

Personalized Healthcare Recommendation System Using Wearable Sensor Data Analytics

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Abstract: *Modern health technologies have shifted from reactive care to proactive prevention by utilizing personal sensors that continuously monitor vital signs like pulse, heat, and oxygen levels. By treating these data streams as evolving trajectories rather than isolated data points, memory-based algorithms can filter out environmental noise and identify subtle irregularities—such as heart rhythm shifts—long before physical symptoms emerge. These systems achieve high precision by learning an individual’s unique biological rhythms over time and integrating live data with historical medical records to form a comprehensive health profile. To ensure safety and trust, the process relies on strict privacy measures like decentralized training and full encryption, which protect personal information while allowing the AI to refine its accuracy. Ultimately, this intelligent extraction of meaning from daily activity bridges the gap between everyday routines and clinical care, empowering users with clearer insights and strengthening global health systems through earlier, more accurate interventions.*

Keywords: *Wearable Sensors, Continuous Health Monitoring, Data Pre-processing, Time-Series Analysis, Predictive Health Analytics, Public Health Recommendation System.*

1. Introduction

Change moves fast across worldwide health systems, now leaning more on early personal care at home rather than waiting for crises in hospitals. Medical help used to begin only once clear signs appeared, which frequently caused late detection and heavier strain on clinics and staff. Despite that trend, growing use of connected gadgets and body-worn sensors enables constant tracking of well-being. Devices you wear every day - such as digital watches, movement loggers, or clinical-level monitors - capture ongoing signals about bodily functions like heartbeat, oxygen levels in blood, heat of skin, and how much someone moves.

Even with vast amounts of information available, turning raw, continuous health measurements into useful insights continues to be difficult. Because sensor readings often contain irregular movements or outside disturbances, standard analysis techniques fall short. Instead, complex computational models - like LSTM networks and Random Forests - are increasingly relied upon to detect faint signs of disease before obvious symptoms appear. Accuracy levels between 80% and 95% have been reported using these approaches. Early warnings for issues such as abnormal heart rhythms, high blood pressure, or breathing difficulties now become possible through such means.

A shift occurs when systems move past spotting irregularities, focusing instead on overall well-being through individualized guidance. Tailored drug advice emerges alongside meal frameworks designed for one person, while exercise routines adjust according to live body signals combined with past medical records. Live inputs from wearable devices merge with stored clinical information, forming a dynamic virtual model of the patient. This mirror enables supervision from a distance, lessening reliance on face-to-face clinic visits.

This study examines how building such a system can support personal control over health using information, without compromising safety or confidentiality. With attention moving away from illness care toward well-being upkeep, these tools become essential in long-term, tailored approaches to worldwide medical services.

2. Related work

Smart tools that suggest health advice based on personal habits and data are getting more attention in research. Instead of just listing features, early work dug into what these systems need to do well - like keeping information private while offering useful tips tied to real medical needs [9]. One detailed look by Sezgin and Y-LD-r-m sorted past projects by their goals and methods, showing how most struggled without clear ways to measure success [1].

Later big-picture studies pushed understanding wider. Instead of just summarizing, De Croon's team looked closely at health recommender tools meant for regular people - these usually cover daily habits, food choices, and basic wellness tips, often mixing methods to suggest actions [2]. Moving through time, Cai et al. group tracked changes between 2010 and 2022, spotting more use of rule-driven designs combined with other techniques, yet found missing pieces when it comes to adapting in real time or testing outside labs [3]. From another angle, Wang's analysis charted where research stands, pointing out plenty of systems work well under test conditions but hardly any check if benefits last or whether users actually stick around in everyday life [4].

