

Integration of an IoT-enabled Biomedical Telemetry System and AI Health Risk Assessment Model based on Fuzzy Logic for Managing Diabetes and Cardiovascular Diseases

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ARTICLE INFO

ABSTRACT

Received: 22 Dec 2024

Revised: 09 Feb 2025

Accepted: 24 Feb 2025

Individuals with diabetes mellitus (DM) and cardiovascular disease (CVD) are on the rise worldwide, affecting both children and adults. Early-onset symptoms of these non-communicable diseases must be monitored and treated to prevent complications and improve people's quality of life. To address this health issue, the following modules were designed, integrated and implemented: (a) a biomedical telemetry system using IoT-enabled Particle photon microcontrollers interfaced with biosensor and switches that remotely monitor physiological symptoms and anthropometric indicators associated with DM and CVD; (b) an AI assessment model based on fuzzy logic which assist endocrinologists, cardiologist, and other medical professionals in evaluating health risks associated with these conditions, and (c) an interactive smartphone application that allows medical professionals to track patients' well-being and make timely interventions or changes to treatment programs, as well as enabling patient to perform tele- or video-consultation with the doctor. All medical data were securely stored and accessible via the ThingSpeak cloud and MariaDB database servers. Based on the experimental data, the designed system demonstrated 96.19% accuracy in analyzing medical data and evaluating the patients' health risk levels associated with DM and CVD when compared to medical algorithms, published clinical practice guidelines, and advice given by medical experts. Furthermore, the estimated anthropometric parameters and body composition metrics calculated using the developed mobile app were comparable to those acquired using various medical algorithms and programs available online. As a whole, the integrated modules contributed to the Society 5.0 initiative by delivering patient-centered healthcare using IoT, mobile computing, and AI technologies.

Keywords: internet of things; fuzzy logic; mobile computing; biomedical telemetry, clinical health risk

INTRODUCTION

Diabetes mellitus (DM) and cardiovascular diseases (CVD) are prevalent non-transmissible ailments that lead to morbidity and mortality globally [1]. In 2020, the global death toll from diabetes was 1.64 million, whereas cardiovascular disease (CVD) accounted for 19.05 million deaths [2]. DM is a persistent medical disorder distinguished by an increase in blood glucose levels greater than or equal to 126 mg/dL when fasting and greater than or equal to 200 mg/dL after 2 hours of eating, resulting from either a complete or partial lack of insulin production or function [3]. CVDs are ailments that impact the function of the heart and blood vessels, including coronary artery disease, congenital heart disease, cerebrovascular disease, rheumatic heart disease, and various vascular diseases [4]. Unhealthy diets, sedentary lifestyles, obesity, family medical history (FMH), elevated total cholesterol (TChol), high blood pressure (BPS/BPD), and increased blood sugar level (BSL), along with rapid urbanization, have led to a rise in the prevalence of DM and CVDs [1], [5], [6]. According to [7], the rise of non-communicable disease (NCD) cases

like as DM and CVD can be minimized by raising health awareness among individuals and conducting research on effective diagnostic platforms.

In response to the concerning issue of rapid growth of NCD cases, a society 5.0-driven healthcare system was designed and implemented using Internet of Things (IoT), mobile computing and artificial intelligence (AI) technologies. The integration of an IoT-enabled biomedical telemetry system (IBTMS) with a fuzzy logic-based clinical health risk assessment model (FLCHRAM) allowed remote monitoring of physiological symptoms and anthropometric signs associated with DM and CVD, as well as enabled health risk analysis and prognosis related to the NCDs. The developed interactive smartphone application facilitated telemedicine services, increased the visualization of the data and enhanced health awareness. The developed system is in line with the aim of society 5.0 framework, which is to provide data-driven, intelligent and patient-centered healthcare solutions [8]. According to [9] and [10], the concept of Society 5.0 refers to a technology-driven and extremely smart society that uses recent developments in information, communication and engineering like AI, IoT and 5G technologies to improve the well-being and security of all citizens.

The IoT-enabled biomedical telemetry system (IBTMS) for managing DM and CVD was designed and implemented with Particle Photon Redboard microcontrollers (PPmc) that read and processed data from electronic sensors to determine an individual's anthropometric parameters such as weight in kg (Wkg), height in cm (Hcm), body mass index (BMI), as well as physiological signs such as number of heartbeat per minute (HRbpm), systolic/diastolic arterial pressure (BPS/BPD), oxygen saturation percentage (SpO₂%), body thermal rate (BTemp) and rate of respiration per minute (RRpm). Additionally, toggle switches were connected to the microcontrollers to collect information regarding the patient's random blood sugar level (RBSL), pain/ache status (PAS), family medical history of diabetes and/or CVD (FMH), gender identity (GI), lifestyle (LFS), and pre-existing medical condition associated with diabetes and/or CVD (PMC). Utilizing the collected data, the microcontroller evaluated if the physiological parameters exceeded the threshold specified in clinical guidelines and computed the Quetelet index (QI), commonly referred to as body mass index (BMI), based on anthropometric metrics. The patient's basic metabolic rate (BMR) and body fat percentage (BFP) were calculated using the age (A), GI, and LFS entered into the developed interactive smartphone app for health monitoring and assessment (ISAHMA). In addition, the doctor entered blood chemistry values of the patient such as FBSL and total cholesterol level (TChol) into ISAHMA based on lab test results obtained from a hospital or clinic for further health risk assessment. The physiological and anthropometric data were saved in Thing Speak cloud platforms as well as in a secured MariaDB database server, which can be accessed remotely and in real-time using mobile computing devices. Using a fuzzy logic approach, a MATLAB-based AI assessment model was developed to determine the clinical health risk level (CHRL) of the patient as normal/very low, low, moderate, high, or very high based on physiological signs, anthropometric indicators, and other DM and CVD-related symptoms such as HRbpm, BPS, BMI, TChol, FMH, PMC, PAS and FBSL. In medical diagnosis, fuzzy inference facilitates the interpretation of ambiguous symptoms and test data that may be incomplete or imprecise [11],[12]. The fuzzy logic-based AI system employs fuzzy input variables, fuzzy rules, and inference processes to produce probabilistic health risk assessments, considering the level of certainty associated with each possible medical condition [12]. Through mobile computing using MIT App Inventor, the system provided individualized recommendations for lifestyle modifications, DM and CVD awareness, and other clinical interventions depending on the patient's specific needs and conditions. Should the system identify a high clinical health risk condition, the ISAHMA will send teleconsultation referral alert to a medical practitioner. Furthermore, IBTMS integrated with the fuzzy logic-based clinical health risk assessment model (FLCHRAM) can assist endocrinologists, cardiologists, dieticians and other medical professionals analyze the medical data and give timely medical interventions. The ISAHMA telehealth platform enables patients to interact with medical professionals from a distance, lessening the necessity for face-to-face appointments and enhancing medical care accessibility for individuals residing in remote or isolated communities. The integration of IBTMS, FLCHRAM, and ISAHMA resulted in a Society 5.0-based healthcare platform that leverages IoT, mobile computing, and AI technologies to monitor patients' well-being, deliver medical services, and provide preventive care.

The second part of the research article presents the recent studies that monitor, assess and predict medical conditions related to DM and CVD using IoT, mobile computing and fuzzy logic (FL). The third part of the paper discusses the designed biomedical telemetry system and the fuzzy AI health risk assessment system in depth. Section IV shows the output of the system and comparative analysis of the experimental results. Part V of the paper presents conclusions drawn from the designed system and proposes improvements to fully meet the goal of society 5.0 framework.

RELATED WORKS

Several research studies have examined the use of physiological parameters, anthropometric measurements and blood chemistry data to track a person's potential risk of developing DM and CVD. Emerging technologies such as IoT, Bluetooth communication, machine learning (ML), fuzzy logic (FL) and Neuro-Fuzzy inferencing have been utilized to implement monitoring and predictions of DM and CVD cases. The primary goal of all these systems is to continuously monitor one's physical health using emerging technologies, foster awareness of physical wellbeing, and curb the increasing rates of DM and CVD.

[13] developed an Arduino-based daily monitoring system for adult obese patients, interfacing an LM35 Btmp sensor, a MAX30100 SpO₂% level sensor, and a blood pressure (BP) sensor with the microcontroller. The ESP8266 Wi-Fi module and ATMEGA 328P were utilized to communicate the acquired medical data to the IoT Gecko cloud server for daily health parameter analysis by obese patients and physicians. An IoT-based platform for estimating BMI and predicting obesity, which employed an ultrasonic sensor to measure a person's tallness and a strain gauge load cell to determine how heavy a person is, was proposed in [14]. The core processing was carried out using an Arduino microcontroller integrated with a Wi-Fi module for transmitting the results to a cloud server, then exported to MATLAB for forecasting obesity condition. [15] designed a Raspberry Pi-based (RPI) system that uses sensing components to track BP, HRbpm and BMI levels of a person, as well as predicting obesity and CVD using ML algorithms such as Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN) and Decision Tree (DT). The data were stored and accessed via a cloud server and Firebase database (DB). In the findings of [15], Random Forest (RF) was the best option among the four ML methods used for predicting obesity and related heart disease.

The utilization of Bluetooth Low Energy (BLE), together with ML-based algorithms and real-time data processing, was proposed by [16] to support diabetic patients in enhancing their self-management of their chronic condition. The BLE devices gather physiological parameters such as BP, HRbpm, and blood glucose level (BGL) from sensor nodes, then transmit them to smartphones. To handle the extensive data acquired through the sensor in a continual basis, real-time data processing was utilized, employing Apache Kafka and MongoDB for storing the patient's sensor-read data. Moreover, [16] employed ML techniques such as multilayer perception (MP) for diabetes prediction and Long Short-term Memory (LSTM) for BGL forecasting. On the other hand, a non-invasive approach of taking BGL was devised by [17] using the combination of NIR diode and photodiode. The readings were processed by ESP8266 module, stored in the AWS cloud and Firebase database, and accessed via a smartphone application developed using Android Studio. [17] also tested different ML models and concluded that SVM is an effective alternative for diabetes prediction with an accuracy of 82% after the tuning of the Practice Fusion dataset using grid Search and K-fold cross-validation. Another non-invasive method of predicting BGL was proposed by [18] using Particle Photon microcontroller interfaced with photodiode and NIR diode. The ML polynomial regression model correctly predicted non-invasive blood glucose levels, with a minor percentage difference of less than 5% when compared to invasive readings from a commercially available glucose monitor [18].

A decision support system based on FL for managing obesity and indicating bariatric surgery was developed in [19], utilizing fuzzy sets for BMI and BF and generating a fuzzy obesity index. On the other hand, [20] devised a fuzzy expert system that determined the likelihood of DM by utilizing input such as A, BGL, BMI, serum insulin (INS), diabetes pedigree function (DPF). Using the developed fuzzy rules, the system assessed the possibility of developing DM as very low, low, medium, high, or very high. Another fuzzy system was designed by [21] to assess abdominal obesity as no central obesity, central overweight and central obese using BMI, waist circumference and waist to height ratio as fuzzy inputs. This research was a proposed entry point to a more intricate fuzzy system for assessing cardio metabolic risk. [22] used FL and a Bootstrap Aggregating algorithm based on Gradient Boosting Decision Tree (GBDT) to process and forecast cardiac illness. It trained and tested the model on the UCI heart disease dataset, which has 14 input variables such as age, heart rate, cholesterol level, blood pressure (BP), and ECG parameters.

[23] developed a prediction system for diabetes and cardiovascular diseases via feature selection-based Adaptive Neuro-Fuzzy Inference System (ANFIS), achieving an accuracy of 81% or greater in comparison to existing neural network techniques. A rule-based clustering method was applied to categorize patient records of individuals with diabetes and cardiovascular diseases. Additionally, a semi-centralized blockchain-based electronic health care platform for the safeguarding and transmission of patient information. Another Fuzzy AI healthcare system was designed by [24] aimed at predicting cardiac disease through the integration of MSSO (Modified Salp Swarm

Optimization) and ANFIS. The system attained an accuracy of 99.45% and a precision of 96.54% in categorizing cardiac conditions based on sensor-derived data for vital signs, patient history, and diagnostic outcomes.

This research paper introduces the following innovations in comparison to the works of [11]-[25]: (a) In addition to medical grade BTemp and RRpm sensors and a more accurate sensor to measure height (Hcm), status switches for GI, PAS, RBSL, FMH, PMC, LFS were interfaced to the IoT-enabled Particle Photon RedBoard microcontrollers to monitor and assess the health status and BMI of patient; (b) A dedicated interactive smartphone application for the system was developed using MIT App Inventor to improve the visualization of data, promote diabetes and CVD awareness, facilitate entry of other parameters needed to evaluate the patient such as age (A), TChol, blood glycemic levels and offer telehealth platform; (c) Using mobile computing, BMR and BFP were determined based on medical information retrieved from the ThingSpeak cloud and MySQL database server, and (d) With the HRbpm, BPS, BMI, TChol, FMH, PMC and FBSL considered as the fuzzy input variables, the AI assessment model based on fuzzy inferencing classified the clinical health risk level associated with DM and CVD (CHRL) as normal/very low (NRM_VLCHR), low risk (L_CHR), moderate risk (M_CHR), high risk (H_CHR), or very high risk (VH_CHR).

MATERIALS AND METHODS

A. Design and implementation of a biomedical telemetry system for managing DM and CVD using IoT and mobile computing

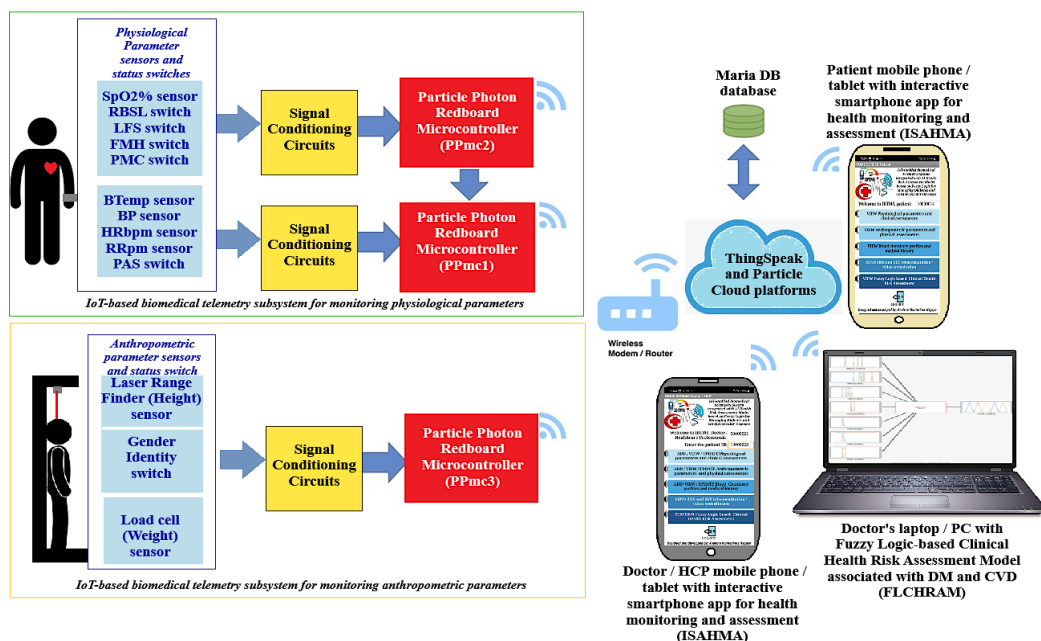


Figure 1: System Block Diagram

The block diagram of the biomedical telemetry system for managing DM and CVD using IoT and mobile computing (IBTMS) integrated with a fuzzy logic-based clinical health risk assessment model (FLCHRAM) is shown in Figure 1. The designed system consists of Wi-Fi enabled Particle Photon RedBoard microcontrollers PPmc1 and PPmc2, which are programmed to read and process physiological parameters and other health-related data from electronic sensors listed in Table 1 and toggle switches in Table 2. The sensor-read parameters include HRbpm, BPS/BPD, SpO2%, BTemp and RRpm. Additionally, input toggle switches are used to gather health information regarding RBSL, PAS, FMH, LFS, and PMC. On the other hand, the anthropometric parameters of the patient are acquired and analyzed by the Particle Photon Redboard microcontroller PPmc3, which is interfaced to a load cell sensor with a HX711 amplifier module to measure the Wkg of the patient, a laser range finder sensor to measure Hcm, and a status switch (GI) to identify the patient's gender identity.

