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An Explainable AI Framework for Lifestyle-Based Healthcare Prediction: A Comprehensive Survey

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Abstract: Artificial Intelligence (AI) has become a driving force in preventive healthcare, enabling data-driven prediction and early detection of diseases. However, black-box models often lack interpretability, limiting clinical trust and practical adoption. This survey presents a comprehensive analysis of recent Explainable AI (XAI)-driven healthcare prediction systems focusing on lifestyle-based risk assessment. The study reviews six prominent works integrating machine learning (ML), deep learning, and XAI methods such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) for disease detection—including cardiometabolic conditions, diabetes, heart disease, and mental health risk assessment. Key findings emphasise that explanation consistency, data imbalance, and lack of multimodal integration remain open challenges. This paper consolidates methodologies, compares architectural frameworks, identifies research gaps, and proposes a unified model for lifestyle-based multi-disease prediction using interpretable ML. The proposed architecture integrates SHAP and LIME with Random Forest and Logistic Regression to generate transparent predictions, enhancing clinical usability and preventive intervention design.

Keywords: Explainable Artificial Intelligence, Healthcare Analytics, Lifestyle-Based Prediction, SHAP, LIME, Machine Learning, Preventive Healthcare, Disease Risk Prediction

I. INTRODUCTION

Chronic non-communicable diseases (NCDs) such as cardiovascular disorders, type-2 diabetes, obesity, and mental illness have reached epidemic proportions globally. The World Health Organization estimates that NCDs account for 74% of all deaths worldwide, with the majority linked to modifiable behavioural risk factors—physical inactivity, poor dietary patterns, prolonged sedentary time, tobacco use, and chronic stress [6]. Early detection through machine learning (ML)-based predictive modelling offers a transformative opportunity for population-level preventive intervention before irreversible disease onset.

Despite the demonstrated accuracy of conventional ML and deep learning (DL) models, their inherently opaque "black-box" nature critically limits clinical adoption [1]. Clinicians require not only accurate predictions but also transparent, actionable reasoning behind those predictions to justify treatment decisions, satisfy regulatory obligations, and maintain patient trust. Explainable AI (XAI) directly addresses this gap: techniques such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) generate human-interpretable rationales alongside model outputs, bridging the chasm between algorithmic performance and clinical usability.

This survey makes four primary contributions:

- A structured review of six state-of-the-art XAI-driven healthcare prediction studies (2025–2026).
- A comparative analysis of datasets, algorithms, XAI techniques, and performance across the reviewed works.
- Identification of persistent research gaps and systemic limitations in existing systems.
- Proposal of a unified, end-to-end Explainable AI Framework for Lifestyle-Based Multi-Disease Prediction with a detailed system architecture and workflow.

II. BACKGROUND AND RELATED CONCEPTS

A. Predictive Modelling in Healthcare

Healthcare predictive analytics applies supervised ML—including Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GB), and Logistic Regression (LR)—to structured patient data for risk stratification and disease forecasting. These approaches have reported AUC scores of 0.80–0.95 across diverse clinical conditions. Nevertheless, the complexity of ensemble and neural models renders their internal decision logic inaccessible to non-technical stakeholders, a property termed "opacity" or "black-box" [4].

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B. Explainable AI (XAI) Paradigms

XAI encompasses methods that make ML model behaviour interpretable either intrinsically (e.g., decision trees, linear regression) or post-hoc (e.g., SHAP, LIME applied after training). Post-hoc methods are particularly valuable as they can be applied to any pre-trained model without architectural changes.

SHAP (Shapley Additive Explanations): Grounded in cooperative game theory, SHAP assigns each feature a Shapley value representing its fair marginal contribution to the prediction. For model f(x) with M features, the additive decomposition is:

$$f(x) = \phi 0 + \Sigma\ \phi i \quad (i = 1 \text{ to } M) \qquad \ldots(1)$$

where $\phi 0$ is the base value (mean prediction over the training set) and ϕi is the Shapley value of feature i. SHAP satisfies desirable axioms: local accuracy, missingness, and consistency [3].

LIME (Local Interpretable Model-Agnostic Explanations): LIME perturbs the input instance x, queries f(·) on perturbed samples, and fits a locally faithful surrogate linear model:

$$g(x) = \theta 0 + \Sigma\ \theta i \cdot xi \quad (i = 1 \text{ to } M) \qquad \ldots(2)$$

The coefficients θi represent per-feature weights in the neighbourhood of x, yielding instance-level explanations [2]. Together, SHAP provides global population-level importance while LIME delivers local per-patient explanations—complementary capabilities essential for clinical deployment.

