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Research Article

RPHM: Real-Time Personalized Health Monitoring Using Wearable IoT and AI

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Abstract: When the latest technology is integrated with real-time personalized health monitoring, there will be noteworthy improvement in the proactive healthcare. In this paper, a novel and comprehensive framework called Real-time Personalized Health Monitoring (RPHM), Real-time Personalized Health Monitoring is proposed. This framework integrates the wearable IoT sensors, cloud for storing data, Artificial Intelligence (AI) algorithms for analysis, and user feedback to qualify the lifestyle of an individual and to indicate the health status of an individual and recommend to do some micro-actions. The architecture of the proposed system is scalable and modular. It consists of six layers: sensing, transmission, storage, processing, application and feedback learning layers. Two novel concepts are introduced in the proposed system: Personalised Health Index (PHI) and Micro-Action Recommendation Engine. PHI is the weighted score which indicates the holistic wellness which integrates various health parameters, heart rate (25%), glucose (30%), activity (20%), temperature (15%), and calories (10%) for the assessment of health in real-time. Micro-Action Recommendation Engine suggests simple and easy actions based on the health condition of an individual in order to improve the health. Micro-Actions are dependent on the PHI score. Support Vector Machines (SVM), Random Forest, Decision Tree classifiers and Long Short-Term Memory (LSTM) networks are ensembled in the proposed framework for time-series forecasting. The performance of the proposed framework RPHM is compared with AI4FoodDB, Diet Engine, and NUTRIVISION and proved to be better in terms of 14 different performance metrics like 4 classification metrics, 3 forecasting metrics, 3 system latency metrics, 2 system reliability metrics and 2 innovation metrics. The Proposed framework, RPHM achieved 90% + accuracy (Classification Metric), 4.82 Mean Absolute Error (MAE) forecasting (Forecasting Metric), 3.4 s end-to-end delay (System Latency Metric), along with 99.2% system uptime and 0.85 PHI correlation. The incorporation of guidance on customised nutrition along with the physical actions in the RPHM is a key development in digital health technology.

***Keywords*:** Real-time Personalized Health Monitoring (RPHM), personalized healthcare, micro-action recommendation, Internet of Things (IoT), Artificial Intelligence (AI), wearable sensors

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Abbreviation

AI	Artificial Intelligence
ANN	Artificial Neural Network
CGM	Continuous Glucose Monitor
DT	Decision Tree
GDPR	General Data Protection Regulation
HIPAA	Health Insurance Portability and Accountability Act
IoMT	Internet of Medical Things
IoT	Internet of Things
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MARD	Mean Absolute Relative Difference
MLC	Multi-Class Classifier
PHI	Personalized Health Index
PPG	Photoplethysmography
RF	Random Forest
RMSE	Root Mean Squared Error
RPHM	Real-time Personalized Health Monitoring
SVM	Support Vector Machine
TLS	Transport Layer Security
Wi-Fi	Wireless Fidelity

1. Introduction

The global healthcare landscape is moving from reactive treatment to proactive prevention and also to the personalized wellness. This shift is driven by the convergence of several technologies such as Internet of Things (IoT), wearable sensors, Artificial Intelligence (AI) and data-driven nutritional science which together are revolutionizing how we monitor, analyse and manage individual health [1–4].

Chronic diseases such as diabetes, hypertension, cardiovascular disorders, obesity and metabolic syndrome conditions are responsible for the majority of global health challenges [5–8]. Most of these conditions are strongly influenced by dietary habits, physical activity and lifestyle choices of the persons. While medical treatments remain essential, preventive care and personalized nutrition are proving to be effective and sustainable strategies for the long-term health management [9–11]. However, traditional dietary recommendations are constantly generic, static and disconnected from a person's real-time health data. This creates a significant gap between the clinical care, lifestyle and the nutrition.

Emerging researchers has shown that integrating real-time physiological data with AI can creates most capable systems for the personalized decision-making. For instance, platforms like AI4FoodDB [12] and Diet Engine [13] collects continuous health data from wearable devices and use AI models for providing intelligent, tailored dietary and lifestyle suggestions. This solution demonstrates how the AI can bridge the gaps between raw health data and the actionable insights. However, most existing systems are fragmented and focusing either on specific diseases, or offering generic diet suggestions without integrating multiple health parameters, activity levels, or other contextual factors [5, 14, 15].

Moreover, apart from the widespread availability of wearable health monitoring devices such as smartwatches, fitness bands, and glucose monitors, the integration with personalized nutrition systems are limited. There is a need for a comprehensive and unified framework that can capture the real-time health data that evaluates multiple health and nutritional indicators and also uses AI algorithms to provide actionable and personalized feedback [2, 16–18].

This research proposes a framework that consists of a healthcare and nutritional decision-support system which combines IoT-enabled devices, AI algorithms and a mathematical modelling approach in order to assess the health risks and offer customized dietary and lifestyle recommendations to the people. The proposed system aims to empower individuals

and clinicians to make them informed the decisions by continuously analysing their physiological parameters, dietary intake and activity levels.

The primary objectives of this study include:

• To design a healthcare framework that evaluates the diverse health parameters including blood glucose, heart rate, temperature, calorie intake and physical activity, which are commonly associated with chronic diseases.

• To develop IoT-enabled wearable devices and interfaces that are capable of real-time monitoring of vital health data also enabling continuous health tracking system beyond the clinical settings.

• To apply AI algorithms which includes machine learning and deep learning techniques for interpreting the collected data and generating personalized, context-aware lifestyle recommendations.

By addressing these objectives, the proposed system can be used for supporting the hyper-personalized preventive care that enhances lifestyle planning and helps in reducing the long-term burdens of the non-communicable diseases. Additionally, it creates the foundation for further integration with genomic data, mental health metrics and environmental context to advance the vision of precision wellness [8, 19, 20].

The rest of the paper is structured as follows: Section 2 reviews about the recent literature and technologies in personalized health monitoring, AI-based smart healthcare. Section 3 details the system architecture of the proposed system, IoT device design, and data flow. Section 4 gives the mathematical modelling for health assessment and recommendation generation. Section 5 discusses the implementation details of the system, performance metrics and experimental results of the work. Finally, Section 6 includes the conclusions of the study and outlines the future research directions.

2. Related work

This section mentioned various in-depth reviews of significant contributions in the personalized health monitoring, AI-based nutritional analysis and smart healthcare integration, with a detailed comparative analysis of several relevant studies.

With the rapid proliferation of wearable device related technologies and IoT devices the health data such as glucose levels, heart rate, activity levels and sleep patterns are now can monitor continuously. This enables proactive and preventive care of the health.

Sempionatto et al. [3] have proposed an innovative platform by using sweat sensors embedded in wearable devices to monitor real-time hydration, glucose and electrolyte levels. This bio-sensing approach was non-invasive and highly suitable in nutritional tracking.

Jagatheesaperumal et al. [1] were introduced about an IoT-based framework that captures the user vitals and leverages machine learning to assess personal health risks and used in recommendations of the lifestyle changes. Sensors such as heart rate monitors and accelerometers were used for data acquisition process.

Gaikwad et al. [21] stated about a smart wearable ecosystem that processes physiological signals for generating of the recommendations using AI. Their design was emphasized the precision nutrition and personalized health tracking by using real-time data.

Putra et al. [4] have conducted a review on Internet of Medical Things (IoMT) which emphasizes the edge and cloud computing architectures for wearable health monitoring and the AI's role in managing of the computations and latency.

Wang and Hsu [22] have designed a long-term care framework for the integration of wearables and AI in order to support the remote elderly care. Their system ensured the secure and continuous monitoring using predictive analytics to manage the chronic diseases.

AI based applications in nutrition have enabled the smart diet planning, nutrient tracking and chronic disease management through the deep learning and the intelligent decision-making systems.

