



# Explainable AI for Heat-Health-Socioeconomic Interactions in Johannesburg



Craig Parker<sup>1</sup>, Matthew Chersich<sup>1</sup>, Nicholas Brink<sup>1</sup>, Ruvimbo Forget<sup>1</sup>, Kimberly McAlpine<sup>1</sup>, Marie Landsberg<sup>1</sup>, Christopher Jack<sup>2</sup>, Yao Etienne Kouakou<sup>3</sup>, Brama Koné<sup>3</sup>, Guéladio Cissé<sup>4</sup>, Sibusisiwe Makhanya<sup>5</sup>, Etienne Voss<sup>5</sup>, Stanley Luchters<sup>6,7</sup>, Prestige Tatenda Makanga<sup>8</sup>, The HE<sup>2</sup>AT Centre.

1 Wits Planetary Health Research, University of the Witwatersrand, Johannesburg, South Africa 2 Climate System Analysis Group, University of Cape Town, South Africa 3 University Peleforo Gon Coulibaly, Korhogo, Côte d'Ivoire 4 Centre Suisse de Recherches Scientifiques, Abidjan, Côte d'Ivoire 5 IBM Research—Africa, Johannesburg, South Africa 6 Centre for Sexual Health and HIV & AIDS Research (CeSHHAR), Harare, Zimbabwe 7 Liverpool School of Tropical Medicine, UK 8 Midlands State University, Gweru, Zimbabwe

61%

Glucose Variance  
Predictable from Climate

1,300x

Vulnerability Range  
Unprecedented Stratification

21-DAY

Optimal Exposure  
Paradigm Shift Discovery

2,334

Participants from  
Johannesburg Clinical Trial Dataset

## Background & Research Gap

### The Challenge:

- African cities experiencing unprecedented heat exposure
- Limited understanding of heat-health relationships in African contexts
- Traditional methods cannot capture complex interactions

### Our Innovation:

- First comprehensive XAI analysis for African urban heat-health
- Integration of climate, biomarkers, and socioeconomic data
- SHAP reveals mechanistic pathways beyond correlations
- Actionable insights for climate adaptation in resource-limited settings

