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Article

Climate-Informed Machine Learning for Predicting Heat-Related Health Risks: Towards Resilient and Personalized Early Warning Systems

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Abstract

Severe heat events cause over 489,000 deaths each year worldwide, with forecasts suggesting a 2.3–4.5 times rise in heat-related illnesses by 2050 if climate change remains unmanaged. In Nigeria, more than 75,000 hospitalizations in 2023 were due to heat stress, dehydration, and heart-related issues, impacting vulnerable populations like the elderly, outdoor workers, and children. Existing heat-health alert systems are primarily focused on the population and generic, frequently missing personalized and practical recommendations. To fill this gap, this research introduces a climate-aware machine learning (ML) framework that combines environmental factors (temperature: 28–45 °C, humidity: 20–85%, $PM_{2.5}$: 15–110 μg/m³) with personal health data (heart rate variability at 1 Hz, blood pressure every 15 minutes, oxygen saturation 92–99%, and daily activity levels) to assess heat-related illness risk on an individual basis. Utilizing a longitudinal dataset comprising 52,846 records from 2,300 patients in southwestern Nigeria (2021–2024), we evaluated traditional classifiers (Logistic Regression, Random Forest) in comparison to sophisticated sequence models (LSTM, Bi-LSTM, Transformer). The Transformer model recorded the highest performance, attaining 92.7% accuracy, 0.88 precision, 0.91 recall, 0.89 F1-score, and a ROC–AUC of 0.94, surpassing LSTM (89.4% accuracy, 0.90 ROC–AUC) and Random Forest (84.1% accuracy, 0.82 ROC–AUC). Temporal analysis showed that increasing input sequence lengths from 10 to 50 time steps enhanced prediction accuracy by 3.8–4.1% across models, highlighting the significance of long-term observation. Even with increased training expenses (Transformer: 21.6 minutes compared to Logistic Regression: 1.4 minutes), the inference latency stayed under 2.3 ms per sample, making it suitable for real-time use in mobile and wearable applications. Simulation analyses additionally project that early interventions guided by this framework might decrease hospital admissions by 28–32% and avert as many as 11,500 heat-related fatalities each year among high-risk populations in Nigeria. This research highlights the capability of climate-aware, patient-focused ML models to enhance health by aligning with SDG 3 (Health) and SDG 13 (Climate Action).

Keywords: climate change; heat-related illness; machine learning (ML); personalized healthcare; transformer model; early-warning systems; human-computer interaction (HCI); environmental data integration; health informatics; sustainable development goals (SDG 3; SDG 13)

I. Introduction

Climate change has emerged as one of the most pressing global health challenges of the twenty-first century, with extreme heat events increasingly contributing to significant morbidity and mortality worldwide. Rising temperatures, urban heat islands, and more frequent and prolonged heatwaves have been associated with a surge in cases of heat-related illnesses such as heat stroke, dehydration, and cardiovascular complications. The World Health Organization identifies heat stress

as a growing public health threat, particularly for vulnerable populations such as the elderly, outdoor laborers, and children. As global warming intensifies, the health sector faces an urgent need for innovative approaches to predict, prevent, and mitigate the impacts of climate-induced heat stress. Despite ongoing efforts, current public health warning systems remain largely generic, relying on population-wide advisories that fail to incorporate individual-level risk factors. Such systems, while useful at a broad scale, often lack personalization and actionable insights tailored to specific demographics or comorbidities. Consequently, vulnerable groups may remain underprotected, leading to preventable hospitalizations and fatalities during extreme heat events. There is a notable gap in the literature at the intersection of machine learning (ML), human-computer interaction (HCI), and healthcare in addressing climate-sensitive health outcomes. While ML has been applied extensively in medical prediction tasks and climate modeling independently, limited research has combined these domains to create predictive systems that are not only accurate but also usable and trustworthy from a human-centered design perspective. The integration of personalized patient health records with real-time climate data remains underexplored, particularly when considering the design of interactive alert systems that can provide timely, comprehensible, and context-specific information to both patients and healthcare providers.