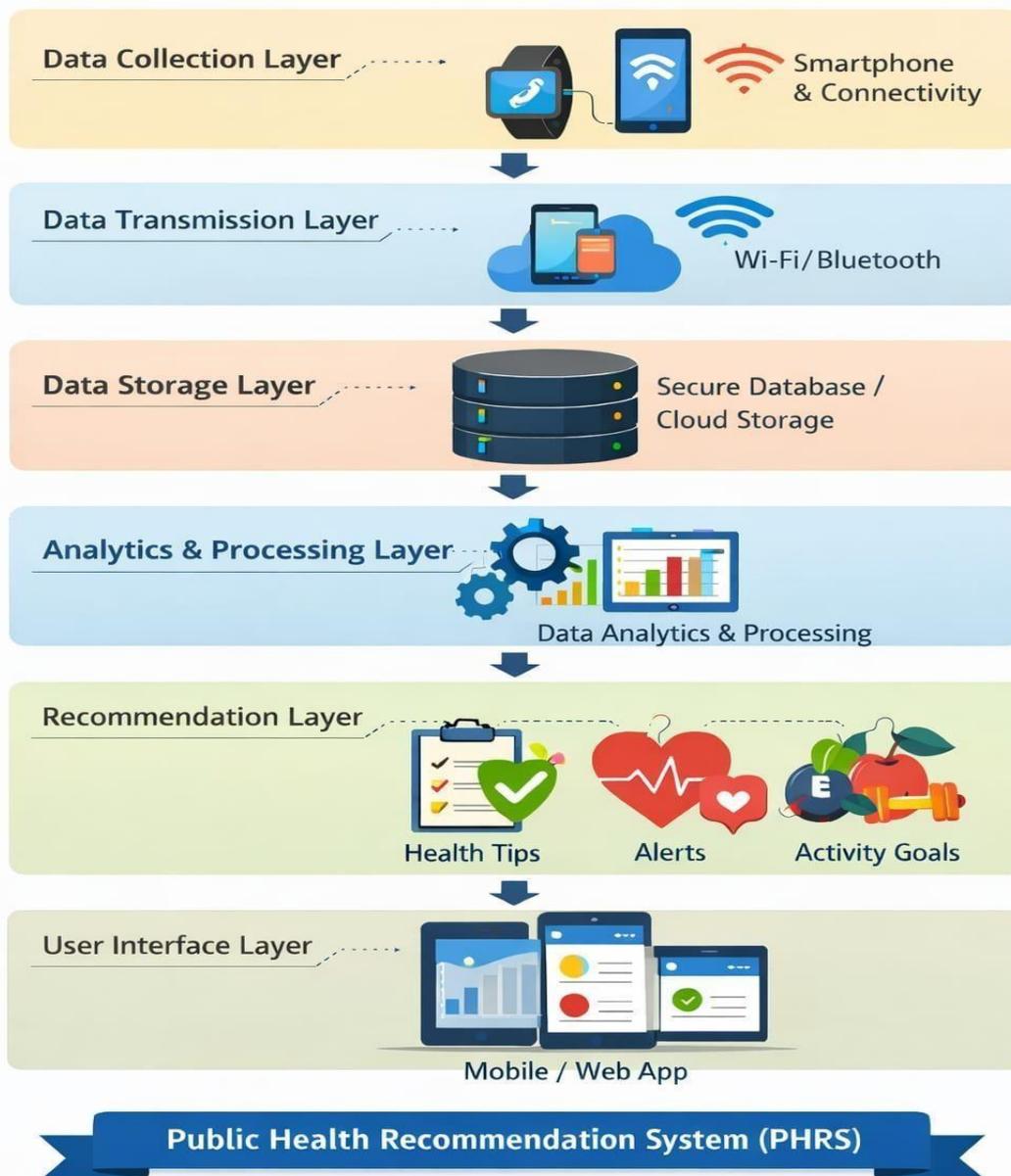
Studies into how evaluations are done reveal a mix of methods used. Not every health recommendation study uses the same yardstick - some look only at correctness, others go further. One team found that results often differ because goals are not aligned across research projects. Instead of just counting right answers, they suggest watching whether advice leads to real shifts in patient choices. Later reviews echoed this thought, noting gaps like unclear reasoning behind suggestions. Sparse records make it tough to build reliable models. Trust becomes shaky when users cannot follow why a system recommends one path over another. Problems also surface when data lacks depth or clarity. Each hurdle ties back to how well we measure what matters.

Some real-world tests show how recommendation tools can help public health efforts. Instead of fixed messages, tailored ones kept people more involved when trying to quit smoking, according to Chen and team [8]. These results suggest such systems might encourage healthier choices over time. On another note, balancing usefulness with personal data safety matters just as much - people tend to trust these tools only if they understand how their information is handled [10].