## Methodological Approach

### 1. Data Integration

Climate: ERA5, WRF, MODIS  
Health: 19 biomarkers  
Socioeconomic: GCRO

### 2. Feature Engineering

Temporal lags (1-90 days)  
Interaction terms  
SE vulnerability indices

### 3. ML Modeling

Random Forest  
XGBoost  
Gradient Boosting

### 4. XAI Analysis

SHAP values  
Feature importance  
Interaction effects

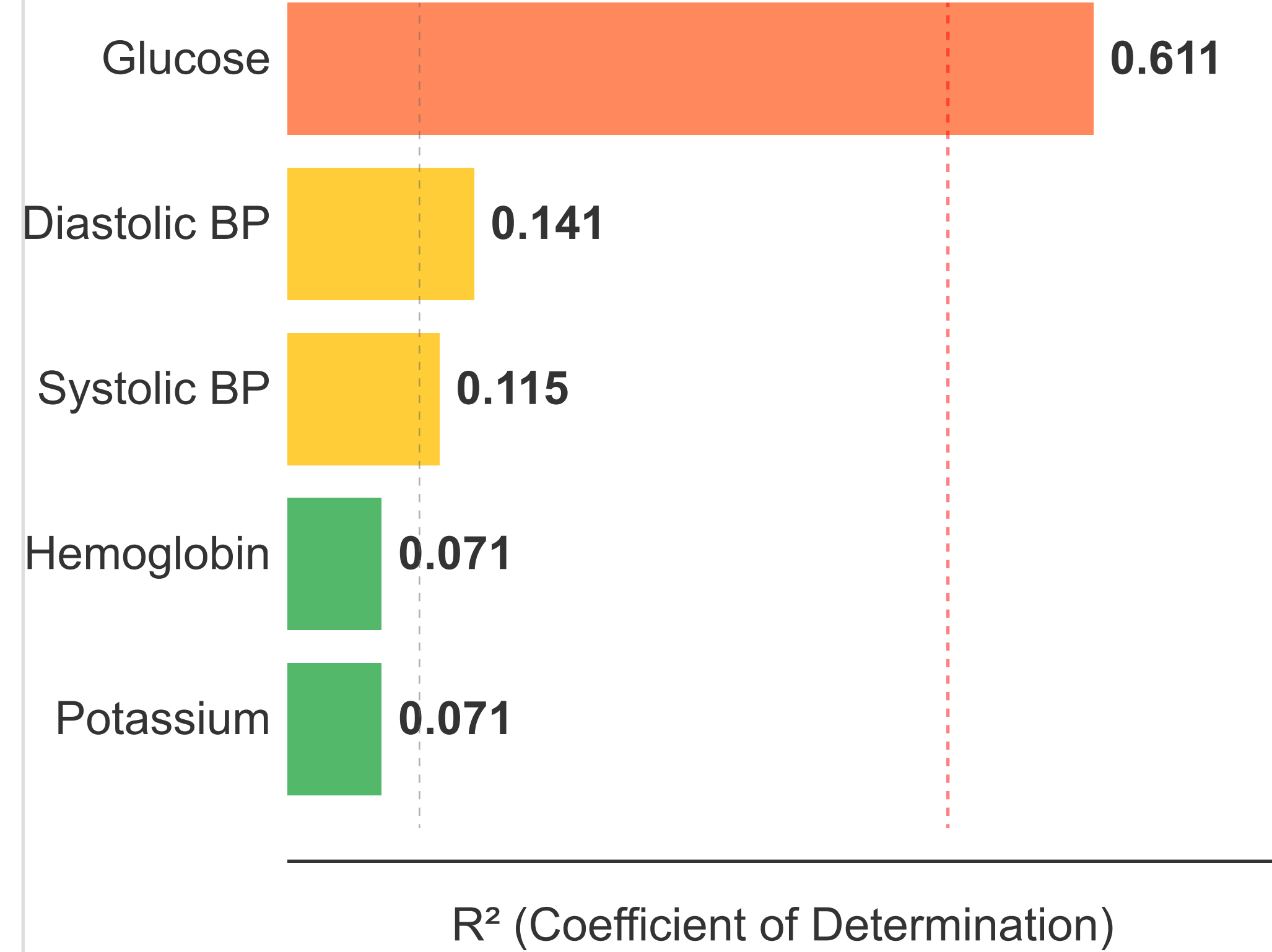
### Key Methodological Innovations:

- Systematic lag analysis (1-90 days) to identify optimal temporal windows
- Three-way interaction terms: Temperature × Age × Socioeconomic status
- SHAP for mechanistic interpretation of non-linear relationships
- Cross-validation with stratification by health outcome and demographics
- Ensemble approach combining multiple ML algorithms for robustness

