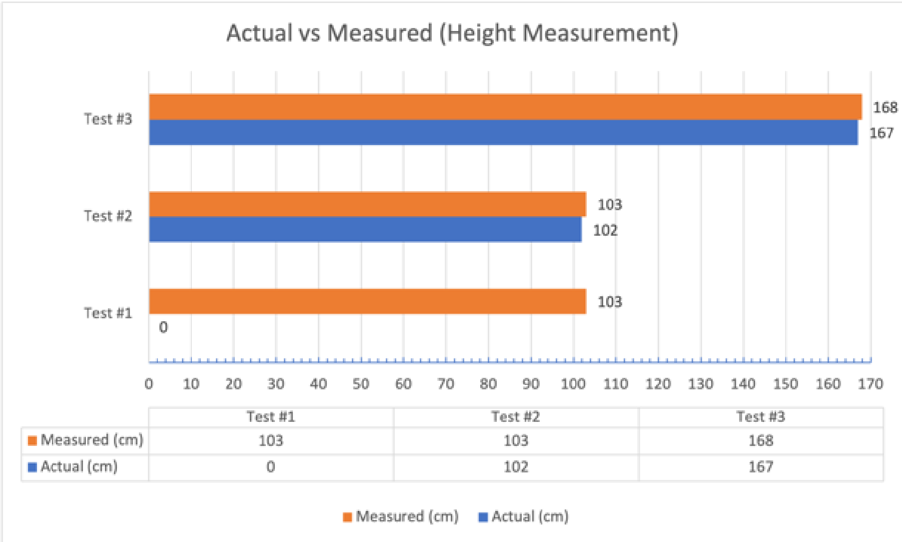
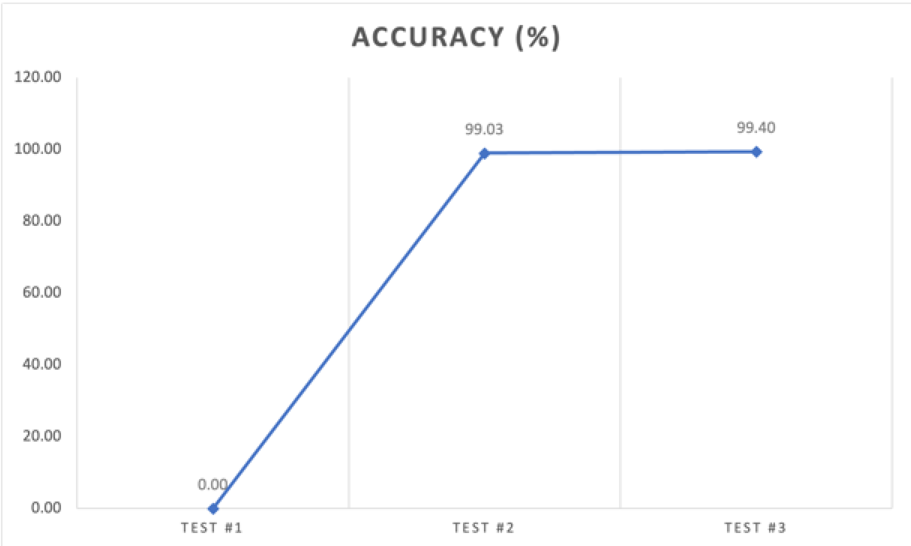
enough, with repeated testing and calibration indicated in Fig. 6. Erine et al. (2020) also obtained similar results in relation to the height measurement accuracy [12].



(a)

