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FitIQ: A Comprehensive Survey on AI-Based Personalized Fitness Recommendation Systems Using Health and Lifestyle Data

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ABSTRACT—

The increasing prevalence of sedentary lifestyles, unhealthy dietary habits, inadequate sleep, and stress has created a growing need for intelligent and personalized fitness guidance. Existing fitness and health systems have demonstrated the effectiveness of machine learning, IoT-based monitoring, and explainable artificial intelligence for activity recognition, health prediction, and personalized recommendations; however, limitations such as static recommendations, limited behavioural tracking, dependence on wearable devices, lack of explainability, and insufficient representation of Indian users remain evident in the reviewed literature. FitIQ will be developed as an AI-based personalized fitness recommendation framework that will integrate biometric, behavioural, lifestyle, and dietary information to provide individualized fitness guidance. The framework will consider parameters such as physical activity, sleep, stress, nutrition, and fitness-related characteristics to support personalized analysis and recommendations. Machine learning techniques will be used for health and fitness analysis, while explainable AI, particularly SHAP-based analysis, will be incorporated to improve the transparency and interpretability of generated recommendations. The framework will further emphasize adaptive and continuous analysis rather than relying solely on static user information, with the objective of supporting personalized exercise, dietary, and wellness recommendations. The Phase-I work will establish the conceptual framework, system architecture, and research foundation required for the subsequent implementation and evaluation of FitIQ.

***Keywords*—Artificial Intelligence, Machine Learning, Personalized Fitness Recommendation, Explainable Artificial Intelligence, Health Analytics, Lifestyle Monitoring, Obesity Prediction, Sleep Analysis, Stress Analysis.**

INTRODUCTION

Maintaining a healthy lifestyle has become increasingly challenging because of sedentary behaviour, unhealthy dietary habits, irregular sleep schedules, and rising stress levels. These factors have contributed significantly to obesity, cardiovascular disorders, diabetes, and numerous chronic diseases across different age groups. Although awareness regarding fitness has increased considerably, many individuals continue to struggle with selecting exercise routines, maintaining consistency, and understanding how daily behavioural factors influence their overall health. As a result, there is a growing need for intelligent digital systems capable of providing personalized fitness guidance based on individual characteristics rather than generic recommendations [5], [6], [7], [16].

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), wearable technologies, and cloud computing have created new opportunities for developing intelligent healthcare and fitness applications. Modern machine learning algorithms are capable of analysing large volumes of biometric, behavioural, and physiological information to generate personalized recommendations that continuously adapt according to user behaviour. Several studies have demonstrated that combining multiple health indicators such as body measurements, physical activity, dietary habits, sleep quality, and stress levels significantly improves recommendation accuracy compared to systems that rely only on biometric information [8], [10], [12], [14].

Research has also highlighted the importance of behavioural health monitoring in improving physical fitness outcomes. Sleep quality, stress level, consistency of exercise, nutrition, hydration, and daily activity patterns have been identified as major contributors to long-term health improvement. Multiple systematic reviews and metaanalyses have established strong relationships between exercise participation, sleep quality, stress management, and successful weight control. These findings indicate that effective fitness recommendation systems should consider behavioural factors alongside conventional physiological measurements to deliver meaningful and sustainable recommendations [6], [7], [15], [16], [19].

Another important development in intelligent healthcare is the emergence of Explainable Artificial Intelligence (XAI). Traditional machine learning models often function as black boxes, making it difficult for users to understand why particular recommendations are generated. Recent research demonstrates that explainability techniques, particularly SHAP, improve transparency, user trust, and acceptance of AI-based decision support systems.

Providing interpretable recommendations becomes especially important in healthcare applications where users expect clear reasoning behind every suggested action [3], [8], [10], [13].

Although numerous intelligent fitness systems have been proposed, existing solutions continue to exhibit several practical limitations. Many studies remain theoretical or laboratory-based without deployment in real-world environments. Several systems depend heavily on wearable devices or specialized hardware, limiting accessibility for general users. Others focus only on obesity prediction or activity classification without providing adaptive recommendations, behavioural monitoring, or long-term user engagement. Furthermore, many published datasets primarily represent Western or elderly populations, creating challenges when applying these models to younger Indian users [1], [2], [5], [9], [11], [17].