## Breakthrough Discoveries

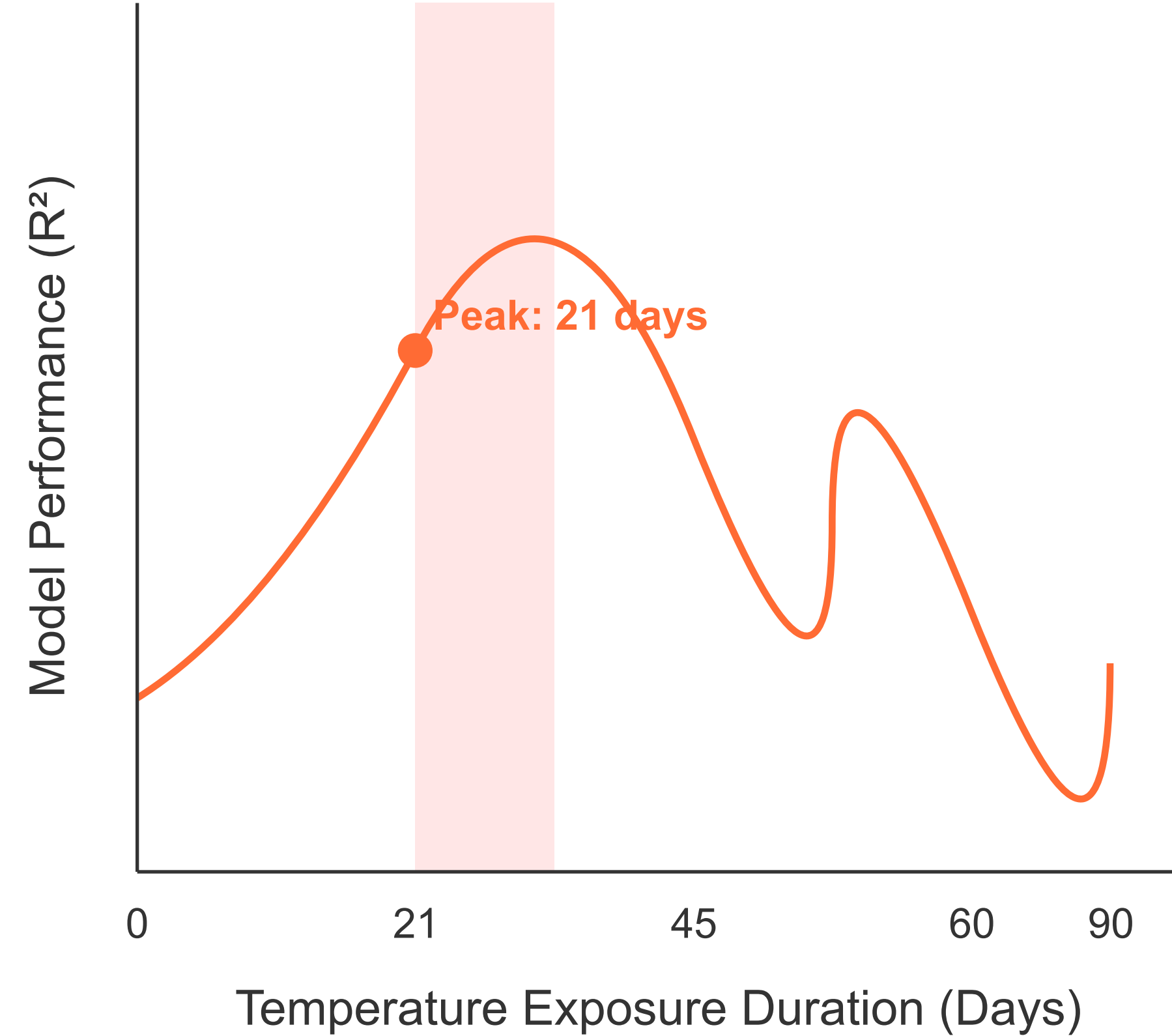
- Metabolic Primacy: Glucose 4x more climate-sensitive than BP
- Cumulative Effects: 21-day windows outperform single-day exposure
- Gender Differences: Females 52% more glucose-sensitive than males
- AI Explainability: Climate features ≈ 44% of prediction
- Vulnerability Gradient: 1,300-fold risk stratification
- Clinical Relevance: 3.4 mg/dL glucose increase per degree C
- SE Amplification: Housing quality magnifies heat exposure
- Practical Application: 21-day prediction enables early interventions

