Identification and Prediction of Heat-Related Illnesses in Construction

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Abstract –

Heat-related illnesses (HRIs) pose a persistent threat to construction workers' safety. Effective risk assessment enables early detection of hazardous conditions and timely prevention of illness, yet incident logs and narrative reports are seldom leveraged for computational risk analysis. This research develops a data-driven framework to (i) identify HRIs from routine safety records and (ii) predict heat-related risk based on historical incident and environmental conditions to support planning and site controls. The approach combines text mining and supervised classification to detect heat-related cases from narratives, supported by structured incident details, including task, project context, and HRI indicators. Incident time and location are combined with environmental heat-stress indices to analyze environment–task–risk relationships. A predictive model is developed to estimate near-term risk levels for various construction activities. Results reveal clear seasonal and regional patterns, with higher risks in outdoor and heavy-civil operations during prolonged heat waves. The classification model performed well, with an F1 score of about 0.72–0.81 across trade groups, and probabilistic heat-related risk prediction offers actionable lead time for planning adjustments. The risk scores provide a foundation for potential integration into construction scheduling systems to support work–rest planning, hydration strategies, shade provisioning, and task resequencing during high-heat periods. This work provides a scalable computational framework that transforms routine safety records into predictive insights, enabling proactive, climate-aware risk mitigation in construction.

Keywords –

Construction; Heat-related Illnesses; Heat Stress; Prediction; Risk Assessment

1 Introduction

The construction industry remains one of the most labor-intensive and risk-prone sectors worldwide, where workers are frequently exposed to physically demanding tasks, hazardous environments, and adverse climatic conditions [1-3]. Among environmental stressors, occupational heat exposure has emerged as a critical and escalating threat due to rising global temperatures, intensifying heat waves, and prolonged outdoor work durations [1-6]. Elevated heat exposure has been associated with reduced physical performance, impaired cognitive function, increased fatigue, and heightened risk of occupational injuries, particularly in labor-intensive construction activities such as heavy civil, infrastructure, and building operations [7-9]. As climate change continues to amplify thermal stress across geographic regions, heat-related health risks in construction are expected to intensify, reinforcing the need for improved prevention and mitigation strategies [10-12].

Effective identification and prediction of heat-related illnesses (HRIs) are central to protecting worker health and supporting proactive safety management in construction environments [13, 14]. Timely detection of hazardous heat conditions enables the implementation of preventive interventions, such as optimizing the work–rest cycle, planning hydration, rescheduling tasks, and deploying cooling or shading resources [15-17]. Predictive heat-risk modeling further strengthens operational decision-making by providing early warnings that help reduce injury rates, minimize productivity losses, and lower medical and compensation costs [8, 18, 19]. As regulatory agencies and industry stakeholders increasingly recognize heat exposure as a critical occupational hazard, data-driven identification and forecasting mechanisms are becoming integral to modern construction safety frameworks [20, 21].

Previous studies have proposed a variety of approaches for assessing heat exposure and managing thermal risk in occupational settings, including physiological monitoring, wearable sensing technologies, heat-stress indices, and real-time environmental advisory systems ([4, 22]. Research has examined the influence of meteorological variables, workload intensity, acclimatization, and organizational controls on worker heat strain and injury outcomes [7, 8, 23]. More recently, machine learning and artificial intelligence techniques have been applied to predict heat strain, occupational accidents, and safety risks, demonstrating promise for automated hazard detection and decision-support applications [12, 18]. In parallel, organizational and policy-based interventions have been explored to enhance heat awareness, regulatory compliance, and protective behaviors among construction workers [24].