Considering these research gaps, this project will develop FitIQ, an AI-based personalized fitness recommendation framework designed to provide adaptive, explainable, and user-centric fitness guidance. The framework will integrate biometric information, behavioural health indicators, dietary preferences, physical activity, sleep quality, stress level, and other lifestyle parameters to generate individualized recommendations. Unlike conventional systems, FitIQ will emphasize transparency, personalization, and practical usability while targeting the Indian population. The framework is expected to provide an intelligent foundation for supporting healthier lifestyle decisions through continuous monitoring and data-driven recommendation generation [9], [10], [12], [18], [20].

EXISTING SYSTEMS

The growing popularity of digital fitness applications has resulted in the development of numerous health monitoring and recommendation systems. Existing platforms commonly utilize user information such as age, gender, body mass index (BMI), calorie intake, physical activity level, and dietary preferences to generate exercise plans and nutrition advice. Several systems further incorporate wearable sensors and Internet of Things (IoT) devices to collect physiological information including heart rate, step count, sleep duration, and energy expenditure. Machine learning algorithms have also been widely employed for activity recognition, obesity prediction, behavioural analysis, and personalized exercise prescription [1], [5], [8], [9], [12].

- Many recent studies have demonstrated that machine learning techniques such as Random Forest, Support Vector Machine, Gradient Boosting, XGBoost, Neural Networks, and ensemble learning significantly improve prediction accuracy compared to traditional statistical approaches. Explainable Artificial Intelligence techniques including

SHAP and LIME have also been introduced to increase user confidence by explaining how input features contribute to prediction results [3], [8], [10], [13], [17].

- Despite these developments, several shortcomings remain evident in current fitness recommendation systems. Many existing applications generate recommendations using static models that do not adapt according to individual behavioural changes over time. Several systems primarily focus on obesity classification or activity recognition without providing comprehensive lifestyle guidance that considers sleep quality, stress level, hydration, nutrition, and long-term behavioural trends [5], [7], [10], [14], [16].

Another major limitation involves dependence on specialized hardware or wearable devices. Some research frameworks require smartwatches, IoT sensors, RFID-based gym infrastructure, or other dedicated equipment for continuous health monitoring. Such requirements increase deployment cost and reduce accessibility, particularly for users who do not possess wearable devices or regularly visit fitness centres. Furthermore, many proposed solutions have been evaluated only using benchmark datasets or controlled laboratory environments without extensive validation using real-world users [1], [5], [9], [18].

Existing research also reveals limited consideration of behavioural and psychological factors that strongly influence physical activity. Numerous studies confirm that inadequate sleep quality, elevated stress levels, and inconsistent exercise behaviour significantly reduce fitness participation and weight-loss success. However, these variables are often treated independently rather than being integrated into a unified recommendation framework capable of generating personalized interventions based on behavioural patterns [6], [7], [15], [19].

Additionally, several published machine learning models have been trained using datasets collected from Western countries, hospital environments, or elderly populations. Such datasets may not accurately represent younger Indian users with different lifestyles, dietary habits, and physical activity patterns. Studies focusing on Indian populations further emphasize the need for localized datasets to improve fairness, accuracy, and practical applicability of intelligent healthcare systems [2], [11], [12], [17].

Therefore, there remains a need for a comprehensive intelligent fitness recommendation framework capable of integrating biometric information, behavioural analytics, explainable artificial intelligence, and personalized health monitoring into a unified platform. The proposed FitIQ framework will aim to address these limitations by providing adaptive recommendations based on multiple health and lifestyle parameters while improving transparency, accessibility, and personalization for the target user population [3], [9], [10], [12], [16].

LITERATURE SURVEY

The development of intelligent fitness recommendation systems has gained significant attention due to advancements in Artificial Intelligence (AI), Machine

Learning (ML), wearable technologies, and health analytics. Existing studies have explored different aspects including personalized exercise recommendation, health monitoring, obesity prediction, behavioural analysis, explainable AI, and time-series health data analysis. The following literature survey categorizes the reviewed works based on their major research themes rather than discussing them individually.

A. AI and Machine Learning-Based Personalized Fitness Recommendation

Machine learning techniques have demonstrated significant potential in developing personalized fitness and healthcare applications by analysing user-specific physiological and behavioural information. Jubair and Mehenaz conducted a systematic review of ML-based personalized workout recommendation systems and analysed 49 studies focusing on activity recognition, vital sign monitoring, and exercise prescription. Their study identified that algorithms such as Random Forest, Support Vector Machine, CNN, and LSTM achieved high accuracy in activity recognition when combined with wearable sensor data. However, the review highlighted limitations including dependence on smartwatches, controlled laboratory environments, and limited real-world deployment [5].

