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A HUMAN-CENTERED ML DSS FOR UNREPORTED HYPERTENSION

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Abstract
Large numbers of adults live with elevated blood pressure without realizing it, often until complications emerge. This study develops a human-centered machine learning (ML) decision support framework that estimates the likelihood of unreported hypertension by fusing routinely captured clinical records with demographic, behavioral, psychosocial, and wearable-derived signals. The framework translates model outputs into clear, context-aware guidance that nudges users toward timely screening and preventive action. Two brief case vignettes—from rural and urban settings—illustrate how alerts can surface hidden risk and reinforce healthy behaviors. In comparative testing, ensemble learners, particularly gradient boosting, delivered stronger discrimination than baseline models while preserving operational practicality. The approach is positioned to complement public-health efforts and clinical care pathways by offering a feasible route to earlier detection and more equitable cardiovascular outcomes.

Keywords: Hypertension prediction, Machine learning, Decision support, Wearable-derived signals, Early detection

1.0 Introduction
Hypertension continues to drive avoidable illness and early death worldwide, yet it frequently progresses without obvious symptoms. Many people do not seek evaluation until severe events occur, underscoring the need for proactive, easy-to-use tools that help the public and frontline teams recognize risk sooner. In contexts where routine screening is inconsistent—or where day-to-day stress, food environments, and access barriers undermine prevention—the detection gap widens. Nigeria exemplifies this challenge: urbanization and changing lifestyles intersect with service constraints to produce high prevalence alongside low awareness and control.

This paper introduces a decision support framework that brings together common health information, everyday behaviors, and community-informed indicators to reveal situations in which hypertension may be present but undocumented. The design emphasizes (a) outputs that people can understand at a glance, (b) frictionless use at the point of need, and (c) recommendations that align with real-world service capacity and accepted care practices.

2.0 Literature Review
2.1 Machine Learning for Cardiovascular and Hypertension Risk
Contemporary ML methods random forests, gradient boosting, support vector machines, and neural networks have become standard options for cardiovascular risk modeling, particularly when non-linear relationships and interactions limit the expressiveness of traditional regression. Analyses leveraging large electronic records further indicate that forecasting blood-pressure control status is

feasible at population scale, informing proactive service delivery planning.

2.2 Decision Support to Strengthen Guideline-Aligned Care

Digital decision support embedded in clinical workflows can standardize treatment steps, prompt follow-up, and reduce omissions—provided it fits existing processes, preserves usability, and rests on reliable data. Trials in primary care settings suggest improvements in guideline-concordant actions when decision support is integrated with the record systems clinicians already use.

2.3 Role of Wearables and Patient-Generated Signals

Wearables contribute behavior-rich signals—activity, sleep, resting heart rate—that refine risk estimates and personalize prevention. At the same time, cuffless blood-pressure estimates should be treated as supportive context rather than diagnostic evidence; confirmation with validated, cuffed measurement remains essential when concern is raised.

2.4 Nigerian Evidence Base and Context

Across Nigeria, high and heterogeneous burden with persistent awareness gaps underscores the value of localized decision layers. Community-anchored programs, task-sharing strategies, and mobile touchpoints can extend reach; a targeted decision layer helps identify people who may be missed by routine screening.

3.0 Methodology

3.1 Designing for People, Data, and Decisions

Data Inputs

To reflect the multi-factor nature of hypertension, inputs were organized into five categories: Clinical (historical blood pressure, BMI, comorbidities, family history); Demographic (age, sex, occupation, residence); Lifestyle (dietary salt, alcohol, tobacco, physical activity); Psychosocial (perceived stress, sleep quality, financial or job insecurity, access to care); and Wearable-derived (sleep continuity/fragmentation, steps or activity intensity, resting heart-rate trends). This structure allowed the model to combine routine data with everyday behaviors and context, improving coverage where clinic readings were sparse.

3.2 Preprocessing and Feature Curation

Missing values were handled using medically informed imputation. Continuous variables were standardized; outliers were checked against physiological bounds and retained only when plausible. Feature curation combined lightweight filter-based screening with expert review to preserve predictors that were both discriminative and actionable.

3.3 Model Suite and Training

Four complementary classifiers were implemented to balance accuracy and interpretability: logistic regression (transparent baseline), random forest (robust non-linear patterns), gradient boosting (fine-grained tabular discrimination), and neural networks (capacity for complex interactions). Hyperparameters were tuned with cross-validation, prioritizing recall on the positive class to reduce missed high-risk cases. Probabilities were calibrated to support practical thresholding downstream.