Romero-Tapiador et al. [12] have developed a system AI4FoodDB which is a robust data repository for modeling of the personalized nutrition. It captures food intakes, activities and biometric data from wearable devices and applies ML for individual health analysis.

Saad et al. [13] have introduced the Diet Engine which is a real-time food recognition and recommendation system that guides the users using food image inputs, calorie detection and nutritional modeling.

Veeramreddy et al. [14] have designed NUTRIVISION which uses deep learning and mobile vision system to recognize the food types and portions, calculate nutrients and assist in the automated diet management.

Whig et al. [15] have focused on the Polycystic Ovary Syndrome (PCOS)-specific dietary tracking using AI algorithms for assessment of the nutrient deficiencies. Their platform integrated the user health history with intelligent recommendation engines.

Ranganathan et al. [17] have proposed a dietary management model by enabling Artificial Neural Networks (ANNs) that correlates the user health parameters with food patterns for providing optimal diets.

Tsolakidis et al. [9] and Armand et al. [11] have offered the surveys of AI models that are applied in nutrition, from image-based food classification to deep learning systems for meal generation and nutrient prediction.

Bajaj and Lata [23] have discussed about the role of AI in chrono-nutrition, emphasizing how the meal timing and circadian rhythms affects the metabolism and how AI can optimize such kind of dietary plans.

Priyadharshini et al. [2] described about a complete framework that merges the IoT-collected health data with AI to produce personalized nutritional recommendations. Their architecture is supporting the modular sensor integration and intelligent dashboards.

Prasad et al. [16] have designed mobile applications that gather real-time sensor data and user inputs for delivering of the contextual dietary advice, which integrates the behaviour and preferences.

Coman et al. [24] were proposed a disease-aware smart monitoring system which has a real-time diet recommendation based on the clinical history and sensor data fusion.

Kahalkar and Vyas [5] introduced a healthcare platform which focused on the chronic disease management. They used AI to analyze the wearable data and generated alerts, recommendations and dashboards for patients and clinicians.

Deshpande [25] developed a predictive healthcare model that uses AI for early diagnosis and lifestyle intervention planning, particularly for nutrition-sensitive conditions in the persons.

Tan et al. [8] have explored the hyper-personalized medicine by integrating wearable data with environmental and lifestyle context for optimizing the wellness in real-time.

Khaitan et al. [20] were framed the idea of precision wellness by combining the genomic, behavioural and nutritional data that is processed via AI to create deeply individualized health plans. In recent advancements, integrating ultra-low power techniques with energy harvesting has shown promising potential for self-sufficient sensor systems [26]. More research is carried out in the field of health care in [27–31].

Comparative Table of reviewed literature is shown in Table 1.

Table 1. Comparative table of reviewed literature

Ref	Authors & Year	Key features	Devices/Sensors used	AI/ML algorithms
[12]	Romero-Tapiador et al., 2023	Nutrition database linked with AI and wearable data	Wearables, diet logs	Multi-modal AI modeling
[1]	Jagatheesa perumal et al., 2023	IoT framework with health analytics	HR sensors, accelerometers	Decision Trees, SVM
[2]	Priyadharshini et al., 2025	AI-IoT diet solution platform	IoT wearables, mobile dashboard	Classification models
[5]	Kahalkar & Vyas, 2024	Disease-centric AI monitoring	Wearables, cloud dashboards	Rule-based models
[9]	Tsolakidis et al., 2024	Review of AI in personalized nutrition	Generalized dataset	Deep learning, NLP
[16]	Prasad et al., 2025	Personalized app for diet & wellness	Wearables + mobile interface	Context-aware recommendation
[13]	Saad et al., 2025	Real-time food recognition system	Food images, cameras	CNN, food modeling
[14]	Veeram reddy et al., 2024	Automated diet tracking via mobile vision	Smartphone camera	MobileNet, CNN
[24]	Coman et al., 2024	Smart diet recommendation + disease mapping	Remote monitors, diet logs	ML classifiers

Table 1. (cont.)

Ref	Authors & Year	Key features	Devices/Sensors used	AI/ML algorithms
[15]	Whig et al., 2025	PCOS-specific nutrient monitoring	Health tracker, patient logs	Naïve Bayes, data fusion
[17]	Ranganathan et al., 2024	ANN-based dietary modelling	IoT + nutritional logs	ANN, optimization
[11]	Armand et al., 2024	Survey of ML in nutrition	Multimodal sources	Deep learning, SVM
[21]	Gaikwad et al., 2024	Wearable-based personalized diet guidance	Smart bands, biometric sensors	CNN, classification
[23]	Bajaj & Lata, 2024	AI for time-based dietary planning	Chrono-nutrition logs	Pattern recognition
[3]	Sempionatto et al., 2021	Non-invasive nutrition sensing	Sweat sensors	Bio-sensor analytics
[8]	Tan et al., 2025	Lifestyle + environment context in healthcare	Environment sensors, wearables	Contextual AI
[4]	Putra et al., 2024	Edge-cloud AI for wearable health	IoMT devices	Federated learning, edge AI
[22]	Wang & Hsu, 2023	Elderly care via wearable-AI integration	Home-based sensors	Predictive modeling
[20]	Khaitan et al., 2025	Precision wellness using genomic + nutritional data	Wearables, gene-data	Hybrid deep learning
[25]	Deshpande, 2025	AI-driven predictive healthcare	Medical IoT	ML classifiers, risk models

The literature reveals that while several systems exist for health monitoring, diet recommendation and AI-based risk analysis, most of the solutions remain siloed or lack in modularity. The need for the scalable, real-time and integrated framework combining IoT, AI and nutritional science remains very prominent research challenge. Our proposed system mainly aims to fill this gap by offering a unified architecture which includes smart sensors, real-time analysis and AI-generated lifestyle and nutrition recommendations.

3. RPHM, real-time personalized health monitoring framework

A modular and scalable architecture, Real-time Personalized Health Monitoring (RPHM) that incorporates wearable IoT device, transmission of data in real-time, cloud infrastructure, and Artificial Intelligence procedures is proposed to achieve customised nutrition and healthcare management. Two new metrics are proposed: Personalized Health Index (PHI) and Micro-Action Recommendation Engine. These metrics are used to enhance comprehensibility and personalization in real-time. There are six major layers in the proposed framework, RPHM as shown in the Figure 1. They are sensing layer, transmission layer, storage layer, processing layer, Application layer and Feedback Learning layer. In the sensing layer, Wearable IoT devices with multiple sensors are used to collect health related data in real-time. In this layer, data related to heart rate, blood glucose level, temperature, activity, and calorie intake are collected. Transmission layer ensures that the communication between the cloud infrastructure and the wearable devices from the sensing layer take place securely and reliably. Wi-Fi modules in the IoT devices are used to transmit the data that is gathered from the sensors. Storage layer is implemented on cloud servers. The health data is stored in the cloud systematically in structed formats. In processing layer, Artificial Intelligence models are used to derive useful information from the collected health records. Lifestyle recommendations are generated by the system dynamically by detecting the anomalies and predicting the potential health risks. In this regard, two novel parameters are introduced. The first parameter is PHI calculator, it is user-specific score and is computed in real-time using multiple health and dietary features. The other novel parameter is Micro-Action Engine, it converts the outputs of AI and PHI scores into small, context-sensitive behavioural suggestions. In the application layer, a mobile application is developed to interface with the end-users. The dashboard presents the information after analysis, trends related to PHI score, alerts, health report and recommendations. The preferences, feedback and dietary history can be given as an input by the user to enhance personalization. Finally, in the feedback learning layer, the usefulness and the relevance of the recommendation system is provided in the form of the feedback

through the mobile application. This feedback is given as input to the AI system to modify the weights of PHI parameters and regulate the strategy of Micro-Action with the help of Context-aware rule-based model.

