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AI-ENABLED HEATWAVE RESILIENCE AND CLIMATE RISK MANAGEMENT IN THE UNITED STATES

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Abstract:
Extreme heat is an escalating climate-health and sustainability challenge in the United States, yet its effects remain uneven because exposure intersects with housing, energy insecurity, occupation, health, transportation, and historical disinvestment. This study examines how artificial intelligence (AI) can support equitable heatwave resilience without obscuring uncertainty or institutional responsibility. It combines an integrative evidence synthesis with an exploratory ecological analysis of publicly reported Centers for Disease Control and Prevention data for the 10 U.S. Department of Health and Human Services regions, comparing 2023 warm-season heat-related illness emergency-department visit rates, historical baseline rates, and days above regional historical thresholds. The regional measures showed strong geographic clustering and persistence, but robust estimation and influence diagnostics demonstrated that the adjusted elevated-day association was unstable in the small sample and should not be interpreted causally. The synthesis therefore develops a five-pillar climate-risk management framework linking hazard anticipation, social vulnerability mapping, targeted intervention, adaptive communication, and ethical governance. The framework positions AI as accountable decision support rather than an autonomous solution. Its sustainability contribution connects predictive capability with material protection, including functional cooling, energy assistance, worker safeguards, transportation, resilient housing, urban heat mitigation, and community participation. AI-enabled heat resilience should be evaluated by transparent validation, equitable service reach, institutional accountability, and measurable reductions in preventable harm.

Keywords: Artificial Intelligence; Climate Resilience; Environmental Justice; Extreme Heat; Social Vulnerability

INTRODUCTION

Extreme heat has moved from the margins of climate policy to the center of public-health and resilience planning in the United States. Across 50 large U.S. cities, average heatwave frequency rose from approximately two events per year in the 1960s to approximately six per year in the 2010s and 2020s, while the average heatwave season lengthened by 46 days (U.S. Environmental Protection Agency [EPA], 2024). Recent average heatwaves in these cities last about four days. These trends show that extreme heat is no longer an occasional summer inconvenience; it is a recurring climate risk that tests health systems, housing, labor protections, emergency management, energy affordability, and local government capacity.

Heat also produces measurable health harm. Howard et al. (2024) identified 21,518 U.S. deaths recorded with heat as an underlying or contributing cause from 1999 through 2023. Annual deaths increased from 1,069 in 1999 to 2,325 in 2023, a 117% increase in the count and a 63% increase in the age-adjusted mortality rate. Mortality is only part of the burden. Emergency department surveillance during the 2023 warm season showed substantial elevations in heat-related illness,

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particularly among males and adults aged 18–64 years (Vaidyanathan et al., 2024). This pattern extends heat-risk planning beyond older adults to working-age populations whose jobs, housing, transportation, or recreational exposure increase risk.

The challenge is not only that the United States is becoming hotter. Heat is socially mediated. Two neighborhoods can receive the same forecast and experience very different outcomes because residents differ in housing quality, air-conditioning functionality, ability to pay utility bills, health status, occupation, transportation, social support, and trust in public institutions. The CDC/ATSDR Social Vulnerability Index (SVI) operationalizes demographic and socioeconomic conditions that influence how communities experience hazards, including poverty, crowded housing, disability, language barriers, and limited vehicle access (CDC/ATSDR, 2024). A heatwave becomes a disaster when hazardous conditions intersect with sensitivity and constrained adaptive capacity.

Maricopa County, Arizona, illustrates the practical consequences. The county recorded 608 heat-related deaths in 2024, down from 645 in 2023 (Maricopa County Department of Public Health, 2025). Among indoor deaths in 2024, 88% of decedents had an air-conditioning unit present, but 70% of those units were not functioning. In addition, 51% of all heat-related deaths occurred on days classified as moderate rather than extreme by HeatRisk. These findings challenge two assumptions: nominal air-conditioning access does not guarantee protection, and fatal outcomes are not confined to the most severe warning category. Functional cooling, affordability, indoor conditions, social isolation, and locally relevant thresholds must be part of heat-risk management.

Heatwave resilience is defined here as the capacity of individuals, households, infrastructure, institutions, and communities to anticipate, withstand, respond to, and recover from extreme heat while reducing future risk. This definition includes preparedness before an event, protection during exposure, recovery after harm, and structural adaptation. It also recognizes unequal starting conditions. People with secure housing, reliable electricity, functioning cooling, paid leave, private transportation, healthcare, and social support can act on warnings more readily than people without those resources. A technically accurate resilience strategy can therefore remain inequitable if it fails to address who can use the information and who receives material protection.

The built environment embeds these disparities. Urban heat islands arise from impervious surfaces, dark roofs, building mass, limited vegetation, and anthropogenic heat. Across 108 U.S. urban areas, formerly redlined "D"-rated neighborhoods were approximately 2.6°C warmer in land-surface temperature than "A"-rated neighborhoods (Hoffman et al., 2020). Across 5,723 urban communities, low-income blocks had 15.2% less tree cover and were 1.5°C hotter than high-income blocks (McDonald et al., 2021). Household energy insecurity compounds these conditions: In 2020, 34 million U.S. households, or 27%, reported difficulty meeting energy needs or maintaining safe indoor temperatures because of cost (U.S. Energy Information Administration [EIA], 2022). These patterns connect present heat exposure to housing discrimination, disinvestment, unequal green infrastructure, and constrained household resources.

Recent work by Damoah and colleagues situates heat and climate risk within a broader environmental-sustainability and social-vulnerability agenda. Damoah and Khalo (2024) link extreme-temperature variability in Mississippi to health, livelihoods, infrastructure, and adaptation needs, while Damoah et al. (2024) describe how industrial development, urbanization, ecosystem loss, and infrastructure pressure compound Gulf Coast climate vulnerability. Damoah (2026) further shows that Gulf Coast early-warning practice can separate hazard information from ecosystem conditions, social vulnerability, accessible communication, and response activation. Related scholarship extends this climate-society perspective: Damoah (2023b) frames climate emergencies as requiring public learning and action, and Agyeman et al. (2025) show how climate stress can cascade

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into livelihood and food-security vulnerability. Together, these studies support an end-to-end approach in which climate intelligence is judged not only by technical accuracy but by whether it reaches exposed populations and enables feasible, equitable action.