3.4 Decision Support Logic

Model outputs were mapped to three action levels: High risk (screen now), Moderate risk (monitor soon), and Low risk (maintain). Recommendations were written in plain language and designed for routine workflows. When concern was raised, users were directed to confirm blood pressure with validated, cuffed measurement rather than relying on unvalidated signals. See figure 2.1 maped **model outputs**

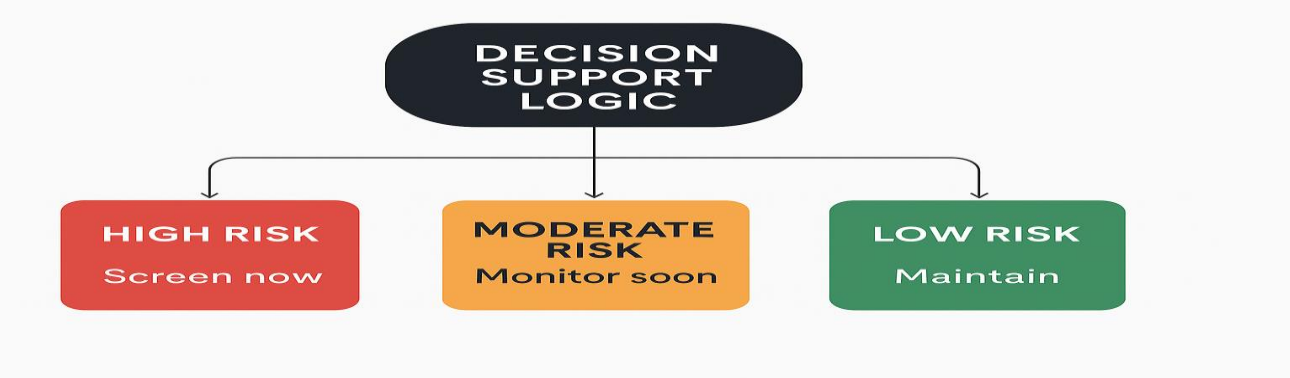

Fig. 2.0 Model outputs mapped to the three action levels.

3.5 Case Illustrations

Case 1

A 48 year old smallholder farmer in a rural area with high dietary salt exposure, short sleep, elevated BMI, and financial stress was flagged high risk. Clinic measurement was 160/100 mmHg; he began salt-reduction counseling, initiated medication, and entered structured follow-up.

Case 2

A 33 year old woman in an urban area Calabar with regular exercise and good sleep hygiene but a strong family history was flagged moderate risk. Clinic reading was 118/76 mmHg, providing reassurance and reinforcing periodic re-screening.

Additional Nigerian Case Studies

Case 3 Urban: Commercial Driver

Profile: Male, 52; intercity commercial driver; irregular meals; long sedentary hours; occasional smoking.

Signals: prior elevated clinic BP (148/92 six months earlier), BMI 29; high-salt snacks/drinks; short/irregular sleep; no wearable.

Model output: High risk — cumulative risk from age, BMI, prior elevated BP, salt/tobacco exposure, disrupted sleep.

Action & outcome: Same-day cuffed measurement 156/98 mmHg; enrolled in sodium/tobacco counseling, medication start, 2-week motor-park follow-up.

Case 4 Rural: Market Trader

Profile: Female, 45; spice trader; daily walking; liberal seasoning-cube use at home.

Signals: no prior BP record; BMI 26; high sodium cooking; low fluid intake during heat; step band ~7,000/day.

Model output: Moderate risk — dietary sodium, heat exposure, limited clinical history.

Action & outcome: Community screening on two days: 145/92 and 148/94 mmHg; diet counseling; clinic confirmation scheduled.

Case 5 — Urban South-South (Calabar): Public-Sector Accountant

Profile: Male, 38; desk-based; maternal hypertension history.

Signals: no recent clinic visit; BMI 27; low activity; fast-food lunches; weekend alcohol; smartwatch shows sleep fragmentation and elevated resting HR during audits.

Model output: Moderate risk — family history + inactivity + sleep/resting HR pattern.

Action & outcome: Workplace cuffed BP 138/88 mmHg (borderline) → 128/82 mmHg after 4 weeks of evening walks and reduced sodium lunches; periodic re-screening set.

Case 6 Urban: Antenatal Clinic Attendee

Profile: Female, 29; first pregnancy; regular ANC visits.

- Signals: prior normal readings; pregnancy-appropriate BMI; moderate salt; active teacher; adequate sleep; no wearable.

- Model output: Low risk — protective profile with routine ANC.

- Action & outcome: Maintain guidance; routine ANC BP within range; symptom education provided; no escalation needed.

Case 7 Urban: University Student (NYSC-ready)

- Profile: Female, 24; exam stress peaks; otherwise highly active; negative family history.

- Signals: BMI 22; low sodium diet; jogging; phone step tracking >10,000/day; low-normal resting HR.

- Model output: Low risk — healthy baseline with transient stress episodes.