PPmc1 evaluates each physiological indicator in accordance with clinical guidelines provided by [26]-[29], as shown in Table 1. On the other hand, PPmc3 computes the QI, also known as BMI, in kg/m² using Equation (1) and classifies it based on the guidelines in [30]. Figure 2 shows the program flowchart for fitness classification based on QI or BMI. The ISAHMA evaluates the blood profile data entered by the physician, including FBSL, RBSL, and TChol, in

compliance with medical standards in [27] and [29]. Using the computed BMI, GI, and Age (A) as inputs, the ISAHMA estimates the BFP in % using Equation (2) from [31] and categorizes it according to [32]. Table 3 presents the fitness classification based on BFP. Using Wkg, Hcm, GI, and A as inputs, the ISAHMA calculates the BMR in Kcal/day using Equation (3), which is derived from [33]. Table 4 shows how to calculate the patient's recommended daily calorie intake based on [34] based on the computed BMR and entered LFS.

$$QI = BMI = Wkg / (Hcm/100)^2 \quad (1)$$

$$BFP = (1.46 * BMI) + (0.14 * A) - (11.6 * GI) - 10 \quad (2)$$

$$BMR = (10 * Wkg) + (6.25 * Hcm) - (5 * A) + (1.66 * GI) - 161 \quad (3)$$

Table 1: Clinical parameters measurement and evaluation based on medical guidelines [26]-[29] and published works of [11] and [18]

Clinical Parameter	Biosensor	Unit	Sensor Read Value	Evaluation
BTemp	MAX30205 body temperature sensor	°C	36.1 - 37.2	Normal BTemp
			37.3 - 38.0	Moderately High BTemp
			35.1 - 36	Low BTemp
			38.1 - 39	High BTemp
			≥ 39.1	Very High BTemp
			≤ 35.0	Very Low BTemp
HRbpm	Sunrom1437 wrist blood pressure and heart rate sensor	bpm	51 - 90	Normal HRbpm
			41 - 50	Low HRbpm
			91 - 110	Moderately High HRbpm
			111 - 130	High HRbpm
			≤ 40	Very Low HRbpm
			≥ 131	Very High HRbpm
SpO2%	MAX30100 pulse oximetry sensor	%	96 - 100	Normal SpO2%
			94 - 95	Moderately Low SpO2%
			92 - 93	Low SpO2%
			≤ 91	Very Low SpO2%
RRpm	MLX90614 sensor measuring change in respiration temperature	brpm	12 - 20	Normal RRpm
			9 - 11	Low RRpm
			21 - 24	High RRpm
			≤ 8	Very Low RRpm
			≥ 25	Very High RRpm
BP = BPS/BPD	Sunrom1437 wrist blood pressure and heart rate sensor	mmHg / mmHg	90 < BPS < 120 and 60 < BPD < 80	Normal BP
			BPS ≤ 90 and BPD ≤ 60	Low BP
			120 ≤ BPS ≤ 129 and BPD < 80	Moderately High BP
			130 ≤ BPS ≤ 139 or 80 ≤ BPD ≤ 89	High BP
			140 ≤ BPS ≤ 180 or 90 ≤ BPD ≤ 120	Very High BP
			BPS > 180 or BPD > 120	Extremely High BP

The physiological parameters, anthropometric indicators, blood chemistry profiles, as well as health status assessments are stored on the ThingSpeak cloud platform and a MariaDB database server, which can be retrieved remotely and in real time via mobile computing devices. FLCHRAM was developed in MATLAB to analyze and

evaluate the clinical health risk associated with DM and CVD in patients. Figures 3 and 4 show the IBTMS prototype used to monitor physiological and anthropometric parameters, respectively.

Table 2: Toggle switch settings corresponding to the clinical parameters

Clinical / Health Parameters	Toggle switch	Unit	Voltage Level	Switch status / Description
GI	Gender identity switch (SW1)	Volts	0 - 0.8	SW is OFF / Female (0)
			3.3 - 5	SW is ON / Male (1)
PAS	Pain/ache status switch (SW2)	Volts	0 - 0.8	SW is OFF / No pain or ache (-)
			3.3 - 5	SW is ON / with pain or ache (+)
RBSL	Random blood sugar level switch (SW3)	Volts	0 - 0.8	SW is OFF if $55 \leq \text{RBSL} \leq 199$ mg/dL (NRM)
			3.3 - 5	SW is ON if RBS > 200 mg/dL (High)
FMH	Family medical history of NCD switch (SW4)	Volts	0 - 0.8	SW is OFF / No family medical history of DM and/or CVD (-)
			3.3 - 5	SW is ON / With family medical history of DM and/or CVD (+)
PMC	Pre-existing medical condition switch (SW5)	Volts	0 - 0.8	SW is OFF / No pre-existing DM and/or CVD (-)
			3.3 - 5	SW is ON / With pre-existing DM and/or CVD (+)
LFS	Lifestyle status switch (SW6)	Volts	0 - 0.8	SW is OFF / Sedentary or Inactive LFS (-)
			3.3 - 5	SW is ON / Active LFS (+)

Table 3: Fitness classification through BFP for (a) adult female and (b) adult male based on [32]

Age (A) in years	Adult Female (GI = 0)			
	Underweight	Normal	Overweight	Obese
$20 \leq A \leq 39$	$\text{BFP} < 21.0\%$	$21.0\% \leq \text{BFP} < 33.0\%$	$33.0\% \leq \text{BFP} < 39.0\%$	$\text{BFP} \geq 39.0\%$
$40 \leq A \leq 59$	$\text{BFP} < 23.0\%$	$23.0\% \leq \text{BFP} < 34.0\%$	$34.0\% \leq \text{BFP} < 40.0\%$	$\text{BFP} \geq 40.0\%$
$60 \leq A \leq 79$	$\text{BFP} < 24.0\%$	$24.0\% \leq \text{BFP} < 36.0\%$	$36.0\% \leq \text{BFP} < 42.0\%$	$\text{BFP} \geq 42.0\%$

(a)

Age (A) in years	Adult Male (GI = 1)			
	Underweight	Normal	Overweight	Obese
$20 \leq A \leq 39$	$\text{BFP} < 8.0\%$	$8.0\% \leq \text{BFP} < 20.0\%$	$20.0\% \leq \text{BFP} < 25.0\%$	$\text{BFP} \geq 25.0\%$
$40 \leq A \leq 59$	$\text{BFP} < 11.0\%$	$11.0\% \leq \text{BFP} < 22.0\%$	$22.0\% \leq \text{BFP} < 28.0\%$	$\text{BFP} \geq 28.0\%$
$60 \leq A \leq 79$	$\text{BFP} < 13.0\%$	$13.0\% \leq \text{BFP} < 25.0\%$	$25.0\% \leq \text{BFP} < 30.0\%$	$\text{BFP} \geq 30.0\%$

(b)

Table 4: Recommended daily calorie intake based on BMR and LFS [34]

LFS Code	LFS	Daily Calorie Intake in Kcal/day
0	Sedentary	BMR * 1.2
1	Lightly Active/ Exercising 1 to 3 times weekly	BMR * 1.375
2	Moderately Active/ Exercising 3 to 5 times weekly	BMR * 1.55
3	Very Active/ Exercising 6 to 7 times weekly	BMR * 1.725
4	Extremely Active/ Exercising 2 times daily	BMR * 1.9

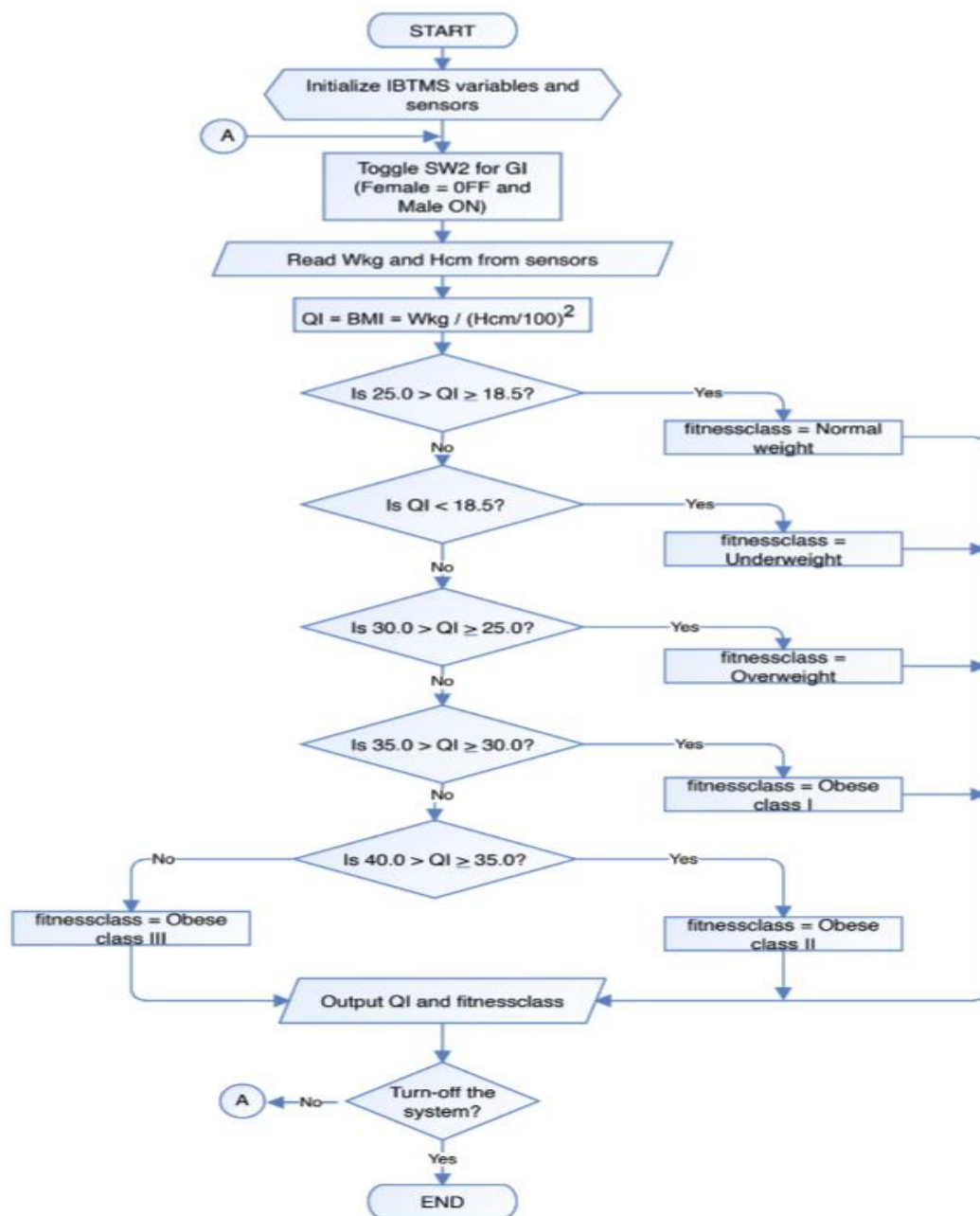


Figure 2: Fitness classification based on Quetelet Index (QI), also known as BMI

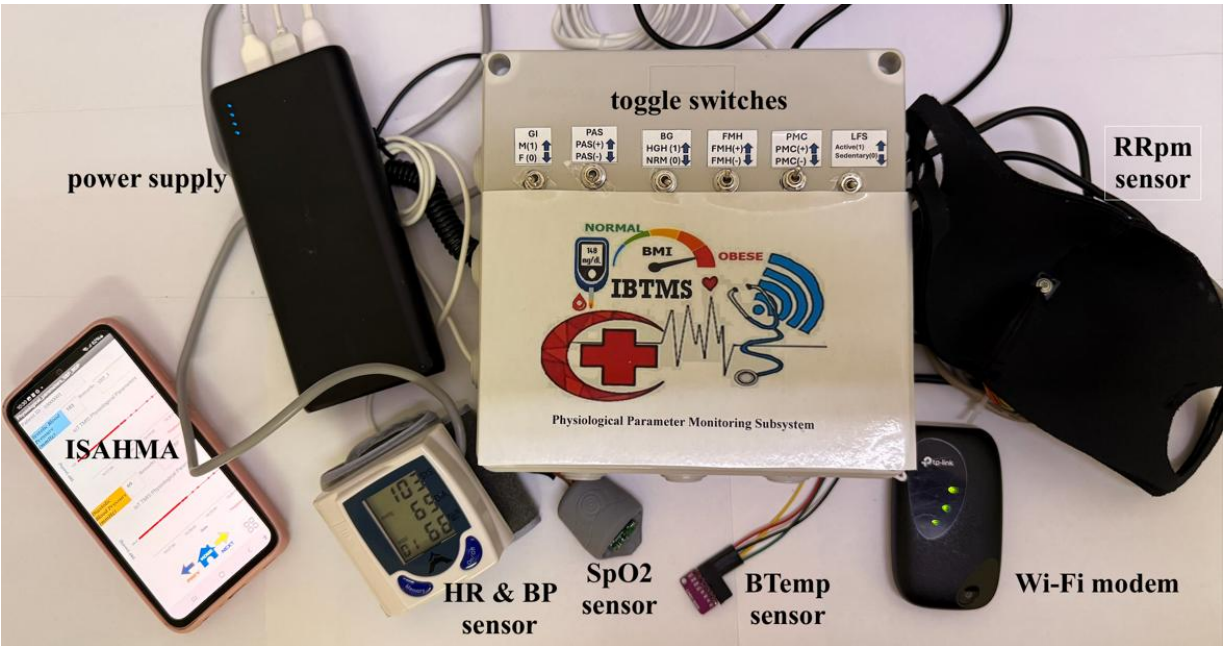


Figure 3: IoT-based biomedical telemetry subsystem for monitoring physiological parameters

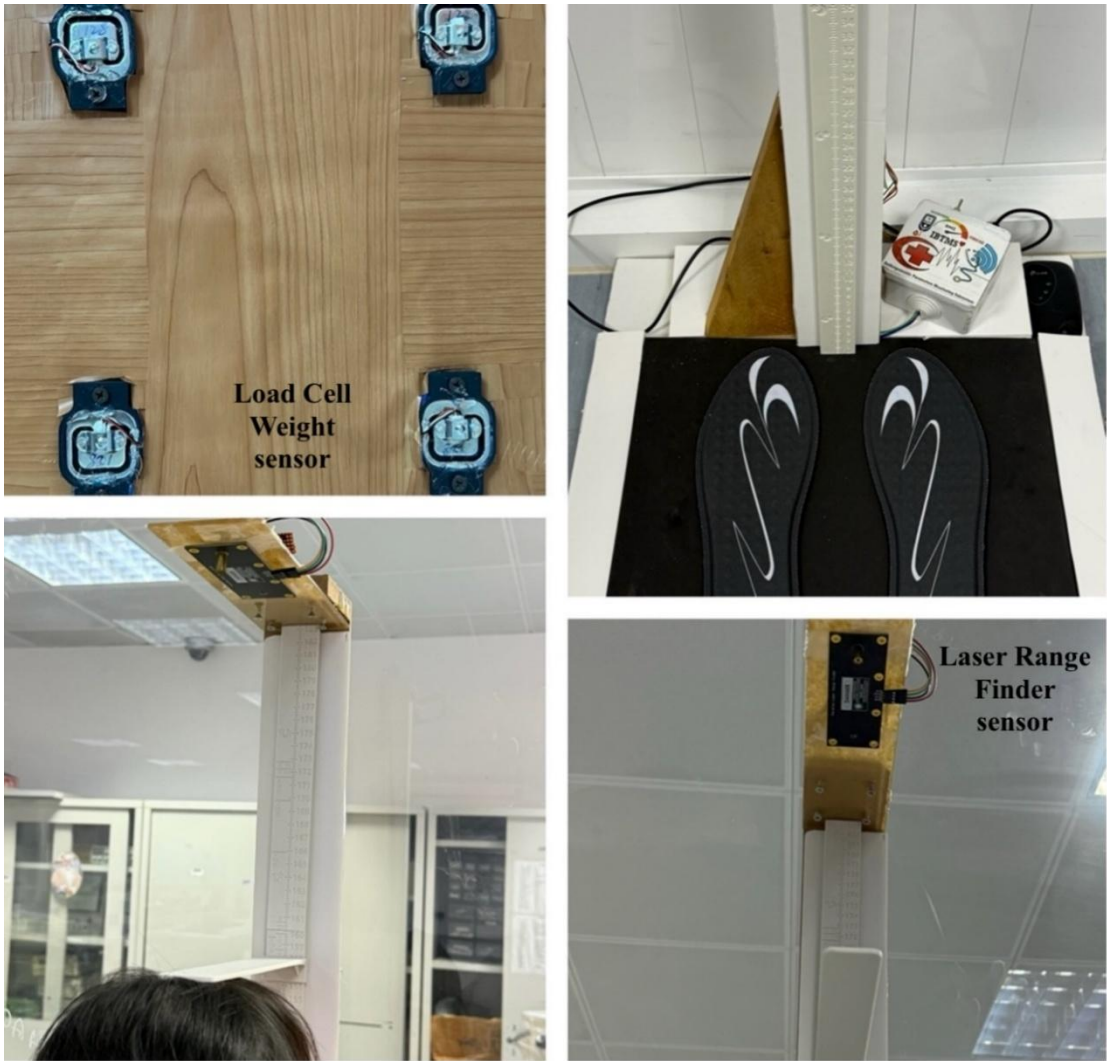


Figure 4: IoT-based biomedical telemetry subsystem for monitoring anthropometric parameters