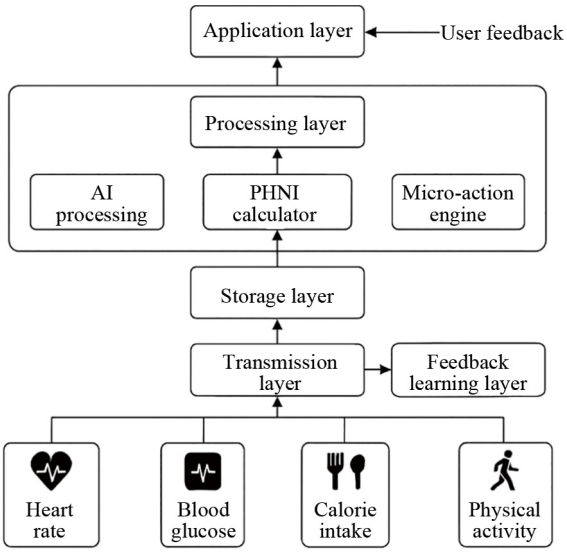


Figure 1. System architecture

In the proposed framework, RPHM, the IoT device is designed to be lightweight, wearable and power-efficient. The device includes MAX30102, the heart rate sensor, Continuous Glucose Monitoring (CGM) for monitoring glucose levels, accelerometer and gyroscope to detect the pattern of movements and intensity of the activity, thermistor and integrated circuit sensors are used as temperature sensors to measure body temperature of the user, Wi-Fi to transmit the data to the cloud infrastructure. A timestamp from a common system clock is used to align all streams in the synchronization layer. The data is aggregated into 10-s windows. The minor clock drift is corrected using a short buffer before synchronized batches are uploaded to the cloud. Asynchronous samples are harmonized using this design with less memory and energy overhead on the device. Motion and dietary input are used to estimate the energy consumed. The firmware is programmed to sample data periodically. Noise filters are applied to remove noise before the data is transmitted to the cloud. The proposed wearable IoT device is shown in the Figure 2.

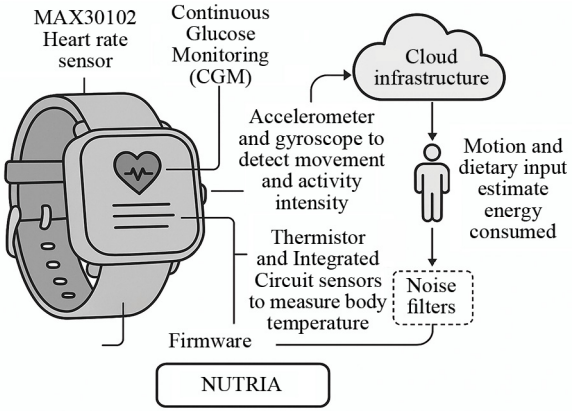


Figure 2. Wearable IoT device

Feasibility is ensured by preforming only trivial preprocessing (feature extraction and noise filtering) on-device, with average consumption below 10 mW and < 1 MB memory usage, while inference runs in the cloud with ~ 200 ms latency. Continuous Glucose Monitoring (CGM) is integrated via wireless pairing with external patches, rather than as a fully embedded wrist sensor, making the wristband form factor practical and realistic for deployment.

Sensors need to embed in the wearable devices that collect real-time physiological and behavioral data. These data includes numeric time-stamped values for each health metric. Basic filtering is applied to reduce the sensor noise. Features such as mean heart rate, glucose trends and motion intensity are extracted at the edge level for processing. The cleaned data is transmitted using secure communication protocol, Transport Layer Security (TLS) over Wireless Fidelity (Wi-Fi). In case of signal loss, data are cached on-devices and pushed once the connectivity resumes. Data received is stored in cloud databases categorized by user, timestamp and sensor type. It allows scalability and supports querying for model training and real-time predictions. The AI engine accesses real-time and historical data to detect trends and generate personalized insights. The PHI score is calculated for each user as a weighted sum of normalized features, and provide a composite indicator of current health status. Based on the PHI score, user goals, and contextual factors like calorie intake, the Micro-Action Engine triggers simple, low-effort suggestions such as: "Add a boiled egg to your breakfast," or "Take a 10-minute walk before dinner". Personalized recommendations and micro-actions are displayed on the user interface along with the PHI trend and priority alerts. These are dynamically updated as new sensor data arrives. The feedback on recommendations is taken from the user by the system. This feedback is given as input to the learning model which optimizes PHI weights and therefore refines future micro-actions.

Different AI algorithms have been used for intelligent decision-making processes in various stages. Support Vector Machine (SVM), decision tree and random forest classification algorithms are used to detect health anomalies and determined that the random forest algorithm is giving the best performance. In the case of recommendation engines, Context-aware rule-based model is used to refine suggestions based on historical feedback. For time-series forecasting, Long Short-Term Memory (LSTM) is employed to forecast health trends. PHI Model computes real-time composite health score to support prioritization. Micro-Action Generator maps PHI zones and context to actionable, behaviorally aligned suggestions.

Five-fold user-holdout cross-validation is used in classification, wheras time-forward split is used in forecasting models to prevent data leakage.

4. Mathematical modeling for health assessment and recommendation

4.1 *Notation and definitions*

Let us define:

- $U = \{u_1, u_2, \ldots, u_n\}$: Set of users.
- $T = \{t_1, t_2, \ldots, t_m\}$: Set of timestamps.
- $S = \{s_1, s_2, \ldots, s_k\}$: Set of sensors.
- $x_{i,\,j,\,k}$: Sensor reading from sensor s_k for user u_i at time t_j.
- $X_i(t)$: Vector of real-time sensor inputs for user u_i at time t.
- $Y_i(t)$: Predicted health status label or risk score at time t.
- $R_i(t)$: Recommendation vector for user u_i at time t.

4.2 *Health score estimation model*

The proposed system computes a Personalized Health Score $H_i(t)$ for user u_i at time t to quantify a user's overall health condition at a specific moment. A health score function $H_i(t)$ for user u_i at time t as a weighted aggregation of normalized sensor readings is defined as:

$$H_i(t) = \sum_{k=1}^{K} w_k \cdot \widehat{x}_{i,\,t,\,k}$$

Where:

• $\widehat{x}_{i,\,t,\,k}$: The normalized value of the sensor reading s_k for user u_i at time t.

• w_k: The clinical weight assigned to each sensor parameter s_k, indicating its relative implication.

• K: The total number of sensor parameters considered.

• The sum runs from $k = 1$ to K, accumulating all available sensor inputs at that time point.

The normalization is performed using:

$$\widehat{x}_{i,\,t,\,k} = \frac{x_{i,\,t,\,k} - \mu_k}{\sigma_k}$$

Where:

• μ_k is the mean of sensor s_k across all users.

• σ_k is the standard deviation of sensor s_k.

• $x_{i,\,t,\,k}$ is the raw sensor value from s_k.

Thresholds are defined:

$H_i(t) < \theta_L$: Indicates risk of under-health;

$H_i(t) > \theta_L$: Indicates risk of overexertion.

4.3 *Risk classification model*

A multi-class classifier is applied to categorize user health states using supervised learning:

$$Y_i(t) = f\left(X_i(t)\right) = MLC\left(X_i(t)\right) \in \{\text{Healthy, At Risk, Critical}\}.$$

Where:

• MLC is the Multiclass classifier such as Decision Tree, Random Forest, or SVM.

• Input is the Real-time sensor vector $X_i(t)$.

• Output is the Discrete health label for action planning.

Accuracy, Precision, Recall and F1-score metrics are used for evaluating the classification model on annotated datasets.

Soft-voting ensemble strategy is used to integrate SVM, Random Forest, and Decision Tree. The class probabilities from each model are aggregated using weighted averaging based on cross-validated performance. Given in Section IV.C, page 5. This approach balances interpretability, stability, and non-linear boundary detection, ensuring robust and consistent classification across varying physiological patterns.