- Action & outcome: Maintain guidance plus NYSC pre-placement tip-sheet (hydration, avoiding stimulants before checks); baseline clinic BP 112/70 mmHg.

Case 8 Urban: Security Guard on Rotating Shifts

- Profile: Male, 41; night-shift rotations; energy drinks; irregular meals.

- Signals: undocumented elevated pharmacy BP; BMI 28; caffeine use; minimal daylight activity; wearable shows short sleep and resting HR spikes post shifts.

- Model output: High risk — shift-work sleep loss + stimulants + prior elevated reading + BMI.

- Action & outcome: Workplace clinic confirmation (two cuffed readings 152/96 and 150/94 mmHg 48 hours apart); lifestyle counseling (caffeine taper, shift-sleep routine) and pharmacotherapy initiated; 1-month review.

4.0 Results

4.1 Model Comparison

Models exhibited expected trade-offs. Logistic regression (~78% accuracy, moderate sensitivity) favored interpretability; random forest (~89%) improved sensitivity and stability; gradient boosting (~92%) provided the strongest overall discrimination; neural networks (~85%) were competitive but less transparent.

4.2 Predictive Drivers

Age, BMI, family history, dietary salt exposure, physical inactivity, perceived stress, and sleep quality consistently influenced risk estimates. Wearable-derived indicators—sleep fragmentation and resting heart-rate trends—added useful signal where clinic readings were infrequent.

4.3 Model Limitations

1. Data completeness and representativeness

Not all users contribute every data type; gaps—especially in wearables and psychosocial inputs—can lower confidence despite imputation.

2. Generalizability across settings

Although retrained and checked across diverse Nigerian contexts, performance elsewhere requires localization and validation.

3. Measurement fidelity and device variance

Wearable signals were treated as supportive; variability in sensors, adherence, and processing introduces noise and cannot replace validated measurement.

4. Label uncertainty and outcome proxies

The target is likely unreported hypertension; proxy labeling introduces inevitable false flags or misses.

5. Temporal drift and changing behaviors

Without monitoring and recalibration, performance may degrade as patterns shift over time.

6. Thresholds and actionability

Mapping probabilities to three tiers simplifies decisions but compresses nuance around cutoffs.

7. Fairness and subgroup performance

Subgroup sample sizes and feature availability vary; periodic audits and targeted data collection are needed.

8. Interpretability in clinical context

Even with factor-level explanations, complex interactions can be hard to relay succinctly.

9. Operational integration

Impact depends on staffing, devices, and referral pathways; alerts alone do not ensure timely confirmation.

10. Security, privacy, and user trust

Continuous attention to data minimization, consent, and access control is essential.

Implication: These constraints define where the system is most reliable and the governance—local validation, threshold tuning, drift monitoring, fairness checks, and workflow support—needed to turn risk signals into earlier, equitable care.

4.5 Model Strengths

1. Human-centered outputs with plain-language recommendations and factor-level explanations.

2. Broad data coverage combining clinical, demographic, lifestyle, psychosocial, and wearable signals.

3. Recall-first training with calibrated probabilities for practical threshold setting.

4. Actionable risk tiers that map to routine frontline workflows.

5. Cautious wearable use that enriches pattern recognition without overclaiming.

6. Localization and equity checks across diverse Nigerian contexts.

7. Balanced model portfolio: transparent baseline and high-performing ensembles.

8. Operational fit: task-sharing, mobile touchpoints, and community follow-up.

9. Resilience to data gaps via imputation, physiological checks, and targeted curation.

10. Governance-ready architecture with logs, drift monitoring, and threshold reviews.

Takeaway: The framework bridges population risk and point-of-care action—helping teams find the right people, at the right time, with guidance they can use immediately.

5.0 Discussion

The framework's value is not limited to its ability to flag elevated risk; it lies in how clearly and promptly it communicates what to do next. By pairing calibrated probabilities with plain-language actions and factor-level explanations, the system supports earlier conversations, timely measurement, and practical follow-through.

Human-centered design choices—minimal friction, clarity on the few drivers that matter, and context-aware messaging—allow both individuals and frontline teams to act without specialized training.

Localization through retraining and consistency checks across varied Nigerian communities reduced bias risk and improved relevance. Implementation planning also embraced task-sharing and mobile delivery to extend reach in urban and rural settings.

Wearable-generated patterns were treated as early signals rather than diagnostic proof. When concern arose, the system routed users to validated, cuffed measurement for confirmation.

The governance approach—data minimization, transparent rationales, and ongoing monitoring—supports informed choice, trust, and safe operation as the system scales.

6.0 Conclusion

A human-centered ML decision support model can help reveal likely unreported hypertension and guide individuals toward timely confirmation and care. By pairing calibrated predictions with actionable steps that fit local capacity, the framework offers a practical path to earlier detection and more equitable cardiovascular outcomes.

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