B. Design and implementation of the AI model based on fuzzy logic for clinical health risk assessment associated with DM and CVD

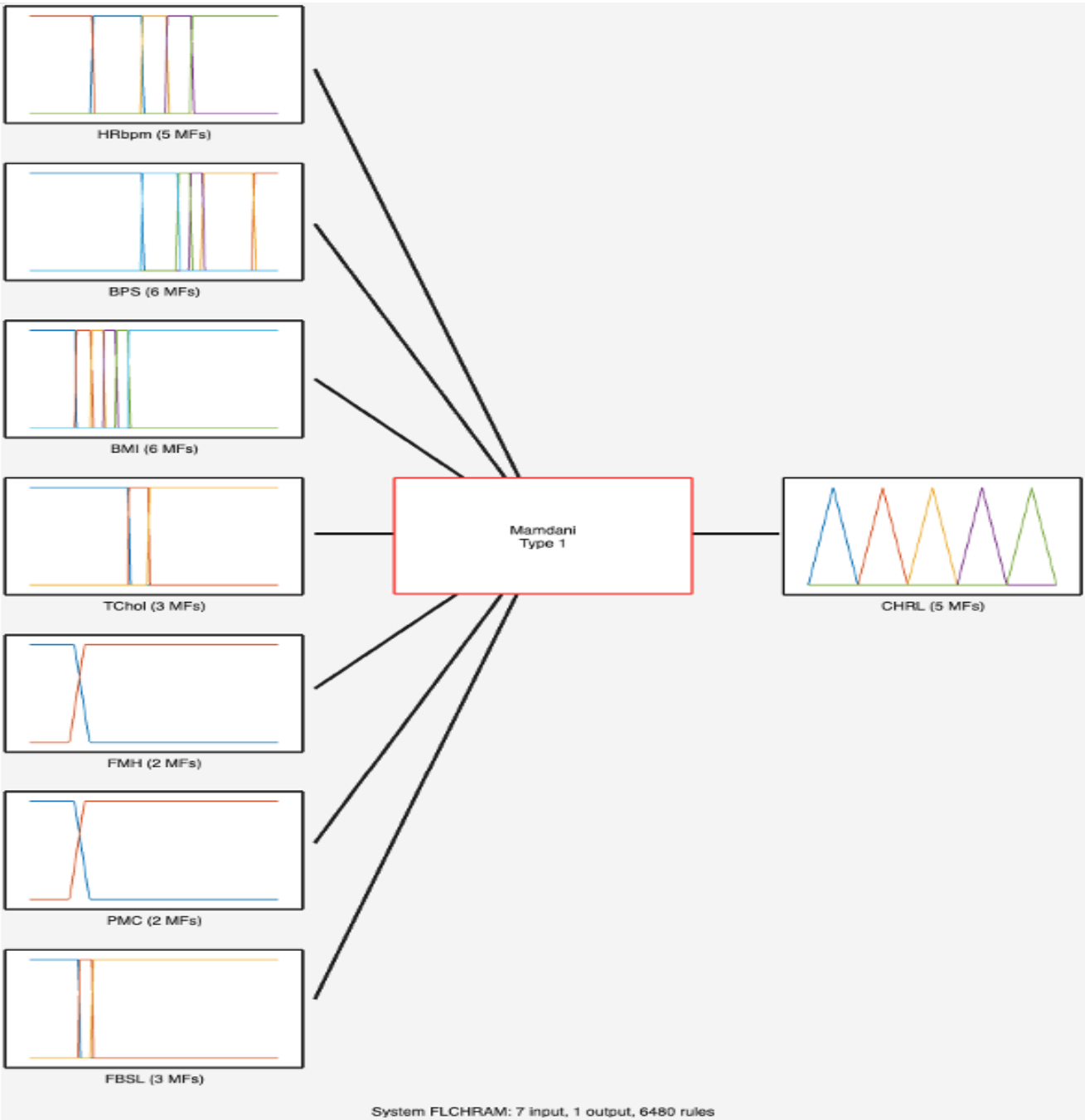


Figure 5: Fuzzy logic-based clinical health risk prediction model (FLCHRAM) properties

AI systems based on fuzzy logic can be utilized in medical fields to aid in risk assessment and detection of illnesses because of their ability to deal with uncertainties and inconsistencies in clinical data [11][35]. Figure 5 shows the fuzzy logic-based clinical health risk assessment model (FLCHRAM) properties which consist of 7 inputs representing physiological and anthropometric health risk indicators associated with DM and CVD, 6480 fuzzy rules (FRs), and 1 output corresponding to the patient's CHRL. The FLCHRAM model's architecture includes four components: the fuzzifier, the rule base, the inference engine, and the defuzzifier. The fuzzifier transformed the crisp input values from sensors, toggle switches, and medical data provided by the doctor via the ISAHMA into fuzzy sets. The process of fuzzification was accomplished by the utilization of membership functions (MFs), which associate degrees of membership in various fuzzy sets with input variables including HRbpm, BPS, BMI, TChol, FMH, PMC and FBSL. The fuzzy trapezoidal linguistic terms and parameters associated with each input variable are shown in Tables 5 to

11. Equations (4) to (30) were utilized to calculate the degree of membership for each fuzzy input using the trapezoid MF. Figures 6 to 12 illustrate the trapezoidal membership function plots corresponding to each fuzzy input variable.

The Mandami FLCHRAM FRs were made up of linguistic terms in if-then constructs to correlate the input data with health risk assessment. The FLCHRAM comprises of 6,480 FRs computed using Equation (31), which simulates how healthcare professionals make clinical decisions using various combinations of fuzzy input variables. The rules were developed to determine the clinical health risk associated with DM and CVD based on medical guidelines, clinical practices and doctor advice. Figure 13 shows some of the FLCHRAM rules as seen in MATLAB. The inference engine applied fuzzy rules to the fuzzified inputs, resulting in fuzzy outputs indicating the CHRL of patients associated with DM and CVD. The significance of each rule was evaluated based on the input data using the AND operation, and the results were then aggregated to generate a fuzzy output set. The defuzzification module translated the triangular fuzzy output set into a crisp value representing the assessed CHRL. The center of gravity (CoG) formula in Equation (32) was utilized in the development of the FLCHRAM, which converted the fuzzy outcomes into a definitive clinical health risk score that may be classified into one of the following levels: normal/very low, low, moderate, high, or very high risk. Figure 14 illustrates a triangular membership function graph for the fuzzy output variable. Table 12 shows the linguistic terms and parameters of the triangular MF for the CHRL. Equations (33) to (37) were used to compute the degree to which an output assessment belonged to a certain fuzzy set using an MF with triangular pattern.

Table 5: The parameters and equations of the trapezoidal MF for HRbpm

Fuzzy Input Variable	Linguistic Terms	Fuzzy Trapezoidal parameters	Trapezoidal MF Equations	
HRbpm	Low HRbpm – Low Health Risk (LHR_LR)	[0, 0, 50, 52]	$\mu_{LHR_LR}(x) = \begin{cases} 1 & \text{if } x \leq 50 \\ (52 - x) / (52 - 50) & \text{if } 50 < x < 52 \\ 0 & \text{if } x \geq 52 \end{cases}$	(4)
	Normal HRbpm – Very Low Health Risk (NRMHR_VLR)	[49, 51, 90, 92]	$\mu_{NRMHR_VLR}(x) = \begin{cases} 0 & \text{if } x \leq 49 \text{ or } x \geq 92 \\ (x - 49) / (51 - 49) & \text{if } 49 < x < 51 \\ 1 & \text{if } 51 \leq x \leq 90 \\ (92 - x) / (92 - 90) & \text{if } 90 < x < 92 \end{cases}$	(5)
	Moderate HRbpm – Moderate Health Risk (MHR_MR)	[89, 91, 110, 112]	$\mu_{MHR_MR}(x) = \begin{cases} 0 & \text{if } x \leq 89 \text{ or } x \geq 112 \\ (x - 89) / (91 - 89) & \text{if } 89 < x < 91 \\ 1 & \text{if } 91 \leq x \leq 110 \\ (112 - x) / (112 - 110) & \text{if } 110 < x < 112 \end{cases}$	(6)
	High HRbpm – High Health Risk (HHR_HR)	[109, 111, 130, 132]	$\mu_{HHR_HR}(x) = \begin{cases} 0 & \text{if } x \leq 109 \text{ or } x \geq 132 \\ (x - 109) / (111 - 109) & \text{if } 109 < x < 111 \\ 1 & \text{if } 111 \leq x \leq 130 \\ (132 - x) / (132 - 130) & \text{if } 130 < x < 132 \end{cases}$	(7)
	Very High HRbpm – Very High Health Risk (VHHR_VHR)	[129, 131, 200, 200]	$\mu_{VHHR_VHR}(x) = \begin{cases} 0 & \text{if } x \leq 129 \\ (y - 129) / (131 - 129) & \text{if } 129 < x < 131 \\ 1 & \text{if } x \geq 131 \end{cases}$	(8)

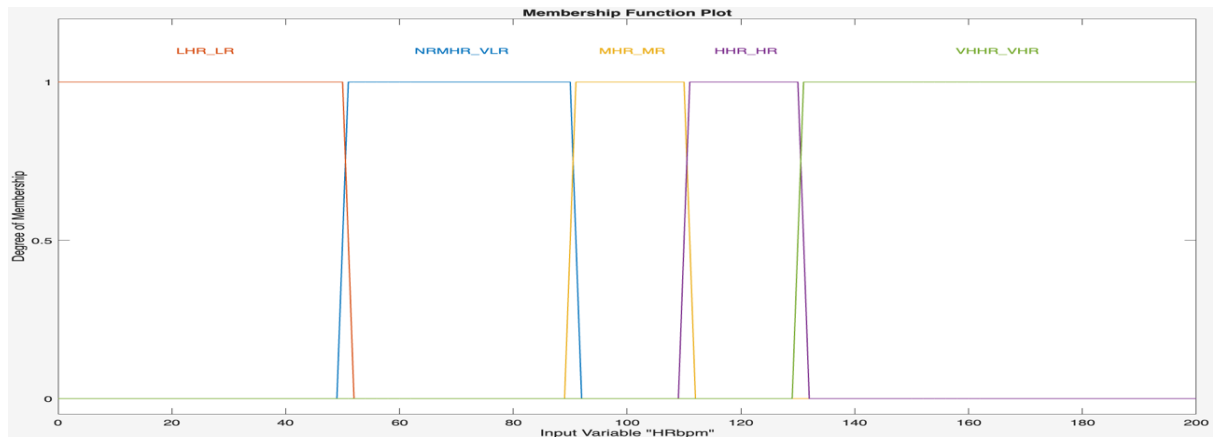


Figure 6: MF plot for HRbpm in trapezoidal pattern

Table 6: The parameters and equations of the trapezoidal MF for BPS

Fuzzy Input Variable	Linguistic Terms	Fuzzy Trapezoidal parameters	Trapezoidal MF Equations	
BPS	Low BPS – Moderate Health Risk (LBPS_MR)	[0, 0, 90, 92]	$\mu_{LBPS_MR}(x) = \begin{cases} 1 & \text{if } x \leq 90 \\ (92 - x) / (92 - 90) & \text{if } 90 < x < 92 \\ 0 & \text{if } x \geq 92 \end{cases}$	(9)
	Normal BPS – Very Low Health Risk (NRMBPS_VLR)	[89, 91, 119, 121]	$\mu_{NRMBPS_VLR}(x) = \begin{cases} 0 & \text{if } x \leq 89 \text{ or } x \geq 121 \\ (x - 89) / (91 - 89) & \text{if } 89 < x < 91 \\ 1 & \text{if } 91 \leq x \leq 119 \\ (121 - x) / (121 - 119) & \text{if } 119 < x < 121 \end{cases}$	(10)
	Elevated BPS – Low Health Risk (ELVBPS_LR)	[118, 120, 129, 131]	$\mu_{ELVBPS_LR}(x) = \begin{cases} 0 & \text{if } x \leq 118 \text{ or } x \geq 131 \\ (x - 118) / (120 - 118) & \text{if } 118 < x < 120 \\ 1 & \text{if } 120 \leq x \leq 129 \\ (131 - x) / (131 - 129) & \text{if } 129 < x < 131 \end{cases}$	(11)
	High BPS – Moderate Health Risk (HBPS_MR)	[128, 130, 139, 141]	$\mu_{HBPS_MR}(x) = \begin{cases} 0 & \text{if } x \leq 128 \text{ or } x \geq 141 \\ (x - 128) / (130 - 128) & \text{if } 128 < x < 130 \\ 1 & \text{if } 130 \leq x \leq 139 \\ (141 - x) / (141 - 139) & \text{if } 139 < x < 141 \end{cases}$	(12)
	Very High BPS – High Health Risk (VHBPS_HR)	[138, 140, 180, 182]	$\mu_{VHBPS_HR}(x) = \begin{cases} 0 & \text{if } x \leq 138 \text{ or } x \geq 182 \\ (x - 138) / (140 - 138) & \text{if } 138 < x < 140 \\ 1 & \text{if } 140 \leq x \leq 180 \\ (182 - x) / (182 - 180) & \text{if } 180 < x < 182 \end{cases}$	(13)
	Extremely High BPS – Very High Health Risk (EHBPS_VHR)	[179, 181, 200, 200]	$\mu_{EHBPS_VHR}(x) = \begin{cases} 0 & \text{if } x \leq 179 \\ (x - 179) / (181 - 179) & \text{if } 179 < x < 181 \\ 1 & \text{if } x \geq 181 \end{cases}$	(14)

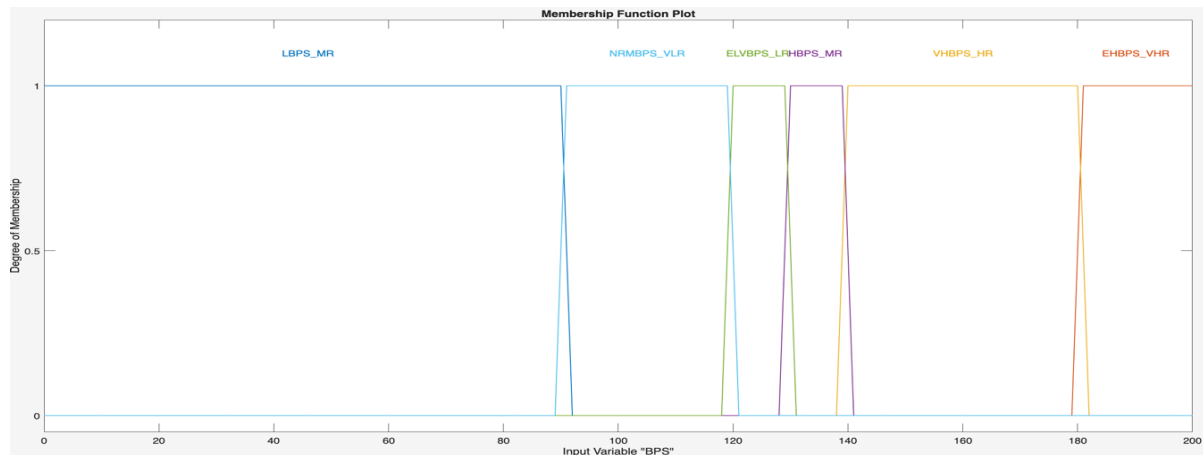


Figure 7: MF plot for BPS in trapezoidal pattern

Table 7: The parameters and equations of the trapezoidal MF for BMI

Fuzzy Input Variable	Linguistic Terms	Fuzzy Trapezoidal parameters	Trapezoidal MF Equations	
BMI	Underweight – Low Health Risk (UW_LR)	[0, 0, 18.4, 18.6]	$\mu_{UW_LR}(x) = \begin{cases} 1 & \text{if } x \leq 18.4 \\ (18.6 - x) / (18.6 - 18.4) & \text{if } 18.4 < x < 18.6 \\ 0 & \text{if } x \geq 18.6 \end{cases}$	(15)
	Normal Weight – Very Low Health Risk (NRM_VLR)	[18.3, 18.5, 24.9, 25.1]	$\mu_{NRM_VLR}(x) = \begin{cases} 0 & \text{if } x \leq 18.3 \text{ or } x \geq 25.1 \\ (x - 18.3) / (18.5 - 18.3) & \text{if } 18.3 < x < 18.5 \\ 1 & \text{if } 18.5 \leq x \leq 24.9 \\ (25.1 - x) / (25.1 - 24.9) & \text{if } 24.9 < x < 25.1 \end{cases}$	(16)
	Overweight – Moderate Health Risk (OW_MR)	[24.8, 25.0, 29.9, 30.1]	$\mu_{OW_MR}(x) = \begin{cases} 0 & \text{if } x \leq 24.8 \text{ or } x \geq 30.1 \\ (x - 24.8) / (25.0 - 24.8) & \text{if } 24.8 < x < 25.0 \\ 1 & \text{if } 25.0 \leq x \leq 29.9 \\ (30.1 - x) / (30.1 - 29.9) & \text{if } 29.9 < x < 30.1 \end{cases}$	(17)
	Obese Stage 1 – High Health Risk (OB1_HR)	[29.8, 30.0, 34.9, 35.1]	$\mu_{OB1_HR}(x) = \begin{cases} 0 & \text{if } x \leq 29.8 \text{ or } x \geq 35.1 \\ (x - 29.8) / (30.0 - 29.8) & \text{if } 29.8 < x < 30.0 \\ 1 & \text{if } 30.0 \leq x \leq 34.9 \\ (35.1 - x) / (35.1 - 34.9) & \text{if } 34.9 < x < 35.1 \end{cases}$	(18)
	Obese Stage 2 – Very High Health Risk (OB2_VHR)	[34.8, 35.0, 39.9, 40.1]	$\mu_{OB2_VHR}(x) = \begin{cases} 0 & \text{if } x \leq 34.8 \text{ or } x \geq 40.1 \\ (x - 34.8) / (35.0 - 34.8) & \text{if } 34.8 < x < 35.0 \\ 1 & \text{if } 35.0 \leq x \leq 39.9 \\ (40.1 - x) / (40.1 - 39.9) & \text{if } 39.9 < x < 40.1 \end{cases}$	(19)
	Obese Stage 3 – Extremely High Health Risk (OB3_EHR)	[39.8, 40.0, 100.0, 100.0]	$\mu_{OB3_EHR}(x) = \begin{cases} 0 & \text{if } x \leq 39.8 \\ (x - 39.8) / (40.0 - 39.8) & \text{if } 39.8 < x < 40.0 \\ 1 & \text{if } x \geq 40.0 \end{cases}$	(20)