The literature relevant to AI-enabled heatwave resilience can be organized into four connected streams: heat-health epidemiology, the social and spatial production of vulnerability, heat-action and warning systems, and AI-supported climate-risk decision-making. These streams have developed unevenly. Epidemiological studies provide strong evidence of health burden, environmental-justice research explains why exposure and adaptive capacity differ across places, and forecasting research has advanced rapidly. The weaker connection lies between these knowledge bases and the institutional mechanisms that convert a warning or risk score into material protection.

The heat-health literature consistently links extreme heat with mortality and multiple forms of morbidity. A systematic review by Arsad et al. (2022) found elevated mortality and morbidity across age groups and identified socioeconomic disadvantages, chronic disease, rural location, and demographic characteristics as important vulnerability factors. U.S. studies add clinical specificity: extreme heat is associated with adult emergency visits for renal disease, mental disorders, and other causes, higher pediatric emergency use, rising heat-related mortality, and severe burdens among people experiencing homelessness (Bernstein et al., 2022; Howard et al., 2024; Sun et al., 2021; Weckstein et al., 2025). This evidence supports multi-outcome surveillance but also shows why heat vulnerability cannot be reduced to a single age category or diagnosis.

A second literature stream locates heat risk in the built environment and in unequal access to adaptive resources. Research on redlining, tree canopy, urban heat islands, energy insecurity, and power outages demonstrates that heat exposure is produced by land-use decisions, housing quality, infrastructure investment, and household affordability (Andresen et al., 2023; Hoffman et al., 2020; Hsu et al., 2021; McDonald et al., 2021). More recent evidence from Los Angeles indicates that contemporary income inequality can be at least as consequential as historical redlining for present thermal disparities (Shreevastava et al., 2025). The implication for AI is methodological as well as ethical: vulnerability models should represent current service and housing conditions rather than rely only on static demographic indices.

A third stream examines heat action plans, warning thresholds, and public communication. A review of 21 local U.S. heat action plans found that jurisdictions commonly included activation triggers, risk communication, cooling centers, surveillance, and interagency coordination, but implementation details and targeted strategies remained uneven (Randazza et al., 2023). A 2025 systematic review of heat-health warning systems similarly concluded that systems rely heavily on temperature-based thresholds and should incorporate local epidemiology, built-environment conditions, and population-specific vulnerability (Chandra N and Lee, 2025). Evidence linking HeatRisk categories with emergency department burden supports impact-based warning, but warning effectiveness still depends on whether messages identify concrete actions and available services (Muscatiello et al., 2025). Communication also becomes more difficult during compound events such as heat and wildfire smoke, when protective guidance can conflict or remain incomplete (Coker et al., 2024).

The fourth stream concerns AI and climate resilience. Systematic reviews show rapid growth in AI applications but also a concentration in hazard prediction, agriculture, and infrastructure rather than health, implementation, or governance. In Ayadi et al. (2025), health represented only a small fraction of the 385 studies reviewed, while transparency, data access, geographic imbalance, and equitable deployment remained persistent concerns. Mehryar et al. (2024) likewise found that

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AI for climate adaptation emphasizes hazard and exposure assessment more than vulnerability reduction, prioritization, implementation, and institutional accountability. The forecasting literature confirms that machine learning can add speed and skill, yet it also documents physical-consistency problems, sensitivity to unprecedented extremes, and contexts in which physics-based models perform better (Bonavita, 2024; Lam et al., 2023; Price et al., 2025; Zhang et al., 2026).

Taken together, the literature reveals three gaps. First, heat-health evidence and AI forecasting are rarely joined to an explicit intervention pathway. Second, vulnerability mapping often identifies high-risk places without specifying which institution must act, what resource should be mobilized, or how access will be verified. Third, model evaluation commonly prioritizes predictive accuracy over service reach, distributive fairness, and health outcomes. The present study addresses these gaps by treating AI as one component of an accountable climate-risk management system rather than as an autonomous solution.

Artificial intelligence (AI) can help integrate environmental, health, social, infrastructure, and service data. Machine-learning systems can support probabilistic forecasting, map neighborhood heat exposure, detect emerging health burdens, identify gaps in cooling access, prioritize outreach, and tailor warnings. Recent systems such as GraphCast and GenCast demonstrate substantial speed and skill in medium-range weather prediction (Lam et al., 2023; Price et al., 2025). However, prediction is not protection. A model that forecasts temperature accurately but overlooks broken cooling systems, energy burden, outdoor labor, or social isolation has limited public value. Likewise, a high-resolution risk map that does not trigger transportation, home repair, utility assistance, or wellness checks remains an analytic product rather than a resilience intervention.

This study asks how AI can support equitable heatwave resilience in high-risk U.S. communities without obscuring uncertainty or institutional responsibility. It makes three contributions. First, it synthesizes current evidence on the climatic, health, infrastructural, occupational, and historical production of heat vulnerability. Second, it provides a transparent exploratory analysis of regional heat-related illness emergency-department surveillance measures to illustrate geographic clustering and the limits of aggregate data. Third, it develops an equity-centered five-pillar climate-risk management framework that links hazard anticipation to vulnerability profiles, interventions, communication, and governance. The central proposition is that AI should be judged by whether accountable institutions use it to reduce preventable harm and strengthen environmentally sustainable, socially equitable adaptation—not only by predictive performance.

METHODS

Study design and evidence synthesis

The study used a mixed conceptual and quantitative design. The conceptual component was an integrative, purposive evidence synthesis rather than a systematic review. The review was organized around four literature streams: heat-health epidemiology; social and spatial vulnerability; heat-action plans, early warning, and risk communication; and AI-enabled forecasting, decision support, and governance. Sources were retained when they directly informed U.S. extreme-heat burden, vulnerability pathways, operational response, or the design and evaluation of AI-supported climate-risk management. Priority was given to peer-reviewed studies published from 2020 through 2026, supplemented by influential earlier work, official federal datasets, and local surveillance reports with verifiable quantitative information. The synthesis compared areas of convergence, disagreement, and omission across the literature and used exposure, sensitivity, adaptive capacity, institutional response, and responsible AI governance as organizing concepts.

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Because the evidence review was not systematic, it did not use a preregistered protocol, exhaustive database search, duplicate screening, formal risk-of-bias tool, or meta-analysis. It should therefore be interpreted as an analytically structured review of representative evidence rather than a complete census of the field. No study counts, pooled effects, or formal evidence grades were inferred from this component. The approach was appropriate for theory building and operational framework development, but it cannot support claims about the prevalence or comparative quality of the entire literature; this limitation is addressed explicitly in the discussion.