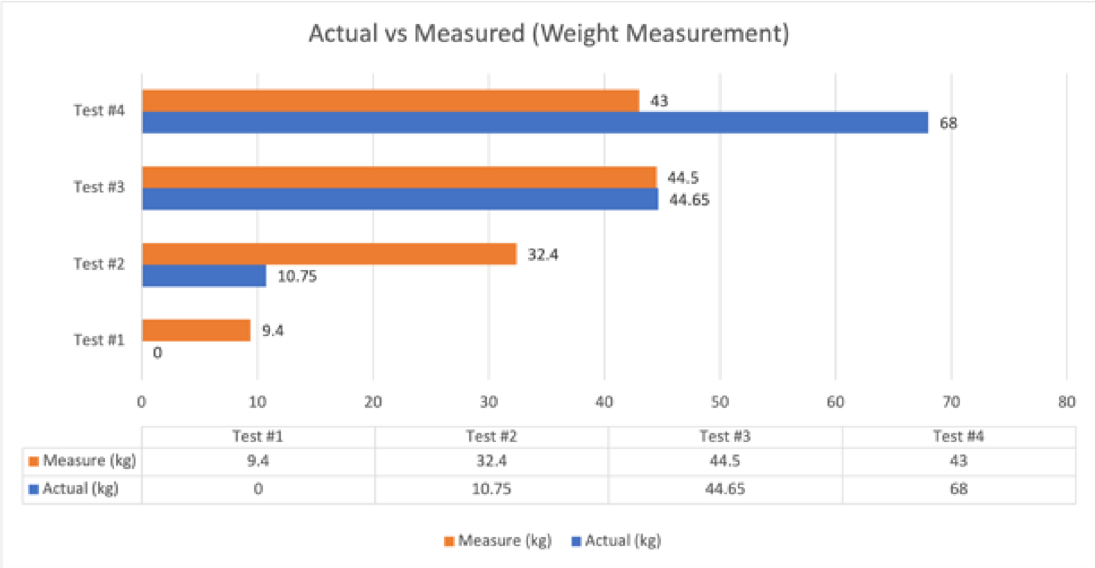


(b)

Fig. 6 *(a) Height measurement test results; (b) Height measurement error analysis*

4.2 Weight Measurement Test

For each weight measurement, the data obtained from the load cell amplifier and the reference weight value from a basic weight scale were recorded. The measured weight was then compared with the reference weight to assess the accuracy of the weight measurement functionality. The actual and measured weight for each test subject is shown in Fig. 7(a). The x-axis represents the measured weight in kilograms, and the y-axis represents the actual weight in kilograms. Test #1 had an actual weight of 0 kilograms and a measured weight of 9.4 kilograms. Test #2 had an actual weight of 10.75 kilograms and a measured weight of 32.4 kilograms. Test #3 had an actual weight of 44.65 kilograms and a measured weight of 44.5 kilograms. Test #4 had an actual weight of 68 kilograms and a measured weight of 43 kilograms. The difference between the actual and measured weight was due to measurement error, which could be caused by calibration of the weighing scale or faulty sensors. The accuracy of weight measurement for each test subject is shown in Fig. 7(b). The x-axis represents the test subject, and the y-axis represents the accuracy of the weight measurement in percentage. Test #1 had an accuracy of 0% because of the minimum actual weight, which starts at 9.4 kilograms. Test #2 had an accuracy of 33.18%, indicating that the measured weight was 66.82% lower than the actual weight. Test #3 had an accuracy of 99.66%, indicating that the measured weight was 0.34% lower than the actual weight. Test #4 had an accuracy of 63.24%, indicating that the measured weight was 36.76% lower than the actual weight. Erine et al. (2020) also obtained similar results in relation to the weight measurement accuracy [12].