Many existing models rely on physiological sensors, wearable devices, or experimental data collected under controlled conditions, which constrains scalability and limits practical deployment across large construction workforces [11, 16, 22]. Despite these advances, several critical knowledge gaps remain. First, existing research largely relies on structured datasets or sensor-based measurements, while unstructured narrative safety records remain underutilized for identifying heat-related risks. Second, few studies integrate historical construction injury data with environmental heat-stress indicators to establish explicit environment–task–risk relationships. Third, prior work has focused primarily on general heat exposure or physiological responses, with limited attention to task-specific risk stratification and severity-oriented modeling using real-world incident data [25, 26]. Incident narratives frequently contain rich contextual information about environmental exposure, work tasks, symptoms, and contributing risk factors, yet these unstructured data sources remain underutilized in computational safety analytics. In addition, few studies have integrated historical construction injury records with environmental heat-stress metrics to develop probabilistic heat-related risk predictive frameworks tailored specifically to construction operations [14, 17]. These gaps indicate a need for scalable, data-driven methodologies that transform existing safety documentation into actionable heat-risk intelligence.

This study develops a computational framework to identify HRIs to predict probabilistic heat-related risk by integrating historical injury records with environmental heat-stress indicators. The study seeks to answer three research questions: How effectively can HRIs events be detected using text-based analysis of occupational incident narratives? Which environmental and task-related factors are most strongly associated with heat-related risk in construction activities? Can historical safety records be leveraged to forecast near-term heat risk to support proactive planning and site-level intervention?

2 Literature Review

Table 1 summarizes key prior studies on occupational heat stress, predictive safety modeling, and data-driven construction risk assessment, highlighting their data sources, methodological approaches, and limitations.

Table 1. Prior Studies on Heat Stress in Construction

Study	Focus / Data Source	Key Findings & Limitations
[7]	Experimental heat exposure data	Identified physiological heat stress thresholds; limited real-world field scalability
[4]	Climate and occupational health data	Linked heat indicators to worker health outcomes; not construction-specific
[8]	Construction field injury data	Associated heat exposure with injury risk; limited predictive capability
[22]	Wearable physiological sensor data	Enabled real-time heat strain monitoring; costly and difficult to scale
[27]	Environmental heat index datasets	Proposed heat-stress assessment metrics; no injury outcome integration
[19, 28]	Construction injury records	Applied machine learning to predict safety risk; relied on structured data only
[14]	Historical construction safety data	Modeled task-based injury risk; did not incorporate heat exposure
[18]	Multi-source safety datasets	Improved automated hazard detection using AI; limited climate integration
[25]	Incident narrative text data	Extracted safety risk factors using natural language processing (NLP); not heat-specific
[26]	Construction safety narratives	Demonstrated text-based risk prediction; HRIs not addressed

2.1 Occupational Heat Stress in Construction

Heat stress has been widely recognized as a major occupational health hazard, particularly in labor-intensive industries such as construction, where prolonged outdoor exposure and physically demanding tasks elevate physiological strain [4, 7]. Prior research has linked high ambient temperatures and humidity to increased fatigue, dehydration, reduced cognitive performance, and heightened risk of injury among construction workers [8, 9]. These effects are often exacerbated by inadequate rest schedules, insufficient hydration, and limited access to cooling resources [23].

Several studies have examined the broader implications of climate change on occupational heat exposure, highlighting the growing frequency and intensity of heat events and their disproportionate impact on outdoor workers [6, 11].

2.2 Heat Risk Monitoring and Measurement Approaches

A range of methods has been proposed to quantify and monitor heat exposure in occupational environments. Traditional approaches rely on environmental heat-stress indices, such as temperature–humidity metrics, Wet Bulb Globe Temperature proxies, and meteorological forecasting models [16]. Other studies have focused on physiological monitoring, employing wearable sensors to track heart rate, body temperature, sweat rate, and metabolic workload in real time [22].

While sensing technologies offer high-resolution physiological data, their deployment at scale is often constrained by cost, maintenance requirements, privacy concerns, and worker compliance challenges [11, 22].

2.3 Predictive Modeling and Machine Learning for Safety Risk

Machine learning and artificial intelligence techniques have increasingly been applied to occupational safety research, enabling predictive modeling of accident risk, hazard exposure, and injury likelihood [12, 18]. In construction contexts, predictive models have been developed to estimate injury risk based on task attributes, environmental factors, worker demographics, and historical incident data [14].