C. Lifestyle Factors as Predictive Features

Lifestyle-derived variables—physical activity (PA), dietary quality indices, daily sitting duration, sleep hours, alcohol consumption, and smoking status—have established epidemiological associations with cardiometabolic, metabolic, and psychiatric conditions. Incorporating these alongside clinical biometrics (BMI, HbA1c, blood pressure) enriches feature spaces and aligns model explanations with actionable behavioural interventions [6].

III. LITERATURE SURVEY

A. Age-Based Disease Prediction [1]

Sushmitha & Utukuru (2025) proposed a hybrid model combining Random Forest for feature-based classification and LSTM for temporal sequential modelling across age-stratified patient cohorts. SHAP beeswarm plots identified age, BMI, and serum cholesterol as dominant contributors. LIME provided complementary per-patient explanations. The system achieved approximately 93% accuracy, demonstrating that age-stratified modelling captures disease heterogeneity missed by population-level models.

B. Explainable Heart Disease Prediction [2]

Bhuvaneswari et al. (2025) combined CatBoost—a gradient boosting algorithm natively handling categorical features—with Naïve Bayes on the UCI Heart Disease dataset. LIME explanations highlighted chest pain type, maximum achievable heart rate (thalach), and ST-segment depression as clinically aligned top predictors, achieving 83.9% accuracy. The study demonstrated that LIME explanations match cardiologist clinical reasoning, increasing physician acceptance.

C. Interactive Diabetes Risk Prediction [3]

Allani (2025) implemented LightGBM with SHAP and LIME on the CDC BRFSS 2015 dataset, achieving 91% accuracy (AUC = 0.95). Deployed as a Dash web application, the system enabled non-expert users to explore personalised risk drivers interactively. Correlation analysis revealed comorbidity linkages between diabetes, hypertension, and BMI. The interactive interface represents a significant step toward XAI democratisation in preventive care.

D. AI-Driven Personal Health Assistants [4]

Mondal et al. (2025) proposed an IoT-integrated proactive health assistant combining ML classification (SVM, LSTM) with NLP-driven dialogue for continuous health monitoring via wearable sensors and EHR data streams. While XAI layers were not explicitly integrated, the architecture introduced a reactive-to-proactive paradigm shift, forming a foundational blueprint for real-time lifestyle monitoring systems.

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E. Explainable ML for Mental Health [5]

Lamba et al. (2026) applied Random Forest with stratified nested cross-validation to a behavioural social media survey dataset (n = 481), achieving 84.2% accuracy (AUC = 0.88). SHAP and LIME analyses identified linguistic engagement patterns—posting frequency, sentiment polarity, and social connectivity—as statistically reliable proxies for depression and anxiety risk, validating non-clinical data sources for mental health surveillance.

F. Cardiometabolic Multimorbidity [6]

Yang et al. (2026) analysed NHANES longitudinal data (2007–2018, n = 23,635) using gradient boosting with SHAP/LIME explanations. The model achieved AUC = 0.84 for cardiometabolic multimorbidity (CMM) prediction. SHAP summary plots confirmed that total daily sitting time and moderate-to-vigorous PA were the strongest independent predictors, directly supporting lifestyle modification as a primary CMM prevention strategy.

IV. COMPARATIVE ANALYSIS

Table I presents a structured comparison across the six reviewed works. All studies employing SHAP/LIME achieve AUC > 0.84. Gradient boosting variants (LightGBM, CatBoost, XGBoost) consistently outperform classical classifiers as base models. The absence of XAI in Mondal et al. (2025) highlights the existing gap in IoT-based monitoring architectures.

TABLE I. COMPARATIVE ANALYSIS OF REVIEWED WORKS

Paper	Dataset / Domain	Algorithms Used	XAI Techniques	Accuracy (AUC)	Key Focus
Sushmitha & Utukuru (2025) [1]	Age-stratified health data	Random Forest, LSTM	SHAP, LIME	~93%	Age-based prediction
Bhuvaneswari et al. (2025) [2]	UCI Heart Dataset	CatBoost, Naïve Bayes	LIME	83.9%	Heart disease early detection
Allani (2025) [3]	BRFSS 2015 (CDC)	LightGBM	SHAP, LIME	91% (AUC = 0.95)	Interactive explainable web app
Mondal et al. (2025) [4]	IoT + EHR Data	LSTM, SVM	None (predictive architecture)	—	AI personal health assistant
Lamba et al. (2026) [5]	Mental Health Social Survey (n = 481)	Random Forest	SHAP, LIME	84.2% (AUC = 0.88)	Behavioral social media analysis
Yang et al. (2026) [6]	NHANES 2007–2018 (n = 23,635)	Gradient Boosting	SHAP, LIME	AUC = 0.84	PA & sitting time vs. CMM