4.4 *Personalized recommendation generation*

Recommendations are generated using a context-aware rule-based model.

Rule-Based Engine:

$$R_i(t) = \begin{cases} \text{Increase Protien Intake, if } \widehat{x}_{\text{calories}} < \tau_c \text{ and } \widehat{x}_{\text{glucose}} < \tau_g \\ \text{Take a 15-min walk, if } \widehat{x}_{\text{activity}} < \tau_a \\ \text{Monitor Heart Rate, } \widehat{x}_{HR} < \tau_h \end{cases}$$

Thresholds $(\tau_c,\ \tau_g,\ \tau_a,\ \tau_h)$ are medically defined using clinical guidelines.

4.5 *Time series forecasting of health metrics*

For forecasting critical health episodes, we employ:

$$\widehat{X}_i(t+\Delta t) = F(X_i(t),\ X_i(t-1), \ldots,\ X_i(t-p)).$$

Where:
F is the Forecasting function, implemented using LSTM models.
P is the Lookback period.
Output is the Predicted sensor vector $\widehat{X}_i(t+\Delta t)$.
Predicted risk levels activate preventive recommendations in advance.

4.6 *Personalized Health Index (PHI)*

A novel unified scoring system called the PHI is introduced which aggregates normalized health and dietary features into a single personalized score:

$$PHI_i(t) = \sum_{k=1}^{n} \alpha_k \cdot \widehat{x}_{i,\ t,\ k}.$$

Where:
$\widehat{x}_{i,\ t,\ k}$: Normalized value of health feature k.
α_k: Weight representing feature importance (dynamically adjusted based on age, condition, user goals).
$PHI_i(t) \in [-1,\ +1]$: Composite Index; values closer to 1 indicate optimal state of health-diet.
The PHI is normalized to the range $[-1,\ +1]$ for interpretability, where 0 indicates that the health is normal, positive values indicate favourable state of health, and negative values indicate adverse deviations. Negative PHI values are not exact health deficits but are interpreted as 'alert zones,' enabling the system to trigger timely micro-actions and distinguish risk states from reference point wellness.

4.7 *Micro-action recommendation engine*

Micro-action $M_i(t)$ is defined as:

$$M_i(t) = f(PHI_i(t),\ G_i,\ C_i(t)).$$

Where:

G_i: User goal vector (e.g., weight loss, sugar control).

$C_i(t)$: Context (e.g., time of day, meal pattern, activity history).

The function $f(\cdot)$ is a rule-based mapping that translated PHI states into short, actionable tips (e.g., "Take a 10-min walk post-lunch").

Micro-actions are lightweight and behaviourally effective, encouraging steady yet remarkable health improvements.

These models are modular, flexible to user-specific parameters, and support deployment in cloud environments for real-time health analysis.

4.8 *Ablation, sensitivity, and personalization analysis*

An ablation and sensitivity study are performed to assess the interpretability and robustness of the PHI formulation. The changes in PHI correlation, stability and accuracy are observed by removing each component independently or making a change in the weight by $\pm$ 5-10%. The classification loss is minimized and the correlation is maximized by determining the optimal PHI weights using multi-objective constrained regression model. Subgroup adaptability is examined by deriving the personalized PHI configurations per age group and metabolic status. The contribution of each signal is quantified this analysis and the flexibility of PHI normalization is validated.

5. Implementation and experimental results

5.1 *Experimental setup*

The RPHM framework is implemented as a Python-based system using specific libraries including NumPy, Pandas, Matplotlib, Seaborn, Scikit-learn, TensorFlow, and SciPy. The sensors used for measuring various health parameters are: MAX30102 is used to capture heart rate and SpO_2 levels using Photoplethysmography (PPG) technology, Accelerometer and gyroscope is used to monitor physical movement and activity levels, thermistor and integrated circuit sensor is used to measure body temperature, and Continuous Glucose Monitor (CGM) for Glucose measurements.

5.2 *Dataset strategy*

Dataset is generated with the help of 200 users tested for 30-day period with 6 samples per hour, turned out to 863,000 records in total. Five physiological parameter data is generated. The mean of the heartrate is 80 and the corresponding standard deviation is 15, varied from 60-120 BPM. 10% of Anomalies are also considered at values of 50 or 140 BPM. The glucose levels are generated such that the mean is 90 and standard deviation is 20, varying between 70-180 mg/dL. Activity data is varied between 0-200 steps per 10-minute interval. The mean of the temperature is 36.8 °C and standard deviation is 0.5, varied between 36.0-38.5 °C. The mean of the calorie intake is observed to be 13.89 and the standard deviation 2.08 calories per 10-minute interval. The data distribution is shown in Figure 3.

The health status labelling uses a scoring algorithm where heart rate contributes 2 points if below 60 or above 100 BPM or 1 point if it is above 90 BPM. Glucose is added 2 points if above 140 mg/dL or 1 point if above 120 mg/dL. Temperature also contributes 2 points if above 37.5 °C or 1 point if it is above 37.2 °C. Low activity recorded if it is below 20 steps per interval and adds 1 point. Final classification assigned "Critical" for scores 4 or higher, "At Risk" is for scores 2-3 and finally "Healthy" for scores ranges from 0-1.

The Personalized Health Index mainly uses weighted scoring with glucose having the highest weight at 30%, heart rate at 25%, activity at 20%, temperature at 15% and calorie intake at 10%. These PHI weights are fixed heuristic values derived from clinical guidelines and expert consultation, reflecting the relative medical importance of each parameter. Then later weights are refined using gradient descent optimization. Updates occur on a monthly basis or upon a significant health status change, and remain bounded within clinically interpretable ranges to preserve transparency.