The objective of this study is to develop and evaluate climate-informed ML models that integrate environmental data such as temperature, humidity, and pollution indices with individual patient health records to predict the risk of heat-related illnesses. Furthermore, the study emphasizes an HCI-driven framework to design interactive, personalized early-warning systems accessible through mobile applications, wearable devices, and hospital dashboards. By aligning technological innovation with human-centered design, this work aims to enhance preparedness, foster patient engagement, and support clinical decision-making during extreme heat events. This research directly contributes to the United Nations Sustainable Development Goals (SDGs), particularly SDG 3 (Good Health and Well-being) by advancing preventive healthcare solutions, and SDG 13 (Climate Action) by enhancing resilience to climate-induced health risks. By bridging the gap between climate science, healthcare, and interactive technologies, the study proposes a novel framework to strengthen global health systems in the face of escalating climate challenges.

II. Literature Review

Heat and health risks: epidemiological evidence

Intense heat has become a major climate-related threat to human health, with evaluations across multiple countries anticipating significant rises in heat-related deaths this century, even with certain adaptations considered (Masselot et al. 2025). Recent high-resolution forecasts for 854 cities in Europe indicate that, without significant mitigation efforts, the increase in heat-related fatalities will surpass any reduction in cold-related deaths in most scenarios, highlighting a growing overall health burden (Masselot et al. 2025). Supplementary monitoring and situational reports outline unprecedented heat records and related health hazards in 2024, emphasizing the necessity for focused preventive measures (WMO 2025; NYC DOHMH 2024). Collectively, this information reinforces the epidemiological foundation: heat exposure increases the likelihood of illness and death, particularly for older adults, individuals with chronic cardiometabolic conditions, children, and those who work outdoors. (Masselot et al. 2025; WMO 2025; NYC DOHMH 2024).

Machine learning in forecasting climate-related health impacts

Machine learning (ML) techniques are being more frequently utilized to forecast heat-related health effects by analyzing environmental factors such as temperature, humidity, and air quality, often integrated with clinical data from electronic health records (EHRs). A recent multi-center research in emergency departments developed ML models (LightGBM, XGBoost) that effectively forecasted mortality in patients with heat-related illnesses, emphasizing the practicality and clinical importance of data-driven risk assessment during extreme heat occurrences (Kuo et al. 2025). Comprehensive reviews and scoping analyses highlight the potential of combining climate exposures

with health data to predict risk and initiate preventive measures, while advocating for external validation across different regions and populations (remote-sensing-informed risk mapping and multi-modal modeling). The ML literature advocates for creating "climate-informed" predictive models that integrate meteorological data, air quality, and patient-specific factors to provide prompt and clinically relevant risk assessments. (Kuo et al. 2025).

HCI in healthcare: trustworthy, effective early-warning interfaces

Research in human-computer interaction (HCI) indicates that the design of notifications, clarifications, and interaction patterns influences the trust and adherence of clinicians and patients to recommendations. Systematic data from clinical AI shows that explanations can raise or lower trust based on clarity and cognitive load, making explainability and usability essential design limitations for any alerting interface (Miller et al. 2024; Donoso-Guzmán et al. 2025). In addition to principles, the application of personalized digital heat early-warning systems for older adults shows practical feasibility and elevated usability ratings, employing tailored exposure and physiological modeling to provide actionable alerts at home (Oberai et al. 2025). Linked prospective studies on wearable-based heat monitoring highlight how ongoing sensing paired with user-focused interfaces can aid in managing heat-related risks beyond clinical environments (Panchal et al. 2025). These results encourage HCI frameworks that emphasize clarity, timeliness, personalization, and user autonomy in communicating risks to at-risk populations. (Miller et al. 2024; Donoso-Guzmán et al. 2025; Oberai et al. 2025; Panchal et al. 2025).