Regional data source and measures

The quantitative component used aggregate regional values published by Vaidyanathan et al. (2024) from the National Syndromic Surveillance Program. The unit of analysis was the U.S. Department of Health and Human Services (HHS) region (n = 10). The outcome was the mean warm-season 2023 HRI ED visit rate per 100,000 ED visits. The first predictor was the number of days in 2023 on which the regional HRI ED visit rate exceeded the region-specific 2018–2022 95th percentile. The second predictor was the 2018–2022 mean regional HRI ED visit rate, used as an indicator of preexisting regional burden. The 20 regional rate values were reconciled directly against Table 1 of the published MMWR report, and the 10 elevated-day totals were independently summed from the May–September 2023 entries in its Table 2. Table 1 reproduces the verified regional observations used in the analysis in full.

The reported average of the 10 regional 2023 rates is an unweighted mean of regional values and is not a population-weighted national rate. Region 2 excludes Puerto Rico and the U.S. Virgin Islands because they did not report to the surveillance system in the cited analysis. No individual-level, identifiable, or restricted health records were accessed.

Statistical analysis

The analysis calculated means, sample standard deviations, ranges, Pearson correlations, and Spearman rank correlations. Two ordinary least squares (OLS) models were estimated. Model 1 regressed the 2023 regional HRI ED rate on elevated HRI days. Model 2 added the 2018–2022 baseline rate. Tests were two-sided with alpha = 0.05. Conventional OLS standard errors are reported to reproduce the initial analysis, and HC3 heteroscedasticity-robust standard errors are reported because the sample is small and regional observations may have unequal residual variance. Calculations were reproduced in Python 3.13.5 with SciPy 1.17.0 and statsmodels 0.14.6, independently checked through direct matrix algebra, and protected by automated assertion tests in Supplementary File 1.

Residual normality, heteroscedasticity, leverage, and Cook's distance were examined as descriptive diagnostics. Given n = 10, diagnostics have low power, and coefficients can be strongly affected by single regions. The statistical analysis is therefore exploratory and ecological. It was not designed to estimate causal effects, predict individual risk, or validate an independent heat-exposure model. In particular, the outcome and elevated-day measure both derive from HRI ED surveillance, creating conceptual and statistical dependence that limits interpretation.

RESULTS

Extreme heat burden and structural vulnerability

The evidence synthesis identified three interacting features of U.S. heat risk: increasing exposure, rising health burden, and unequal adaptive capacity. EPA indicators document more frequent and longer heatwaves in major cities, while the Fifth National Climate Assessment concludes that climate change affects every U.S. region and disproportionately burdens communities already facing social and environmental stressors (EPA, 2024; U.S. Global Change Research Program [USGCRP], 2023). Heat differs from visually destructive hazards because severe

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physiological stress, chronic-disease exacerbation, emergency care, and mortality can rise without obvious physical damage.

Mortality and morbidity evidence shows a broad and growing burden. Heat-related deaths increased markedly from 1999 to 2023 (Howard et al., 2024). Adult emergency department visits rise on extreme-heat days for heat-related illness, renal disease, mental disorders, and other causes (Sun et al., 2021). Higher warm-season temperatures are also associated with increased pediatric emergency department visits (Bernstein et al., 2022). Together, these findings support surveillance that extends beyond narrowly coded heat stroke and includes multiple clinical pathways and age groups.

Regional evidence identifies substantial geographic heterogeneity. HHS Region 6, which includes Arkansas, Louisiana, New Mexico, Oklahoma, and Texas, had the highest reported mean warm-season 2023 HRI ED visit rate and the most days above its historical threshold (Vaidyanathan et al., 2024). Hot climate, humidity, outdoor work, rapid urban growth, rural healthcare constraints, energy burden, and power disruption can converge in this region. Maricopa County shows a related local pattern in which severe mortality occurs through both outdoor exposure and failed indoor cooling (Maricopa County Department of Public Health, 2025).

Occupational and housing conditions broaden the at-risk population. In 2023, 33.0% of workers were regularly exposed to outdoor conditions as part of their job (Bureau of Labor Statistics [BLS], 2024). Construction, agriculture, logistics, sanitation, utilities, public safety, and airport operations can involve high heat, radiant exposure, exertion, and limited control over pace or rest. Heat alerts have limited protective value when workers cannot modify schedules or access water, rest, shade, acclimatization, and anti-retaliation protections.

People experiencing homelessness face direct exposure, limited hydration and sanitation, chronic illness, and few safe recovery spaces. National emergency department data show substantially higher heat-related illness among people experiencing homelessness than among housed populations (Weckstein et al., 2025). Protective mapping can guide mobile cooling, hydration, medical outreach, and transportation, but the same location data can enable displacement or punitive enforcement. The intended use and governance of risk data therefore form part of the intervention itself.

Indoor risk depends on affordability, building performance, and power reliability. Energy-insecure households may reduce cooling, defer repairs, or keep homes at unsafe temperatures (EIA, 2022). Power outages also disproportionately affect lower-income households, racial and ethnic minority communities, children, older adults, and rural residents (Andresen et al., 2023). Treating air-conditioning access as a binary variable can therefore misclassify protection. Functional status, operating cost, insulation, outage exposure, and medically sensitive household needs are more decision-relevant measures.

The social production of vulnerability is also spatial. Older adults and people with chronic illness face physiological sensitivity, but their actual risk depends on cooling, housing, transportation, healthcare, and social support. Renters may have limited authority to repair failing systems or modify buildings. Historically disinvested neighborhoods often have more impervious surface and less tree canopy, and contemporary income inequality continues to shape intra-urban heat disparities (Hoffman et al., 2020; Hsu et al., 2021; McDonald et al., 2021; Shreevastava et al., 2025). These conditions are not fixed attributes of populations; they result from policy, infrastructure, labor, housing, and resource allocation.

Cooling-center access illustrates why spatial proximity is insufficient. A center may be technically nearby but practically inaccessible because of limited transit, unsafe walking exposure,

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disability barriers, operating hours, pet restrictions, distrust, or lack of medical support. In Arizona, older adults reported limited awareness of cooling-center locations and transportation barriers, and mapping that combined service locations with SVI data revealed gaps between hazard, vulnerability, and usable protection (Mallen et al., 2022). AI-enabled planning must therefore evaluate service networks and lived accessibility, not point locations alone.