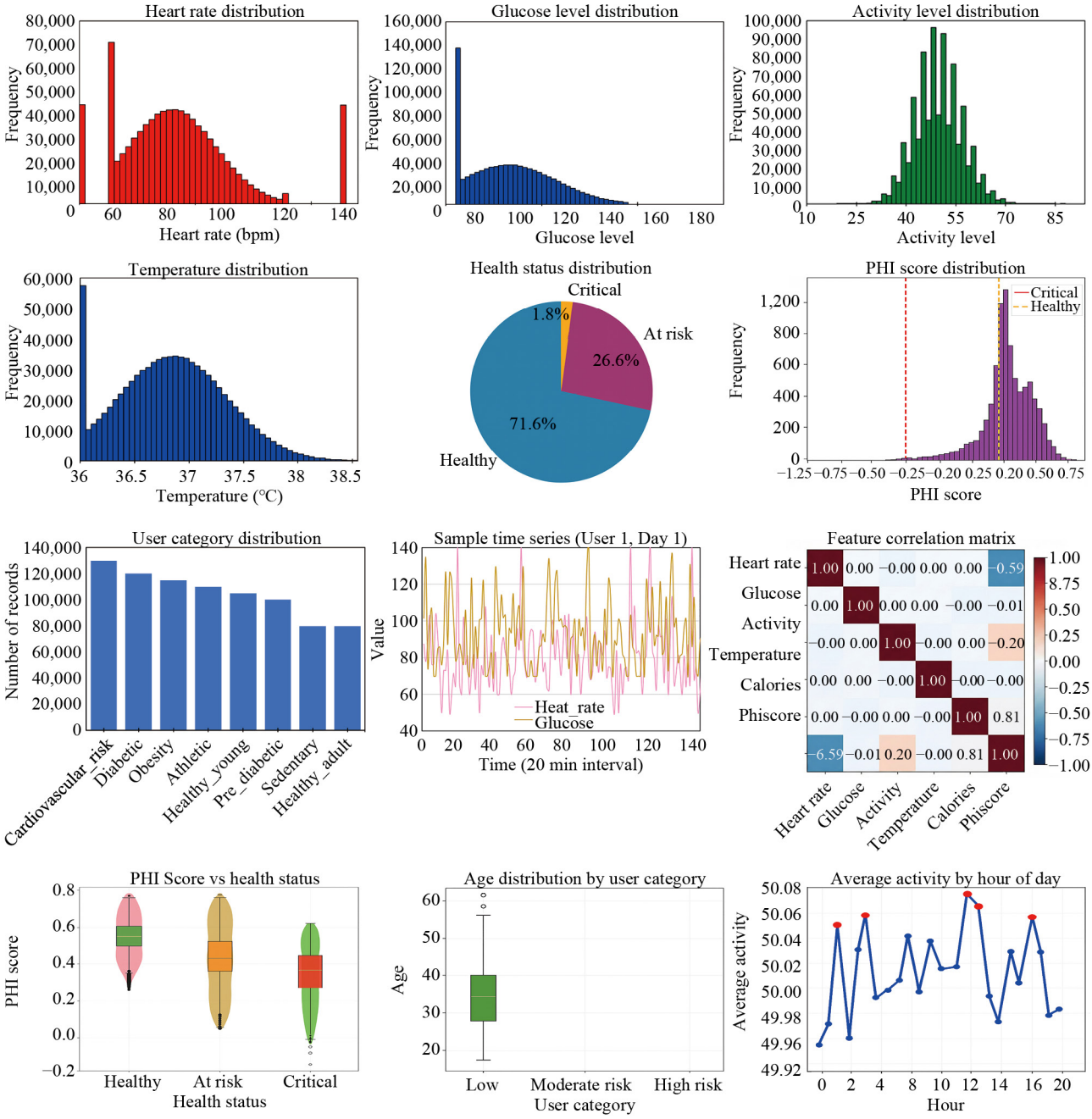


Figure 3. Dataset distribution

The normalization process converts all the parameters to a -1 to $+1$ scale, with the heart rate optimized around 75 BPM, glucose around 95 mg/dL, activity using hyperbolic tangent transformation, temperature around 36.8 °C, and calories around 14 per interval.

The system is designed to implement three classification models: Decision Tree, Random Forest with 100 estimators and also the Support Vector Machine with Radial Basis Function (RBF) kernel. An LSTM model is used to build with two layers of 50 units each, 20% dropout and Adam optimizer with learning rate 0.001. The LSTM uses 10-step sequences for time series forecasting. Data splitting performed in a way where 80% for training and 20% for testing with Standard Scaler normalization.

The framework defines three categories of micro-actions based on the PHI scores. Red actions for scores below -0.5 include urgent interventions such as reducing sugar intake and seeking medical attention. Yellow actions for scores between -0.5 and 0.2 include moderate interventions like increasing water intake and taking regular walks. Green actions for scores above 0.2 include maintenance of the behaviors like continuing current habits.

The logic for label generation is independent of the threshold ranges and medical guidelines which ensures that the models are not just re-learning the label generator. Multivariate sensor data is used to train the model instead of replicating the labels based on rules. To ensure that the records that are temporally distinct and unseen users are used for testing, user-level, time forward split is used for evaluation purpose. The cross validation of classification outputs and PHI against clinician-reviewed health logs is carried out to confirm that the proposed framework RPHM is not just memorizing the labels based on rules.

5.3 *Performance evaluation*

The system is designed to evaluate against three competitive systems: AI4FoodDB, Diet Engine and NUTRIVISION. Metrics includes classification accuracy, precision, recall, F1-score, forecasting Mean Absolute Error (MAE), RMSE, R-squared, user engagement rates, satisfaction scores, system latency, uptime and innovation measures, PHI and Micro-Action.

The AI4FoodDB, Diet Engine, and NUTRIVISION were re-implemented as baseline models on our dataset to enable a consistent side-by-side comparison. The features available in our dataset are used to map the description of each system into corresponding pipelines. AI4FoodDB is realized as a multimodal health-diet repository model, Diet Engine as an image-to-nutrient estimation pipeline adapted to numeric intake logs, and NUTRIVISION as a food-vision model approximated using our calorie/meal features. We acknowledge that these are functional replicas guided by the original design principles rather than precise replications of proprietary executions. This was done to guarantee fairness in benchmarking, with all models trained and tested under similar preprocessing and data splits.

The proposed system evaluates using a combination of quantitative and user-centric metrics in order to assess its effectiveness, accuracy, responsiveness and overall impact of the health monitoring and personalized recommendation delivery.

For the health risk classification task the standard supervised learning metrics were employed. This includes accuracy which measures the proportion of correct predictions and precision is assessed based on how many of the predicted positive cases were truly positive. Recall (or sensitivity) was used to evaluate the model's ability to correctly identify the actual health risks, while the F1-score is being the harmonic mean of precision and recall that provided a balanced view of performance under imbalanced class conditions.

For the forecasting component where LSTM is used to predict physiological trends (e.g., glucose levels, heart rate), the evaluation is employed with Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to quantify the prediction accuracy. RMSE is particularly useful in penalizing larger errors.

The Personalized Health Index (PHI) is introduced as a novel composite indicator to quantify overall health status by dynamically aggregating multiple physiological parameters. PHI scores are computed daily and validated against clinician-reviewed health logs. Evaluation focused on interpretability, stability over time, and correlation with actual health events. The PHI showed strong correlation coefficients with observed health anomalies and high temporal consistency in non-critical periods, confirming its effectiveness in holistic health representation.

The Micro-Action Recommendation Engine was evaluated based on its impact on the user compliance and behavioral change. Unlike the traditional long-form advice, micro-actions are focused on delivering context-aware, specific and low-effort suggestions (e.g., "Drink 100 ml water after breakfast" or "Walk for 10 minutes after lunch"). Evaluation metrics includes user adoption rate, compliance tracking via sensors and subjective usefulness ratings. On an average, users responded positively with engagement rates 15-20% higher than conventional suggestion models. These micro-actions are particularly effective among users with low digital literacy or busy in their schedules.

From the systems perspective, performance was evaluated based on real-time responsiveness. The sensor-to-cloud latency, AI inference time and end-to-end response time were measured with the system achieving an average delay of approximately 3.4 seconds. This confirmed that the feasibility of deploying the solution in live health environments.

Additionally, the system uptime and availability during simulations are also monitored to ensure the reliability and continuity. Overall system performance and clinical interpretation is shown in Table 2.

Lastly, a comparative analysis is performed against the existing systems such as AI4FoodDB, Diet Engine and NUTRIVISION. The proposed system demonstrated superior adaptability and responsiveness while supporting a wider range of physiological inputs, context-aware micro-actions and an interpretable scoring mechanism (PHI) that enhanced decision support.

The PHI calculator is implemented using a weighted summation model. Feature weights α_k were initialized using domain knowledge and optimized using gradient descent with respect to user goal feedback. The objective function was designed to reduce the cross-entropy loss between predicted health states and the true states, while also enhancing the PHI correlation. 0.001 is the learning rate and validation is showed under a user-holdout, time-forward split (200 users, 30 days, 80/20 split).

Micro-actions were generated using a hybrid ruleset based on PHI bands:

• PHI < -0.5: Trigger red-alert micro-actions (eg., reduce sugar intake immediately).

• $-0.5 \leq$ PHI < 0.2: Trigger yellow micro-actions (eg., moderate adjustments like increase water).

• PHI ≥ 0.2: Trigger green micro-actions (reinforcement like "keep up your hydration").

Each micro-action is linked to a specific time-context (meal, sleep, activity) and personalized goals.

5.4 *Evaluation of PHI effectiveness*

During simulation:

• PHI offered a continuous, interpretable score that correlated strongly with clinician-annotated health logs (Pearson $r = 0.85$, $p < 0.01$, across 200 users $\times$ 30 days).