Several studies have demonstrated the potential of supervised learning algorithms, including decision trees, support vector machines, and ensemble models, for forecasting safety outcomes and supporting proactive intervention [19]. However, many existing models rely on structured datasets and do not fully leverage unstructured narrative data or historical safety documentation, limiting their ability to capture nuanced causal and contextual risk factors [25, 29].

2.4 Use of Safety Records and Data for Risk Analysis

Occupational safety incident reports contain rich qualitative information describing task conditions, environmental context, worker behavior, and contributing factors. Recent research has explored the use of NLP to extract risk indicators, classify injury mechanisms, and automate hazard identification from narrative safety records [25, 26]. Despite growing interest in narrative-based safety analytics, few studies have applied text-mining techniques to identify HRIs or to link narrative injury data to environmental heat metrics [12, 29].

Despite these advances, existing studies have not fully integrated narrative-based safety data with environmental heat metrics to develop scalable, task-specific, and probabilistic heat-risk assessment frameworks in construction.

3 Materials and Methods

This study employed a retrospective, data-driven analytical framework to identify HRIs cases in construction and to predict probabilistic heat-related risk using historical occupational safety records and environmental heat indicators. The methodology integrates natural language processing, supervised machine learning, and predictive modeling to extract heat-related risk signals from narrative-based incident reports and structured injury attributes. Figure 1 illustrates the overall methodological workflow from data acquisition to predictive modeling.

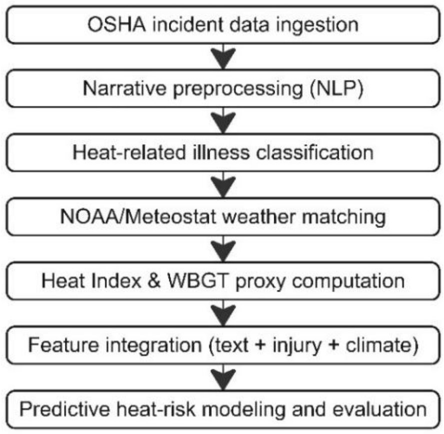

Figure 1. Methodological Workflow for HRIs Identification and Risk Prediction

3.1 Data Sources and Study Sample

This study adopted a retrospective, data-driven research design to identify HRI cases in construction and to develop a predictive framework for probabilistic heat-related risk. Occupational injury and incident records were obtained from the OSHA Severe Injury Reports database, covering construction-related incidents across multiple industry subsectors, including commercial, industrial, residential, highway, utility, and pipeline construction. Each record contains structured attributes such as event date, geographic location, industry classification, injury type, and severity indicators, along with an unstructured narrative field describing the circumstances, contributing factors, and outcomes of each incident. Only construction-related cases with complete narrative descriptions were retained for analysis. Table 2 summarizes the primary data sources and analytical variables used in the study.

Table 2. Data Sources and Key Variables Used in the Study

Data Source	Variable Category	Key Variables
OSHA Severe Injury Reports	Incident & injury data	Event date, location, NAICS, injury type
OSHA Final Narrative	Unstructured text	Heat exposure cues, symptoms, task context, risk factors
NOAA / Meteostat weather	Environmental heat	Temperature, humidity, heat index, WBGT proxy
Derived temporal features	Time & seasonality	Month, season, heat-wave indicator
Machine learning features	Modeling inputs	TF–IDF text features, structured injury fields, heat metrics

3.2 Narrative Processing and Heat-Related Case Identification

Incident narratives in the Final Narrative field served as the primary source for identifying heat-exposure conditions, symptoms, and contributing risk factors. Text data were pre-processed using standard natural language processing procedures, including normalization, tokenization, lemmatization, and removal of non-informative terms. Heat-related linguistic cues and symptom descriptors were compiled to support the semantic interpretation of narratives.