Exploratory regional HRI ED analysis

Table 1 presents the 10 regional observations. The unweighted mean of the regional warm-season 2023 HRI ED rates was 193.2 per 100,000 ED visits (SD = 138.1; range 51–483). The mean number of elevated HRI days was 16.4 (SD = 17.0; range 3–56). Region 6 reported the highest 2023 rate (483) and elevated-day count (56), while Region 2 reported the lowest 2023 rate (51). These descriptive contrasts illustrate the concentration of reported acute heat-health burden across regions.

Table 1

CDC Regional Dataset Used for the Exploratory Ecological Analysis

HHS region	Included states	2023 HRI ED rate	2018–2022 baseline rate	Elevated HRI days
1	CT, ME, MA, NH, RI, VT	69	92	3
2	NJ, NY	51	66	4
3	DE, DC, MD, PA, VA, WV	121	144	5
4	AL, FL, GA, KY, MS, NC, SC, TN	226	183	35
5	IL, IN, MI, MN, OH, WI	102	109	5
6	AR, LA, NM, OK, TX	483	254	56
7	IA, KS, MO, NE	327	248	15
8	CO, MT, ND, SD, UT, WY	127	120	11
9	AZ, CA, HI, NV	298	247	21
10	AK, ID, OR, WA	128	131	9

Note. HRI ED rates are per 100,000 emergency department visits. Elevated HRI days are days in 2023 when the regional HRI ED visit rate exceeded the region-specific 2018–2022 95th percentile. Region 2 excludes Puerto Rico and the U.S. Virgin Islands because they did not report to NSSP in the cited analysis.
Source: Vaidyanathan et al. (2024), Tables 1–2.

Bivariate associations were strong (Table 2). Elevated HRI days correlated with the 2023 rate (Pearson r = 0.874, p = 0.001; Spearman rho = 0.924, p < 0.001). The 2018–2022 baseline rate also correlated with the 2023 rate (Pearson r = 0.938, p < 0.001; Spearman rho = 0.964, p < 0.001). Figure 1 displays the association between elevated days and the regional 2023 rate. The pattern indicates regional clustering within the surveillance measures. However, it should not be interpreted as an independent effect of meteorological duration because elevated days are defined using the same HRI ED surveillance process as the outcome. These descriptive associations provide the immediate context for the exploratory regression models that follow.

Table 2

Bivariate Associations With the 2023 Regional HRI ED Visit Rate

Predictor	Pearson r	p	Spearman rho	p
Elevated HRI days in 2023	0.874	0.001	0.924	<0.001

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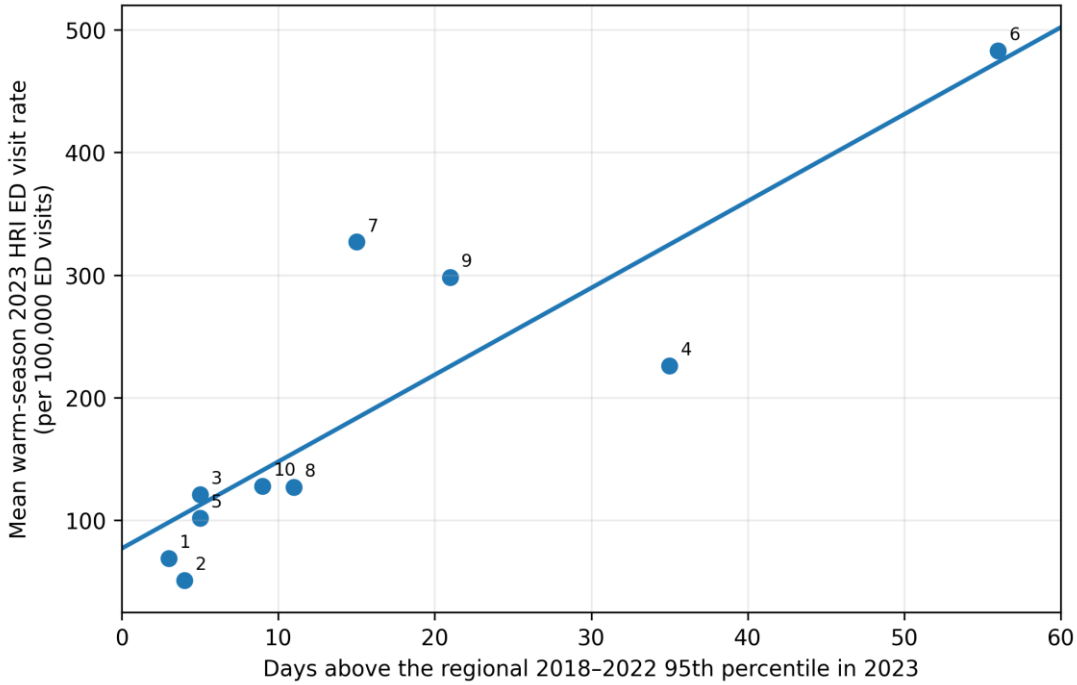
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Predictor	Pearson r	p	Spearman rho	p
2018–2022 baseline HRI ED rate	0.938	<0.001	0.964	<0.001

Note. n = 10 HHS regions. Associations are ecological. The elevated-day predictor and outcome are derived from the same HRI ED surveillance series and are not statistically independent constructs.

Source: Authors' calculations based on Vaidyanathan et al. (2024).

Figure 1. Association between elevated HRI burden days and mean warm-season 2023 HRI ED visit rates across HHS regions



Note. Each point is labeled with its HHS region number. The fitted line is the simple OLS association. Rates are per 100,000 ED visits. The plot illustrates an ecological association within related surveillance measures and does not establish causality.

Source: Authors' analysis of Vaidyanathan et al. (2024).

In conventional OLS Model 1, each additional elevated day was associated with 7.08 additional HRI ED visits per 100,000 ED visits (95% CI 3.86–10.30; p = 0.001), and the model explained 76.3% of regional variation (Table 3). HC3-robust inference produced a similar coefficient (95% CI 4.52–9.64; p < 0.001). In conventional Model 2, the elevated-day coefficient decreased to 3.32 (p = 0.007), while the baseline coefficient was 1.28 (p = 0.001); R^2 was 0.961.

Sensitivity diagnostics materially qualified the adjusted model. With HC3 robust standard errors, the elevated-day coefficient in Model 2 was not statistically distinguishable from zero (95% CI −3.23–9.86; p = 0.270), whereas the baseline coefficient remained associated with the 2023 rate (95% CI 0.49–2.07; p = 0.007). HHS Region 6 had the largest Cook's distance (D = 4.58), indicating substantial influence on the two-predictor model. These findings reinforce a descriptive interpretation: the regional data reveal persistent and clustered heat-health burden, but the sample is too small and internally dependent to support causal attribution or stable multivariable prediction. Table 3 summarizes the conventional and HC3-robust estimates underlying this interpretation.