Naveed et al. developed an IoT-based health monitoring system, FitScan Pro, which integrated biometric measurement, machine learning-based diet and exercise recommendation, and calorie monitoring. The system demonstrated the feasibility of combining IoT and ML for automated fitness assistance. However, recommendations were mainly static and focused on gym users, without considering behavioural parameters such as sleep, stress, nutrition patterns, or long-term user adaptation [9].

Woll et al. investigated personalized fitness recommendation using machine learning models by integrating biometric, behavioural, and demographic features from large-scale health datasets. Their study demonstrated that clustering techniques such as K-Means and hierarchical clustering can effectively categorize users according to activity levels and health risks. However, the system focused on population-level health strategies rather than individual adaptive recommendations [12].

The effectiveness of machine learning-based fitness interventions has also been evaluated through systematic reviews. Kozan Cikirikci and Esin analysed multiple studies involving ML-driven physical activity interventions and concluded that supervised learning approaches provide measurable improvements in health outcomes. However, the authors identified limitations such as insufficient behavioural feature integration, limited long-term evaluation, and lack of personalization in many existing systems [16].

B. Explainable Artificial Intelligence for Transparent HealthRecommendations

Although machine learning models provide accurate predictions, their black-box nature creates challenges in healthcare and fitness applications where users require understandable explanations. Explainable Artificial Intelligence (XAI) has emerged as an important approach to improve transparency and trust in intelligent recommendation systems.

Jamloki et al. proposed an explainability framework combining SHAP-based feature importance analysis with Large Language Models (LLMs) to generate humanreadable explanations for clinical predictions. Their findings demonstrated that combining SHAP values with natural language explanations improved interpretability. However, the approach involved significant computational requirements and was mainly evaluated using clinical datasets rather than fitness-related data [3].

Görmez et al. developed an obesity prediction model using machine learning algorithms integrated with XAI techniques. Their work compared SHAP and LIME approaches and demonstrated that SHAP provided more reliable feature-level explanations. The study showed that explainability improves user trust in AI-driven health predictions. However, the model generated classification results only and did not provide adaptive fitness recommendations or continuous monitoring [10].

A meta-analysis conducted by Jamal et al. reviewed 62 studies related to explainable AI in clinical decision support systems. The study identified SHAP as one of the most widely adopted explainability methods and emphasized that interpretable AI models improve acceptance among users. However, the review primarily focused on clinical applications and identified the lack of XAI adoption in personalized wellness and fitness systems as an important research gap [13].

Random Forest-based behavioural prediction research by Zhang et al. further demonstrated the usefulness of SHAP for identifying important lifestyle factors affecting physical activity. The study revealed that behavioural characteristics often contribute more significantly than demographic attributes. However, the research focused only on prediction and did not implement a recommendation framework for users [8].

C. Behavioural Factors: Sleep, Stress, and Physical ActivityAnalysis

Recent research has highlighted that fitness outcomes depend not only on exercise but also on behavioural and psychological factors such as sleep quality, stress level, and lifestyle consistency. Integrating these parameters into intelligent fitness systems can improve recommendation accuracy and user adherence.

Wang et al. analysed the relationship between sleep quality, stress, and physical activity participation among college students. The study identified that increased stress negatively affects exercise participation and that sleep quality independently influences physical activity behaviour. However, the research was based on a cross-sectional survey and did not integrate findings into a digital fitness recommendation platform [6].

Li et al. conducted a systematic review and meta-analysis investigating the impact of exercise interventions on sleep quality and weight loss among individuals with obesity. The findings indicated that exercise improves both sleep quality and weight management outcomes, with combined exercise approaches showing stronger effects. However, the study provided population-level observations rather than personalized recommendations [7].

The relationship between sleep and weight management was further examined by Kaur et al. through a scoping review of longitudinal weight-loss studies. The study established that sleep quality acts as an important predictor of weight-loss success. However, existing research lacked real-time monitoring and personalized intervention mechanisms [19].