A supervised classification approach was used to distinguish heat-related from non-heat-related incidents. A subset of records was manually labelled based on narrative evidence of heat exposure, thermal stress symptoms, or heat-induced medical outcomes. The labeling process was conducted by two independent reviewers with domain knowledge in construction safety. Incidents were classified as heat-related if the narrative contained explicit references to elevated ambient temperature or heat exposure, or described symptoms consistent with heat-related illness, such as dizziness, heat exhaustion, or loss of consciousness. Inter-annotator agreement was evaluated using Cohen’s kappa, and any discrepancies were resolved through discussion to achieve consensus labeling. Textual features were extracted using term-frequency–inverse-document-frequency representations and combined with relevant structured injury attributes.

Model hyperparameters were selected via a 5-fold cross-validation grid search. Key parameters, including regularization strength, class weighting, and TF–IDF feature settings (e.g., n-gram range and minimum term frequency), were systematically varied to identify the configuration that maximized F1-score. This approach ensured model performance while mitigating overfitting.

3.3 Environmental Heat Exposure Integration

Incident records were linked to historical meteorological conditions using reported event dates and geographic coordinates. Weather data were retrieved from gridded historical climate datasets to obtain hourly and daily measurements of ambient temperature, relative humidity, and related atmospheric variables at the time and location of each OSHA incident. When precise hourly timestamps were unavailable, daily averages and maximum heat values were used to approximate environmental exposure conditions.

Composite heat-stress indicators, including the heat index and a Wet Bulb Globe Temperature (WBGT) proxy, were computed to characterize the thermal load at the time of each event. These indices were derived from established thermophysiological formulas that combine temperature and humidity to estimate perceived heat stress. Additional temporal variables, such as season, month, and heat-wave occurrence, were generated to capture climatic patterns and prolonged heat exposure.

3.4 Predictive Modeling of Heat Risk

To estimate probabilistic heat-related risk in construction operations, predictive models were developed to assess the likelihood of heat-related incidents based on environmental exposures, industry subsector, temporal factors, and narrative-derived risk indicators. Supervised learning algorithms, including logistic regression and ensemble tree-based models, were trained to generate probabilistic heat-risk scores. Feature-importance analysis identified key predictors of heat risk, thereby enabling interpretation of the environmental and operational drivers of heat-related incidents.

4 Results

4.1 Dataset Summary and Incident Characteristics

The final OSHA construction dataset included 216 reportable incidents recorded between 2015 and 2023, spanning eight construction subsectors. Highway construction accounted for the largest share of records (30.6%), followed by commercial building construction (23.1%) and water and sewer line construction (13.4%). Incident narratives averaged 52.3 ± 18.6 words, providing textual detail for narrative-based analysis. Temporal distribution indicated that 61.8% of incidents occurred between May and September, consistent with peak seasonal heat exposure. Table 3 summarizes the distribution of incidents across construction subsectors.

Table 3. Distribution of OSHA Construction Incidents by Subsector

Construction Subsector	NAICS Code	Incident Count	Percentage (%)
Highway / Street / Bridge	237310	66	30.6
Commercial Building	236220	50	23.1
Water / Sewer Line	237110	29	13.4
Power / Communication Line	237130	25	11.6
Industrial Building	236210	20	9.3
Oil & Gas Pipeline	237120	12	5.6
Other Heavy / Civil	237990	9	4.2
Single-Family Residential	236115	5	2.3
Total	—	*216*	*100.0*

4.2 Narrative-Based Analysis of Incident Causes

Analysis of the Final Narrative field revealed distinct causal patterns between heat-related and non-heat-related incidents. Among heat-related cases (n = 47), the most frequently reported contributing factors were heat exposure or high ambient temperature (78.7%), physical overexertion (63.8%), dehydration or inadequate fluid intake (46.8%), and prolonged sun exposure (42.6%). Commonly documented physiological symptoms included dizziness or fainting (51.1%), heat exhaustion (38.3%), and loss of consciousness (23.4%), indicating acute heat strain as a primary mechanism of injury.