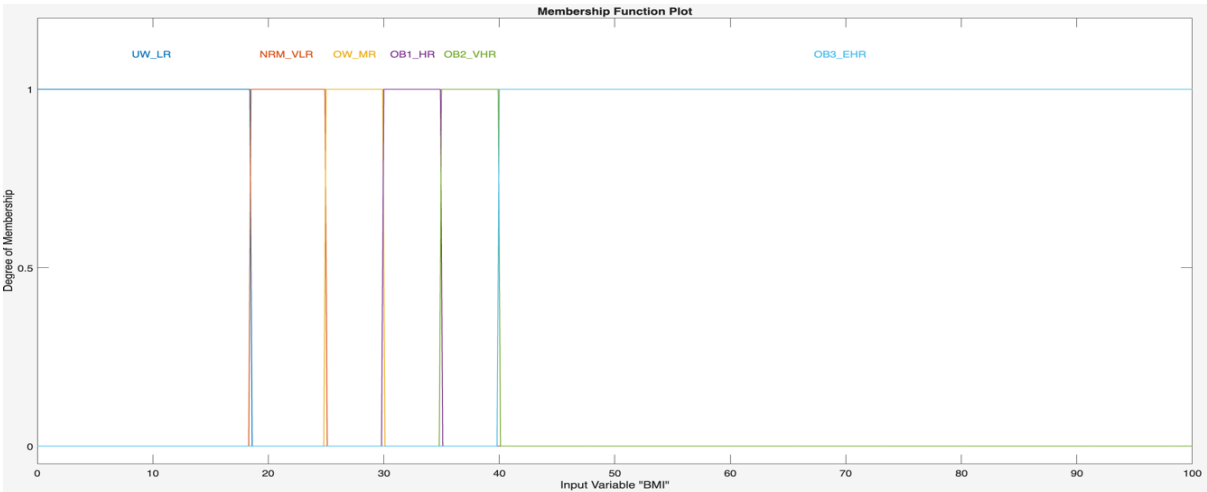


Figure 8: MF plot for BMI in trapezoidal pattern

Table 8: The parameters and equations of the trapezoidal MF for TChol

Fuzzy Input Variable	Linguistic Terms	Fuzzy Trapezoidal parameters	Trapezoidal MF Equations	
TChol	Normal TChol–Low Health Risk (NRMTChol_LR)	[0, 0, 199, 201]	$\mu_{NRMTChol_LR}(x) = \begin{cases} 1 & \text{if } x \leq 199 \\ (201 - x) / (201 - 199) & \text{if } 199 < x < 201 \\ 0 & \text{if } x \geq 201 \end{cases}$	(21)
	Moderately High TChol – Moderate Health Risk (MHTChol_MR)	[198, 200, 239, 241]	$\mu_{MHTChol_MR}(x) = \begin{cases} 0 & \text{if } x \leq 198 \text{ or } x \geq 241 \\ (x - 198) / (200 - 198) & \text{if } 198 < x < 200 \\ 1 & \text{if } 200 \leq x \leq 239 \\ (241 - x) / (241 - 239) & \text{if } 239 < x < 241 \end{cases}$	(22)
	High TC – High Health Risk (HTChol_HR)	[238, 240, 500, 500]	$\mu_{HTChol_HR}(x) = \begin{cases} 0 & \text{if } x \leq 238 \\ (x - 238) / (240 - 238) & \text{if } 238 < x < 240 \\ 1 & \text{if } x \geq 240 \end{cases}$	(23)

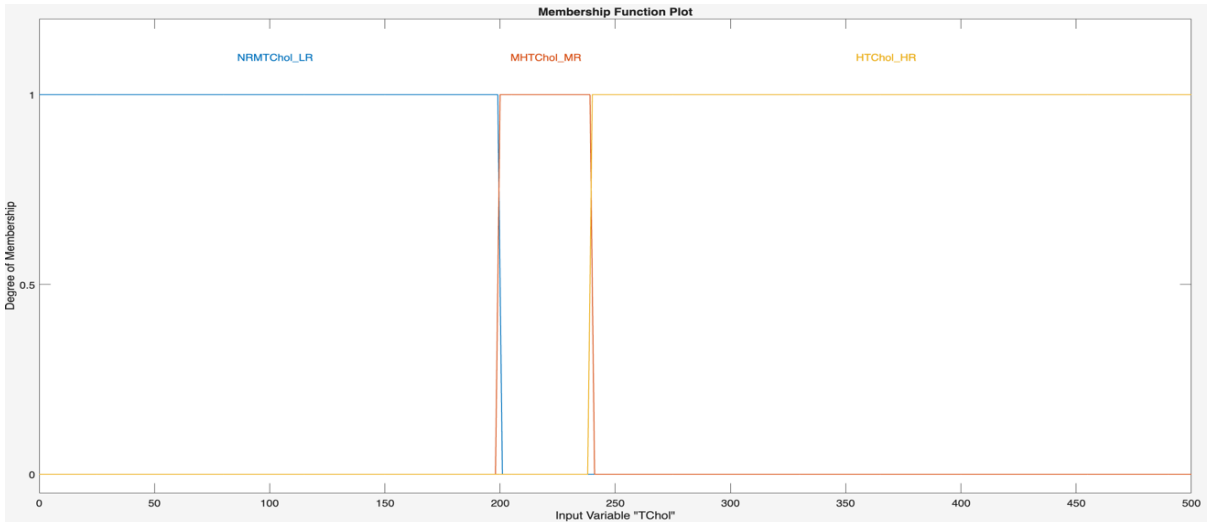


Figure 9: MF plot for TChol in trapezoidal pattern

Table 9: The parameters and equations of the trapezoidal MF for FMH

Fuzzy Input Variable	Linguistic Terms	Fuzzy Trapezoidal parameters	Trapezoidal MF Equations
FMH	No family medical history of DM and/or CVD (FMH-)	[0, 0, 0.9, 1.1]	$\mu_{FMH-}(x) = \begin{cases} 1 & \text{if } x \leq 0.9 \\ (1.1 - x) / (1.1 - 0.9) & \text{if } 0.9 < x < 1.1 \\ 0 & \text{if } x \geq 1.1 \end{cases} \quad (24)$
	With family medical history of DM and/or CVD (FMH+)	[0.8, 1, 5, 5]	$\mu_{FMH+}(x) = \begin{cases} 0 & \text{if } x \leq 0.8 \\ (x - 1) / (1 - 0.8) & \text{if } 0.8 < x < 1 \\ 1 & \text{if } x \geq 1 \end{cases} \quad (25)$

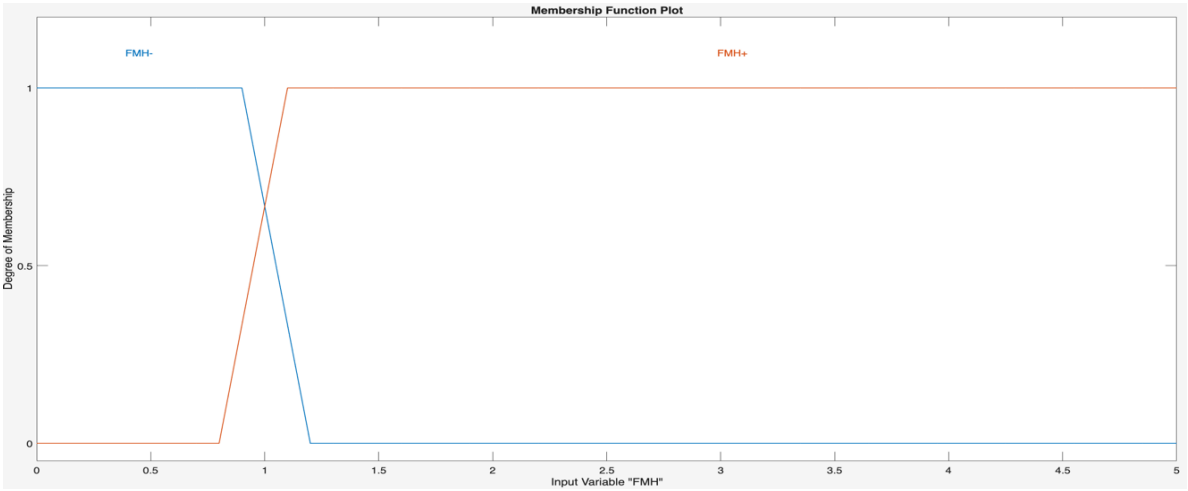


Figure 10: MF plot for FMH in trapezoidal pattern

Table 10: The parameters and equations of the trapezoidal MF for PMC

Fuzzy Input Variable	Linguistic Terms	Fuzzy Trapezoidal parameters	Trapezoidal MF Equations
PMC	No Pre-existing DM and/or CVD (PMC-)	[0, 0, 0.9, 1.1]	$\mu_{PMC-}(x) = \begin{cases} 1 & \text{if } x \leq 0.9 \\ (1.1 - x) / (1.1 - 0.9) & \text{if } 0.9 < x < 1.1 \\ 0 & \text{if } x \geq 1.1 \end{cases} \quad (26)$
	With Pre-existing DM and/or CVD (PMC+)	[0.8, 1, 5, 5]	$\mu_{PMC+}(x) = \begin{cases} 0 & \text{if } x \leq 0.8 \\ (x - 1) / (1 - 0.8) & \text{if } 0.8 < x < 1 \\ 1 & \text{if } x \geq 1 \end{cases} \quad (27)$

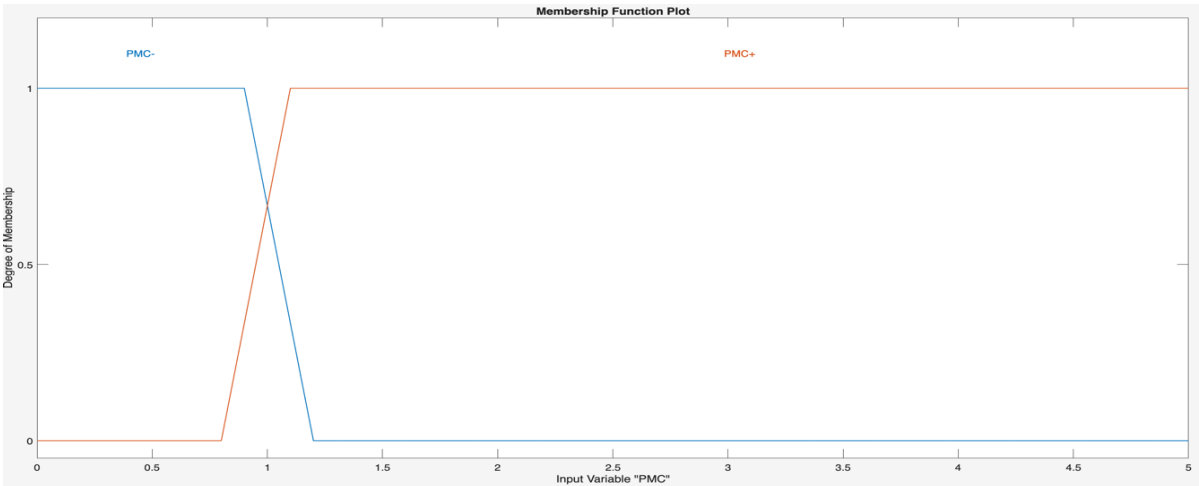


Figure 11: MF plot for PMC in trapezoidal pattern

Table 11: The parameters and equations of the trapezoidal MF for FBSL

Fuzzy Input Variable	Linguistic Terms	Fuzzy Trapezoidal parameters	Trapezoidal MF Equations	
FBSL	Normal FBSL–Low Health Risk (NRMFBSL_LR)	[0, 0, 99, 101]	$\mu_{\text{NRMFBSL_LR}}(x) = \begin{cases} 1 & \text{if } x \leq 99 \\ (101 - x) / (101 - 99) & \text{if } 99 < x < 101 \\ 0 & \text{if } x \geq 101 \end{cases}$	(28)
	Pre-Diabetes Mellitus FBSL – Moderate Health Risk (PreDM_MR)	[98, 100, 125, 127]	$\mu_{\text{PreDM_MR}}(x) = \begin{cases} 0 & \text{if } x \leq 98 \text{ or } x \geq 127 \\ (x - 98) / (100 - 98) & \text{if } 98 < x < 100 \\ 1 & \text{if } 100 \leq x \leq 125 \\ (127 - x) / (127 - 125) & \text{if } 125 < x < 127 \end{cases}$	(29)
	Diabetes Mellitus – High Health Risk (DM_HR)	[124, 126, 500, 500]	$\mu_{\text{DM_HR}}(x) = \begin{cases} 0 & \text{if } x \leq 124 \\ (x - 124) / (126 - 124) & \text{if } 124 < x < 126 \\ 1 & \text{if } x \geq 126 \end{cases}$	(30)