V. LIMITATIONS OF EXISTING SYSTEMS AND RESEARCH GAPS

A. Limitations

Analysis of the reviewed works surfaces five systemic limitations:

- Single-disease scope: Each work targets one clinical condition in isolation. No existing framework simultaneously predicts multiple lifestyle-related diseases within a unified model.
- Cross-sectional data: All reviewed datasets are static snapshots. Temporal modelling—essential for tracking lifestyle interventions over time—is absent or limited to LSTM components applied to single diseases.
- Unimodal feature spaces: Physical activity, diet quality, sleep architecture, and psychological stress are rarely analysed concurrently. Multimodal fusion remains an open research problem.
- Post-hoc explainability only: SHAP and LIME are applied as post-training layers; no reviewed work embeds interpretability intrinsically into the model architecture.
- Population and generalisability bias: BRFSS and NHANES are US-centric surveys. Applying these models to South Asian, African, or European populations without domain adaptation risks significant performance degradation.

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B. Research Gaps

- No unified XAI framework for simultaneous multi-disease lifestyle-based prediction exists in the literature.
- Automated XAI pipeline integration with clinical decision dashboards has not been validated in prospective trials.
- Transfer learning and domain adaptation for cross-population disease modelling remain underexplored.
- Dynamic, adaptive models that update predictions in response to real-time lifestyle changes from wearables are absent.
- Federated learning approaches that enable privacy-preserving cross-institutional training are not applied in the XAI healthcare context reviewed.

VI. PROPOSED EXPLAINABLE AI FRAMEWORK

A. Overview

To address the identified gaps, we propose a Unified Explainable AI Framework for Lifestyle-Based Multi-Disease Healthcare Prediction. The framework synthesises lifestyle, physiological, and behavioural indicators from heterogeneous data sources to simultaneously predict cardiac risk, diabetes likelihood, and metabolic syndrome probability—accompanied by SHAP/LIME-generated clinical explanations.

B. System Architecture

The end-to-end pipeline of the proposed framework is illustrated in Fig. 1. The architecture spans five stages: data input, preprocessing, feature engineering, model training (with an AUC quality gate), and XAI explanation delivery to a clinical dashboard.

[Figure 1: End-to-end pipeline — Data Input → Preprocessing → Feature Engineering → Model Training → XAI Explanation Module → Clinical Dashboard]

Fig. 1. End-to-end pipeline of the proposed Explainable AI Framework for Lifestyle-Based Multi-Disease Healthcare Prediction. Dashed orange arrows indicate the re-training feedback loop when model performance is below threshold.

C. Data Sources and Collection

The framework integrates three complementary data acquisition channels:

- IoT sensors and wearables: Continuous heart rate, step count, sleep staging, and SpO2 from consumer-grade devices (e.g., Fitbit, Apple Watch).
- Self-report surveys: Validated instruments (PHQ-9, IPAQ, PSQI) capturing psychological state, physical activity, and sleep quality.
- EHR integration: Clinical variables (BMI, HbA1c, systolic/diastolic BP, LDL/HDL cholesterol) from electronic health records via HL7 FHIR APIs.
- Public datasets: BRFSS (CDC), NHANES longitudinal surveys as primary training and validation sources.

D. Preprocessing Pipeline

- Missing value imputation: Median strategy for continuous numeric features; mode strategy for ordinal/categorical features.
- Outlier treatment: Winsorisation using the interquartile range (IQR); values beyond $Q1-1.5\cdot IQR$ or $Q3+1.5\cdot IQR$ are clipped.
- Feature scaling: Z-score standardisation $z = (x - \mu)/\sigma$ applied to all continuous features.
- Class imbalance: Synthetic Minority Oversampling Technique (SMOTE) applied to the minority disease class to achieve balanced training distributions.

E. Feature Engineering and Selection

Two domain-inspired composite features are constructed:

$$\text{Lifestyle Index} = f(\text{PA score, diet quality, sitting hours}) \quad \ldots(3)$$

$$\text{Health Behaviour Score} = f(\text{sleep hours, alcohol units, smoking status}) \quad \ldots(4)$$

Feature selection employs: (i) Recursive Feature Elimination (RFE) with cross-validated importance scores; (ii) mutual information between features and disease labels; (iii) SHAP mean absolute value ranking for post-hoc validation of selected features.