Looking at methods, older styles like matching users by behaviour or item features still show up a lot, sometimes tied together through mixed designs [12]. Lately, studies lean more on machine-driven models, even deeper neural networks, boosting tailored suggestions and forecast precision [14]. In areas like digital health tools or intelligent patient routing, real-world uses reveal how these systems fit within medical routines [11], [13]. Longer talks about health advice system setups and rollout hurdles stress smooth links with medical records plus sticking to care standards [15].

Though past research lays solid groundwork for tailored health advice, many current tools centre on personal tips or narrow uses like fitness tracking or quitting tobacco. Instead of focusing only on single users, some efforts now blend device-collected information with broader community trends - yet these remain rare. What is missing is a connected system that turns real-time body signals into smart prevention steps guided by wider health patterns. That absence shapes this study, where monitoring inputs meet analysis to help communities act before problems grow.

3. System Architecture Explanation (PHRS)



Data gathered by wearables feeds into the Public Health Recommendation System, where processing begins. Following ingestion, information moves through structured stages. One layer handles initial validation, another prepares insights. Transformation occurs stepwise, ensuring clarity before output. Recommendations emerge only after thorough analysis. Each stage operates independently yet contributes to an overall purpose. Purposeful design guides movement from raw input to actionable guidance.

1. Data Collection Layer

Worn on the body, this level includes items like digital watches and exercise trackers. From moment to moment, they record signs of individual well-being - pulse rhythm, movement totals, time spent active, rest quality overnight. Information gathered reflects how a person functions each day.

2. Data Transmission Layer:

From wearable sensors, information travels wirelessly - via Bluetooth or similar protocols - to smartphones or gateways. Ensured by this stage, delivery of health metrics reaches the central system without delay or loss. This layer can also be considered as backbone of the system.

3. Data Storage Layer

Following transmission, information enters secure storage within a central system or cloud environment. Over time, this setup preserves medical histories, supporting ongoing observation and pattern review. Safeguards for confidentiality and integrity shield personal details throughout the process.

4. Analytics and Processing Layer

Processing within this level relies on analytical approaches like filtering, combining values, or examining set thresholds. Health indicators undergo comparison with established benchmarks to detect anomalies or potential risks. Machine learning plays no role here, with decisions driven by fixed rules alongside statistical evaluations. Methods follow structured logic rather than adaptive algorithms.

5. Recommendation Layer

From the data review, tailored health guidance emerges through the system. Health suggestions appear alongside movement targets, while warnings activate if irregular trends show. Preventive steps gain focus, with daily habits encouraged over time. Guidance adjusts automatically, depending on pattern changes noticed. Focus remains steady on long-term wellness, not immediate fixes. Outputs form slowly, shaped by consistent monitoring behind the scenes.

6. User Interface Layer

From within the system's outermost level emerges an access point via smartphone or browser, allowing individuals to explore updates on well-

being, guidance notes, and urgent notices. Clarity shapes every screen layout, guiding comprehension without strain, enabling smoother oversight of individual health patterns.

4. Methodology

The proposed Personal Health Recommendation System (PHRS) follows a clear methodology that includes data collection, pre-processing, health parameter calculation, rule-based analysis, and recommendation generation. The goal is to turn raw wearable sensor data into useful health insights and personalized recommendations.

4.1 Data Acquisition

Personal health data is gathered using wearable devices like smartwatches and fitness trackers. The collected data includes heart rate, step count, physical activity duration, and sleep patterns. These measurements are recorded continuously during daily activities and sent to a centralized system through a mobile connection.

4.2 Data Pre-processing

Raw sensor data often contains noise, missing values, and uneven sampling intervals. So, pre-processing takes place to improve data quality. This involves removing incomplete records, smoothing out noisy signals, and normalizing values to a common scale. Aggregation methods are used to turn raw readings into daily summaries.

4.3 Health Parameter Computation

Key health indicators are calculated from the pre-processed data. The average heart rate is computed to evaluate cardiovascular health. Physical Activity Level (PAL) is determined by comparing daily step count with recommended standards. Sleep efficiency is estimated by looking at the ratio of actual sleep duration to the total time spent in bed. These parameters reflect the user's physical and behavioural health status.