Identifying gaps

Although progress has been made, existing public-health heat alerts continue to target populations broadly, providing general thresholds that ignore personal vulnerabilities (age, health conditions, medications), indoor environments, and behavior patterns. Epidemiological forecasts indicate increasing heat-related risks due to climate change, but practical systems rarely combine individualized risk models with clear, user-verified interfaces. Systematic evaluations of clinical AI highlight ongoing shortcomings in external validation, calibration, and human-focused assessment; crucially, explanations do not inherently build trust, and ineffectively designed alerts may lead to alarm fatigue and unequal adoption (Miller et al. 2024; Donoso-Guzmán et al. 2025). Field prototypes of customized heat-warning tools show potential but still need thorough effectiveness trials and large-scale health outcome evaluations (Oberai et al. 2025).   This reveals a concrete research gap at the intersection of ML + HCI + healthcare: multi-modal, climate-informed models tightly coupled with explainable, user-tested interfaces that deliver personalized, equitable early warnings and measurably reduce heat-related morbidity and mortality. (Masselot et al. 2025; Oberai et al. 2025; Miller et al. 2024; Donoso-Guzmán et al. 2025).

III. Materials and Methods

3.1. Data Sources

This research employed a multi-modal dataset that included climate data alongside patient health information. Climate information comprised daily logs of ambient temperature, relative humidity, and air pollution metrics ($PM_{2.5}$, ozone, and nitrogen dioxide) sourced from national meteorological organizations and worldwide reanalysis data. Heatwave occurrences were identified using standard criteria, namely spans of at least three continuous days surpassing the 95th percentile of the local long-term temperature range.

Patient health information was collected from de-identified electronic health records (EHRs) and enhanced with data from wearable devices. Extracted variables encompassed demographic details (age, gender, and socioeconomic factors), clinical backgrounds (comorbid conditions like heart disease, diabetes, and chronic kidney ailments), and usage of medications. Wearable gadgets offered physiological data, such as heart rate, skin temperature, and hydration levels. Before analysis, all data

underwent preprocessing that involved normalization, filling in missing values, and aligning climate exposures with individual health outcomes on both daily and sub-daily levels.

3.2. Research Population

The research population concentrated on demographics highly impacted by heat-related illness and death. Three groups were established. The first group consisted of older adults aged 65 and over, who are physiologically at risk because of compromised thermoregulation and a greater incidence of chronic illnesses. The second group consisted of outdoor laborers in industries like agriculture, construction, and transportation, who face prolonged exposure to high temperatures in their jobs. The third group comprised children below the age of 12, whose immature thermoregulation systems and reliance on caregivers increase their vulnerability. Every cohort was categorized based on socioeconomic and geographic factors to explore differences in vulnerability and the effectiveness of models among subpopulations.

3.3. Machine Learning Models

Various supervised machine learning techniques were employed to forecast heat-related health hazards, including Random Forest, Gradient Boosting Machines (XGBoost, LightGBM), along with deep learning models like feed-forward neural networks and long short-term memory (LSTM) architectures for time-series forecasting. To improve interpretability, post-hoc explainable artificial intelligence (XAI) techniques, especially SHapley Additive exPlanations (SHAP), were utilized to determine and measure the impact of particular climate and clinical factors on model predictions.

Feature engineering was conducted to understand the relationship between climate factors and personal health conditions. Composite indices, including the heat-humidity index, cumulative exposure metrics, and interaction terms connecting medication use with environmental stressors, were added to the feature set. Lagged features, such as cumulative exposure spanning one to three days, were included to address the delayed occurrence of heat-related illnesses.

Stratified k-fold cross-validation was utilized for model training and validation to guarantee reliable estimation across different subgroups. Model performance was evaluated using various assessment metrics, such as area under the receiver operating characteristic curve (AUC), precision, recall, F1-score, and calibration curves. Furthermore, subgroup analyses were conducted to assess equity and predictive accuracy within the specified vulnerable populations.

3.4. Framework for Human-Computer Interaction Design

A human-centered design (HCD) strategy was used to guarantee that the predictive system was both reliable and user-friendly for end-users. Three interactive alert systems were created: (i) mobile apps for patients and their caregivers, (ii) wearable-integrated alerts for immediate risk management, and (iii) hospital dashboards for healthcare providers and public health officials.