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Table 3
Exploratory OLS Models Predicting the 2023 Regional HRI ED Visit Rate

Model	Predictor	B	OLS SE	OLS p	HC3 SE	HC3 p
1	Intercept	77.08	32.12	0.043	23.79	0.012
1	Elevated HRI days	7.08	1.39	0.001	1.11	<0.001
2	Intercept	-64.92	27.78	0.052	29.94	0.067
2	Elevated HRI days	3.32	0.88	0.007	2.77	0.270
2	2018–2022 baseline rate	1.28	0.22	0.001	0.33	0.007

Note. Model 1: $R^2 = 0.763$, adjusted $R^2 = 0.733$, $F(1, 8) = 25.77$, $p = 0.001$. Model 2: $R^2 = 0.961$, adjusted $R^2 = 0.949$, $F(2, 7) = 85.27$, $p < 0.001$. HC3 estimates are heteroscedasticity-robust. HC3 95% CIs were 4.52–9.64 for Model 1 elevated days, −3.23–9.86 for Model 2 elevated days, and 0.49–2.07 for the Model 2 baseline rate. Model 2 was highly sensitive to Region 6 (Cook's D = 4.58); results are exploratory.
Source: Authors' calculations based on Vaidyanathan et al. (2024).

AI-enabled climate risk management functions

The synthesis identified five linked functions for AI-enabled heat-risk management: hazard anticipation, social vulnerability mapping, public-health surveillance, targeted intervention, and adaptive communication. Existing AI-and-climate research is concentrated in hazard and exposure assessment, with less attention to vulnerability, prioritization, implementation, and governance (Mehryar et al., 2024). A 385-study systematic review likewise found rapid growth but fragmented sectoral coverage, limited health applications, and persistent challenges in data access, transparency, and equitable deployment (Ayadi et al., 2025).

Hazard anticipation can extend lead time and represent forecast uncertainty. GraphCast and GenCast show that machine-learning weather prediction can generate skillful global forecasts rapidly (Lam et al., 2023; Price et al., 2025). For heat action, speed can support earlier activation of cooling sites, outreach teams, utility coordination, work modifications, and school or event decisions. However, global skills do not guarantee local performance. Machine-learning models may struggle with physical consistency, mesoscale processes, or unprecedented extremes, and physics-based models can outperform current AI systems for some record-breaking events (Bonavita, 2024; Zhang et al., 2026). High-stakes use should therefore combine AI with operational numerical prediction, local calibration, uncertainty communication, and expert review.

Social vulnerability mapping should integrate environmental layers—air temperature, humidity, nighttime minimum temperature, land-surface temperature, impervious surface, canopy, and building density—with social and service layers such as poverty, disability, language access, vehicle access, outdoor work, energy burden, housing conditions, homelessness, chronic illness, and cooling availability. The SVI provides a starting point, and Heat.gov already combines projected heat with social vulnerability (CDC/ATSDR, 2024; Heat.gov, 2024). AI can model nonlinear interactions, but outputs should be interpretable vulnerability profiles rather than a single opaque score.

Public-health surveillance can detect unusual increases in symptoms, emergency calls, and healthcare demand. CDC's Heat & Health Tracker provides local information on exposure, health outcomes, and protective assets (Centers for Disease Control and Prevention [CDC], 2026). AI could support anomaly detection, short-term burden forecasts, and resource planning, but health and

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utility data require minimization, aggregation, access controls, and purpose limitation. Surveillance should be restricted to public-health protection rather than secondary enforcement.

Targeted intervention is the decisive step. Risk classifications should map to predefined actions, responsible agencies, activation thresholds, and evaluation metrics. Depending on the vulnerability profile, actions may include cooling-center hours, transportation, mobile outreach, air-conditioning repair, energy assistance, utility shutoff protection, building inspection, worker protection, shaded transit, tree canopy, or cool roofs. Without this operational linkage, AI becomes a dashboard rather than resilience infrastructure.

Adaptive communication should translate forecasts into audience-specific, multilingual, accessible, and resource-linked guidance. NWS HeatRisk offers a seven-day, impact-oriented framework that incorporates local climatology and health evidence (National Weather Service [NWS], 2025). Higher HeatRisk levels were generally associated with higher HRI ED visit rates in New York during May–September 2024 (Muscatiello et al., 2025). Climate-education scholarship likewise emphasizes that risk information becomes consequential when it is understandable, socially relevant, and connected to action (Damoah, 2023b). AI can help tailor messages, but trusted public-health professionals and community organizations should review content and deliver it through channels residents use.

These functions are organized into the five-pillar framework in Table 4. Hazard anticipation identifies when and where conditions may become dangerous; social vulnerability mapping identifies why risk is uneven; targeted intervention specifies what action follows; adaptive communication connects warnings to usable resources; and ethical governance defines accountability, privacy, validation, contestability, and evaluation. The framework treats AI as decision support that should make institutions more responsive rather than transfer responsibility to an algorithm.

Table 4
Five-Pillar Framework for AI-Enabled Heatwave Resilience

Pillar	AI-enabled function	Climate risk management contribution	Minimum governance requirement
Hazard anticipation	Probabilistic forecasting of intensity, duration, nighttime heat, humidity, and compound hazards	Earlier activation of heat action plans and contingency resources	Local validation, uncertainty display, and operational meteorologist review
Social vulnerability mapping	Integration of environmental, health, housing, energy, labor, mobility, and service data	Identification of place-specific drivers of exposure and limited adaptive capacity	Interpretable component profiles, data-quality flags, and community validation
Targeted intervention	Risk-informed prioritization of cooling, repair, transport, outreach, labor protection, greening, and health services	Movement from risk identification to funded protective action	Predefined activation pathways, responsible agencies, and equitable allocation criteria
Adaptive risk communication	Audience-specific, multilingual, accessible, and resource-linked guidance	Improved ability to act on warnings and use services	Human review, trusted messengers, accessibility testing, and feedback mechanisms
Ethical governance	Privacy, documentation, audit, contestability, procurement safeguards, and outcome evaluation	Prevention of surveillance misuse, false precision, bias, and responsibility gaps	Purpose limitation, independent audit, public accountability, and appeal mechanisms

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Note. The framework positions AI as accountable decision support linking prediction to social vulnerability reduction and intervention.
Source: Authors' synthesis of the reviewed literature.