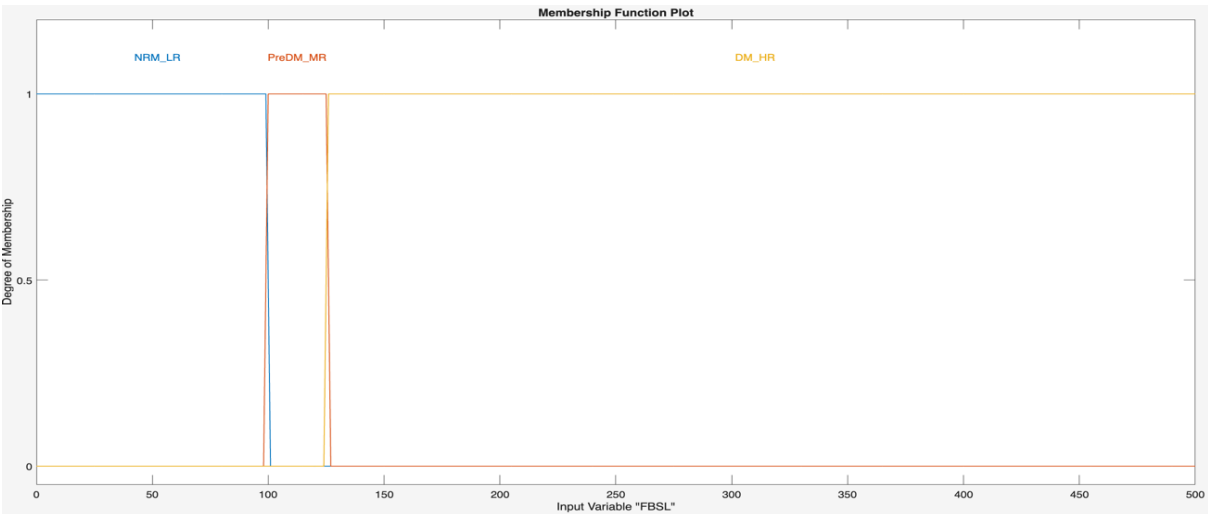


Figure 12: MF plot for FBSL in trapezoidal pattern

	Rule
1	If HRbpm is NRMHR_VLR and BPS is LBPS_MR and BMI is UW_LR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is M_CHR
2	If HRbpm is LHR_LR and BPS is LBPS_MR and BMI is UW_LR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is M_CHR
3	If HRbpm is MHR_MR and BPS is LBPS_MR and BMI is UW_LR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is M_CHR
4	If HRbpm is HHR_HR and BPS is LBPS_MR and BMI is UW_LR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is H_CHR
5	If HRbpm is VHHR_VHR and BPS is LBPS_MR and BMI is UW_LR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is VH_CHR
6	If HRbpm is NRMHR_VLR and BPS is EHBPS_VHR and BMI is UW_LR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is VH_CHR
7	If HRbpm is LHR_LR and BPS is EHBPS_VHR and BMI is UW_LR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is VH_CHR
8	If HRbpm is MHR_MR and BPS is EHBPS_VHR and BMI is UW_LR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is VH_CHR
9	If HRbpm is HHR_HR and BPS is EHBPS_VHR and BMI is UW_LR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is VH_CHR
10	If HRbpm is VHHR_VHR and BPS is EHBPS_VHR and BMI is UW_LR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is VH_CHR
51	If HRbpm is NRMHR_VLR and BPS is ELVBPS_LR and BMI is NRM_VLR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is L_CHR
52	If HRbpm is LHR_LR and BPS is ELVBPS_LR and BMI is NRM_VLR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is L_CHR
53	If HRbpm is MHR_MR and BPS is ELVBPS_LR and BMI is NRM_VLR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is M_CHR
54	If HRbpm is HHR_HR and BPS is ELVBPS_LR and BMI is NRM_VLR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is H_CHR
55	If HRbpm is VHHR_VHR and BPS is ELVBPS_LR and BMI is NRM_VLR and Tchol is NRMTchol_LR and FMH is FMH- and PMC is PMC- and FBSL is NRM_LR then CHRL is VH_CHR
56	If HRbpm is NRMHR_VLR and BPS is NRMbps_VLR and BMI is NRM_VLR and Tchol is NRMTchol_LR and FMH is FMH+ and PMC is PMC- and FBSL is NRM_LR then CHRL is NRM_VLCHR
57	If HRbpm is LHR_LR and BPS is NRMbps_VLR and BMI is NRM_VLR and Tchol is NRMTchol_LR and FMH is FMH+ and PMC is PMC- and FBSL is NRM_LR then CHRL is L_CHR
58	If HRbpm is MHR_MR and BPS is NRMbps_VLR and BMI is NRM_VLR and Tchol is NRMTchol_LR and FMH is FMH+ and PMC is PMC- and FBSL is NRM_LR then CHRL is M_CHR
59	If HRbpm is HHR_HR and BPS is NRMbps_VLR and BMI is NRM_VLR and Tchol is NRMTchol_LR and FMH is FMH+ and PMC is PMC- and FBSL is NRM_LR then CHRL is H_CHR
60	If HRbpm is VHHR_VHR and BPS is NRMbps_VLR and BMI is NRM_VLR and Tchol is NRMTchol_LR and FMH is FMH+ and PMC is PMC- and FBSL is NRM_LR then CHRL is VH_CHR
6476	If HRbpm is NRMHR_VLR and BPS is NRMbps_VLR and BMI is OB3_EHR and Tchol is HTchol_HR and FMH is FMH+ and PMC is PMC+ and FBSL is DM_HR then CHRL is VH_CHR
6477	If HRbpm is LHR_LR and BPS is NRMbps_VLR and BMI is OB3_EHR and Tchol is HTchol_HR and FMH is FMH+ and PMC is PMC+ and FBSL is DM_HR then CHRL is VH_CHR
6478	If HRbpm is MHR_MR and BPS is NRMbps_VLR and BMI is OB3_EHR and Tchol is HTchol_HR and FMH is FMH+ and PMC is PMC+ and FBSL is DM_HR then CHRL is VH_CHR
6479	If HRbpm is HHR_HR and BPS is NRMbps_VLR and BMI is OB3_EHR and Tchol is HTchol_HR and FMH is FMH+ and PMC is PMC+ and FBSL is DM_HR then CHRL is VH_CHR
6480	If HRbpm is VHHR_VHR and BPS is NRMbps_VLR and BMI is OB3_EHR and Tchol is HTchol_HR and FMH is FMH+ and PMC is PMC+ and FBSL is DM_HR then CHRL is VH_CHR

Figure 13: Some FLCHRAM fuzzy rules as seen in MATLAB

$$FR_{total} = MF_{HRbpm} \times MF_{BPS} \times MF_{BMI} \times MF_{Tchol} \times MF_{FMH} \times MF_{PMC} \times MF_{FBSL}$$

$$FR_{total} = 5 \times 6 \times 6 \times 3 \times 2 \times 2 \times 3 = 6480 \text{ rules} \quad (31)$$

$$CoG = \frac{\sum_{j=1}^N \mu(x_j) * x_j}{\sum_{j=1}^N \mu(x_j)} \quad (32)$$

Where:

CoG is the center of gravity which represents the balance point of a fuzzy set.

x_j represents each discrete output variable values.

$\mu(x_j)$ denotes the membership function value or degree of membership at each x_j .

N represents the total number of discrete points or fuzzy output values in the fuzzy set.

$\sum \mu(x_j) * x_j$ is the sum of the products of each value x_j and its corresponding membership value $\mu(x_j)$.

$\sum \mu(x_j)$ is the total sum of all membership values, ensuring normalization.

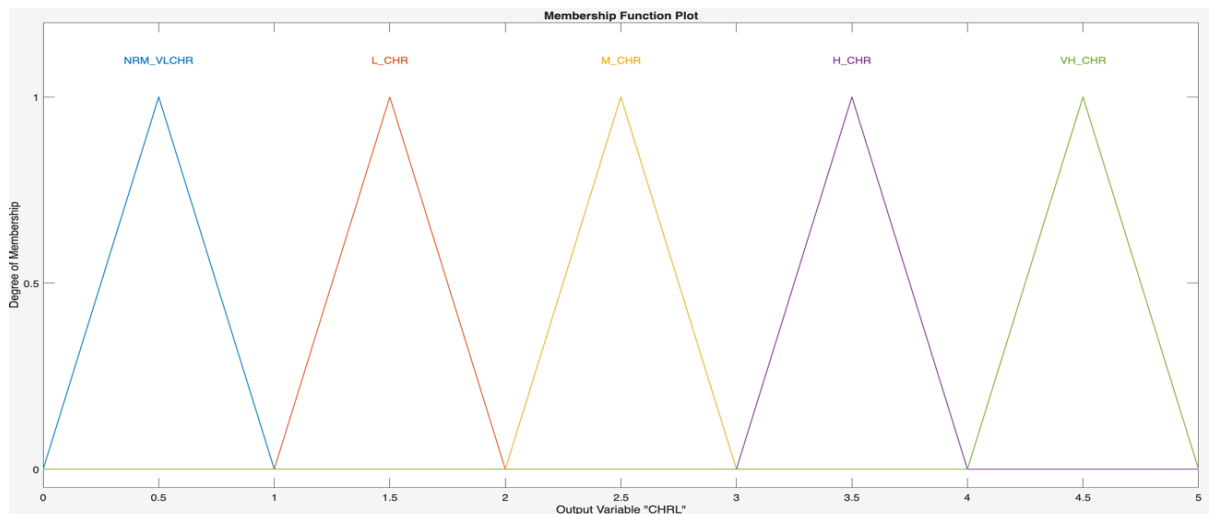


Figure 14: MF plot for CHRL in triangular pattern

Table 12: The parameters and equations of the triangular MF for CHRL

Fuzzy Output Variable	Linguistic Variables	Fuzzy Triangular parameters	Triangular MF Equations	
CHRL	Normal / Very Low Clinical Health Risk Level (NRM_VLCHR)	[0, 0.5, 1]	$\mu_{NRM_VLCHR}(x) = \begin{cases} 0 & \text{if } x < 0 \\ (x - 0) / (0.5 - 0) & \text{if } 0 \leq x \leq 0.5 \\ (1 - x) / (1 - 0.5) & \text{if } 0.5 < x \leq 1 \\ 0 & \text{if } x > 1 \end{cases}$	(33)
	Low Clinical Health Risk Level (L_CHR)	[1, 1.5, 2]	$\mu_{L_CHR}(x) = \begin{cases} 0 & \text{if } x < 1 \\ (x - 1) / (1.5 - 1) & \text{if } 1 \leq x \leq 1.5 \\ (2 - x) / (2 - 1.5) & \text{if } 1.5 < x \leq 2 \\ 0 & \text{if } x > 2 \end{cases}$	(34)
	Moderate Clinical Health Risk Level (M_CHR)	[2, 2.5, 3]	$\mu_{M_CHR}(x) = \begin{cases} 0 & \text{if } x < 2 \\ (x - 2) / (2.5 - 2) & \text{if } 2 \leq x \leq 2.5 \\ (3 - x) / (3 - 2.5) & \text{if } 2.5 < x \leq 3 \\ 0 & \text{if } x > 3 \end{cases}$	(35)
	High Clinical Health Risk Level (H_CHR)	[3, 3.5, 4]	$\mu_{H_CHR}(x) = \begin{cases} 0 & \text{if } x < 3 \\ (x - 3) / (3.5 - 3) & \text{if } 3 \leq x \leq 3.5 \\ (4 - x) / (4 - 3.5) & \text{if } 3.5 < x \leq 4 \\ 0 & \text{if } x > 4 \end{cases}$	(36)
	Very High Clinical Health Risk Level (VH_CHR)	[4, 4.5, 5]	$\mu_{VH_CHR}(x) = \begin{cases} 0 & \text{if } x < 4 \\ (x - 4) / (4.5 - 4) & \text{if } 4 \leq x \leq 4.5 \\ (5 - x) / (5 - 4.5) & \text{if } 4.5 < x \leq 5 \\ 0 & \text{if } x > 5 \end{cases}$	(37)

C. Design and implementation of the Interactive Smartphone Application for Health Monitoring and Assessment (ISAHMA)

The interactive smartphone application for health monitoring and assessment (ISAHMA) was created using MIT App Inventor 2. MIT App Inventor is a programming environment that uses virtual blocks to create mobile applications for smartphones and tablets operating on Android or iOS systems [25], [36]. Designed as an interface with IoT devices, the ISAHMA connects to the internet to access ThingSpeak cloud, retrieve data from the MariaDB database, and interact with other web interfaces. The text-to-speech component in MIT App Inventor shows how Natural Language Programming (NLP), a form of AI, was integrated with ISAHMA to make the system easier to navigate and improve its functionality [37]. The ISAHMA provides users with instructions and results by touching the speaker icon on the app screen.

Figure 15(a) shows the ISAHMA splash screen, which provides system information and enables users to log in or register as new users. Upon successful registration, access can be gained by entering the correct username and password on the login screen, as illustrated in Figure 15(b). With the entry of invalid credentials, the ISAHMA will revert to the welcome page. After three failed attempts, the user is blocked and must contact the administration at email@btms.cloud to restore access. Figure 16 displays the home screens for the patient and doctor, respectively, after a successful login, indicating the user's access privileges. The auditory instructions guide the user through the several options accessible by pressing the speaker icon. Figure 16(a) illustrates that the ISAHMA enables patients to upload, view, and save their physiological and anthropometric data, health reports, and clinical recommendations

obtained from the IBTMS. Patients can also use ISAHMA to access their own blood chemistry profiles taken in hospitals or entered into the system by the doctor, input their FMH and PMC, view their FLCHRAM results, perform tele-video conferencing with the doctor, send SMS to schedule consultations, and share images of medical results with healthcare professionals (HCP). As shown in Figure 16(b), ISAHMA allows doctors to add, view, and store physiological and anthropometric parameters of registered patients collected remotely using the IBTMS. ISAHMA also enables doctors to add and view blood chemistry profiles of patients obtained from hospitals or polyclinics, use the FLCHRAM for health risk assessment, update the clinical recommendations, conduct tele-video consultations, share medical results and prescriptions with patients, and send text messages to patients.

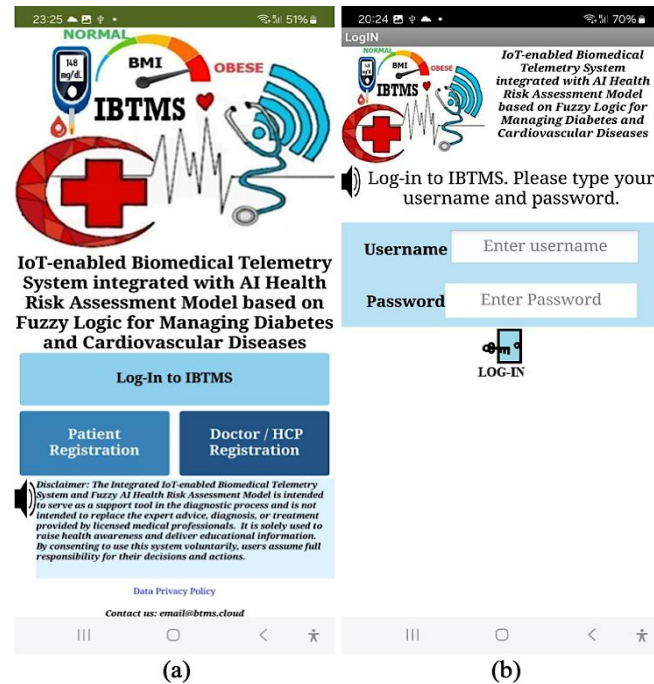


Figure 15: ISAHMA introductory screens: (a) splash screen and (b) log-in screen

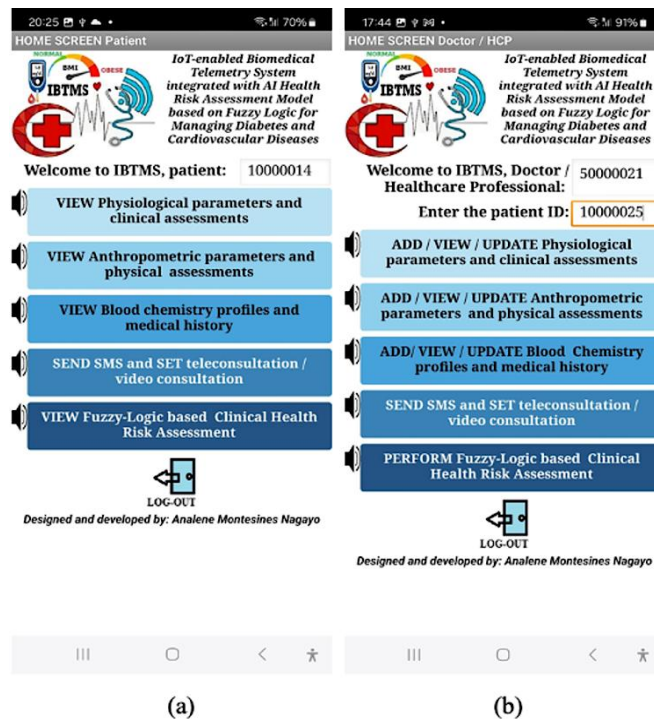


Figure 16: Home Screen for (a) patient and (b) doctor

ISAHMA telemedicine services were created using MIT App Inventor's non-visible social components and the WhatsApp tool extension. Figure 17(a) shows how the patient booked an appointment with the doctor by sending a text message via the ISAHMA and Figure 17(b) illustrates the SMS received on the doctor's phone. Figure 18 illustrates how the IMABTMS telemedicine platform allowed the patient to request and participate in video conferences with healthcare experts.

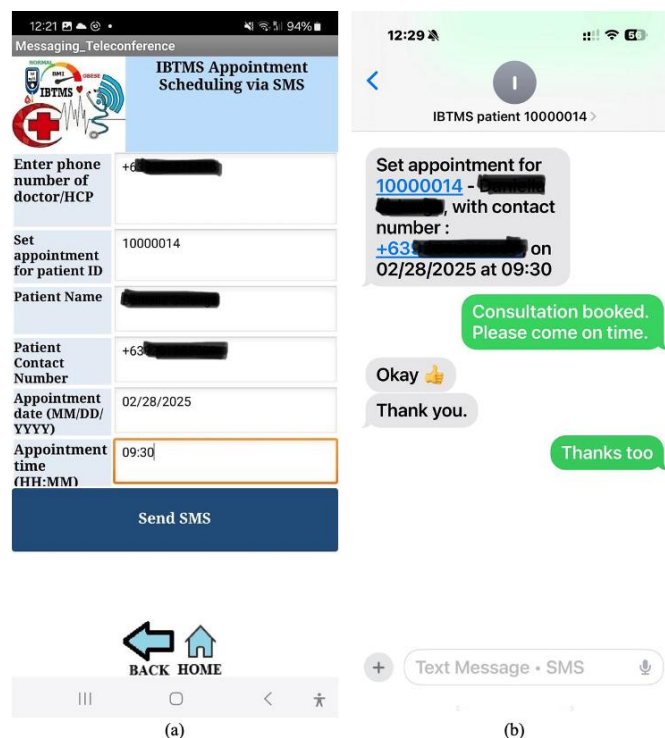


Figure 17: (a) Sample medical consultation booking utilizing the ISAHMA via SMS, and (b) the corresponding SMS received on the doctor's phone.