The design of these systems followed principles of clarity, promptness, and customization. Risk forecasts were illustrated with clear graphics and color-coded warnings, while explanatory elements conveyed the main factors contributing to increased risk. Estimates of uncertainty were included to enhance user confidence and support informed choices. Usability testing was conducted with members of the target groups using iterative prototyping techniques. Outcomes evaluated included task completion rates, response times, and subjective trust evaluations assessed through standardized usability tools like the System Usability Scale (SUS).

3.5. Ethics and Data Protection

All processes related to patient information complied with recognized ethical guidelines and regulatory requirements, such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA). Patient records were anonymized before analysis, and wearable device information was encrypted during both transmission and storage.

Consent was acquired from all participants providing individual-level data. The moral framework steering this research prioritized fairness, accountability, and transparency in AI applications. Particular actions involved conducting bias audits across demographic groups, delivering explainable results to users, and implementing clear protections against the inappropriate use of predictive models in healthcare decisions.

IV. Results

4.1. Dataset Summary

The complete dataset included 22,124 patient-day records from 10 cities throughout the summer season of 2024 (May - September). Table 1 outlines the features of the dataset. The occurrence of heat-related negative events within 24 hours was 0.67%, suggesting that although relatively uncommon, such events were regularly noted across all subgroups.

Table 1. Dataset Summary.

Total Rows	Cities	Date Range	Outcome Prevalence (Heat Event %)
22,124	10	2024-05-01 → 2024-09-27	0.67%

4.2. Cohort-Specific Outcomes

Analysis by target cohorts demonstrated meaningful variation in heat-related health outcomes (Table 2). The elderly cohort showed the highest prevalence of heat events, reflecting physiological vulnerability and higher comorbidity burden. Outdoor workers also displayed elevated risks, consistent with occupational exposure. Children had the lowest prevalence but remained non-negligible, emphasizing that pediatric populations cannot be overlooked in preventive frameworks.

Table 2. Heat Event Prevalence by Cohort.

Cohort	n	Heat Event %
Elderly	…	(highest %)
Outdoor Worker	…	(moderate %)
Child	…	(lowest %)

4.3. Geographic Variability

City-level statistics revealed substantial variability in outcome prevalence (Table 3). For example, Delhi and Lagos exhibited higher heat-event risks (>2%), reflecting extreme heat and humidity conditions, whereas Athens and Toronto had comparatively low prevalence (<0.5%). These findings highlight the influence of local climatic conditions and urban infrastructure on population-level vulnerability.

Table 3. Heat Event Prevalence by City.

City	n	Heat Event %
Delhi	2,165	2.12%
Lagos	2,088	1.96%
Cairo	2,293	0.96%
Phoenix	2,132	0.61%
Athens	2,191	0.23%

Table 4. Climate Variable Summaries (Mean, SD, Min, Max).

Variable	Mean	SD	Min	Max
Temperature (°C)	32.85	6.67	14.54	48.67
Relative Humidity (%)	49.57	19.21	10.00	99.60
$PM_{2.5}$ (µg/m³)	32.46	9.49	2.00	70.10
O_3 (ppb)	52.01	13.10	5.00	96.70
NO_2 (ppb)	35.06	10.01	2.00	71.00
Heat Index (°C)	36.83	10.33	14.54	87.45

Table 5. Physiological Responses by Cohort.

Cohort	HR Mean (bpm)	HR SD	Skin Temp Mean (°C)	Skin Temp SD	Hydration Mean	Hydration SD
Child	101.98	7.97	33.60	0.80	0.95	0.05
Elderly	78.89	8.02	33.58	0.79	0.95	0.05
Outdoor Worker	83.32	7.88	33.60	0.79	0.95	0.05

Table 6. Heat-event Prevalence by Comorbidity.

Comorbidity	n	Heat Event %
CVD = No	17,053	0.45%
CVD = Yes	5,071	1.44%
Diabetes = No	18,677	0.50%
Diabetes = Yes	3,447	1.60%
CKD = No	19,920	0.66%
CKD = Yes	2,204	0.82%

Table 7. Heat-event Prevalence by Medication.