Li et al. also investigated different physical activity interventions and their impact on women's sleep quality. Their network meta-analysis demonstrated that aerobic exercise, yoga, and combined exercise approaches significantly improve sleep outcomes. However, personalization based on individual sleep patterns was not explored [15].

D. Obesity Prediction and Health Risk Assessment Using Machine Learning

Obesity prediction has been one of the major application areas of machine learning in healthcare analytics. Several studies have explored classification models using demographic, behavioural, and physiological information.

Genc and Arican evaluated multiple machine learning algorithms for obesity classification without using weight and height information. Their findings demonstrated that behavioural and demographic characteristics alone can provide meaningful obesity predictions. However, the model was static and did not generate personalized health recommendations [14].

Rajesh et al. introduced a hybrid ensemble machine learning approach combining Extra Trees, Random Forest, and Gradient Boosting algorithms for obesity prediction. The study demonstrated that ensemble models improve classification performance, particularly when handling class imbalance. However, the model was limited to prediction tasks without real-time monitoring or recommendation generation [17].

Wood et al. explored obesity trend prediction using big data analytics by combining electronic health records, wearable data, and social media health information. Their research showed that multi-source data integration can identify hidden population-level health patterns. However, the system focused on trend prediction rather than individual fitness guidance [18].

Lee et al. evaluated fairness issues in machine learning models for obesity prediction across socioeconomic and caste groups in India. The study highlighted the importance of using region-specific datasets and analysing algorithmic bias. However, the dataset focused on older adults and did not include fitness-related behavioural parameters [11].

E. Health Data Management, Clustering, and Time-Series Analysis

Large-scale health data analysis requires efficient methods for identifying patterns, detecting abnormalities, and maintaining privacy. Several studies have explored clustering, anomaly detection, and intelligent health monitoring approaches.

Venkata Krishna et al. introduced BRPHM, a blockchainenabled health management framework combining IoT sensors, federated learning, and AI-based health scoring. The framework addressed privacy and data integrity challenges in healthcare monitoring. However, the system was theoretical, relied on synthetic datasets, and lacked real-user validation [1].

Adhikari et al. applied weighted K-Means clustering on large-scale healthcare records to identify meaningful patient groups based on chronic conditions. Their study demonstrated the effectiveness of clustering methods for health segmentation. However, the research focused on elderly clinical populations and did not include fitnessrelated behavioural attributes [2].

Wang et al. investigated the cost-effectiveness of lightweight language models for time-series anomaly detection. The study demonstrated that fine-tuned lightweight models can achieve effective anomaly detection while balancing computational cost. However, healthcare and fitness applications were not evaluated [4].

Lai et al. presented a comprehensive survey on deep learning-based time-series anomaly detection techniques.

The study reviewed architectures including Autoencoders, LSTM, GRU, and Transformer-based approaches. Although deep learning methods achieved strong performance, computational requirements and dependency on labelled datasets remain major challenges for lightweight fitness applications [20].

TABLE 1: COMPARISON TABLE

Ref.	Research Focus	Technique	Limitation
[1], [5], [9], [10]	Personalized health monitoring, workout rec., IoT fitness, obesity prediction	Federated Learning, Blockchain, IoT, ML, Random Forest, XGBoost, SHAP, LIME	No real-user deployment; static recs; synthetic data only
[12]	ML-based personalized fitness strategy	ML classification and clustering	Population-level focus only

Ref.	Research Focus	Technique	Limitation
[13]	Explainable AI in healthcare	SHAP, LIME, XAI methods	Limited application to fitness domain
[17], [20]	Obesity prediction enhancement, timeseries anomaly detection	Ensemble ML models, Deep Learning, LSTM, Transformer	Prediction only, no deployment; high computation cost

Research Gap Analysis

From the reviewed literature, several research gaps have been identified. Existing machine learning-based fitness systems demonstrate promising prediction capabilities; however, many approaches remain limited to static recommendations without continuous adaptation according to user progress [5], [9], [12]. Several studies depend on wearable devices, specialized sensors, or controlled environments, reducing accessibility for general users [1], [5], [9].

Although behavioural factors such as sleep quality, stress, and lifestyle consistency have been identified as important contributors to fitness outcomes, they are often analysed independently rather than being integrated into a unified recommendation framework [6], [7], [19]. Furthermore, many existing obesity prediction models focus only on classification without generating personalized exercise, nutrition, or lifestyle recommendations [10], [14], [17].