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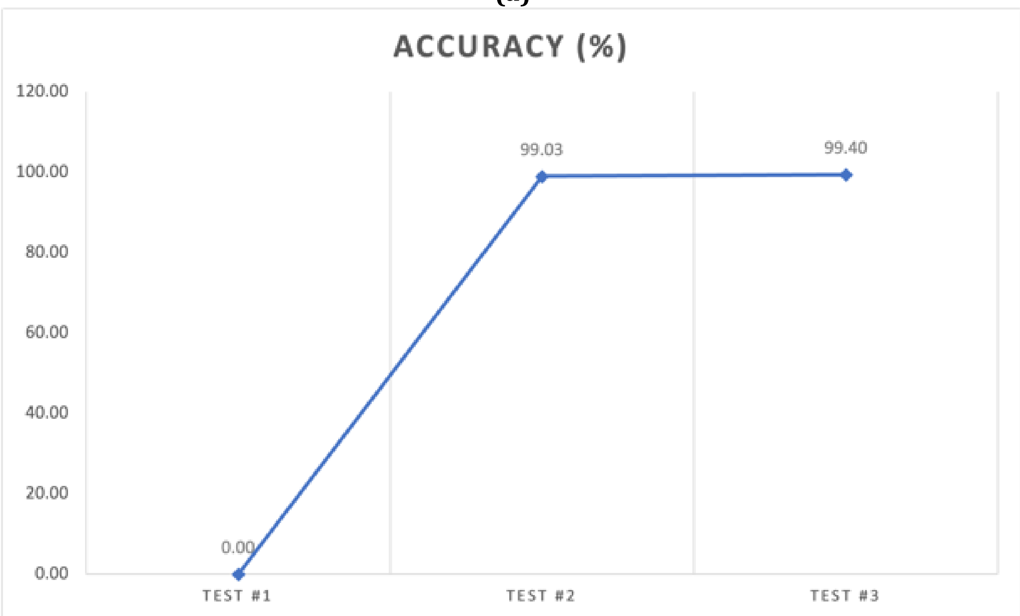
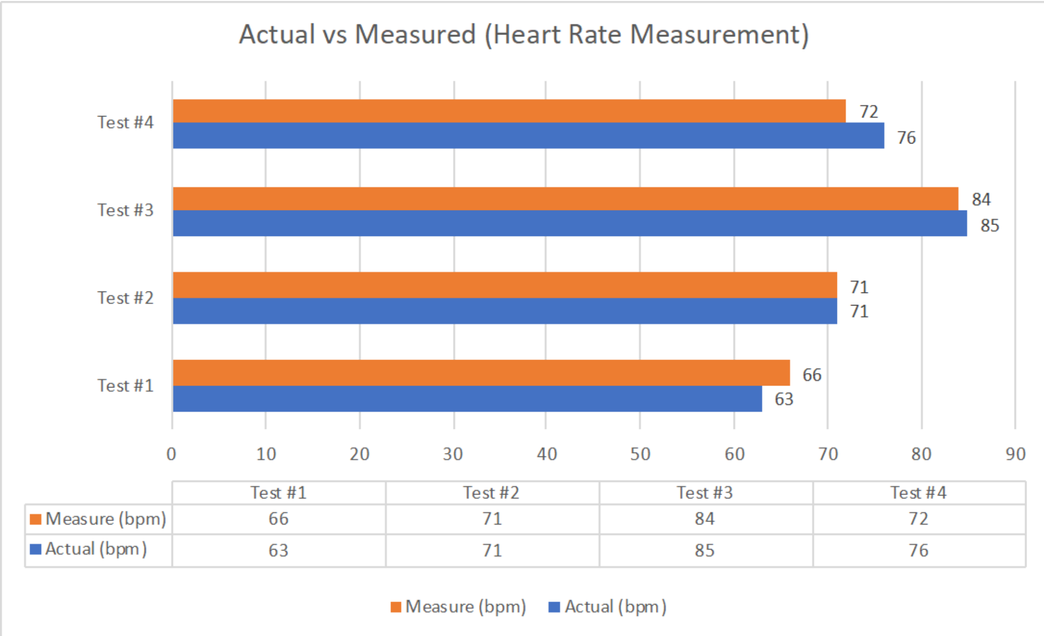


(b)

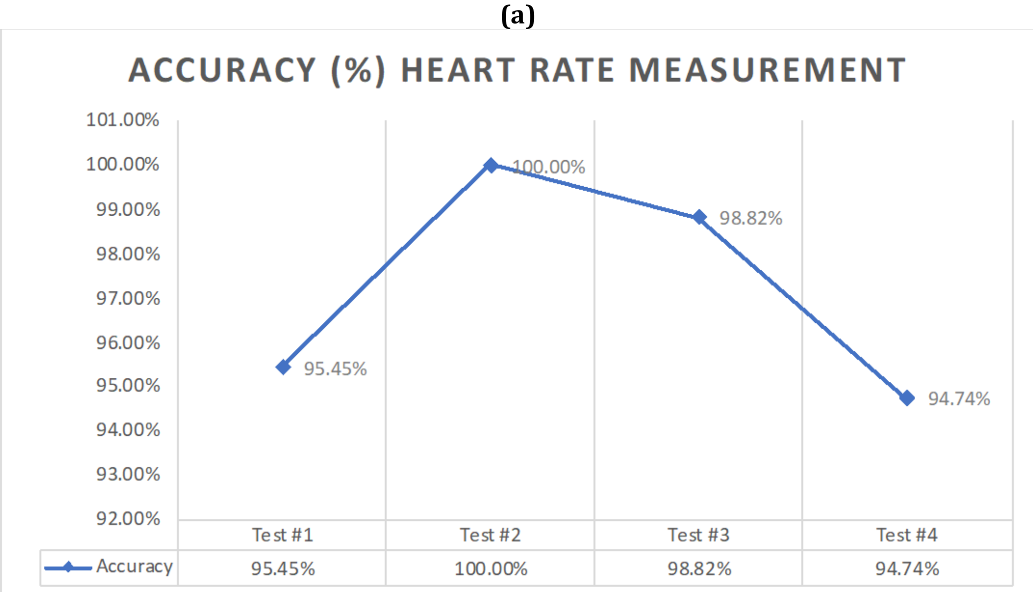
Fig. 7 *(a) Weight measurement test results; (b) Weight measurement error analysis*