DISCUSSION

The study produced three main findings. First, the U.S. heat burden is simultaneously climatic, clinical, infrastructural, and social. Rising heat exposure interacts with housing, energy, labor, health, transportation, and historical land-use patterns. Second, the regional HRI ED analysis reveals strong clustering and persistence in aggregate surveillance measures, but robust inference and influence diagnostics show why small ecological models should not be presented as causal validation. Third, the most defensible role for AI is not autonomous prediction; it is governed integration of forecasts, vulnerability information, services, and accountable action.

The statistical qualification is important. The strong correlations are partly expected because the outcome and elevated-day count are derived from the same regional HRI ED series. Model 2 also contains only seven residual degrees of freedom, and Region 6 strongly influences the fit. The revised interpretation is therefore narrower than the original draft: the data illustrate that persistent baseline burden and repeated high-utilization days coincide geographically. They do not show that elevated days cause regional mean rates, that AI improves outcomes, or that the proposed framework has been empirically validated.

Even with these limits, the descriptive pattern has operational relevance. A climate risk management system should track not only forecast temperature but also prior health burden, current syndromic signals, cooling functionality, outage risk, service accessibility, and response capacity. The purpose of integration is to identify jurisdictions where hazardous conditions and constrained adaptive capacity converge early enough to mobilize protection.

These findings are consistent with the broader heat-health evidence but sharpen its operational meaning. Systematic and epidemiological studies show that heat affects mortality, renal and cardiovascular stress, mental health, pediatric care, and people experiencing homelessness, while vulnerability varies by health status, income, occupation, housing, and locality (Arsad et al., 2022; Bernstein et al., 2022; Sun et al., 2021; Weckstein et al., 2025). The present framework interprets these differences not as a list of vulnerable groups but as distinct intervention needs. The same forecast may call for worker protections in one area, cooling repair and utility assistance in another, and home-based outreach where older adults live alone.

The results also reinforce environmental-justice research showing that thermal risk is embedded in urban form and resource distribution. Redlining, low canopy, impervious surfaces, housing disinvestment, and contemporary income inequality affect both exposure and the capacity to act on warnings (Hoffman et al., 2020; Hsu et al., 2021; McDonald et al., 2021; Shreevastava et al., 2025). This literature cautions against treating vulnerability as a stable trait of a population. A neighborhood can become safer through cooling repairs, shaded transit, tenant protection, and reliable power, or more vulnerable through displacement, utility shutoffs, and infrastructure failure. AI systems should therefore update decision-relevant conditions rather than reproduce static labels.

The warning-system literature further supports an end-to-end interpretation. U.S. heat action plans commonly identify triggers, communication, cooling centers, surveillance, and coordination, yet the details needed to reach and protect high-risk residents remain inconsistent (Randazza et al., 2023). Recent review evidence calls for warning thresholds that integrate local epidemiology, built-environment conditions, and population sensitivity rather than temperature alone (Chandra N and Lee, 2025). Damoah (2026) reaches a parallel conclusion for Gulf Coast hazards: forecast capability does not guarantee equitable warning reach or feasible response. The five-pillar framework adds

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value by making intervention activation and governance part of the warning architecture rather than treating them as downstream considerations.

The study also extends the AI-and-resilience literature. Ayadi et al. (2025) and Mehryar et al. (2024) identify fragmentation, limited health applications, weak attention to implementation, and unresolved questions of transparency and equity. The framework responds by shifting the unit of evaluation from the model to the sociotechnical system. Forecast skill remains necessary, but the more consequential outcomes are whether agencies act earlier, whether resources reach high-risk communities, whether false negatives are concentrated among marginalized groups, and whether illness and mortality decline. This emphasis is consistent with broader sustainability scholarship showing that climate hazards propagate through livelihoods, resource systems, and social vulnerability rather than remaining isolated environmental events (Agyeman et al., 2025).

Implications for environmental sustainability and climate-risk practice

The framework aligns closely with climate risk management because it links predictive modeling to decisions, anticipatory action, public health, equity, and technology governance. Local governments should embed AI tools within heat action plans, emergency protocols, housing enforcement, labor protections, utility regulation, adaptation budgets, and community partnerships rather than procure stand-alone dashboards. Table 5 translates the framework into implementation priorities and measurable outcomes.

Table 5
Priority Implementation Pathways and Outcome Measures

Priority	AI-supported decision	Required institutional action	Illustrative outcome measures
Functional cooling	Identify buildings or areas with high indoor heat, repair, energy burden, and outage risk.	Coordinate repair, weatherization, energy assistance, and shutoff protection.	Repairs completed before heat events; indoor temperature reduction; service uptake
Cooling service access	Estimate demand, travel-time, operating-hour, and accessibility gaps	Open or extend centers; provide transport, mobile cooling, and trusted outreach	Population within usable service coverage; visits; unmet demand
Occupational heat protection	Flag high-risk work periods and sectors	Require water, rest, shade, acclimatization, schedule changes, training, and inspections.	Compliance; heat-illness incidents; protected work hours
Health surveillance and outreach	Detect unusual HRI, EMS, and hospital demand and prioritize wellness checks.	Activate health-system surge plans and community outreach	HRI ED rates; EMS calls; patients reached; time to activation
Urban heat mitigation	Prioritize low-canopy, high-exposure, socially vulnerable blocks	Fund canopy, shade, cool roofs, reflective surfaces, maintenance, and anti-displacement safeguards	Canopy and shade gains; surface/air temperature change; beneficiary retention
Risk communication	Tailor multilingual messages to risk profile and available services	Use trusted messengers and test accessibility and comprehension	Reach; comprehension; protective action; service use
Governance and evaluation	Monitor model drift, subgroup errors, resource allocation, and downstream outcomes.	Audit models, publish performance, enable appeals, and revise interventions.	Calibration; false-negative rates; equity of allocation; preventable morbidity and mortality

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Note. Select measures with community partners and disaggregate where feasible to identify inequitable performance.
Source: Authors' synthesis.

Functional cooling should be treated as health infrastructure. Agencies need indicators of whether cooling systems work, whether households can afford to operate them, whether buildings retain dangerous heat, and whether outages threaten medically vulnerable residents. Public-health departments, utilities, energy-assistance programs, housing agencies, and community organizations should share only the minimum data needed to coordinate repair, weatherization, shutoff protection, and emergency outreach.