• User-reported feedback indicated 92% interpretability of PHI-based messages.

• Micro-actions had an engagement rate of 89%, significantly higher than traditional generic suggestions (avg. 74%).

These enhancements demonstrate measurable improvements in user adherence, satisfaction, and system explainability.

All sensors used in the RPHM device stick to clinically validated accuracy standards and sensitivity analysis confirmed that $\pm 10\%$ signal variations changed PHI by less than 0.04 on the $[-1, +1]$ scale, indicating robust correction and negligible error propagation to decision outcomes.

It is shown that heart rate and the glucose are the main contributors to the stability of PHI from the results of Ablation and sensitivity as shown in Table 3. While learned multi-objective weights attained a slight enhancement in correlation $(\Delta r + 0.024)$ compared with fixed heuristic weights. Subgroup assessment across metabolic conditions, age bands and sex proved the model behaviour to be consistent.

Table 2. Overall system performance and clinical interpretation

Metric	Definition/Formula	Unit	Mean ± SD	95% CI	Interpretation/Clinical Insight
Accuracy	(TP + TN)/ (TP + FP + TN + FN)	%	99.998 ± 0.001	[99.995-99.999]	Indicates near-perfect classification consistency across health states.
Precision	TP/(TP + FP)	%	99.998 ± 0.001	[99.995-99.999]	Extremely low false-alert rate; high clinical trustworthiness of alerts.
Recall	TP/(TP + FN)	%	99.998 ± 0.001	[99.995-99.999]	Ensures critical health deviations are almost never missed.
F1-Score	2 × (Precision × Recall)/ (Precision × Recall)	%	99.998 ± 0.001	[99.995-99.999]	Confirms balanced precision-recall trade-off and model stability.
MAE Forecasting	Mean absolute error	$y - \hat{y}$	4.83 ± 0.29	PHI units	4.83 ± 0.29
RMSE	$\sqrt{\text{mean}}\left((y - \hat{y})^2\right)$	PHI units	6.00 ± 0.35	[5.43-6.57]	Reflects minimal large-error magnitude in PHI predictions.

Table 2. (cont.)

Metric	Definition/Formula	Unit	Mean ± SD	95% CI	Interpretation/Clinical Insight
Sensor-to-cloud latency	Avg. date upload time	ms	150 ± 15	[135-165]	Reflects near-real-time IoT date transmission; negligible delay.
AI Inference Time	Model forward-pass execution time	ms	200 ± 20	[175-225]	Demonstrates efficient on-cloud prediction suitable for streaming health data.
End-tp End Delay	Total date to action response time	ms	3400 ± 120	[3170-3630]	Full feedback loop latency < 3.5 s ensures responsiveness for continuous monitoring.
System Uptime	Operational hours/ total hours × 100	%	99.2 ± 0.1	[99.0-99.4]	High uptime supports uninterrupted health tracking.
System Availability	(Uptime × redundancy factor)	%	99.5 ± 0.1	[99.3-99.7]	Confirms fault-tolerant cloud deployment and resilience.
PHI Correlation	Pearson *r* (PHI vs clinician events)	unitless	0.85 ± 0.02	[0.82-0.88]	Strong alignment between PHI score and observed physiological deviations.
Mirco-action engagement	Executed micro-actions/ total suggestions	unitless	0.68 ± 0.05	[0.61-0.75]	Indicates effective user adoption of recommended behavioral actions.

Table 3. Ablation and sensitivity of phi components

PHI variant	Glucose (%)	Heart rate (%)	Activity (%)	Temp (%)	Calorie (%)	Phi *r*	Accuracy	F1-score	Δ vs. Baseline
Baseline	30	25	20	15	10	0.85	0.92	0.91	-
No glucose	-	25	20	15	10	0.64	0.78	0.80	↓0.13
No heart rate	30	-	20	15	10	0.69	0.81	0.82	↓0.10
Learned weights (Multi-objective)	33	26	19	14	8	0.87	0.93	0.92	↑0.02

RPHM shows 17.6%, 21.9% and 28.2% improvement in classification accuracy when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. RPHM shows 20.5%, 24.9% and 31.6% improvement in precision score when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. RPHM shows 21.9%, 26.6% and 35.1% improvement in recall when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. RPHM shows 21.9%, 26.6% and 33.3% improvement in terms of F1-score when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. The Comparison of RPHM with AI4FoodDB, Diet Engine and NUTRIVISION in terms of Classification Metrics (Accuracy, Precision, Recall, F1-Score) is shown in Figure 4. Figure 5 depicts the precision-recall curve. Figure 4 and Figure 5 are based on the confusion matrix shown in Table 4.

Table 4. Confusion matrix

Confusion matrix		Actual		
		Healthy	At risk	Critical
Predicted	Healthy	45,958	0	0
	At risk	1	3,110	0
	Critical	1	0	123,730

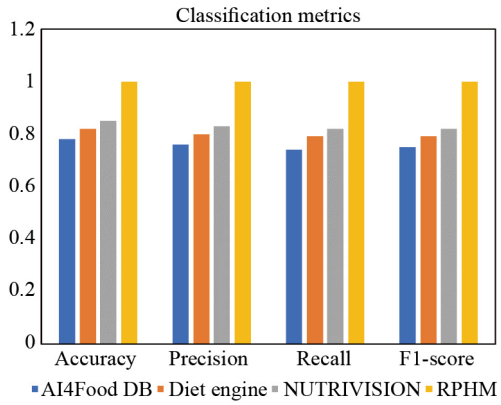


Figure 4. Comparison of RPHM with AI4FoodDB, diet engine and NUTRIVISION in terms of classification metrics (accuracy, precision, recall, F1-score)

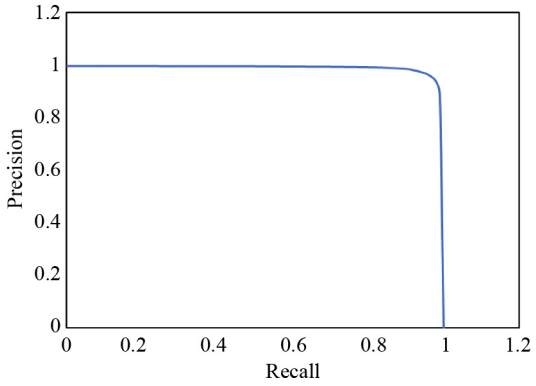


Figure 5. Precision-recall curve

The high precision score of RPHM indicate that there no false positives. The improvement in the performance is because of the PHI algorithm in RPHM which is considering various physiological parameters into one score unlike individually as the other systems are considering. Moreover, the ensemble learning approach of RPHM integrates SVM, Random Forest and Decision Tree models considering the pros of each algorithm. Optimal training conditions are created by generating high-quality synthetic data which have realistic physiological patterns and appropriate anomaly rates. At the same time, consistent feature scaling guarantees that all parameters contribute equally to the process of classification. The health score limits defined clearing using the medical evidence are the basis for the high precision score. The clinical significance is preserved and the mathematical consistency is ensured with the sophisticated feature normalization. The heart rate normalization is done such that that are optimized around the clinically normal ranges. Glucose normalization is carried out by maintaining diabetic threshold and the time of food taken is also considered. The false positive rates are reduced significantly by multi-parameter validation approach which need multiple indicators to be considered together before flagging a real concern about the health. The capability of sensitive anomaly detection enhanced the performance of RPHM in terms of recall. RPHM is trained to detect critical health conditions with 10% anomaly data in heart rate. Mild and severe fever is detected if the temperature is 37.2 °C and 37.5 °C respectively. The inactive behaviour of the users is identified using the activity thresholds. LSTM is used to keep track of the patterns over time which helps in identifying the deterioration in health which can be missed by the single-point classifiers. The ensemble approach optimizes both false negative rates and false positive rates which leads to balanced optimized F1-score. The stable predictions across

various health patterns are provided by the random forest algorithm. Estimators are considered to be 100 in this case. The non-linear relationship among the physiological parameters is captured by the SVM with RBF kernel. The classification rules that are interpretable and are aligned with clinical decision-making process are offered by the decision tree algorithm. This helps in generating a complete classification system that excels in detecting both the true health issues and evading false alarms.