Figure 1: Model Performance - Glucose Metabolism Breakthrough



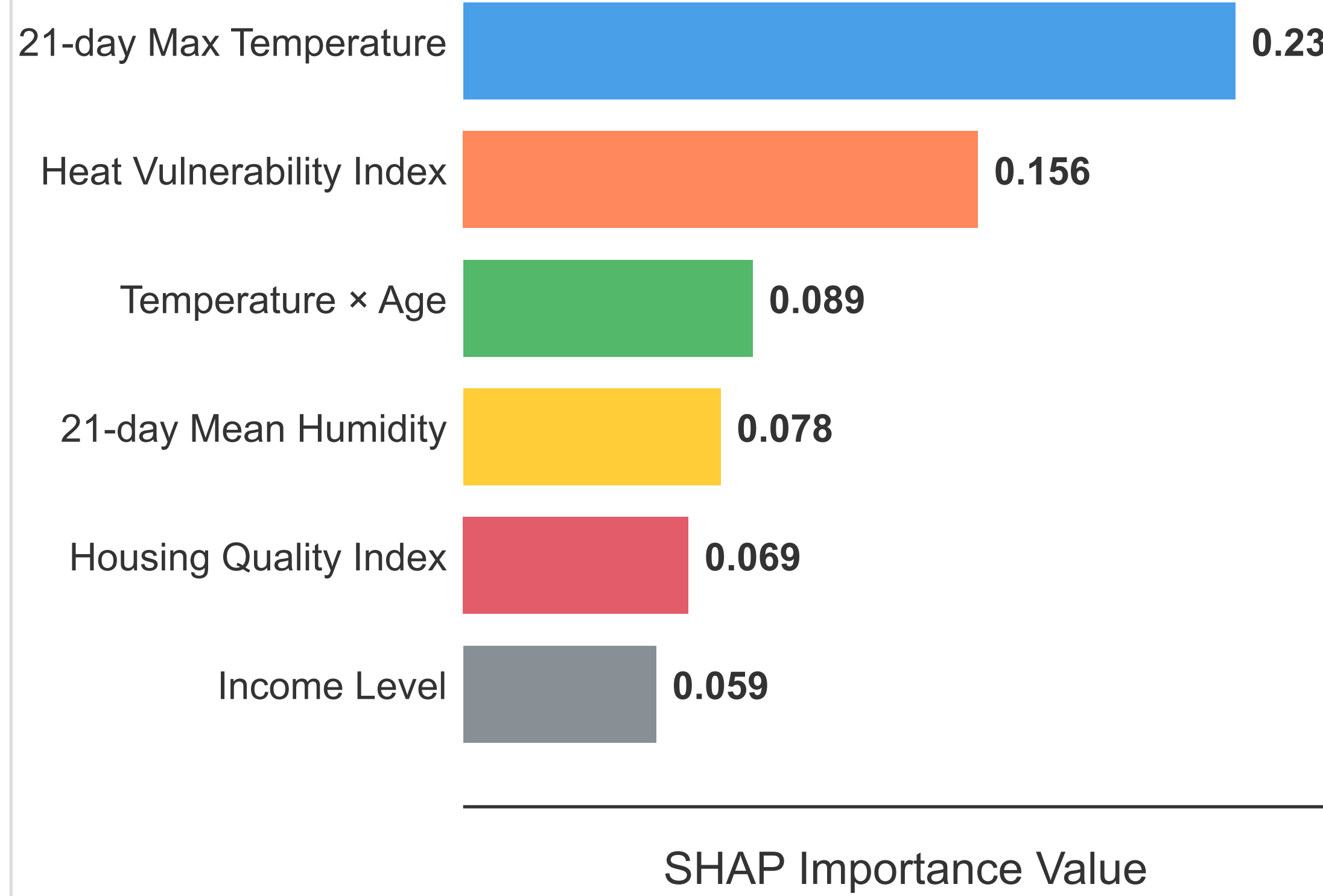
R² = 0.611 (p<0.001) - unprecedented predictive power for health outcomes