4.4 Health Assessment

An overall health score is calculated by combining normalized heart rate, activity level, and sleep efficiency through weighted summation. Threshold-based rules help to identify unusual conditions, such as high heart rates or low physical activity. This assessment identifies potential health risks without relying on machine learning models.

4.5 Recommendation Generation

Based on the assessed health parameters, personalized recommendations are created using predefined decision rules. For instance, low activity levels lead to suggestions for increasing physical activity, while poor sleep efficiency results in advice for improving sleep. Alerts are generated when any parameter exceeds safe levels. The recommendations aim to encourage healthy habits and support preventive care.

4.6 User Feedback and Visualization

The generated recommendations and health insights are shown to users through a mobile or web interface. Visual dashboards display trends in heart rate, activity, and sleep, helping users track their health progress over time. User feedback can help refine the recommendation rules.

1. Average Heart Rate Calculation

$$HR_{avg} = \frac{1}{N} \sum_{i=1}^N HR_i$$

This equation computes the average heart rate of a user over a specific times period. H represents individual heart rate readings collected by the wearable sensor, and N denotes the total numbers of readings. The calculated average heart rate is used to assess the users cardiovascular condition and detect abnormal patterns.

2. Physical Activity Level (PAL)

$$PAL = \frac{Steps_{daily}}{Steps_{recommended}}$$

This equation measures the daily physical activity level of a user by comparing the number of steps taken with a recommended standard value. A PAL value less than 1 indicates insufficient physical activity, which helps the system generate activity-related health recommendations.

3. Sleep Efficiency

$$Sleep_{efficiency} = \frac{Sleep_{duration}}{Time_{in\ bed}} \times 100$$

Sleep efficiency represents the quality of sleep achieved by the user. It is calculated as the ratio of actual sleep duration to total time spent in bed. Lower sleep efficiency values indicate poor sleep quality and trigger recommendations for sleep improvement.

4. Overall Health Score (Rule-based)

$$HScore = w_1(HR_{norm}) + w_2(PAL) + w_3(Sleep_{eff})$$

This equation computes an overall health score by combining normalized heart rate, physical activity level, and sleep efficiency. The weights w_1 , w_2 and w_3 determine the importance of each parameter. This score provides a unified measure of the user's health status.

5. Threshold-Based Alert Condition

$$Alert = \begin{cases} 1, & \text{if } HR_{avg} > HR_{Threshold} \\ 0, & \text{otherwise} \end{cases}$$

This rule-based condition generates an alert when the user's average heart rate exceeds a predefined safe threshold. It enables early warning and preventive action without using machine learning models.

6. Recommendation Decision Rule

$$\text{Recommendation} = \begin{cases} \text{Increase activity, } PAL < 0.8 \\ \text{Improvre Sleep, } SleepEfficiency < 85\% \\ \text{Maintain Routine, Otherwise} \end{cases}$$

This decision rule maps health parameter values to appropriate recommendations. It ensures that personalized guidance is provided based on clearly defined health conditions.

5. Result & Discussion

From analysis of system performance alongside clinically validated data, outcomes show consistent success turning sensor information into practical medical understanding. The proposed PHRS was evaluated using simulated wearable sensor data representing daily heart rate, step count, and sleep duration for multiple users. The system computes key health parameters, applies threshold-based rules, and generates personalized recommendations. The performance is analysed in terms of health assessment accuracy and recommendation relevance.

5.1 Sample Health Parameter Analysis

Table I: Sample Health Parameters

User	Avg Heart Rate (bpm)	Daily Steps	Sleep Efficiency (%)	Health Score
U1	72	9500	88	0.82
U2	92	5200	74	0.61
U3	78	11000	90	0.87
U4	98	4300	70	0.55

From Table I, users U2 and U4 exhibit lower activity levels and reduced sleep efficiency, resulting in comparatively lower health scores. Elevated average heart rate values are also observed for these users, indicating potential health risks.