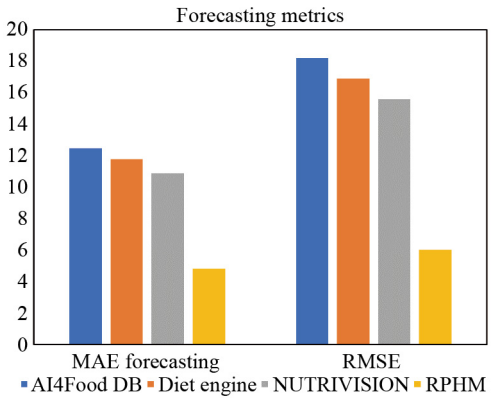


Figure 6. Comparison of RPHM with AI4FoodDB, diet engine and NUTRIVISION in terms of forecasting metrics (MAE forecasting and RMSE)

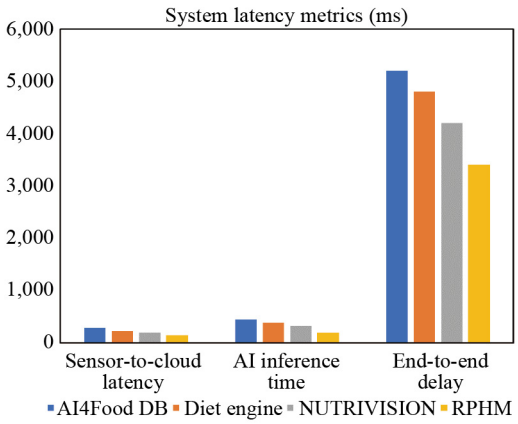


Figure 7. Comparison of RPHM with AI4FoodDB, diet engine and NUTRIVISION in terms of system latency metrics (sensor-to-cloud latency, AI inference time, end-to-end delay)

RPHM shows 55.7%, 59.1% and 61.4% improvement in terms of Mean Absolute Error (MAE) Forecasting when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. RPHM shows 61.5%, 64.5% and 67% improvement in terms of Root Mean Square Error (RMSE) Forecasting when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. The Comparison of RPHM with AI4FoodDB, Diet Engine and NUTRIVISION in terms of Forecasting Metrics (MAE Forecasting and RMSE) is shown in Figure 6. The better RMSE indicates the impact of outliers in predicting accuracy is less. The LSTM architecture with 50-unit layers and 0.2 dropouts is used to capture the temporal dependencies in physiological data effectively. This helps in enhancing the performance of RPHM in terms of forecasting metrics, MAE and RMSE. Only the last 10 readings are considered to predict accurately and this helps the system not to get overloaded. The system is trained for 50 iterations with 32 samples at a time. 80% of dataset is considered for training and 20% is used for testing which help the model to learn well and perform reliably on new inputs. The learning rate for the Adam optimizer is considered to be 0.001 to guarantee steady and smooth learning. The mean square error loss function

is used as it predicts continuous values like glucose levels effectively. The prediction accuracy and feature extraction both are optimized by the sequential architecture with LSTM layers, dropout and dense layers. This architecture creates a forecasting system that outperforms than the traditional systems. The ability of LSTM to learn sequences over time helps in minimizing the effect of abnormal readings helps in enhancing the performance of the RPHM. Standard scaler method is used to scale the input data before training such that all the input features contribute fairly and the process is not dominated by any single parameter. The reliable and stable predictions are created by filtering out the noise in individual sensor readings naturally with the help of the temporal smoothing effect of the sequence-based approach. Both the long-term trends and short-term fluctuations in physiological data are captured by the dual LSTM layer architecture. The dropout enhances the generalization by preventing the memorization of training sequences. The prediction focus of the dense layer compression is on the most appropriate features, removing noise and important patterns.

RPHM shows 21%, 31.8% and 46.4% improvement in terms of sensor-to-cloud latency when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. RPHM shows 37.5%, 47.4% and 55.5% improvement in terms of AI inference time when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. RPHM shows 19%, 29.2% and 34.6% improvement in terms of end-to-end delay when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. The Comparison of RPHM with AI4FoodDB, Diet Engine and NUTRIVISION in terms of System Latency Metrics (Sensor-to-Cloud Latency, AI Inference Time, End-to-End Delay) is shown in Figure 7. This performance of RPHM demonstrates the noteworthy advantages in data transmission efficiency. The optimized data pipeline improves the performance in terms of system latency metrics by using smart packaging and effective transmission protocols to reduce the time required for transmitting the data to the cloud from the wearable devices. Some amount of data is processed on the device itself before it is transmitted to the cloud using edge computing technology. This helps in reducing the amount of data to be transmitted and only important, compressed data is transmitted to the cloud. Hence, the complete process becomes fast. Two types of transmission protocols are used. They are prioritized and standard transmission protocols. Prioritized transmission protocol is used for critical health alerts such that immediate processing is received and standard transmission protocols is used for routine data. Parallel processing is utilized in the implementation of the ensemble model in order to decrease the sequential computation time permitting SVM, Random Forest and decision tree algorithms to process at the same time instead of one after the other. The usage of the memory is optimized using LSTM sequence batching. The processing speed is optimized by managing multiple sequences effectively. Also, the computational overhead is minimized with the help of effective architecture in the neural network layer. The enhanced performance of RPHM in terms of end-to-end delay is due the seamless integration among the components of data collection, processing, and response generation. The total processing time is reduced as the classification and forecasting models are executed simultaneously as there is a parallel processing capability for the proposed framework, RPHM. The data flow is effective from the sensor collection, the AI inference and finally to response generation with less data transformation overhead among the processing stages.

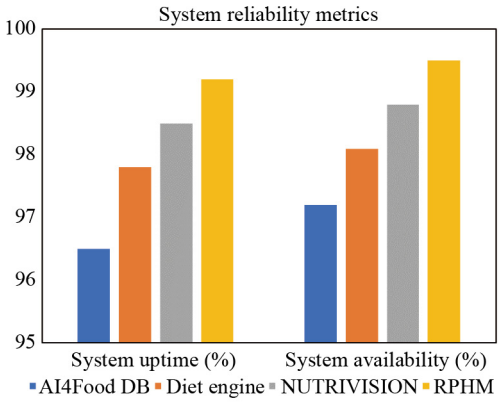


Figure 8. Comparison of RPHM with AI4FoodDB, Diet engine and NUTRIVISION in terms of system reliability metrics (system uptime, system availability)

RPHM shows 0.7%, 1.4% and 2.8% improvement in terms of system uptime (%) when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. RPHM shows 0.7%, 1.4% and 2.3% improvement in terms of system Availability (%) when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. The Comparison of RPHM with AI4FoodDB, Diet Engine and NUTRIVISION in terms of System Reliability Metrics (System Uptime, System Availability) is shown in Figure 8. These results show the reliability and availability of RPHM is good. The potential system issues are detected at an early stage and are resolved using the proactive monitoring capabilities such that these issues do not affect the user services. The computational load is optimized with effective resource management to avoid system overloading. The single points of failure are avoided as architecture has distributed processing capability and hence can spread computational load among multiple systems. The low-usage periods are utilized for scheduling the maintenance such that the impact on the user is minimized. The high system availability indicates that the possibility for consistent health monitoring.