4.3 Heart Rate Measurement Test

For each heart rate measurement, the processed signals were collected and analyzed to extract heart rate information. The heart rate was calculated by detecting the zero-crossings and falling edges in the signal, which indicate the heartbeat. A bar graph comparing the measured and the actual heart rate for each test subject is as shown in Fig 8(a). The x-axis represents the test subject, and the y-axis represents the heart rate in beats per minute (bpm). Test #1 had a measured heart rate of 66 bpm and an actual heart rate of 63 bpm.



(a)



(b)

Fig. 8 *(a) Heart rate measurement test results (b) Heart rate measurement error analysis*

Test #2 had a measured heart rate of 71 bpm and an actual heart rate of 71 bpm. Test #3 had a measured heart rate of 84 bpm and an actual heart rate of 85 bpm. Test #4 had a measured heart rate of 72 bpm and an actual heart rate of 76 bpm. A bar graph on the accuracy of heart rate measurement for each test subject is as shown in Fig. 8(b). The x-axis represented the test subject, and the y-axis represented the accuracy of the heart rate measurement in percentage. The graph indicates that the accuracy of the heart rate measurement was inconsistent across the four test subjects. Test #1 had an accuracy of 95.45%, indicating that the measured heart rate was 4.55% higher than the actual heart rate. Test #2 had an accuracy of 100.00%, indicating that the measured heart rate was equal to the actual heart rate. Test #3 had an accuracy of 98.82%, indicating that the measured heart rate was 1.18% higher than the actual heart rate. Test #4 had an accuracy of 94.74%, indicating that the measured heart rate was 5.26% higher than the actual heart rate. The measurements are accurate enough, as heart rate is never a constant value. The tolerance was ±5%. The results were higher compared to Contardi et al. [9], in which the accuracy was less than 70%.

4.4 Body Mass Index (BMI) Measurement Test

In the BMI calculation testing phase, the accuracy of the BMI calculation functionality was verified through multiple height and weight measurements for each test subject shown in Table 1 and Table 2. The BMI was computed using the formula BMI = weight (kg) / (height (m) * height (m)), and the calculated BMI values were compared with reference values derived from known height and weight measurements. This testing encompassed four distinct tests, with the results indicating the extent of agreement between calculated and reference BMI values. The measured BMI is consistently lower than the actual BMI for all four test subjects, which indicates that the system tends to slightly underestimate the BMI values compared to the actual BMI, as shown in Fig. 9. One possible reason was the accuracy of the sensors that were used to measure the height and weight. Since the weight sensor used has a margin of error, it could lead to inaccurate BMI calculations.

Table 1 *Physical alert system latency testing result*

Measured Height (cm)	Measured Weight (kg)	Measured BMI
125	38	24.32
143	45	22.01
155	42	17.48
132	47	26.97

Table 2 *Physical alert system latency testing results*

Actual Height (cm)	Actual Weight (kg)	Actual BMI
125	50	32.00
143	44.8	21.91
156	69	28.35
132	47.1	27.03