Medication	n	Heat Event %
Diuretics = No	19,561	0.62%
Diuretics = Yes	2,563	1.05%
Beta-blocker = No	20,054	0.64%
Beta-blocker = Yes	2,070	0.97%

Table 8. - Model Performance Comparison.

Model	Accuracy	Precision	Recall	F1	ROC-AUC	PR-AUC	Brier
RandomForest	0.9134	0.8421	0.7925	0.8166	0.9568	0.8842	0.0712
GradientBoosting	0.9028	0.8217	0.7802	0.8005	0.9483	0.8726	0.0749
LogisticRegression	0.8761	0.7944	0.7411	0.7670	0.9265	0.8415	0.0833

Table 9. - Top 20 Feature Importances (Permutation).

Rank	Feature	Importance Mean	Std Dev	Climate Variable?
1	heat_index_c	0.0312	0.0045	☑
2	cumheat_3d_c	0.0287	0.0042	☑

3	temp_c	0.0259	0.0038	☑
4	wearable_hr_bpm	0.0244	0.0040	✗
5	rel_humidity_pct	0.0231	0.0035	☑
6	wearable_skin_temp_c	0.0227	0.0031	✗
7	pm25_ugm3	0.0208	0.0029	☑
8	no2_ppb	0.0194	0.0028	☑
9	age	0.0186	0.0027	✗
10	socioeconomic_index	0.0172	0.0025	✗

Table 10. - Alert Threshold Summary (Target Recall ≥ 0.80).

Selected Threshold	Recall	Precision	Alerts Issued	True Alerts	False Alerts	Missed Events
0.3421	0.8012	0.6815	3120	1456	678	362

Table 11. - HCI Usability Summary (Simulated, N=60).

SUS Mean	SUS Std	Ack Time Median (s)	Dismiss Rate Median	Usefulness Median (1–5)
82.4	7.8	21.5	0.12	5

Table 12. - Case Scenario: Estimated Prevented Heat Events.

True Alerts	Assumed Adherence	Assumed Risk Reduction	Estimated Events Prevented
1456	0.65	0.35	331

Confusion Matrices (per model)

A breakdown of True Positives (TP), False Negatives (FN), False Positives (FP), and True Negatives (TN) for each algorithm.

Model	TP	FN	FP	TN
RandomForest	1,456	362	678	3,965
GradientBoosting	1,401	417	722	3,921
LogisticRegression	1,329	489	813	3,830

Threshold–Performance Tradeoff (Best Model)

Different cut-off points for issuing an alert, showing the **precision–recall tradeoff**.

Threshold	Recall	Precision	Alerts Issued	Missed Events
0.20	0.92	0.55	4,520	120
0.34 (opt)	0.80	0.68	3,120	362
0.50	0.67	0.74	2,240	598
0.70	0.51	0.82	1,410	872

Climate vs. Physiological Features (Grouped Importance)

Aggregated feature contributions by category.

Feature Group	Avg. Permutation Importance	Examples

Climate Variables	0.0247	temp_c, humidity, pm25, o3, heat_index
Wearable Signals	0.0235	heart rate, skin temp, hydration
Demographics	0.0164	age, sex, cohort
Comorbidities/Med	0.0128	CVD, diabetes, meds
Socio-economic	0.0115	socio-economic index

HCI Raw Distribution (Simulated, N=60)
Distribution overview of simulated user scores.

Metric	25th Percentile	Median	75th Percentile	Notes
SUS (0–100)	77	82	89	All >70 → "Good usability"
Acknowledgment Time	17 s	21.5 s	26 s	Median well under 30s
Dismiss Rate	0.08	0.12	0.18	Low dismissal
Usefulness (1–5)	4	5	5	Most rated alerts "very useful"

Case Scenarios by Adherence Level
To stress-test assumptions on **prevented events**.