Explainability has become an essential requirement for trustworthy AI-based health applications. However, most existing XAI studies focus on clinical decision support systems rather than fitness and wellness applications [3], [13]. Additionally, several models are trained using datasets from non-Indian populations, creating challenges related to demographic suitability and fairness [11], [12].

Therefore, a comprehensive fitness recommendation framework is required that combines machine learning, behavioural monitoring, explainable AI, and personalized recommendations while remaining accessible without mandatory wearable devices. FitIQ will aim to address these gaps by integrating biometric information, lifestyle parameters, adaptive recommendations, and transparent AIdriven insights into a unified fitness recommendation framework.

PROPOSED SYSTEM

FitIQ will be an AI-based personalized fitness recommendation framework designed to provide adaptive and user-centric health guidance by analysing multiple dimensions of an individual's lifestyle and physical condition. Unlike conventional fitness applications that mainly provide generalized workout or diet suggestions, FitIQ will integrate biometric information, behavioural characteristics, lifestyle patterns, and fitness objectives to generate personalized recommendations. The framework will consider parameters such as age, gender, height, weight, Body Mass Index (BMI), activity level, dietary preference, sleep quality, stress level, water intake, daily steps, and exercise frequency for developing a comprehensive user health profile.

The framework will employ machine learning techniques to analyse user data and identify meaningful patterns associated with fitness improvement. Previous studies have demonstrated that combining physiological and behavioural attributes produces more effective health predictions compared to relying only on biometric parameters [8], [12]. Therefore, FitIQ will incorporate both physical and behavioural indicators to improve recommendation accuracy. The system will continuously analyse user information and provide recommendations related to exercise routines, nutritional planning, hydration goals, calorie requirements, and lifestyle improvement.

The framework will consist of multiple intelligent components responsible for health analysis, recommendation generation, and user engagement. The initial component will perform user health assessment by calculating important indicators such as BMI, Basal Metabolic Rate (BMR), Total Daily Energy Expenditure (TDEE), and overall health score. These measurements will help establish the user's current fitness condition and provide the foundation for personalized recommendations. Machine learning models will then analyse user characteristics and classify suitable fitness strategies based on individual requirements.

A recommendation engine will be incorporated to generate personalized exercise and nutrition suggestions. The engine will consider user fitness goals such as weight loss, weight gain, or maintaining current health status along with activity level and lifestyle patterns. Research studies have shown that machine learning-based recommendation systems can outperform static fitness plans by adapting suggestions according to user-specific characteristics [5],

[12], [16]. Therefore, FitIQ will focus on adaptive recommendations rather than fixed predefined fitness plans.

Explainability will be an important feature of FitIQ to improve user trust and understanding. The framework will integrate Explainable Artificial Intelligence techniques, particularly SHAP-based analysis, to identify the contribution of different user attributes towards generated recommendations. Previous studies have demonstrated that SHAP provides reliable feature-level explanations and improves transparency of machine learning-based healthcare decisions [3], [10], [13]. In FitIQ, these explanations will be converted into understandable insights, allowing users to understand the reasons behind their personalized recommendations.

The framework will also incorporate behavioural monitoring by considering factors such as sleep quality, stress level, exercise consistency, and lifestyle habits. Research indicates that sleep and stress significantly influence physical activity participation and weight management outcomes [6], [19]. By integrating these factors, FitIQ will aim to provide recommendations that consider overall wellness rather than focusing only on physical measurements.

Furthermore, the framework will support continuous health improvement through progress tracking and adaptive recommendation updates. Unlike existing systems that generally provide static predictions [9], [14], FitIQ will analyse changes in user behaviour and fitness progress over time. This approach will enable the system to modify recommendations according to changing user requirements and encourage long-term fitness adherence.

SYSTEM ARCHITECTURE

The architecture of FitIQ will consist of multiple interconnected layers responsible for user interaction, data collection, processing, machine learning analysis, and recommendation generation. The user interaction layer will provide a web-based interface through which users will register, enter their health information, define fitness goals, and monitor their progress. User data collected through this layer will include demographic information, biometric measurements, lifestyle attributes, dietary preferences, and fitness-related parameters. The collected information will be securely stored and processed for further analysis. Similar approaches combining biometric and behavioural information have demonstrated improved performance in personalized fitness and health recommendation systems [5], [12].