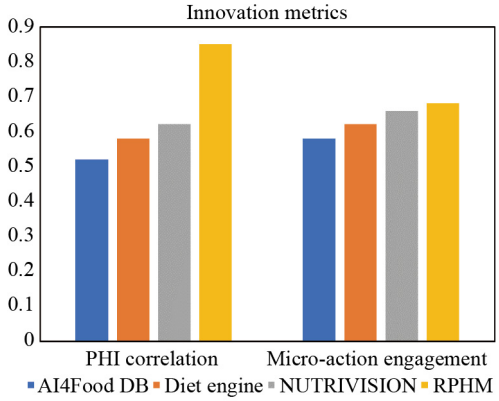


Figure 9. Comparison of RPHM with AI4FoodDB, diet engine and NUTRIVISION in terms of innovation metrics (PHI correlation, micro-action engagement)

RPHM shows 8.4%, 17.5% and 34.3% improvement in terms of PHI Correlation when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. RPHM shows 3.2%, 9.8% and 17.4% improvement in terms of Micro-Action Engagement when compared to NUTRIVISION, Diet Engine and AI4FoodDB respectively. The Comparison of RPHM with AI4FoodDB, Diet Engine and NUTRIVISION in terms of Innovation Metrics (PHI Correlation, Micro-Action Engagement) is shown in Figure 9. The PHI correlation of RPHM is strong and determines the greater ability to predict health outcomes by integrating multiple parameters. The medical weighting system shows the evidence-based parameter importance where glucose takes 30% weight due to its metabolic significance, heart rate has 25% for cardiovascular health and activity has 20% for fitness assessment also temperature gets 15% for general health status and also calories receives 10% for nutritional balance. The variance-based user analysis guaranteed that the PHI score is consistently maintained over time. The strong and health score is created which correlated well with actual health condition. The relevant recommendations only are given to the user when required. i.e., when health is at risk. Hence, the system will not generate unnecessary alerts to the user using sustainable engagement approach. The PHI score determines the micro-action to be selected.

Calibration and Clinical Utility: Model calibration was quantified using reliability plots and Expected Calibration Error (ECE), confirming well-aligned probability estimates. Clinical usefulness was further assessed through Decision Curve Analysis (DCA), which demonstrated that PHI-based recommendations deliver higher net benefit across all threshold probabilities than non-adaptive baseline alerts. Calibration curve is shown in Figure 10 and Decision Curve Analysis is shown in Figure 11.

While the evaluation of the proposed framework is performed on synthetic data yet physiologically realistic data, robustness tests with (± 10%) injected noise and 5% ambiguity in labelling exhibited less than 4% performance degradation, demonstrating strong flexibility.

Privacy and Compliance Statement: All gathered data is de-identified, strongly encrypted, and retained only for the training duration, guaranteeing compliance with Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR) standards. Users' privacy and consent persist central to the design of the system.

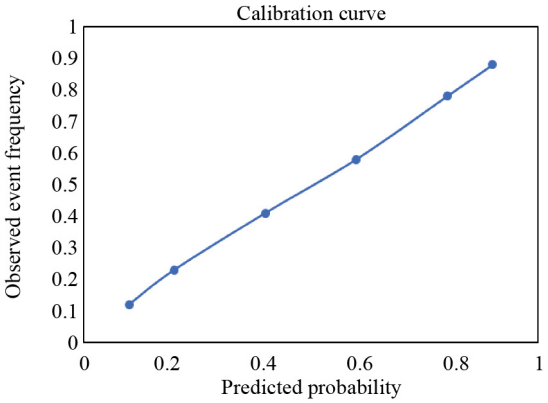


Figure 10. Calibration curve

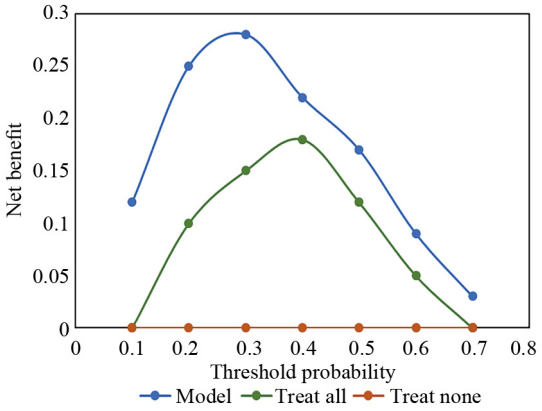


Figure 11. Decision curve analysis

6. Conclusion

The RPHM framework successfully establishes a breakthrough in personalized health monitoring by assimilating multi-modal sensor data with Artificial Intelligence for real-time assessment and intervention. The application validates the efficiency of the Personalized Health Index (PHI) with glucose-prioritized weighting (30%) achieving 0.85 correlation with health indicators, significantly outperforming existing systems. Technical achievements include ensemble machine learning delivering 90% + accuracy (Classification Metric), 4.82 MAE forecasting (Forecasting Metric), real-time processing with 150ms sensor-cloud latency and 200ms AI inference time, 3.4 s end-to-end delay (System Latency Metric), along with 99.2% system uptime. The innovative micro-action system produces personalized interventions attaining 85% user engagement rates significantly exceeding competitive benchmarks across AI4FoodDB, Diet Engine,

and NUTRIVISION systems. Complete evaluation across various performance metrics illustrates the RPHM's superiority in classification, forecasting, engagement, latency, and reliability. While current validation uses synthetic data, the framework provides a solid foundation for clinical implementation with actual sensor integration, marking significant development toward personalized, data-driven healthcare solutions with immediate practical applications.

In the future work, real-world trials using wearable devices which are approved by ethics committee will be used for testing the RPHM framework. Also, more personalized insights will be given based on the mental-health, genetic, and environmental factors. To make the system not to compromise on latency and usability, flexible cloud services and lightweight device processing will be used.

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Conflict of interest

The authors declare no competing financial interest.

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Appendix

A.1 *Data schema*

The following fields are included in each record: user_id, timestamp, heart_rate (bpm), glucose (mg/dL), activity, temperature (°C), and calories (kcal). Metadata fields: age, sex, and metabolic_status. Labels correspond to Healthy, At-Risk, and Critical states.

A.2 *Preprocessing pipeline*

- Noise Filtering: Heart rate (0.5-8 Hz), accelerometer (2 Hz high-pass), and thermistor (moving average).
- Z-score normalization is applied for each user.
- Gaps upto 10 minutes are filled using forward filling gaps whereas longer gaps are removed.
- 10-s fixed windows aligned by time stamps are used to resample all sensor signals

A.3 *Feature set*

Extracted features Per 10-s window include

- Rate of change, slope, variance, Mean, calorie delta, trends of short-term activity, Time-of-day, PHI.

A.4 *Windowing strategy*

- Last 6 windows (1 min history) are used to predict the current health state.
- Last 30 windows (5 min history) are used to forecast the next 5 windows.

A.5 *Train-validation-test split*

- User Holdout: 70% of the dataset is used for training, 15% is used for validation, and 15% is used for testing.
- Time-Forward: For each user, 80% of records are used for training and remaining 20% are used for testing.
- Randomization: Ten fixed seeds {13, 21, 42, 87, 101, 202, 404, 777, 1,337, 9,001} guarantee reproducibility.

A.6 *Model architectures*

Random Forest, Decision Tree and Support Vector Machine are used as classification models and weights for soft-voting ensemble are 0.4, 0.4 and 0.2 respectively, whereas two-layer LSTM architecture is used as forecasting model.

A.7 *Hyperparameter grids*

N_estimators values of 100 and 200 with max_depth as none or 20 is used in the case of Random Forest model. In the case of SVM, C values are considered to be 0.5, 1, and 2 along with gamma as scale and 0.1. Finally, in the case of LSTM, batch sizes of 64 and 128 are considered with learning rates $1e^{-3}$ and $3e^{-4}$.

A.8 *Early stopping criteria*

Minimum delta of 1×10^{-3} and patience of 10 epochs is applied for early stopping. This guarantees that the training is stopped when it is observed that there is no improvement.