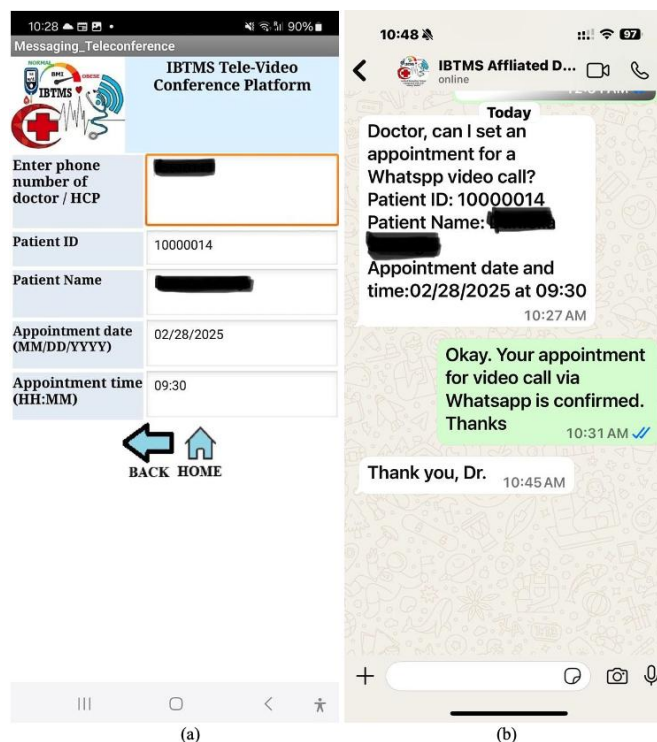


Figure 18: (a) Sample tele-video consultation booking utilizing the ISAHMA via WhatsApp, and (b) the corresponding WhatsApp message received on the doctor's phone.

RESULTS AND DISCUSSION

A. Results and discussion of the IoT-based Biomedical Telemetry System (IBTMS) for monitoring and analyzing physiological parameters

The physiological parameters of 50 adult human subjects, ages 20–65, who volunteered to act as patients, were measured non-invasively through the attachment of the IBTMS prototype. Each volunteer signed a consent form before proceeding with the testing. The sensors used in the system were calibrated with commercially available medical equipment before their deployment for testing, as conducted by [11] and [25]. Figure 19 illustrates the process of measuring the patient's physiologic signs using the IBTMS. The MAX30205 BTemp sensor was attached to the patient's body. The SpO2% level was measured by inserting the pointing finger into the IBTMS pulse oximeter with the MAX30100 sensor. The RRpm was determined while wearing a mask with an MLX90614 non-contact IR temperature sensor attached to it for monitoring changes in the inhale and exhale breathing temperatures. The PAS of the patient was set by toggling SW2 in the IBTMS prototype. Figure 20 shows that the sensor-read parameters of the IBTMS for patient 10000001 were comparable to the measurements obtained from medical-grade testing instruments, with minor discrepancies due to sensor placement and motion artifacts. Referring to Figure 20, the percent differences between the BTemp, RR, and SpO2 readings from the two systems were 0%. On the other hand, the two systems' BPS and HRbpm values differ by 1.98% and 1.63%, respectively.



Figure 19: Physiological signs measurement using the IBTMS prototype

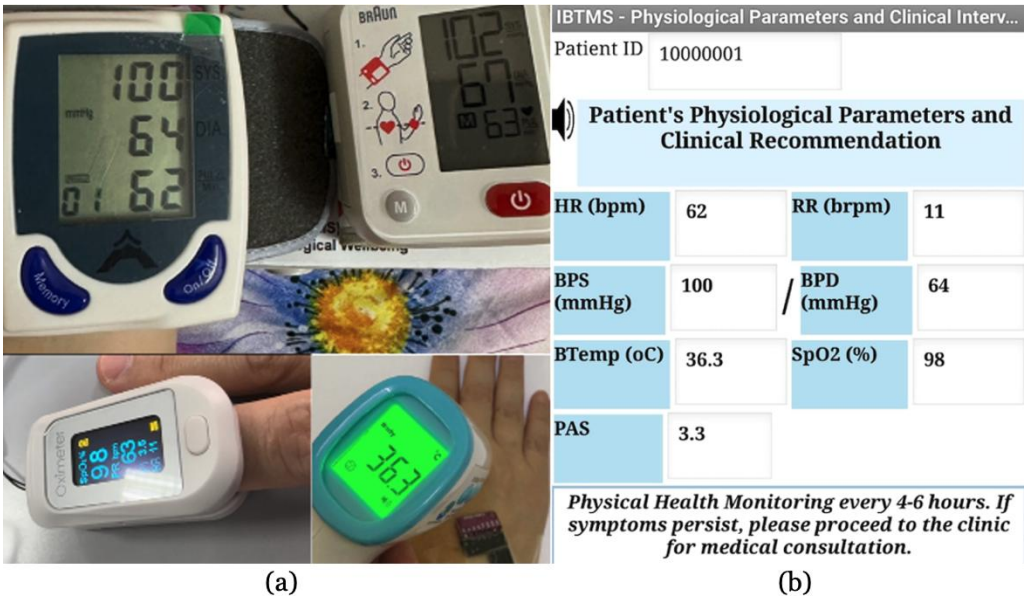


Figure 20: Sensor-read data using (a) medical-grade test devices and (b) IBTMS as displayed on ISAHMA screen

Figure 21 shows sample physiological signs and health assessments of patient 10000014 that were gathered from the IBTMS prototype and shown in the ISAHMA screens. The ISAHMA interface displayed the real-time graphs for each physiological parameter reading obtained from the ThingSpeak cloud. The assessment for each parameter based on Table 1 was also shown on screen. Based on Figures 21(a) and 21(c), the patient had a normal BTemp, HRbpm, RRrpm, and SpO2%. The patient was not experiencing any pain during the test as indicated in Fig. 21(d). However, the BP shown in Figure 21(b) was moderately high, so the system recommended the monitoring of vital signs on a 12 to 24 hour basis. The system generated the clinical recommendation based on the published works of [11] and the clinical guidelines of [28] and [38]. All physiological values and assessments were kept in the MariaDB database server for medical record purposes, as indicated in Figure 21(f).

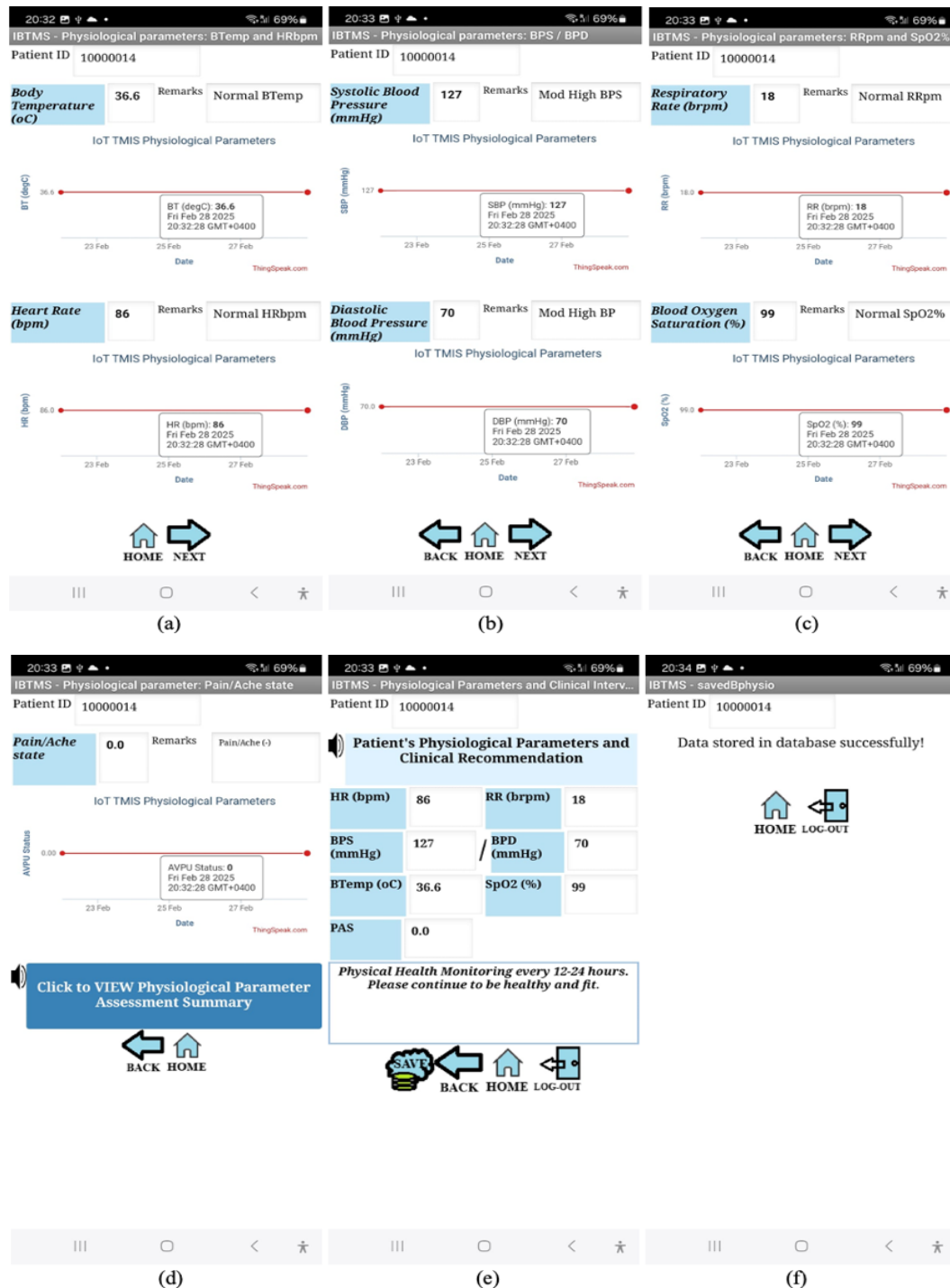


Figure 21: Sample physiological parameters and health assessments of patient 10000014 obtained using the IBTMS prototype

B. Results and discussion of the monitoring and analysis of anthropometric parameters using the Internet of Things-based Biomedical Telemetry System (IBTMS) and Interactive Smartphone Application for Health Monitoring and Assessment (ISAHMA)

Calibration procedures were performed on the IBTMS prototype, which was done for ensuring reliable measurements. The weight and height values were calibrated by comparing them to those from a commercially available weighing scale and stadiometer, respectively. Figure 22 indicates that the sensor-acquired Wkg and Hcm of patient 10000001 utilizing the IBTMS prototype were identical to those obtained with commercially available equipment, with slight difference due to patient position and weight distribution. Based on Figure 22, the patient's Wkg obtained with the IBTMS prototype was 62.1 kg, but the Wkg obtained using a commercially available digital weighing scale was 62.0 kg. Figure 22 shows that the Hcm measurement using the IBTMS was 157.98 cm, whereas the Hcm measurement using a stadiometer stick was 158 cm. The percent differences between the Wkg and Hcm readings from the two systems were 0.161% and 0.013%, respectively.

Figures 23(a) and 23(b) present samples of anthropometric measurements, fitness evaluations, and wellness recommendations for patients 10000001 and 10000014, respectively, seen in the ISAHMA screens. The BMI, BFP, and BMR were calculated using mobile technology, with Wkg, Hcm, and GI acquired from the IBTMS prototype, while A and LFS were entered using a mobile device. The BMI measurements calculated by the ISAHMA were close to the value acquired from a web-based adult BMI calculator found on [39], with percent differences of no more than 0.147%, as shown in Table 13. Based on Table 14, the ISAHMA-computed BFP values were comparable to those obtained using the online BFP calculator from [40], with percentage differences of no more than 0.148%. Furthermore, the ISAHMA-calculated BMR values in Table 15 were identical to those generated using the online BMR calculator from [41], with percent differences of less than 0.1%. The small percentage differences were obtained in BMI, BFP and BMR due to rounding conventions between the two systems. According to the fitness assessment, wellness recommendations from [32] and recommended daily calorie intake from [33] were displayed on the smartphone screen to help the patient maintain a healthy lifestyle. To keep the fitness assessments for future use, ISAHMA prompts the user to click the save icon on the screen, which stores the results to the ThingSpeak and MariaDB database servers.

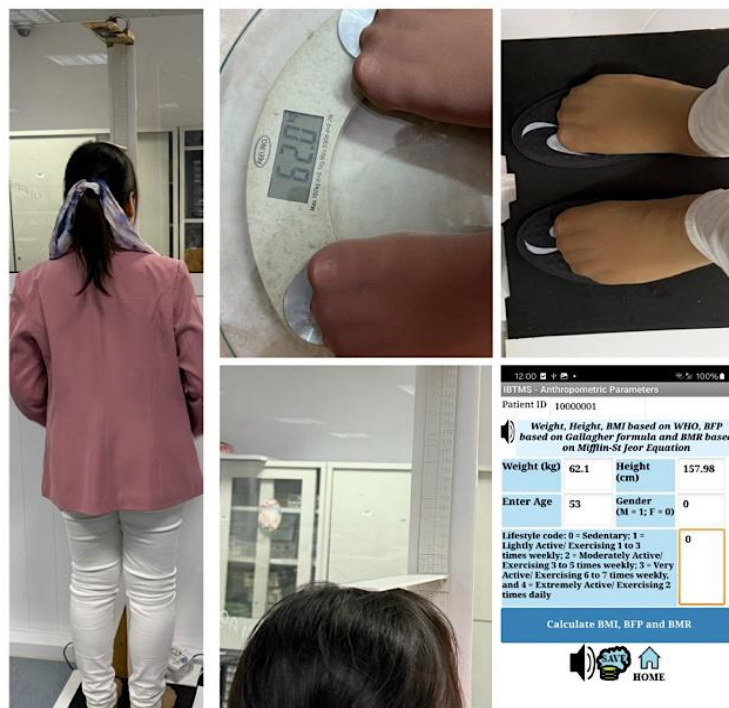


Figure 22: Wt and Hcm measurements using the IBTMS prototype and commercially available equipment

Table 13: Comparison table of computed BMI and classifications using ISAHMA and online BMI calculator on [39]

Patient ID	Wkg	Hcm	QI / BMI using ISAHMA	QI / BMI classification from ISAHMA	QI / BMI using [43]	QI / BMI classification using [43]	% difference between BMI measurements
10000001	62.1	157.98	24.88	Normal	24.9	Normal / Healthy Weight	0.080
10000002	67.0	165.10	24.58	Normal	24.6	Normal / Healthy Weight	0.081
10000007	68.0	158.00	27.24	Overweight	27.2	Overweight	0.147
10000008	84.0	176.00	27.12	Overweight	27.1	Overweight	0.074
10000009	71.0	170.18	24.52	Normal	24.5	Normal / Healthy Weight	0.082
10000011	64.0	152.40	27.56	Overweight	27.6	Overweight	0.145
10000012	90.0	154.00	37.95	Obese class II	37.9	Obese class II	0.132
10000014	82.6	163.00	31.09	Obese class I	31.1	Obese class I	0.032
10000025	76.0	164.00	28.26	Overweight	28.3	Overweight	0.141
10000028	74.5	164.59	27.50	Overweight	27.5	Overweight	0.000

Table 14: Comparison table of calculated BFP using ISAHMA and online BFP calculator on [40]

Patient ID	Wkg	Hcm	GI	A	LSF	QI / BMI	BFP using ISAHMA	PBF classification	BFP using [44]	% difference between BFP values
10000001	62.1	157.98	0	53	0	24.88	33.75	Normal	33.7	0.148
10000002	67.0	165.10	1	51	0	24.58	21.43	Normal	21.4	0.140
10000007	68.0	158.00	1	53	1	27.24	25.59	Overweight	25.6	0.039
10000008	84.0	176.00	1	46	0	27.12	24.43	Overweight	24.4	0.123
10000009	71.0	170.18	1	57	0	24.52	22.17	Overweight	22.2	0.135
10000011	64.0	152.40	0	63	0	27.56	39.05	Overweight	39.1	0.128
10000012	90.0	154.00	0	27	0	37.95	49.19	Obese	49.2	0.020
10000014	82.6	163.00	0	27	0	31.09	39.17	Obese	39.2	0.077
10000025	76.0	164.00	0	27	0	28.26	35.04	Overweight	35.0	0.114
10000028	81.2	164.59	1	53	1	29.97	29.58	Obese	29.6	0.068

Table 15: Comparison table of calculated BMR using ISAHMA and web-based BMR calculator on [41]

Patient ID	Wkg	Hcm	GI	A	LSF	BMR using ISAHMA	BMR using [45]	% difference between BMR values	Wellness recommendation from [32] and suggested daily caloric intake from [33]
10000001	62.1	157.98	0	53	0	1182	1182	0.000	Continue eating healthy food. Keep your calorie intake to 1418.85 Kcal / day. Maintain your body weight. Do exercise and sleep well.
10000002	67.0	165.10	1	51	0	1452	1452	0.000	Continue eating healthy food. Keep your calorie intake to 1742.25 Kcal / day. Maintain your body weight. Do exercise and sleep well.
10000007	68.0	158.00	1	53	1	1408	1408	0.000	Eat balanced diet. Keep your calorie intake to 1935.3125 Kcal / day. Increase physical activity.
10000008	84.0	176.00	1	46	0	1715	1715	0.000	Eat balanced diet. Keep your calorie intake per day to 2058 Kcal/day. Increase physical activity. Do exercise for 150 to 300 minutes per week.
10000009	71.0	170.18	1	57	0	1494	1494	0.000	Continue eating healthy food. To maintain your body weight, keep your calorie intake to 1792.35 Kcal/day. Do exercise and sleep well.
10000011	64.0	152.40	0	63	0	1116	1117	0.090	Eat balanced diet. Keep your calorie intake per day to 1339.8 Kcal/day. Increase physical activity. Do exercise for 150 to 300 minutes per week.
10000012	90.0	154.00	0	27	0	1566	1567	0.064	Eat balanced diet. Keep your calorie intake to 1879.8 Kcal / day. Do exercise for 150 to 300 minutes per week. Consult with endocrinologist and dietitian.
10000014	82.6	163.00	0	27	0	1549	1549	0.000	Eat balanced diet. Keep your calorie intake per day to 1858.5 Kcal/day. Do exercise for 150 to 300 minutes per week. Consult with endocrinologist and dietitian.
10000025	76.0	164.00	0	27	0	1489	1489	0.000	Eat balanced diet. Keep your calorie intake per day to 1786.8 Kcal/day. Do exercise for 150 to 300 minutes per week. Consult with endocrinologist and dietitian.
10000028	81.2	164.59	1	53	1	1581	1581	0.000	Eat balanced diet. Keep your calorie intake per day to 2173.44531 Kcal/day. Increase physical activity.