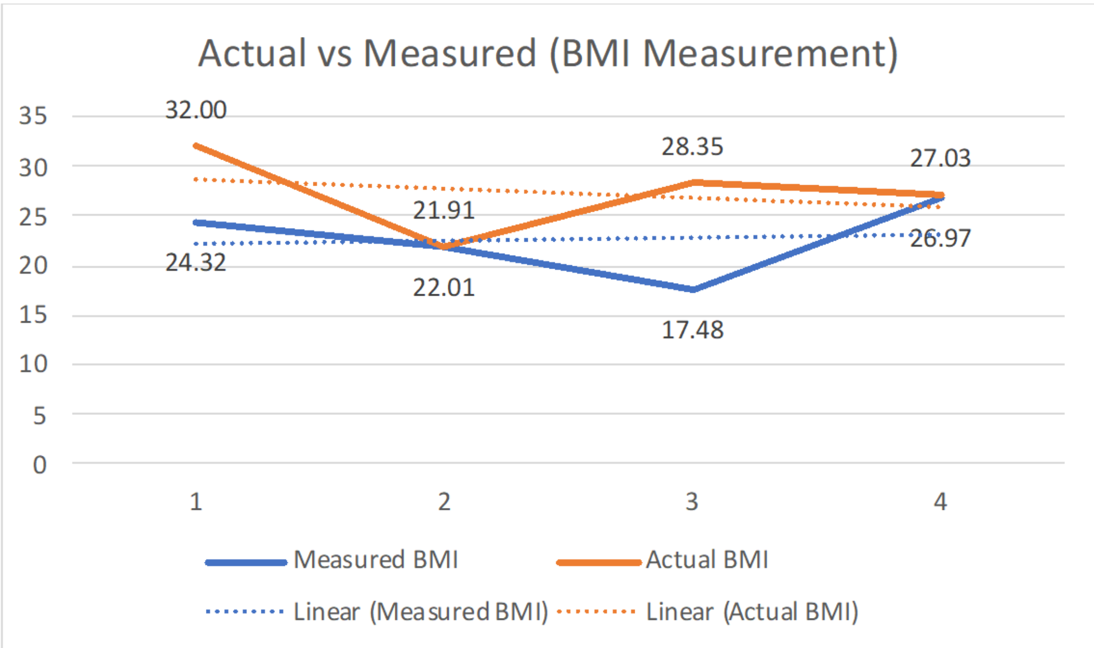
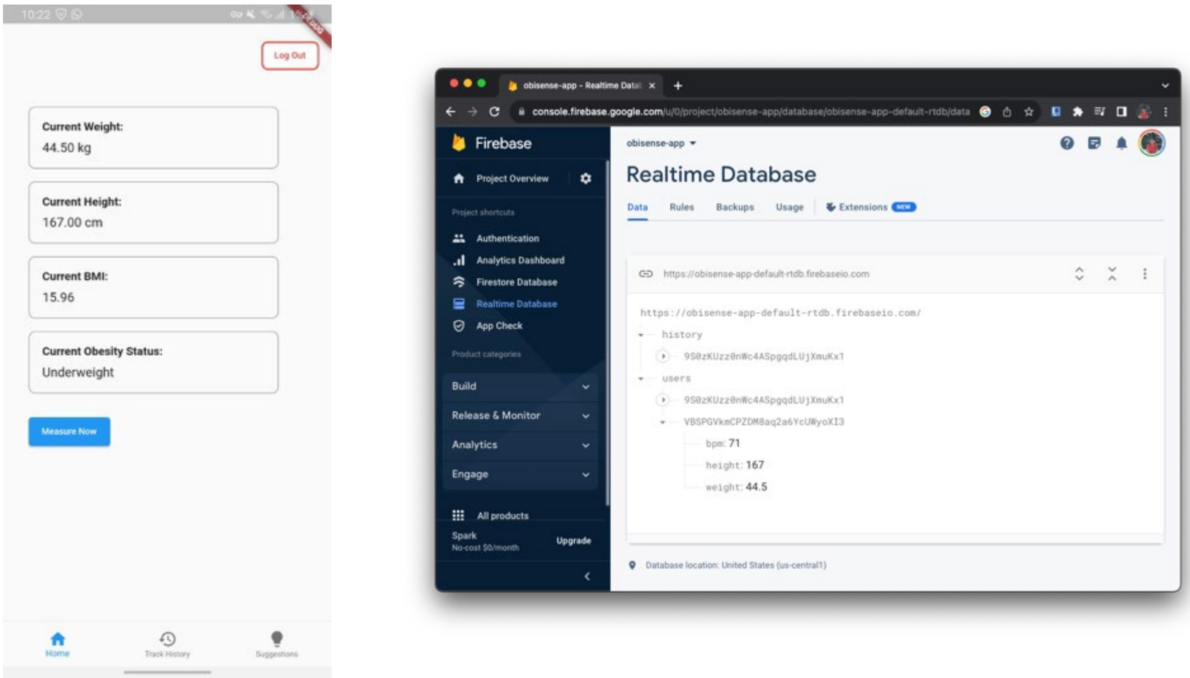


Fig. 9 *Comparison of calculated BMI and reference BMI values*

During system integration testing, several tests were conducted to ensure that each component was functioning correctly and that the data from each sensor was accurately integrated into the system shown in Fig. 10(a). Different scenarios, such as simultaneous height and weight measurements, were simulated to assess the system's ability. For each test case, the data generated by the system was collected in the OBISENSE app and directly updated to the Firebase Realtime Database shown in Fig. 10(b). The height, weight, and heart rate measurements were accurate and consistent, and the calculated BMI and obesity status were correct based on the collected data. Mae et al. (2020) obtained similar results [4].