Occupational protection should also be integral to heat resilience. AI-supported forecasts can identify high-risk work periods, but protection depends on enforceable standards for water, rest, shade, acclimatization, schedule modification, training, and anti-retaliation. Forecasts should guide inspections and preparedness, not replace employer duties or shift responsibility to workers.

Urban heat mitigation should prioritize historically underserved areas while guarding against displacement. Tree canopy, cool roofs, reflective surfaces, parks, shaded transit, and building retrofits can reduce exposure, but benefits depend on maintenance and tenant protections. Community participation is necessary to identify appropriate locations, monitor who benefits, and prevent adaptation investments from increasing housing costs or displacing residents.

Cooling services must be evaluated as networks. Placement, operating hours, transit, disability access, language, pet policies, trust, and medical support determine practical use. Demand models can estimate coverage gaps, but community organizations often know barriers that administrative data miss. Mobile and home-based interventions may be more effective than fixed centers for some residents.

Health systems can combine HeatRisk, syndromic surveillance, and patient outreach to prepare for emergency demand and support high-risk patients. Risk communication should state what action to take, what service is available, how to reach it, and whom to contact. Messages should be tested with intended audiences and evaluated for reach, comprehension, service uptake, and health outcomes rather than judged only by delivery counts.

This end-to-end orientation is consistent with Damoah's (2026) Gulf Coast analysis, which emphasizes integrating vulnerability information with warning thresholds, accessible dissemination, and response activation. For heat-risk management, technical accuracy should therefore be evaluated alongside message reach, comprehension, service access, and the feasibility of protective action.

The framework's practical contribution is intervention matching. A composite risk score can rank places, but it cannot by itself determine what protection is required. Agencies should retain component-level profiles and pre-agree the action associated with each risk pattern. High nighttime heat combined with older housing may trigger building inspections and cooling repair; high occupational exposure may trigger worksite enforcement; high transit dependence may trigger mobile cooling and extended transit; and elevated syndromic signals may trigger health-system surge preparation. This design reduces the distance between analysis and action.

Evaluation should proceed across four levels. Technical metrics should assess forecast error, calibration, geographic transportability, and uncertainty. Operational metrics should assess lead time, activation speed, data latency, and agency coordination. Equity metrics should examine coverage, subgroup false-negative rates, service accessibility, and the distribution of public resources. Health metrics should assess emergency visits, hospitalizations, mortality, and avoided

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harm. A system that performs well technically but fails operationally or distributes protection inequitably should not be considered successful.

Policy responsibilities are distributed across levels of government. Federal agencies can support interoperable data standards, HeatRisk and surveillance infrastructure, model documentation, and funding for local implementation. States can coordinate public-health, labor, utility, housing, and emergency-management authorities. Local governments can define activation thresholds, maintain service inventories, contract with trusted community organizations, and evaluate post-event performance. Clear authority is essential because AI cannot resolve institutional fragmentation on its own.

Ethical governance and accountability

Data bias is the first governance challenge. Standard datasets often miss broken air conditioners, informal caregiving, undocumented work, indoor temperature, landlord neglect, social isolation, and distrust of government. An absence of records may indicate weak reporting rather than low risk. Models should therefore display uncertainty and allow local knowledge to correct or supplement administrative data.

False precision is a related risk. Detailed maps and scores can appear objective even though they reflect data quality, model choices, temporal mismatch, and classification thresholds. A single composite score may hide whether a neighborhood needs cooling repairs, transportation, worker protection, or canopy investment. Decision-makers should receive component profiles, uncertainty intervals where feasible, and clear explanations of why a location is classified as high risk.

Privacy protections are especially important when models combine health, utility, housing, emergency-call, mobility, or social-service data. Data should be aggregated whenever possible, personally identifiable information minimized, access logged, retention limited, and secondary uses prohibited. Heat-risk data should not be repurposed for eviction, policing, immigration enforcement, or punitive benefit surveillance.

Accountability cannot be delegated to a model. Public agencies, vendors, and decision-makers should define responsibility before deployment, maintain documentation and audit trails, conduct independent validation, and publish post-event evaluations. Procurement should require data provenance, interoperability, model documentation, audit access, and exit provisions that avoid vendor lock-in. The environmental footprint of AI also matters; data-center electricity demand is projected to rise substantially, making efficient models and proportionate computing part of responsible adaptation (International Energy Agency [IEA], 2025).

Legitimacy depends on whether communities see tangible benefits. Residents should participate in selecting variables, interpreting outputs, defining intervention thresholds, and evaluating performance. They should also have a mechanism to contest classifications and report missing conditions. Broader environmental-governance research is not heat-specific, but it reinforces the underlying principle: perceived institutional inaction can intensify public mobilization, while weak service delivery and conflict can generate additional environmental harm (Damoah, 2023a; Damoah et al., 2023). Community participation is therefore not an optional ethical addition; it improves data validity, service design, trust, and accountability.

Governance requirements should be proportional to the consequences of the decision. A model used to support broad situational awareness may require less stringent review than a system that prioritizes household outreach, allocates limited cooling assistance, or directs inspections. High-consequence applications should undergo documented validation, subgroup testing, independent review, human authorization, and post-deployment monitoring. Agencies should also maintain a safe fallback process when data feeds fail or predictions conflict with field observations.

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Human oversight must be substantive, not ceremonial. Decision-makers need enough information to understand model limitations, override outputs, document reasons, and learn from errors. Community organizations and frontline workers should be treated as knowledge partners because they can identify conditions that administrative records miss. Their participation should be funded and incorporated into operating procedures rather than confined to one-time consultation.

Equity, implementation, and institutional capacity

Implementation capacity is itself a determinant of climate risk and environmental sustainability. Some jurisdictions have strong forecasting and data systems but limited staff, transportation, cooling infrastructure, housing enforcement, or discretionary funds. In those settings, additional analytics can expose need without creating the capacity to respond. Funding decisions should therefore pair digital tools with operational resources, maintenance, workforce development, and protections for households whose livelihoods and basic needs are already sensitive to climate stress.

A minimum viable heat-resilience system does not require the most complex model. It requires reliable weather and health signals, a current inventory of services, clearly assigned authority, trusted communication channels, and predefined actions. Add more advanced AI only when it improves a specific decision and can be validated against a simpler baseline. This principle guards against technology-centered procurement and directs scarce resources toward the point at which they reduce harm.