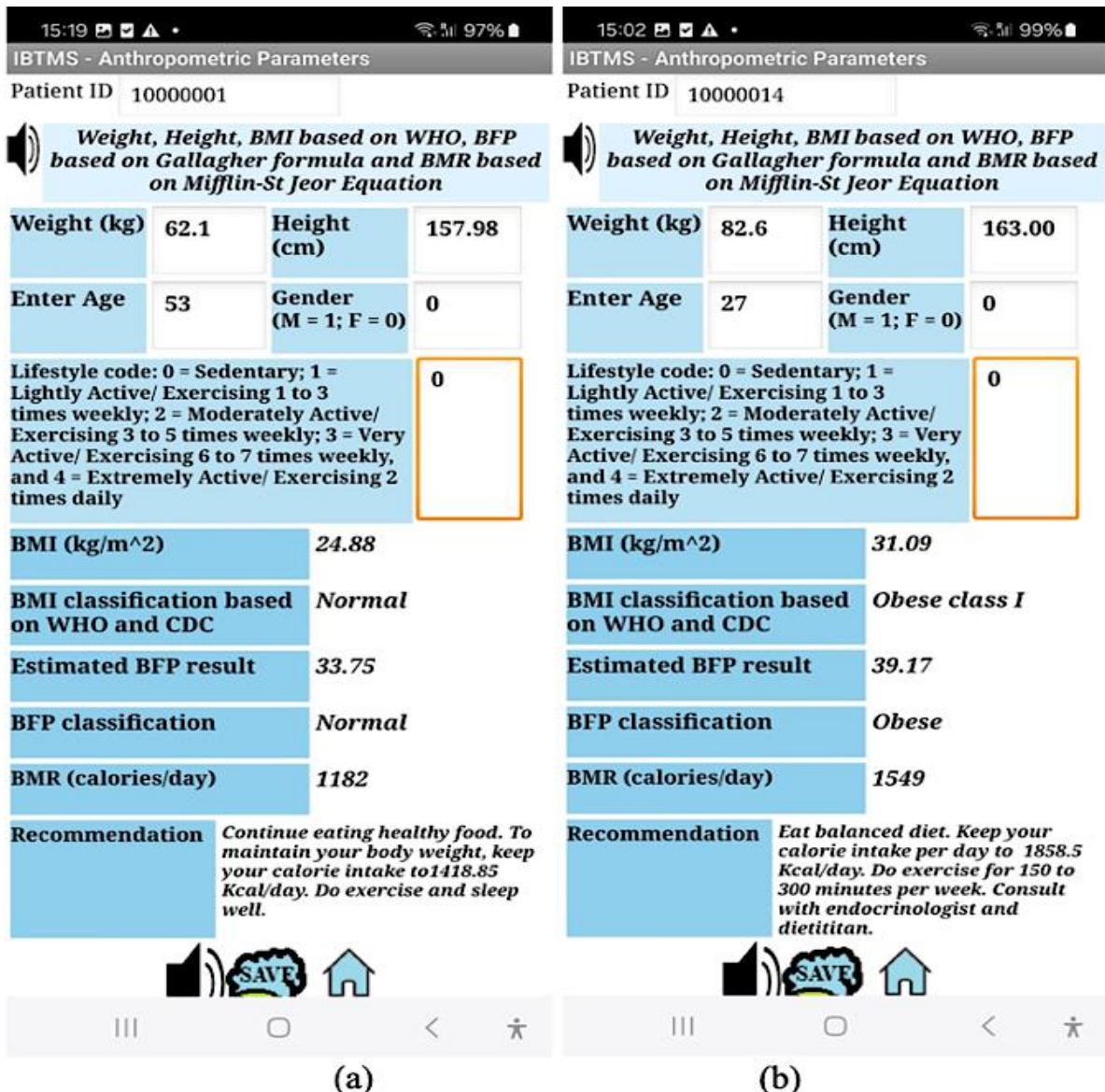


Figure 23: Sample anthropometric measurements, fitness assessments and wellness recommendations for patient (a) 10000001 and (b) 10000014 obtained using the IBTMS prototype

C. Results and discussion of the monitoring and evaluating blood chemistry profiles using the Internet of Things-based Biomedical Telemetry System (IBTMS) and Interactive Smartphone Application for Health Monitoring and Assessment (ISAHMA)

The ISAHMA screens for uploading and evaluating blood chemical profiles, as well as entry of FMH and PMC information for the patient, are shown in Figure 24. The smartphone application was developed to assess the patient's FBSL, RBSL, and TChol in accordance with medical standards. To provide FMH and PMC data, the patient toggles SW4 and SW5 in the IBTMS prototype and inputs the age on the mobile phone screen. The doctor or HCP enters the patient's FBSL and RBSL values in mg/dL into the ISAHMA app. Figure 24(a) shows a screen display of the blood glucose testing results based on [27] and [38]. ISAHMA characterizes a patient's TChol level after 8 hours of fasting as normal if it is less than 180 mg/dL, moderately high if it is between 180 and 240 mg/dL, and high if it is more than or equal to 240 mg/dL [29],[42]. According to the blood chemical profiles, ISAHMA determines the appropriate treatment method and makes recommendations for a healthy lifestyle, as seen in Figure 24(a). After entering the patient's FMC and PMC, ISAHMA prompts the user to save the data to the cloud platform and MariaDB database by clicking the appropriate button, as shown in Figure 24(b).

Referring to Figure 24(a), patient 10000002 had a normal FBSL of 93 mg/dL and an RBSL of 136 mg/dL. According to medical guidelines [27], normal FBSL is less than 100 mg/dL, and normal RBS is less than 140 mg/dL. On the

other hand, patient 10000014 was found to have pre-diabetes by the ISAHMA because the patient’s FBSL level was 102 mg/dL, as shown in Figure 25(a). According to [27], the pre-diabetes level for FBSL is 100 mg/dL to 125 mg/dL, while RBSL is 140 mg/dL to 199 mg/dL. Patient 10000007 was assessed as diabetic by the ISAHMA due to the patient's FBSL level of 184 mg/dL and RBSL of 188 mg/dL, as seen in Figure 26(a). Based on [27], an FBS of greater than or equal to 126 mg/dL or an RBS of 200 mg/dL or greater suggests diabetes. The results of the ISAHMA blood sugar test also matched the diagnosis made by a healthcare professional.

Furthermore, patient 10000014 showed a high TChol level of 263 mg/dl. According to established medical practices and guidelines, TChol values above 240 mg/dL are considered high, putting patients at risk for CVD [29], [42]–[43]. On the other hand, patient 10000002 had normal TChol levels of 145 mg/dL. According to [26], the TChol level should be less than 180 mg/dL to reduce cardiovascular risk. Patient 10000007 was found to have a moderately high TChol level of 210 mg/dL, according to the guidelines in [29] and [42]. In Figure 25(a), ISAHMA recommended patient 10000014, who had a high TC and was pre-diabetic, to minimize saturated fat intake, exercise regularly, and consult an endocrinologist. As shown in Figures 26(a) and 26(b), since patient 10000007 had a high FBSL, a family medical history of DM, and was pre-diagnosed with DM, ISAHMA advised the patient to follow a low-carbohydrate diet, exercise regularly, and consult an endocrinologist.

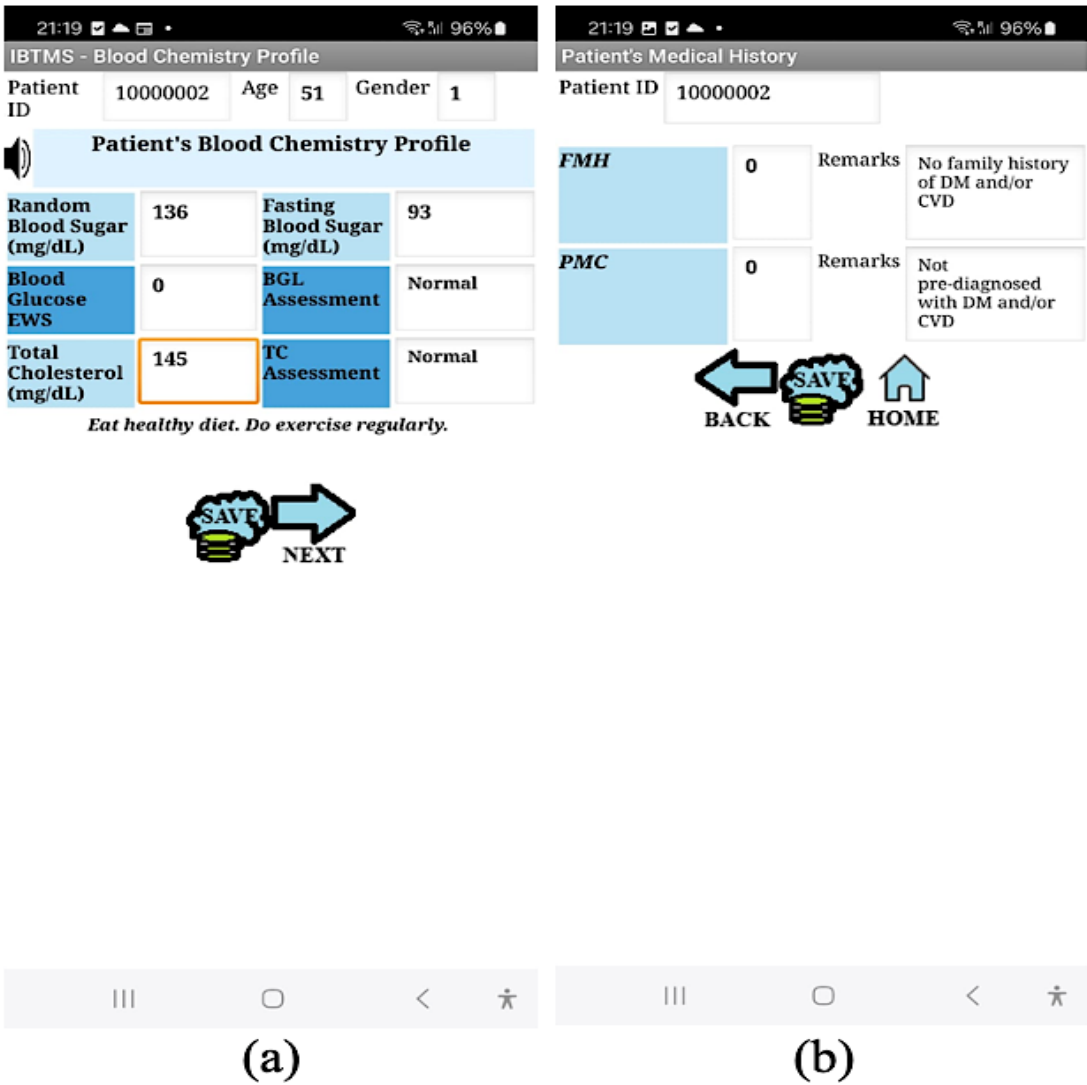


Figure 24.: Blood chemistry profile and medical history of patient 10000002

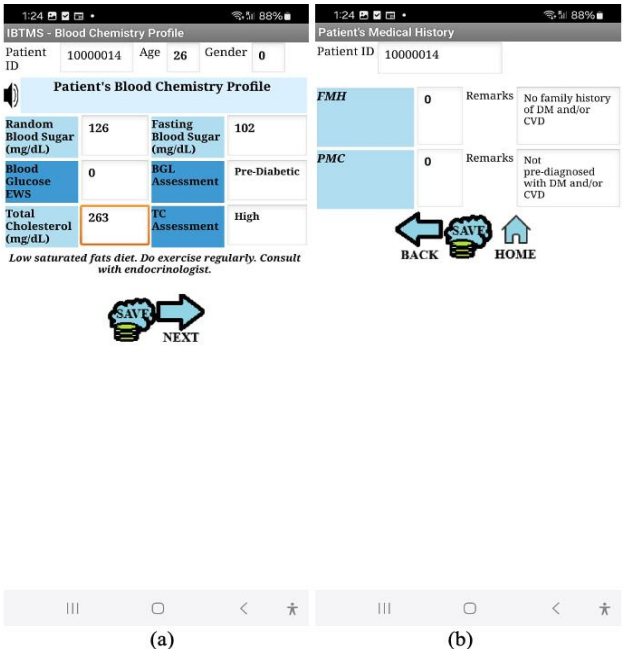


Figure 25:. Blood chemistry profile and medical history of patient 10000014

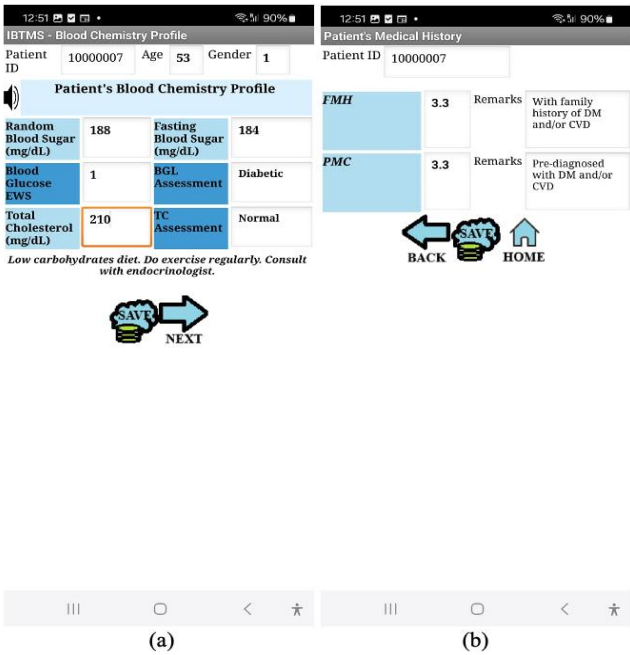


Figure 26. Blood chemistry profile and medical history of patient 10000007

D. Results and discussion for the Fuzzy Logic-based Clinical Health Risk Assessment Model (FLCHRAM)

The Fuzzy Logic-based Clinical Health Risk Assessment Model (FLCHRAM) was evaluated using the CAIR-CVD-2025, a CVD risk assessment dataset from [44] as well as actual parameters from 50 volunteer patients who signed consent forms to participate in the study. Multiple imputation was employed to manage missing parameters in the datasets, substituting them with reliable estimates [45]. HRbpm was missing from the CAIR-CVD-2025 dataset, so clinically predicted values were used to maintain physiological plausibility. For patients with hypertension and CVD PMC, HR values greater than 100 bpm were substituted. For patients without hypertension or PMC of CVD, HR values were substituted within the normal range of 60 to 100 bpm.

Figure 27 depicts the ISAHMA displays for preprocessing the input parameters of FLCHRAM. To query the MariaDB database for fuzzy input parameters such as HRbpm, BPS, BMI, TChol, FMH, PMC, and FBSL, the user must select

the import button shown in Figure 27(a). The PHP program code was created to obtain the FLCHRAM input parameters from the database. The parameters are then sent to the ThingSpeak cloud by clicking the export button, as illustrated in Figure 27(b). The user runs the FLCHRAM.m MATLAB script, which imports the parameters using the thingSpeakRead () function, assesses the CHRL, and outputs the result using the thingSpeakWrite () function. The CHRL is retrieved from the ThingSpeak cloud and displayed on the ISAHMA screen, as seen in Figure 27(c). The user is then prompted to store the results in MariaDB by clicking the required buttons.