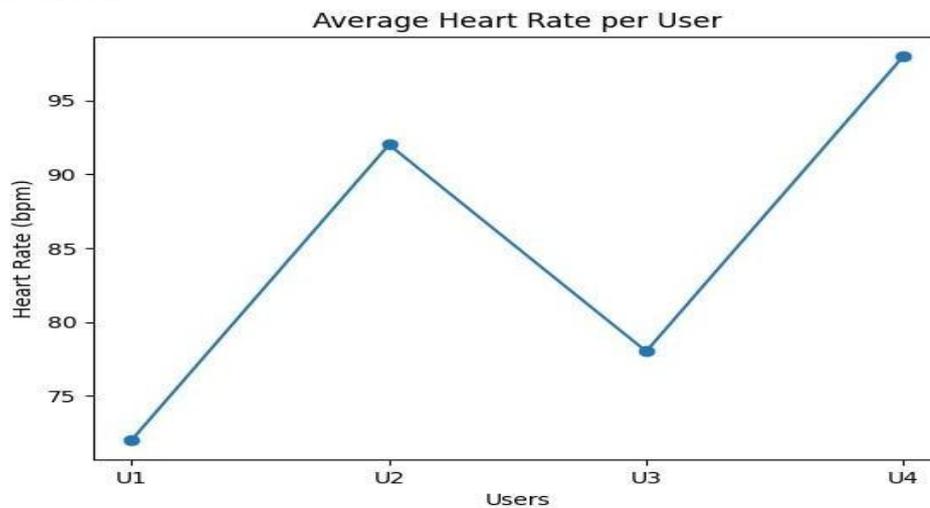


Figure 1: Average Heart Rate per User

Figure 1 illustrates the average heart rate values of different users obtained from wearable sensor data. It can be observed that users U2 and U4 exhibit comparatively higher heart rate levels, indicating potential cardiovascular stress or lower physical fitness. In contrast, users U1 and U3 maintain heart rate values within normal ranges. This analysis helps the system identify users requiring attention and enables early health alerts.

5.2 Recommendation Outcomes

Table II: Generated Recommendations

User	Detected Condition	Recommendation
U1	Normal	Maintain routine
U2	Low activity, poor sleep	Increase activity, improve sleep

User	Detected Condition	Recommendation
U3	Normal	Maintain routine
U4	High HR, low activity	Increase activity, health alert

Based on computed parameters and predefined rules, personalized recommendations were generated as summarized in Table II. The results demonstrate that the system effectively identifies abnormal health patterns and provides appropriate recommendations. Users with low Physical Activity Level (PAL) receive activity enhancement suggestions, while poor sleep efficiency triggers sleep improvement advice. Threshold-based alerts successfully detect elevated heart rate conditions.