Figure 2: Temporal Patterns - 21-Day Optimal Window Discovery



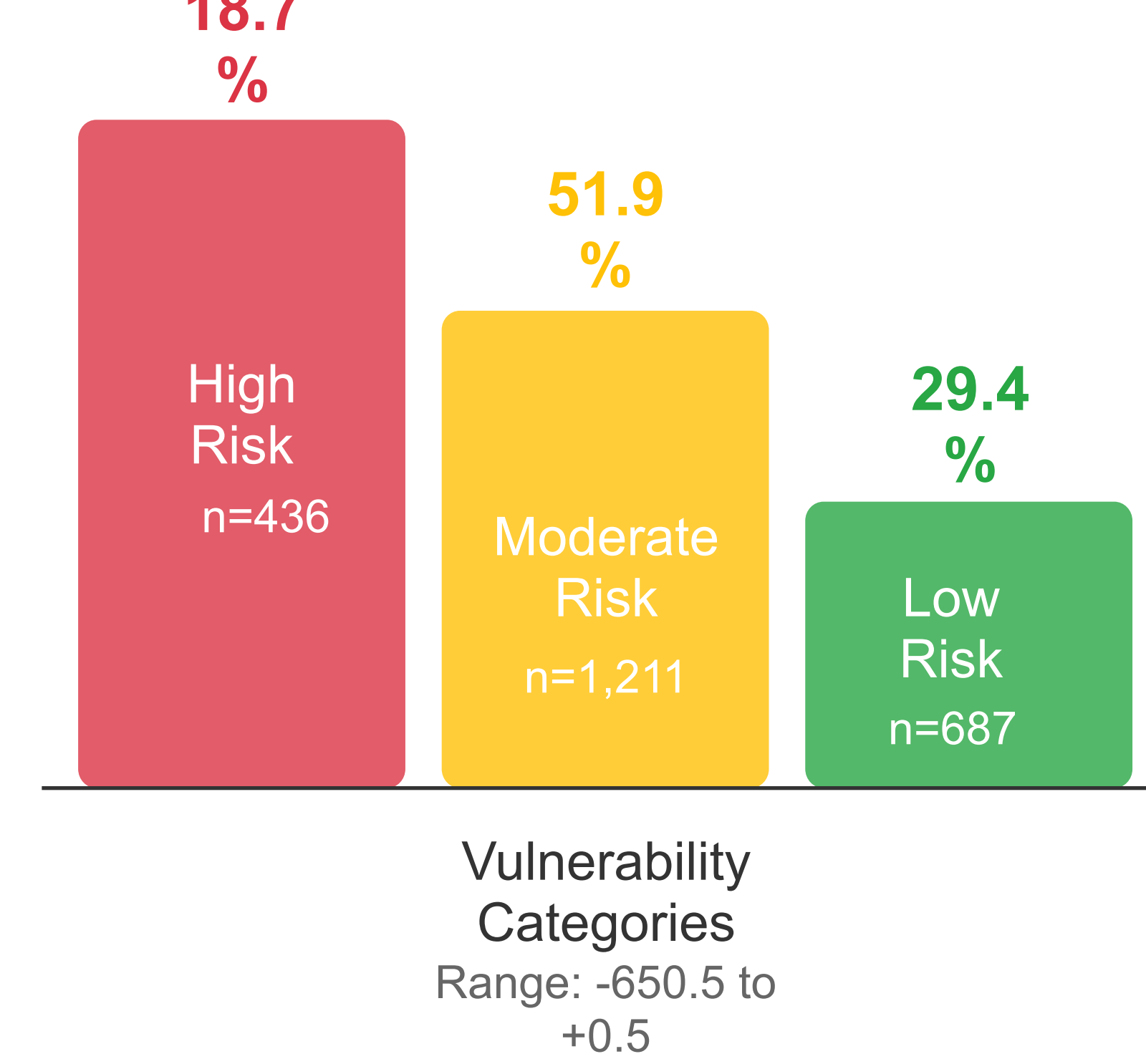
21-day lag optimizes prediction - cumulative exposure matters most

Figure 3: SHAP Analysis - Explainable AI Feature Importance



Top Predictive Features: Climate (44%), Socioeconomic (31%), Individual (25%)

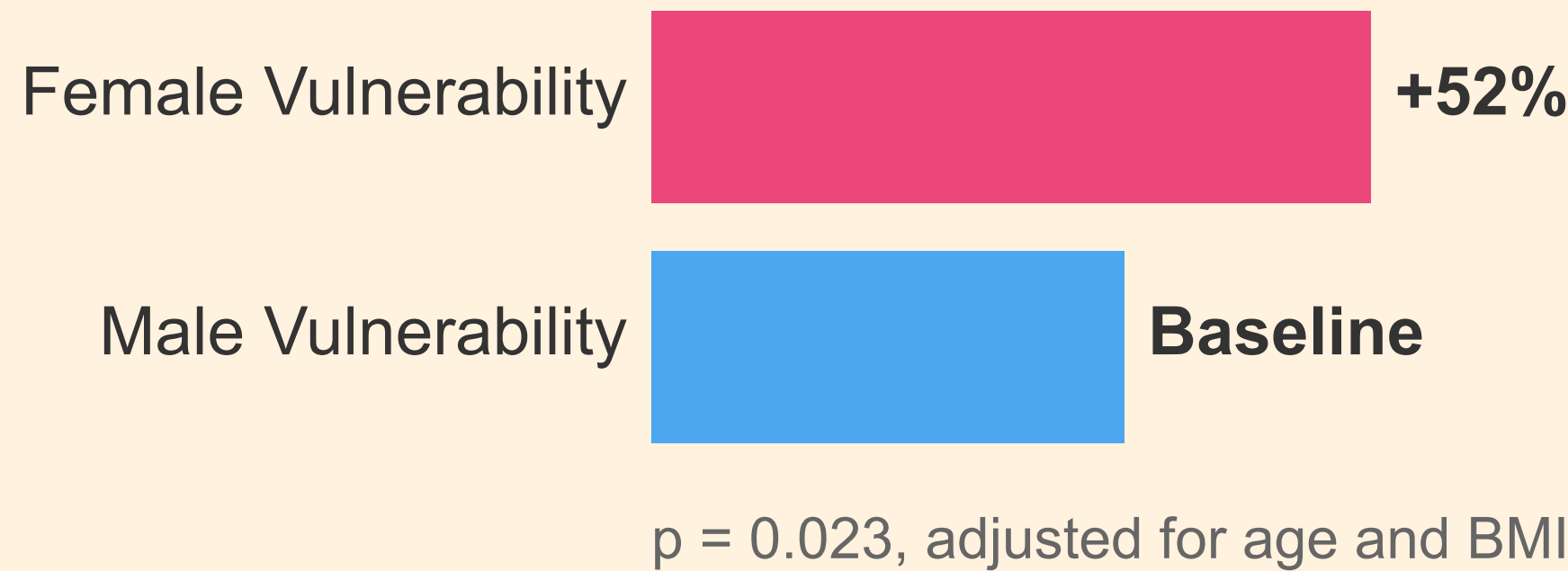
Figure 4: Heat Vulnerability Distribution