Figure 28 shows that patient 10000014 had a high CHRL due to pre-diabetes, an obese class I weight classification, elevated BPS and a high cholesterol level of 263 mg/dL. Fuzzy rule number 2631 was used to evaluate this case. The CHRL prediction was consistent with medical guidelines and practices published in [26], [27], [29], [42] and [46], which suggested that patients with high cholesterol are more likely to acquire CVD and associated complications. Furthermore, [47] stated that obesity increases the chance of prediabetes progressing to DM. The FLCHRAM results further confirmed the doctor's assessment that the patient's health was at risk due to elevated TC levels and obesity. As seen in Figure 29, the CHRL evaluation related with DM and CVD of patient 10000002 was very low risk because all physiological, anthropometric, and blood chemistry parameters were within normal ranges. This was assessed in MATLAB using fuzzy rule 56 to determine the patient's CHRL.

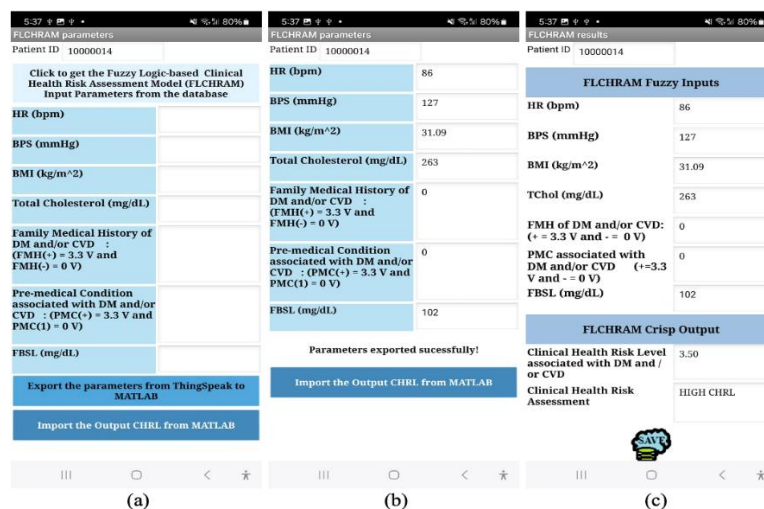


Figure 27: ISAHMA screens of FLCHRAM for (a) importing the fuzzy inputs from the MariaDB database to ThingSpeak cloud, (b) exporting the fuzzy inputs from ThingSpeak cloud to MATLAB and (c) viewing the FLCHRAM crisp output

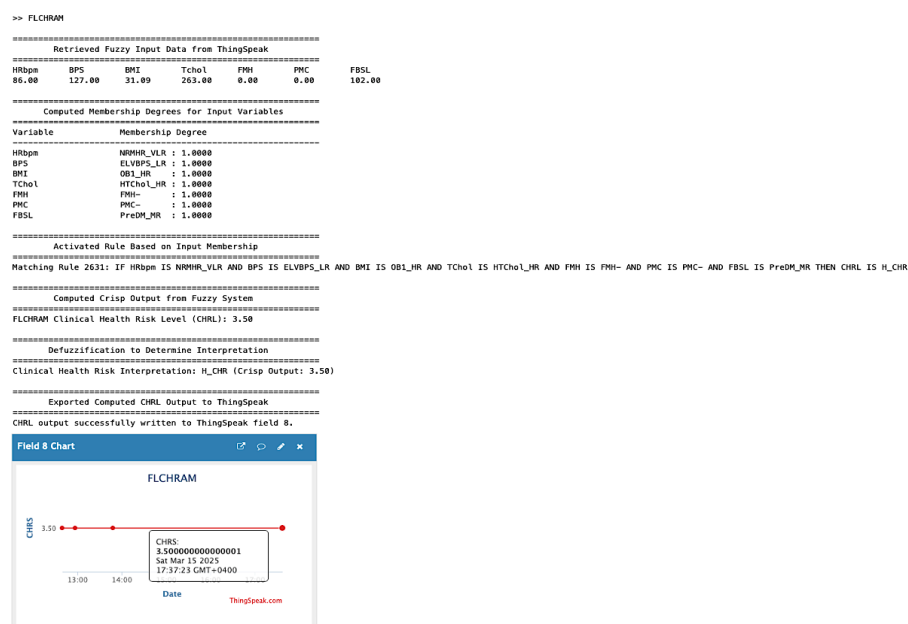


Figure 28: FLCHRAM output as seen in MATLAB and ThingSpeak cloud for patient 10000014

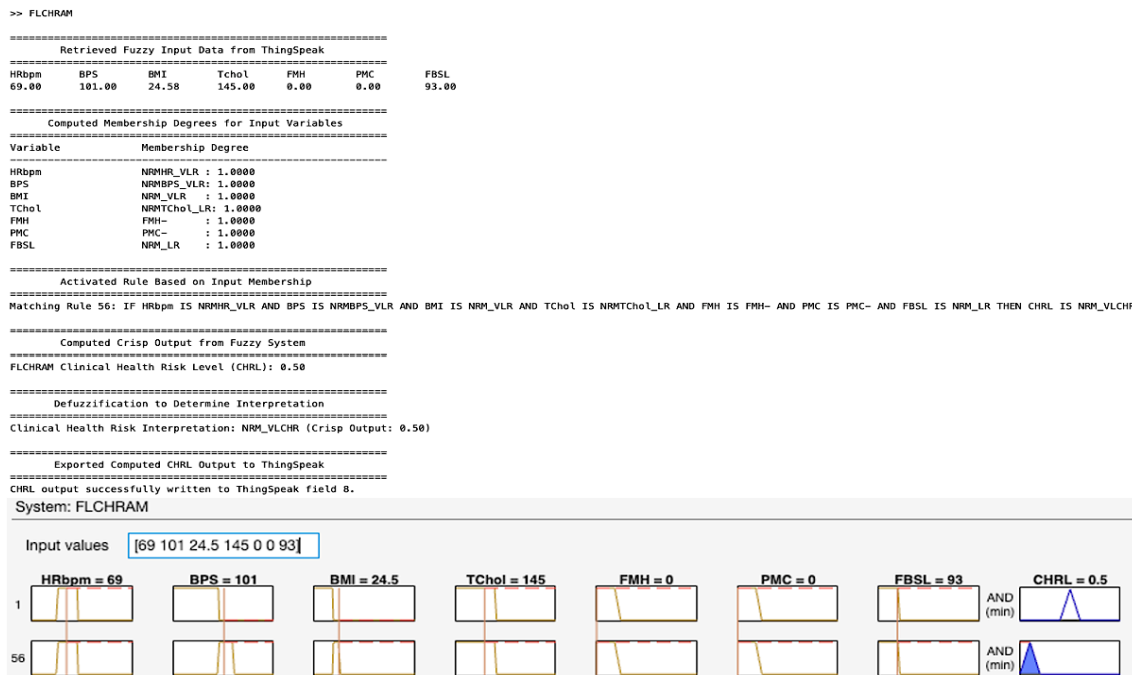


Figure 29: FLCHRAM output as seen in MATLAB for patient 10000002

Figure 30 shows that patient 10000007 had a high BPS of 133 mmHg, an overweight BMI, a pre-diagnosed DM, a family history of CVD and DM, and a high FBSL level, all of which contributed to a high CHRL. This example was evaluated using the fuzzy rule 6195. The CHRL assessment aligned with the clinical guidelines and practices published in [26], [27], [29], [42] and [46]. High BP is a significant risk factor for the onset of CVD, which can lead to heart failure and stroke [48]. According to [49] and [50], patients with diabetes have a heightened risk of developing CVD when their BMI increases. Furthermore, the FLCHRAM result validated the doctor's prognosis that the patient's physical health was at risk due to diabetes and associated complications. Figure 31 illustrates the FLCRAM output for patient from CAIR-CVD-2025 dataset. The patient's CHRL was evaluated as moderate risk by FLCHRAM due to the patient's overweight status, pre-diabetic condition, and family medical history of CVD. This assessment was consistent with the CVD risk assessment in the dataset, which is intermediate risk, as well as clinical guidelines from [26], [27] and [50]. According to [51], patients with a familial history and genetic predisposition to NCDs such as CVD and DM have a higher risk of acquiring these conditions.

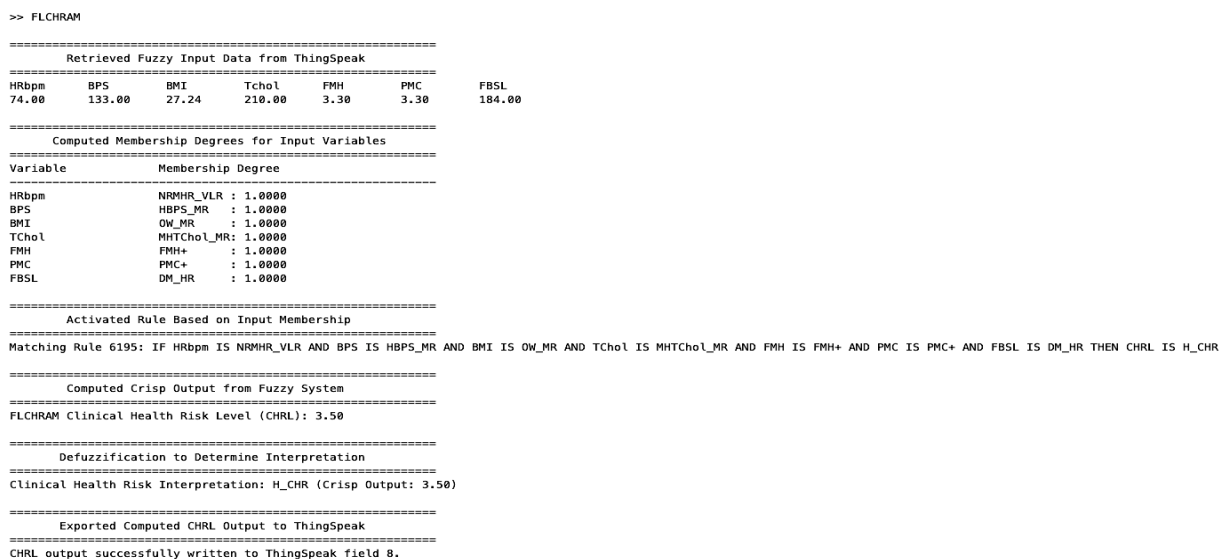


Figure 30: FLCHRAM output as seen in MATLAB for patient 10000007

```

>> FLCHRAM
=====
Retrieved Fuzzy Input Data from ThingSpeak
=====
HRbpm    BPS    BMI    Tchol    FMH    PMC    FBSL
70.00    104.00  26.90  103.00   3.30   0.00   114.00

=====
Computed Membership Degrees for Input Variables
=====
Variable      Membership Degree
=====
HRbpm         NRMHR_VLR : 1.0000
BPS           NRMbps_VLR : 1.0000
BMI           OW_MR    : 1.0000
Tchol         NRMHTchol_LR : 1.0000
FMH           FMH+    : 1.0000
PMC           PMC-    : 1.0000
FBSL          PredM_MR : 1.0000

=====
Activated Rule Based on Input Membership
=====
Matching Rule 2786: IF HRbpm IS NRMHR_VLR AND BPS IS NRMbps_VLR AND BMI IS OW_MR AND Tchol IS NRMHTchol_LR AND FMH IS FMH+ AND PMC IS PMC- AND FBSL IS PredM_MR THEN CHRL IS M_CHR

=====
Computed Crisp Output from Fuzzy System
=====
FLCHRAM Clinical Health Risk Level (CHRL): 2.50

=====
Defuzzification to Determine Interpretation
=====
Clinical Health Risk Interpretation: M_CHR (Crisp Output: 2.50)

=====
Exported Computed CHRL Output to ThingSpeak
=====
CHRL output successfully written to ThingSpeak field 8.

```

Figure 31: FLCHRAM output as seen in MATLAB for patient from CAIR-CVD-2025 dataset

To test the accuracy of the developed FLCHRAM, 55 simulations were ran using the CAIR-CVD-2025 dataset, and 50 runs were done with the fuzzy inputs from the volunteered patients. The accuracy of an AI system can be computed by dividing the total number of correct predictions by the total number of predictions, as described in Equation (38) [52]. Due to borderline cases, four of the FLCHRAM's 105 predictions did not correspond to the doctor's assessments or clinical practice guidelines. Figure 32 depicts a sample of FLCHRAM assessment for borderline cases of BMI and Tchol. Patient 10000028 had a Tchol of 239 mg/dL, which is in the upper limit of a moderately high level, and a BMI of 29.97 kg/m², which is in the upper limit of the overweight class. The FLCHRAM rated the patient as high risk, although clinical guidelines indicated moderate risk. This demonstrates that FLCHRAM can predict higher risk levels in borderline cases, suggesting that it can detect early manifestations of diabetes or cardiovascular disease. According to the confusion matrix in Table 16, the FLCHRAM made 101 correct predictions out of 105 total predictions, resulting in an overall accuracy of 96.19% when the results of volunteered patients and datasets were combined.

$$Accuracy = \frac{\text{number of correct CHRL prediction}}{\text{number of total CHRL prediction}} * 100 = \frac{101}{105} * 100 = 96.19\% \quad (38)$$

```

>> FLCHRAM
=====
Retrieved Fuzzy Input Data from ThingSpeak
=====
HRbpm    BPS    BMI    Tchol    FMH    PMC    FBSL
85.00    104.00  29.97  239.00   3.30   0.00   83.00

=====
Computed Membership Degrees for Input Variables
=====
Variable      Membership Degree
=====
HRbpm         NRMHR_VLR : 1.0000
BPS           NRMbps_VLR : 1.0000
BMI           OW_MR    : 0.6500 OB1_HR : 0.8500
Tchol         NRMHTchol_MR : 1.0000 HTchol_HR : 0.5000
FMH           FMH+    : 1.0000
PMC           PMC-    : 1.0000
FBSL          NRM_LR   : 1.0000

=====
Activated Rule Based on Input Membership
=====
Matching Rule 1016: IF HRbpm IS NRMHR_VLR AND BPS IS NRMbps_VLR AND BMI IS OB1_HR AND Tchol IS HTchol_HR AND FMH IS FMH+ AND PMC IS PMC- AND FBSL IS NRM_LR THEN CHRL IS H_CHR

=====
Computed Crisp Output from Fuzzy System
=====
FLCHRAM Clinical Health Risk Level (CHRL): 3.03

=====
Defuzzification to Determine Interpretation
=====
Clinical Health Risk Interpretation: H_CHR (Crisp Output: 3.03)

=====
Exported Computed CHRL Output to ThingSpeak
=====
CHRL output successfully written to ThingSpeak field 8.

```

Fig. 32: FLCHRAM output as seen in MATLAB for patient 10000028

Table 16: Confusion Matrix for the FLCHRAM's CHRL output

CHRL based on doctor's assessments, medical guidelines and clinical practices	CHRL results of the FLCHRAM					
		NRM_VLCHR	L_CHR	M_CHR	H_CHR	VH_CHR
	NRM_VLCHR	20	1	0	0	0
	L_CHR	0	13	1	0	0
	M_CHR	0	0	19	2	0
	H_CHR	0	0	0	29	0
	VH_CHR	0	0	0	0	20

CONCLUSION

A Society 5.0-driven IoT-based biomedical telemetry system (IBTMS) combined with a fuzzy logic-based clinical health risk assessment model (FLCHRAM) was successfully designed, configured, and implemented, allowing for proactive healthcare management. The proposed system aligns with the Society 5.0 goal of developing a patient-centered and technologically integrated healthcare ecosystem. This system allows for real-time health monitoring, risk prediction for DM and CVD, and individualized medical interventions by incorporating advanced technologies such as AI and IoT. Based on the experimental results, the sensor-acquired physiological parameters from the IBTMS and commercially available medical devices were comparable with percent differences of less than 5%. The IBTMS sensor-read and ISAHMA-computed anthropometric parameters were identical with the commercially available equipment and online medical calculators, with percent differences of less than 1%. The CHRL of the FLCHRAM were comparable to published clinical guidelines, medical practices and healthcare professional advice with a calculated accuracy of 96.19%.

The developed user-friendly mobile application utilizing MIT App Inventor gave patients direct access to their own vital data and medical health history. The secure IoT cloud storage and MariaDB database server configurations provided real-time monitoring and long-term data accessibility, allowing healthcare practitioners to efficiently collect and analyze patient data. Overall, the research project not only promotes patient health awareness and self-management, but it also facilitates more effective communication with healthcare professionals via the developed telemedicine service platform, resulting in individualized and timely therapeutic recommendations.

The future directives of the current research work includes: (a) the use of advanced AI models like deep learning and neural networks to find patterns in patient data that may indicate early signs of disease, (b) the utilization of IBTMS and FLCHRAM in assessing the clinical health risks associated with various NCDs such as chronic renal disease and chronic lung disease, (c) the incorporation of a mental health monitoring module to the Society 5.0's patient-centered system for providing a more comprehensive and proactive approach to enhancing individuals' well-being in all aspects of their lives, (d) the implementation of machine learning algorithms to perform extensive body composition analysis, providing information on muscle mass, fat proportion, and metabolic health, and (e) the integration of various physiological sensors, such as ECG and EEG sensors, to monitor heart function and brain activity, respectively, in order to determine physical and mental health risk.

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