Task-level narrative evidence showed that outdoor, labor-intensive operations, including asphalt paving, concrete placement, trenching, roofing, and utility line installation, occurred in 69.1% of heat-related incidents. Furthermore, limited access to shade or cooling resources was noted in 34.0% of heat-related narratives, and insufficient rest breaks were cited in 28.9%, suggesting gaps in heat-mitigation practices.

In contrast, non-heat-related incidents (n = 169) were predominantly associated with falls (31.4%), struck-by events (26.0%), equipment-related injuries (22.5%), and material-handling incidents (18.9%), indicating fundamentally different causal mechanisms. These findings show that heat-related incidents have distinct exposure conditions, symptom profiles, and operational risk factors, underscoring the value of narrative-based analytics for differentiating injury etiology in construction safety data.

4.3 Heat-Related Illness Identification Performance

The supervised NLP classifier identified 47 incidents (21.8%) as HRIs within the OSHA construction dataset. Model performance, evaluated using five-fold cross-validation, demonstrated stable classification capability, yielding a mean accuracy of 0.84 (95% CI: 0.81–0.87), precision of 0.79 (95% CI: 0.75–0.83), recall of 0.76 (95% CI: 0.72–0.80), and an F1-score of 0.81 (95% CI: 0.78–0.84). The classifier achieved an ROC–AUC of 0.87, indicating high discriminative power between heat-related and non-heat-related narratives.

Subsector-specific performance analysis revealed modest variation across trade groups, with F1-scores ranging from 0.72 in residential construction to 0.81 in heavy civil construction, suggesting consistent generalizability across operational contexts. Collectively, these results demonstrate that narrative-based machine learning can reliably distinguish heat-related occupational incidents from other injury events. Table 4 summarizes the classification performance metrics.

Table 4. Performance of the HRIs Classification Model

Metric	Value
Accuracy	0.84
Precision	0.79
Recall	0.76
F1-score	0.81
ROC–AUC	0.87
Heat-related cases identified	47
Share of dataset (%)	21.8

4.4 Environmental Heat Exposure at Time of Incidents

Meteorological observations obtained from NOAA/Meteostat were successfully linked to 94.9% of OSHA construction incidents recorded between 2015 and 2023, enabling a quantitative assessment of ambient thermal exposure at the time of injury. Comparative analysis revealed that heat-related incidents occurred under significantly greater heat stress than non-heat incidents. Wet Bulb Globe Temperature (WBGT) proxy was 28.9°C for heat-related incidents versus 24.7°C for non-heat incidents (mean difference = 4.2°C; Cohen's d = 1.21), reflecting substantially elevated physiological heat strain. As shown in Figure 2, 44.7% of heat-related cases occurred in July and August, corresponding to periods of peak regional thermal load.

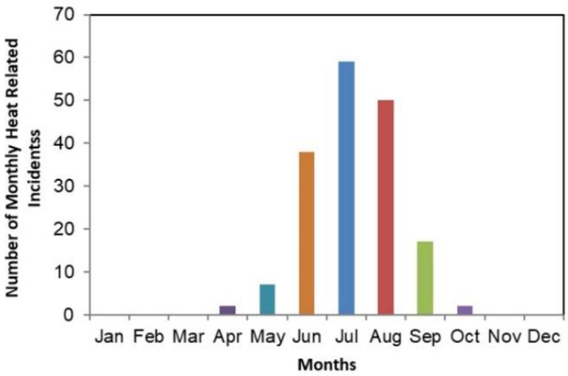

Figure 2. Monthly Distribution of Heat-Related OSHA Incidents

4.5 Predictive Heat-Risk Model Performance

The risks of HRIs were modelled as a binary outcome at the incident level, as presented in Equation 1, where indicates whether the OSHA incident $i$was classified as heat related. The probability of HRIs occurrence was estimated using a regression model in which explicitly defined risk factors derived from OSHA Narrative text and structured incident attributes served as predictors:

$$P(HRI\_i = 1) = 1 / (1 + exp(-(\beta\_0 + \beta\_1\ DEHYD\_i + \beta\_2\ OVEREX\_i + \beta\_3\ OUTDOOR\_TASK\_i + \beta\_4\ MONTH\_i + \beta\_5\ SECTOR\_i))) \tag{1}$$