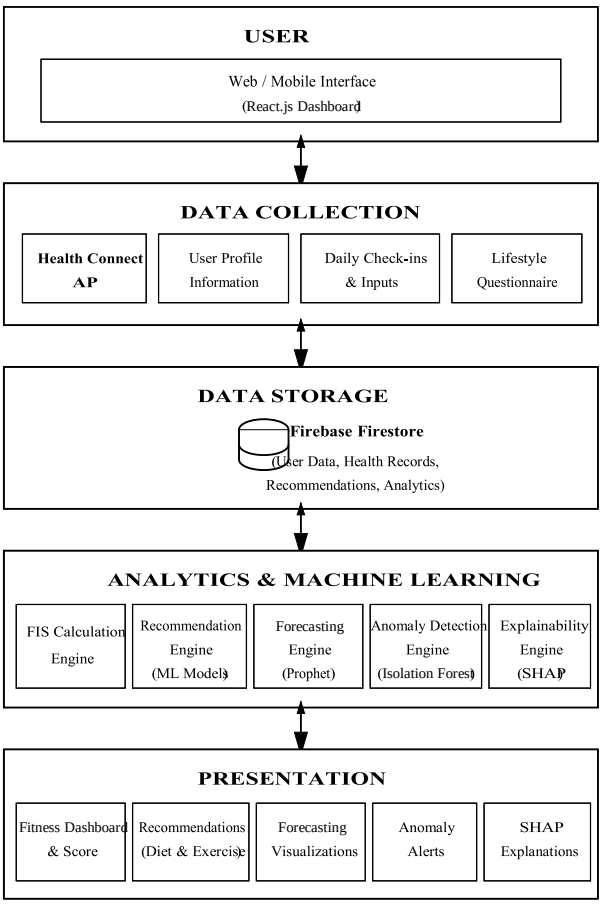


Figure 1: System Architecture of the Proposed System

The data processing and intelligence layer will perform health analysis, feature processing, and recommendation generation. Initially, the collected user information will be processed to calculate health indicators such as BMI, BMR,

TDEE, and health scores. Machine learning models will then analyse processed features to identify suitable fitness recommendations. Algorithms such as Random Forest, XGBoost, clustering techniques, and explainable AI methods have demonstrated effectiveness in health classification and personalized recommendation tasks [8], [10], [17]. The machine learning layer will generate personalized exercise plans, nutritional suggestions, and lifestyle improvement strategies based on user requirements.

The architecture will also include a behavioural analysis module responsible for monitoring lifestyle factors such as sleep, stress, physical activity, hydration, and consistency. These factors will be incorporated into the recommendation process because previous research has established their significant influence on fitness outcomes and health improvement [6], [7], [19]. By analysing behavioural trends,

FitIQ will be able to provide more meaningful recommendations compared to systems that depend only on static biometric information.

An Explainable AI module will enhance transparency by analysing the contribution of different input features towards generated recommendations. SHAP-based explanation techniques will be used to identify important factors influencing model decisions. The explanation layer will convert model outputs into user-friendly insights, enabling users to understand why specific recommendations are provided. This approach addresses the limitation of traditional black-box machine learning models identified in previous studies [3], [13].

The final layer of the architecture will consist of the recommendation and visualization module, where users will receive personalized fitness guidance through dashboards and progress reports. The module will display health scores, recommendation explanations, fitness goals, and improvement suggestions. Through continuous monitoring and feedback analysis, FitIQ will support adaptive fitness planning and encourage users to maintain healthier lifestyle practices.

CONCLUSION

The literature survey highlights the potential of Artificial

Intelligence and Machine Learning techniques in developing intelligent fitness recommendation systems while identifying limitations in existing approaches, including limited personalization, lack of behavioural analysis, insufficient explainability, and restricted real-world deployment. The FitIQ framework will address these challenges by integrating biometric information, lifestyle factors, behavioural parameters, and explainable AI techniques to generate personalized fitness recommendations. By considering factors such as physical activity, sleep quality, stress level, dietary preferences, and fitness goals, the system will aim to provide adaptive and transparent guidance for users. The Phase-I study has established the research foundation and conceptual architecture for FitIQ, and future work will focus on implementation, model development, and validation to evaluate its effectiveness in supporting sustainable health and fitness improvements.

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