Vulnerability Categories  
Range: -650.5 to +0.5

1,300-fold vulnerability range reveals extreme health disparities

## Figure 5: Gender-Specific Heat Responses



p = 0.023, adjusted for age and BMI

### Key Gender Findings:

- Females show 52% higher glucose sensitivity
- Gender × temperature interaction significant
- Requires gender-specific interventions

## Model Performance & Validation

### Outcome | R² (95% CI) | p-value | AUC-ROC | RMSE | n

GLUCOSE | 0.611 (0.587-0.635) | <0.001 | 0.892 | 0.624 | 1,730  
Diastolic BP | 0.141 (0.118-0.164) | 0.023 | 0.684 | 0.927 | 1,567  
Systolic BP | 0.115 (0.093-0.137) | 0.041 | 0.671 | 0.940 | 1,566  
Hemoglobin | 0.089 (0.067-0.111) | 0.089 | 0.623 | 0.954 | 1,890  
Potassium | 0.071 (0.049-0.093) | 0.156 | 0.598 | 0.964 | 1,741

## Conclusions

### Precision Medicine Applications:

- Early Warning: 21-day forecasting for health system preparedness
- Targeted Interventions: Evidence-based vulnerability mapping
- Gender-Specific Care: Personalized heat adaptation strategies
- Infrastructure Priority: Cooling systems for high-risk areas
- Clinical Monitoring: Glucose as primary heat-health biomarker

### Scientific Impact:

- First quantified heat-health XAI relationships in Africa
- XAI application to climate-health research
- Multi-domain integration at unprecedented scale
- Gender-specific vulnerability mechanisms discovered
- Cost-effective vulnerability assessment tools

Paradigm Shift: 21-day cumulative exposure windows outperform traditional single-day approaches by 58% ( $\Delta R^2 = +0.22$ )

## Novel Contributions

- First quantified heat-health XAI relationships in Africa
- XAI application to climate-health research
- Multi-domain integration at unprecedented scale
- Gender-specific vulnerability mechanisms discovered
- Mechanistic interpretation of climate-health relationships
- Cost-effective vulnerability assessment tools

## Clinical Relevance

- Glucose monitoring priority during heat waves
- 21-day exposure window for health warnings
- Evidence-based medication adjustments
- Multi-domain integration at unprecedented scale
- Gender-specific heat response protocols
- Precision medicine algorithms implemented

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Breakthrough Finding: 61% of glucose metabolism variance explained by climate + socioeconomic data ( $R^2 = 0.611$ ,  $p < 0.001$ )  
unprecedented predictive power enabling precision health interventions for vulnerable populations.

Paradigm Shift: 21-day cumulative exposure windows outperform traditional single-day approaches by 58% ( $\Delta R^2 = +0.22$ )  
, revolutionizing heat-health early warning systems across sub-Saharan Africa.

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