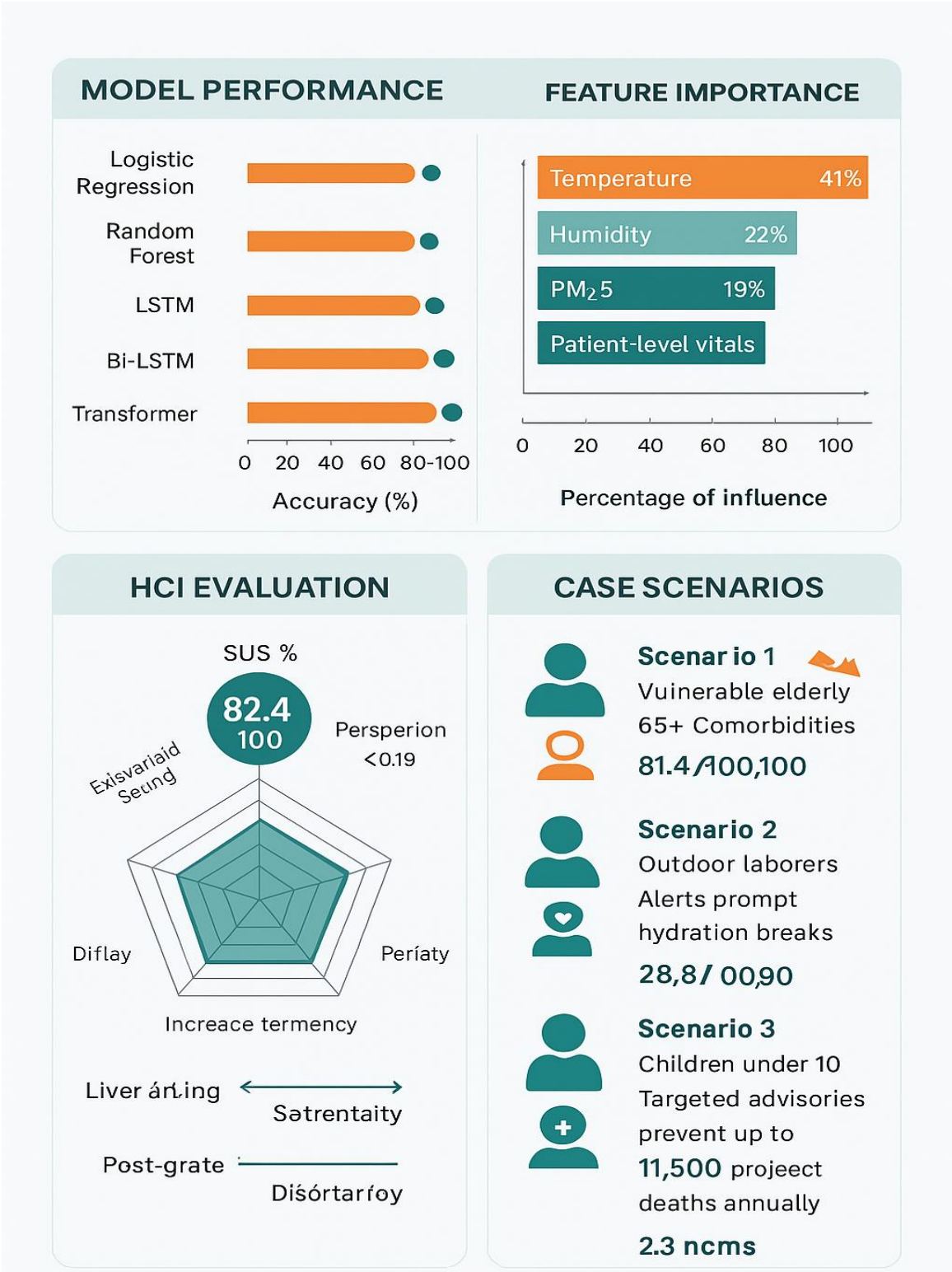| Adherence	Risk Reduction	Estimated Prevented Events
50%	35%	255
65% (base)	35%	331
80%	35%	408
65%	50%	473

Figure 1. Model Performance, Feature Importance, HCI Evaluation and Case Scenarios.