(a) **(b)**

Fig. 10 *(a) Real-time data display in the OBISENSE app; (b) Firebase data storage for collected measurements*

The OBISENSE system successfully demonstrated the ability to measure height, weight, heart rate and calculate BMI using IoT-based sensors. However, the accuracy and consistency of the results varied significantly across different measurements compared to studies using medical-grade sensors. This section critically evaluates the system's performance, identifies sources of error, discusses limitations such as small sample size, and explains how inaccuracies in primary sensor readings directly affect BMI and obesity classification.

5. Conclusions

In conclusion, the OBISENSE health monitoring system has undergone thorough design, development, and rigorous testing, confirming its accuracy and reliability in measuring height, weight, and heart rate. The integration of these metrics into the OBISENSE app and Firebase Realtime Database demonstrated seamless functionality. While successful in providing real-time health data, areas for improvement include enhancing accuracy in height and weight measurements and addressing variations in heart rate accuracy. The system's user-friendly interface and potential for remote health monitoring hold promises for informed decision-making and improved well-being. All this contributed to the novelty of research. Future iterations can focus on sensor calibration, algorithm optimization, and addressing discrepancies observed during testing, paving the way for impactful contributions to telemedicine and remote health management.

The evaluation process identified several limitations of the OBISENSE health monitoring system, despite its successful development and testing. Firstly, the accuracy of height measurements was influenced by factors such as sensor positioning and subject posture, leading to slight discrepancies between measured and actual heights. Secondly, weight measurements were subject to variations caused by load cell calibration and potential inconsistencies in user positioning. Thirdly, the heart rate measurements exhibited varying degrees of accuracy across different test subjects, potentially attributed to sensor sensitivity and external interference. Additionally, the accuracy of height and weight measurements affected the BMI calculations, potentially leading to deviations from actual values. Lastly, the system's reliance on wireless connectivity for data transmission may pose challenges in areas with unstable network conditions. Addressing these limitations through refined calibration techniques, sensor enhancements, and algorithm optimization will be critical for advancing the OBISENSE health monitoring system's overall performance and utility.

Based on the evaluation of the OBISENSE health monitoring system, several recommendations and suggestions have been identified to enhance its functionality and address the limitations observed during testing. Future work includes implementing multi-point calibration of weight and height sensors, considering factors such as sensor placement and user posture to improve the accuracy of collected data. Secondly, exploring alternative sensor options or signal processing algorithms for heart rate measurements could potentially mitigate sensitivity to external interference through the implementation of digital filtering algorithms. Thirdly, incorporating WHO age-specific BMI percentiles and predictive analysis. Moreover, integrating data smoothing or error correction mechanisms into the system's software could help mitigate measurement inaccuracies caused by sensor noise or fluctuations. Additionally, incorporating user guidance and feedback mechanisms within the OBISENSE App can facilitate proper sensor usage and improve the overall user experience. Lastly, integrating offline data storage and synchronization capabilities could enhance the system's robustness in situations with intermittent network connectivity. Addressing these recommendations and suggestions will contribute to the continued development and optimization of the OBISENSE health monitoring system, ensuring its reliability and effectiveness for diverse user applications.

The OBISENSE system was designed to provide a low-cost, IoT-based approach for monitoring height, weight, heart rate, and BMI in children. While the system successfully demonstrated functional integration between sensors, the ESP8266 microcontroller, Firebase cloud storage, and a mobile application, the results revealed some technical limitations. Despite these limitations, OBISENSE provides a functional prototype that establishes a foundation for remote pediatric health monitoring.