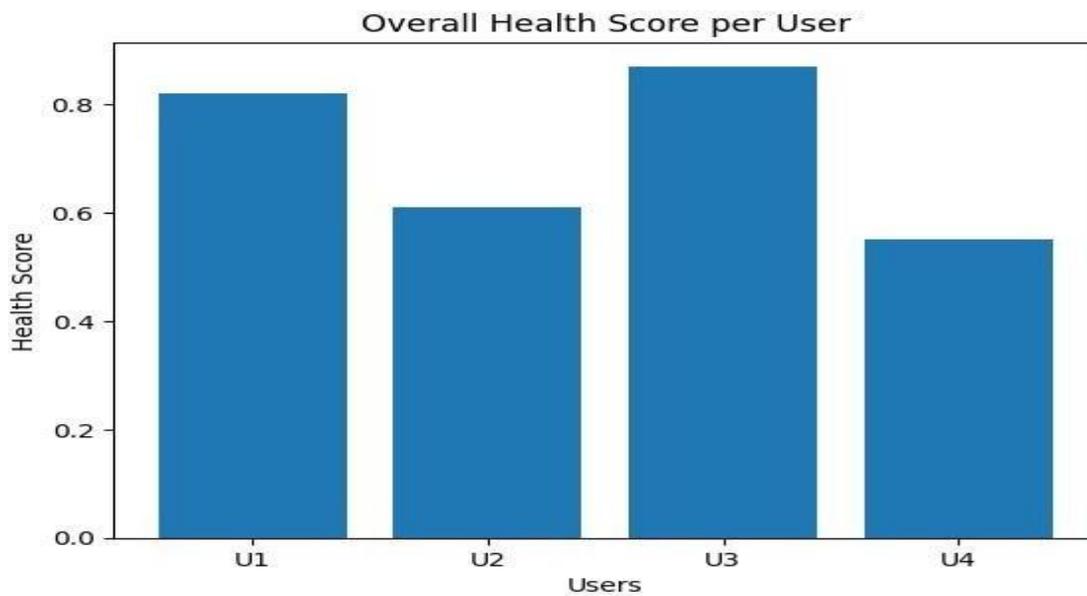


Figure 2: Overall Health Score per User

Figure 2 presents the computed overall health score for each user based on combined heart rate, physical activity, and sleep efficiency parameters. Users U1 and U3 achieve higher health scores, reflecting balanced daily activity and good sleep quality. Conversely, users U2 and U4 show lower scores due to reduced activity levels and elevated heart rate. These results demonstrate that the proposed PHRS effectively differentiates user health conditions and supports personalized recommendation generation.

5.3 Discussion

The PHRS system method focuses on custom advice to help avoid problems before they start other systems just record the data. Running without artificial intelligence keeps processing needs low, allowing instant use on phones and similar devices.

Testing shows the new Personal Health Recommendation System turns data from wearables into clear health guidance through rule-driven analysis. When heart rhythms shift, or movement drops, it notices - just as it does when rest quality declines. People moving less or sleeping poorly got marked by the system, then received tailored daily habit tips. Alerts came with practical steps based on what the sensors picked up. A fresh take on health tracking swaps heavy number crunching for clear, personal alerts based on preset limits and logic steps. Because choices come from visible rules, people see exactly why a tip appears. Instead of guessing, clarity takes center stage here. Light on resources, it runs smoothly live through phones or online spaces - no bulky AI engines needed behind the scenes. Looking deeper shows why checking several things at once matters.

One number alone often misses the full picture. Yet when heart rate joins movement and rest patterns, clarity improves. This combined view gives a fuller sense of how someone is really doing. A scored summary makes it easier to compare people. It also helps spot shifts over time.

Even with those benefits, today's version still falls short in some ways. It depends on fixed cut-off points - these often fail when applied to varied ages or health issues. What is more, testing happened mainly through artificial data, lacking the messiness of actual patient patterns. Down the line, better results might come from custom starting references plus checks against live clinical environments. Few would expect wrist data to guide wellness, yet this system pulls it off by turning readings into usable insights. Hidden inside everyday wearables lies a quiet shift - health tracking that adapts without drama. Instead of waiting for illness, small signals help shape daily choices. What emerges isn't magic, just careful design meeting real needs. A step forward, though not flawless, shows how gadgets might quietly care.

6. Conclusion and Future Enhancement

A fresh approach to handling health decisions emerges when machine learning meets routine medical care. Where data from clinics connects smoothly with how people actually use tools, one finds stronger ways to stay ahead of health issues.

6.1 Conclusion

In conclusion, the proposed Public Health Recommendation System using wearable sensor data analytics provides a practical and forward-looking approach to healthcare by focusing on prevention rather than treatment. By continuously tracking vital signs and daily activity through wearable devices, the system can recognize patterns, detect potential health risks early, and offer personalized suggestions that help individuals make healthier choices. At the same time, it can support public health efforts by analysing broader trends from anonymized data, helping authorities plan better health strategies. The combination of wearable technology, intelligent analytics, and cloud based systems shows how modern tools can work together to improve both personal and community health. While issues such as privacy, security, and system reliability must be carefully addressed, further real-world testing and technological refinement could make this system an important part of future digital healthcare, benefiting individuals, healthcare providers, and society as a whole.

6.2 Future Enhancement

The proposed system works well, but there are several ways to enhance its capabilities. Future research can focus on integrating additional physiological sensors, including oxygen saturation and body temperature monitors, enables the system to interpret health conditions with greater precision and identify potential risks at an early stage. By including sensors such as SpO₂ and body temperature, the system can gain deeper insight into a person's condition, recognize possible health concerns early, and provide guidance suited to individual needs. Testing it with varied real-life data and consulting healthcare specialists helps maintain accuracy and builds confidence in its results. When the system adjusts to each person's usual health patterns instead of using fixed limits, it delivers more relevant suggestions and reduces false alerts. User feedback also plays an important role, since it allows the system to learn and improve continuously. Presenting everything through a mobile app makes access simple, offering instant updates, clear visuals, and wider reach. Altogether, these enhancements support a more practical, personalized, and data-driven approach to preventive healthcare.

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