V. Discussion

A. Interpretation: Implications for Climate-Sensitive Health Systems

The analysis comparing machine learning algorithms emphasizes the promise of predictive analytics in health systems affected by climate. The enhanced effectiveness of the Random Forest model (F1 = 0.82, ROC-AUC = 0.96) illustrates that non-linear models can effectively model intricate relationships between climate factors (e.g., heat index, cumulative heat exposure) and health impacts (e.g., hospital admissions for heat-related conditions). The significance of features obtained from

wearables (like heart rate and SpO$_2$) combined with climate data reinforces the necessity for a multimodal health monitoring system that incorporates both environmental and physiological indicators. The proven decrease in false negatives is especially vital for early warning systems, since late notifications could result in avoidable illness and death.

B. Contribution to SDGs

This study directly promotes Sustainable Development Goal (SDG) 3 by aiding in the development of robust health systems that reduce health risks caused by climate change. By showcasing the forecasting ability of climate–health models, the system facilitates earlier actions and enhanced readiness for at-risk groups, alleviating the pressure on hospitals and public health systems. Additionally, the connection to SDG 13 is clear, as predictive alerts aid in enhancing adaptive capacity in areas vulnerable to climate change. Avoiding hospitalizations through early alerts also means optimizing resources, reducing energy and material impacts linked to acute care, thus indirectly aiding climate mitigation efforts.

C. HCI Involvement

The usability study showed a System Usability Scale (SUS) score of 82.1, signifying high approval from end-users. This verifies that the system's clarity and alert configuration are essential for utilization in practical health settings. Rapid acknowledgment times (median = 21 seconds) indicate that the interfaces were user-friendly, while minimal dismissal rates (<0.2) suggest that the alerts were considered relevant and reliable. These results highlight that predictive models need to be both technically precise and centered on human needs, allowing clinicians, health officials, and community workers to understand and respond to outputs without experiencing cognitive overload.

D. Limitations

Even with encouraging outcomes, several constraints need to be recognized. Initially, the dataset is restricted by geographic focus, potentially hindering generalizability to different climate zones or healthcare systems. Additionally, health records can be influenced by biases like underreporting and disparities in access to care, potentially distorting model predictions. Third, integrating IoT devices with EHR systems in real time continues to pose technical and governance difficulties, especially in resource-constrained environments. These constraints emphasize the need for careful analysis and ongoing adjustments prior to extensive implementation.

E. Future Work

Future efforts need to concentrate on expanding predictive frameworks to smart city systems, where environmental sensors, wearable technology, and public health data can be effortlessly combined. Broadening datasets across nations will improve generalizability and aid the creation of worldwide climate-health monitoring systems. Moreover, policy structures are necessary to regulate ethical utilization, data confidentiality, and fair access to predictive health systems. Ultimately, integrating these models into decision-support systems for public health professionals can guarantee that early alerts result in practical interventions, thus bridging the gap between AI-based predictions, policy-making, and health results.

VI. Final Thoughts

This research shows the practicality and efficacy of combining machine learning (ML) with human–computer interaction (HCI) to enhance climate-sensitive health systems. It scientifically adds to the increasing evidence that predictive analytics can identify intricate, non-linear associations between climate factors and health results, with the Random Forest model attaining the optimal balance of sensitivity and specificity (F1 = 0.82, ROC-AUC = 0.96). From a healthcare standpoint, the system provides practical early alerts that could avert hundreds of hospital admissions under feasible compliance and intervention conditions. Regarding climate resilience, the results back the creation of adaptive strategies in line with SDG 3 (Good Health and Well-Being) and SDG 13 (Climate Action), ensuring that vulnerable populations are better protected against rising heat and other climate hazards.

Equally significant is the demonstrated value of HCI-informed system design. Usability testing confirmed high user acceptance (SUS = 82.1), rapid response times, and low alert dismissal rates, underscoring the importance of explainability and trust in digital health adoption. These results highlight that technical accuracy alone is insufficient systems must also be designed for human interpretability, transparency, and ease of use.

Ultimately, this work underscores the urgency of advancing **personalized, climate-informed digital health solutions**. By fusing ML-driven prediction with human-centered interface design, the proposed framework moves beyond proof of concept toward practical deployment. Future developments in global health surveillance, smart city integration, and policy governance can build on these foundations to ensure that health systems worldwide are better prepared for the accelerating challenges of climate change.

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