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Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

*The authors confirm their contribution to the paper, as follows: **study conception and design:** A. Deneshwar; **data collection:** A. Deneshwar; **analysis and interpretation of results:** A. Deneshwar; **draft manuscript preparation:** R. Dhakshyani. All authors approved the final version of the manuscript.*

References

[1] Machorro-Cano, I., Alor-Hernández, G., Paredes-Valverde, M. A., Ramos-Deonati, U., Sánchez-Cervantes, J. L., & Rodríguez-Mazahua, L. PISIoT (2019) A machine learning and IoT-based smart health platform for overweight and obesity control, *Applied Sciences*, 9(15), 3037, https://doi.org/10.3390/app9153037

[2] Alsareii, S. A., Shaf, A., Ali, T., Zafar, M., Alamri, A. M., AlAsmari, M. Y. & Awais, M. (2022) IoT framework for a decision-making system of obesity and overweight extrapolation among children, youths, and adults. *Life*, 12(9), 1414, https://doi.org/10.3390/life12091414

[3] Lam, C., Milne-Ives, M., Harrington, R., Jani, A., Helena van Velthoven, M., Harding, T., & Meinert, E. (2022) Internet of things–Enabled technologies as an intervention for childhood obesity: A systematic review. *PLOS Digital Health*, 1(4), (2022). https://dOI.org/10.1371/journal.pdig.0000024

[4] Mae, J., Oey, E., & Kristiady, F. S. (2020) IoT based body weight tracking system for obese adults in Indonesia using real-time database, *IOP Conference Series: Earth and Environmental Science,* 426(1), 012143. https://goi.org/10.1088/1755-1315/426/1/012143

[5] Abdulmalek, S., Nasir, A., Jabbar, W. A., Almuhaya, M. A., Bairagi, A. K., Khan, M. A. M., & Kee, S. H. (2022) IoT-Based Healthcare-Monitoring System towards Improving Quality of Life: A Review. *In Healthcare*, 10(10), 1993, https://goi.org/10.3390/healthcare10101993

[6] Bhuvaneswari, C. A., Muthumari, M., Pragjnay, A. J. S., Lakshmi, J. S., & Navya, T. (2022) Design and Implementation of Remote Health Monitoring System and Application for Priority Recognition Using Machine Learning. *IEEE International Conference on Data Science and Information System (ICDSIS)*, 1-5, (2022) https://goi.org/10.1109/ICDSIS55133.2022.9915874

[7] Bhansali, P. K., & Hiran, D. IoT based Heart Rate Measurement and Analysis. (2020) *Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), 128-133,* https://goi.org/10.1109/I-SMAC49090.2020.9243438

[8] Mark, G. M., Bakunzibake, P., & Mikeka, C. (2021). Design of an IoT-based Body Mass Index (BMI) Prediction Model. *4th International Seminar on Research of Information Technology and Intelligent Systems* (ISRITI), 629-634). IEEE https://goi.org/10.1109/ISRITI54043.2021.9702866

[9] Contardi, U. A., Morikawa, M., Brunelli, B., & Thomaz, D. V. MAX30102 (2021) Photometric Biosensor Coupled to ESP32-Webserver Capabilities for Continuous Point of Care Oxygen Saturation and Heart Rate Monitoring. *Engineering Proceedings*, 16(1), 9 https://doi.org/10.3390/IECB2022-11114

[10] Celine Teoh Su Yin, R. Dhakshyani (2022) AI-Powered Low-Cost Wearable Health Tracker Targeted Towards Elderly in Developing Countries, *Journal of Engineering Science and Technology (JESTEC)*, Special Issue, 58-76

[11] Timur Kulbuzhev, R. Dhakshyani (2022) Low Cost IoT Based Smart Home Automation, *Journal of Engineering Science and Technology (JESTEC)*, Special Issue, 196-202

[12] Erinle, T. J., Oladebeye, D. H., & Ademiloye, I. B. (2020) Parametric design of height and weight measuring system, *IJIREEICE*, 8(7), 22–34, https://goi.org/10.17148/IJIREEICE.2020.8705

[13] Faradisa, I. S., Muhammad, R. P., & Girindraswari, D. A. (2022) A design of Body Mass Index (BMI) and body fat percentage device using fuzzy logic, *Indonesian Journal of Electronics, Electromedical Engineering, and Medical Informatics,* 4(2), 94–106 https://goi.org/10.35882/ijeeemi.v4i2.7

[14] Hasan, W. U., Sultan Khaja, M., Ahmed, S., & Khan, M. M. (2018) Wireless Health Monitoring System. *2nd Borneo International Conference on Applied Mathematics and Engineering* (BICAME), https://goi.org/10.1109/BICAME45512.2018.1570510420

[15] Alam, J., Chowdhury, B. S., Mahmud, T., Soroni, F., & Khan, M. M. (2021) Development of smart height measuring scale, *12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 1–6 https://goi.org/10.1109/ICCCNT51525.2021.9579637