Equity also requires attention to maladaptation. Tree planting, cool-roof programs, and neighborhood retrofits can reduce exposure, but they may raise rents or accelerate displacement without tenant protections and affordability measures. Digital outreach may miss residents without stable internet access, and data-sharing agreements may expose communities to secondary surveillance. Each intervention should therefore be assessed for who benefits, who bears new costs, and whether the strategy changes the structural conditions that created vulnerability.

Institutional learning should continue after every heat event. Agencies should document forecast performance, activation decisions, unmet demand, service use, complaints, adverse events, and community feedback. Public post-event reviews can identify where the chain failed—prediction, communication, transportation, staffing, power, cooling functionality, or trust—and convert those lessons into revised thresholds and operating procedures.

Research agenda

The framework requires stronger empirical testing. A national extension could use counties, while tract-level studies in heat-prone metropolitan areas would better capture neighborhood variation. Outcomes could include HRI ED visits, hospitalizations, mortality, emergency medical calls, or locally verified heat deaths. Exposure variables should include maximum and minimum temperature, humidity, HeatRisk, duration, and land-surface temperature. Social and service variables should include SVI components, energy burden, outdoor work, tree canopy, building conditions, homelessness, chronic disease, transport, and functional cooling.

Analyses should account for distribution and spatial dependence. Count outcomes may require negative binomial models with population offsets; rate outcomes may use generalized linear models with robust errors. Test spatial autocorrelation, and consider spatial lag, spatial error, or multilevel models where appropriate. Machine-learning classifiers may identify nonlinear interactions, but they should be evaluated through geographic and temporal validation, calibration, subgroup performance, recall for high-risk communities, and explainable outputs. Performance outside training geographies and during unprecedented extremes is especially important.

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The most consequential studies will evaluate interventions rather than risk scores alone. Quasi-experimental or stepped-wedge designs could test whether AI-supported outreach, cooling repair, transportation, or worksite targeting reduces emergency visits, improves service uptake, or lowers mortality. Evaluation should examine fairness in resource allocation, false-negative rates in vulnerable communities, community trust, and cost-effectiveness. The relevant question is not only whether a model predicts risk, but whether the institutional system using it reduces risk.

A validation hierarchy would strengthen this research agenda. Studies should first establish data quality and temporal alignment, then compare AI models with transparent statistical or rule-based baselines, test calibration and subgroup performance, validate across geography and time, and finally evaluate decision and health outcomes. This sequence would reduce the risk of treating a high in-sample fit as evidence of public-health value.

Research should also examine compound and cascading hazards. Heat may coincide with wildfire smoke, drought, grid stress, flooding after tropical systems, or outages caused by severe storms. Protective guidance can conflict—for example, opening windows may reduce indoor heat but increase smoke exposure. Multi-hazard models and communication protocols should therefore be tested with public-health agencies and affected communities rather than developed solely as technical exercises (Coker et al., 2024).

Limitations

The study has several limitations. The evidence synthesis was purposive rather than systematic, so it may omit relevant studies and cannot support a formal assessment of publication bias or evidence quality. The quantitative analysis used 10 aggregate HHS regions, not counties, tracts, households, or individuals. It did not include independent meteorological exposure, SVI, housing, energy, or intervention variables. HRI ED visits capture acute healthcare utilization but not all morbidity, mortality, indoor exposure, or people who do not seek care.

The regional predictors are also statistically dependent on the outcome because elevated days were defined from the same HRI ED series, and the adjusted model was sensitive to influential observations. The framework is therefore a theoretically and empirically informed proposal, not a validated AI system. Local data availability, governance capacity, institutional authority, and community trust vary widely, so implementation should be tested and adapted rather than assumed to transfer across jurisdictions.

The integrative review also reflects the availability and framing of published evidence. English-language peer-reviewed and official sources are more visible than local evaluations, community reports, and unpublished operational lessons. The review may therefore underrepresent failed implementations, rural practices, Tribal knowledge, and community-led heat responses. Future systematic or scoping reviews should use explicit protocols and include gray literature and participatory evidence.

Finally, the evidence base is changing quickly. AI weather models, HeatRisk operations, surveillance coverage, state heat standards, and local adaptation programs will continue to evolve. The framework should be treated as a testable structure that can incorporate new evidence, not as a fixed classification of technologies or policies.

CONCLUSIONS

Extreme heat is an environmental-sustainability and public-health challenge because meteorological exposure is filtered through housing, energy, work, mobility, infrastructure, and institutional capacity. The exploratory regional analysis is intentionally bounded: it does not establish an independent causal effect or validate an AI model. Its value is to demonstrate why heat-

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health intelligence must be interpreted alongside persistent regional burden and the social conditions that determine whether protective action is feasible.

The five-pillar framework reframes AI-enabled heat resilience as a sociotechnical governance problem. Hazard anticipation, vulnerability mapping, targeted intervention, adaptive communication, and ethical governance must operate as one accountable chain. Under this approach, AI is useful only when it improves a specific public decision and when performance is assessed through transparency, service reach, distributive equity, institutional accountability, and health protection.

For environmental sustainability and social science, the central implication is that adaptation should be judged by whether institutions convert climate intelligence into durable, accessible protection without creating new inequities. This shifts attention from technological capability alone to the governance, resource allocation, and community relationships through which resilience is actually produced.

RECOMMENDATION

For practice, state and local agencies should begin with decision inventories rather than AI procurement: identify the heat-risk decision to be supported, the populations most likely to face barriers, the responsible institution, the intervention that can be mobilized, and the metric used to verify reach. Pilot applications should be compared with transparent rule-based baselines and should include community review, privacy safeguards, and post-event evaluation.

For research, county- and tract-level studies should test the framework with independent meteorological exposure, social-vulnerability, service-access, and health-outcome data. Geographic and temporal validation should precede claims of transferability, and future evaluations should test whether AI-supported interventions improve service uptake and reduce heat-related illness, not just improve predictive performance.

Data availability statement

All regional observations used in the exploratory ecological analysis are reported in Table 1 of the main manuscript. The underlying values were derived from publicly available data reported by Vaidyanathan et al. (2024). Reproducible Python code with automated verification checks and supporting statistical and source-audit documentation are provided with the supplementary materials.

Ethics statement: Not applicable

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Author contributions

SA: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, and Visualization.

BD: Conceptualization, Formal analysis, Writing – original draft, and Writing – review and editing. All authors contributed to the article and approved the submitted version.

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