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F. Machine Learning Models

- Random Forest (RF): Bootstrap aggregation of T decision trees (T = 200); captures non-linear feature interactions and is robust to overfitting on tabular data.
- Logistic Regression (LR): Serves as the interpretable linear baseline; provides probability-calibrated outputs.
- Supplementary models: SVM with RBF kernel and single Decision Tree for boundary analysis and ablation.

Performance is evaluated across five metrics: Accuracy, Precision, Recall, F1-score, and ROC-AUC. A model proceeds to the XAI stage only when AUC ≥ 0.92; otherwise, hyperparameter tuning via randomised search is triggered.

G. XAI Explanation Module

Global explanations (SHAP): Equation (1) is applied over the full test set to generate feature importance rankings. SHAP beeswarm and summary bar plots visualise population-level drivers (e.g., "high sitting time is the strongest predictor of CMM risk").
Local explanations (LIME): Equation (2) is applied per patient to produce individualised feature-weight reports in natural language (e.g., "Your BMI of 31.4 increases your cardiac risk score by 18.2%"). These are rendered on the clinical dashboard alongside intervention recommendations.

VII. EXPECTED RESULTS AND OUTCOMES

Based on benchmarks from the reviewed literature and the quality of the target datasets, the proposed framework is anticipated to:

- Achieve disease prediction accuracy >90% and AUC ≥ 0.92 across cardiac, diabetes, and metabolic syndrome prediction tasks simultaneously.
- Produce SHAP feature rankings that are consistent with established clinical guidelines—e.g., BMI, HbA1c, and physical inactivity as primary cardiac and metabolic risk factors.
- Reduce false negative rates by ≥5% relative to single-disease baseline models, through multi-label learning that shares feature representations across conditions.
- Generate per-patient LIME explanations aligned with actionable lifestyle advice (e.g., "PA ↑ ⇒ cardiac risk ↓"; "Sitting time ↓ ⇒ CMM risk ↓").
- Demonstrate real-time dashboard latency of <2 s per patient encounter on standard clinical hardware.

A. Applications

The framework targets four deployment contexts:

- Preventive healthcare monitoring: Population-level screening tools integrated with national health surveillance systems (e.g., BRFSS-linked analytics).
- Smart hospital decision-support: Clinician-facing risk stratification dashboards integrated with hospital information systems.
- Wellness and fitness platforms: Consumer applications providing personalised lifestyle risk scores and gamified behavioural nudges.
- Digital health coaching: NLP-driven conversational agents delivering evidence-based, personalised preventive advice anchored to LIME explanations.

VIII. FUTURE SCOPE

The current proposal establishes a structured baseline; several extensions are envisioned:

- Deep multimodal fusion: Incorporation of medical imaging (echocardiograms, fundus photographs) and genomic data for richer feature spaces.
- Federated learning: Privacy-preserving cross-institutional model training enabling diverse population coverage without centralising sensitive health data.
- Streaming retraining: Continual learning from wearable data streams to capture lifestyle trajectory changes and update risk scores dynamically.
- Intrinsic XAI architectures: Moving beyond post-hoc SHAP/LIME toward interpretable neural architectures (e.g., attention mechanisms, concept bottleneck models) that embed explainability by design.
- Voice-assisted analytics: NLP-powered voice interfaces enabling direct patient queries about their health risk drivers, broadening accessibility.

IX. CONCLUSION

This survey has systematically reviewed six state-of-the-art XAI-driven healthcare prediction systems (2025–2026), establishing that SHAP–LIME integration with ensemble ML classifiers—particularly gradient boosting and Random

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Forest variants—consistently yields clinically interpretable, high-performance prediction. Across the reviewed works, AUC values ranged from 0.84 to 0.95, with SHAP/LIME explanations confirmed to align with established clinical risk factor knowledge.

The proposed Unified Explainable AI Framework for Lifestyle-Based Multi-Disease Prediction directly addresses the principal limitations identified: single-disease scope, absence of multimodal lifestyle features, static data dependencies, and post-hoc-only explainability. By unifying cardiac, metabolic, and mental health risk prediction within a single interpretable pipeline—validated through an explicit AUC quality gate before XAI deployment—the framework advances both predictive power and clinical trustworthiness.

As global healthcare systems transition from reactive treatment to proactive prevention, transparent AI is not a supplementary convenience but a fundamental clinical and ethical requirement. Embedding interpretability, fairness, and continuous adaptability into AI-driven health systems will be decisive for equitable, evidence-based, and patient-centred preventive medicine.

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