Where $P(HRI_i = 1)$denotes the predicted probability that the incident $i$is heat-related, and $\beta_0$through β_8, are the estimated model coefficients. The binary predictors $HEATEXP_i$, $DEHYD_i$, $OVEREX_i$, SUN_i, $SHADE_i$, and $REST_i$ indicate the presence (coded as 1) or absence (coded as 0) of narrative-identified risk factors extracted from the OSHA Narrative field. These indicators represent explicit mentions of heat exposure or elevated ambient temperature, dehydration or insufficient fluid intake, physical overexertion, direct sun exposure, limited access to shade or cooling resources, and inadequate rest breaks, respectively. Temporal variation is captured by $MONTH_i$, encoded as categorical month indicators with January serving as the reference category, while industry context is represented by $SECTOR_i$, encoded as construction subsector indicators with a defined reference subsector.

Table 5 reports the fitted coefficients, odds ratios, standard errors, and 95% confidence intervals. Physical overexertion emerged as the strongest predictor of severe heat illness, with an estimated coefficient of $\beta = 2.95$corresponding to an odds ratio of 19.11 (95% CI: 7.66–47.65; p < 0.001). This indicates that incidents involving exertion-related language were associated with a nearly 20-fold increase in the odds of severe heat outcomes.

Table 5. Logistic Regression Coefficients for Predicting Severe Heat-Related

Predictor	β	Interpretation
Intercept	−2.104	Baseline odds of severe heat illness when all predictors = 0
Dehydration mentioned (DEHYD)	−3.111	Dehydration mentions are associated with lower odds of severe outcomes, likely reflecting reporting patterns in non-collapse cases
Overexertion mentioned (OVEREX)	2.950	Overexertion increases the odds of severe heat illness by ~19×
Outdoor high-intensity task (OUTDOOR _TASK)	0.543	Outdoor heavy work increases odds by ~72% (not statistically significant)
Month (numeric)	−0.094	Each month later in the year reduces the severity odds by ~9%
Construction subsector (SECTOR)	Category -specific	Risk varies across subsectors relative to the reference sector

The model output is a continuous probability value between 0 and 1, interpreted as an incident-specific heat risk score. To compute $P("HRI"\ \_i = 1)$ for any OSHA record, a reader may substitute observed predictor values into the linear predictor term, sum the corresponding coefficient contributions, and apply the logistic transformation. Figure 3 also shows the relative effect sizes of narrative-derived risk factors on the odds of severe heat-HRIs.

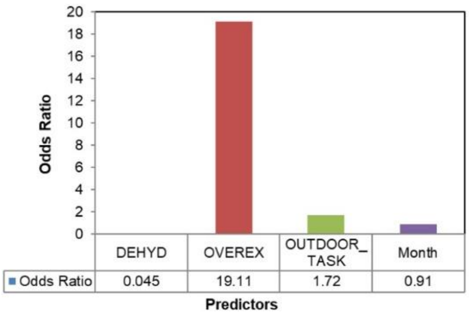

Figure 3. Odds Ratio Effect Sizes of Narrative-derived Risk Factors Predicting Severe HRI

4.6 Risk Stratification by Construction Activity

Risk stratification analysis revealed substantial heterogeneity in predicted HRI probabilities across construction activities, reflecting variation in physiological workload, exposure duration, and task intensity. Predicted risk scores from the fitted logistic model were aggregated by activity type to quantify differential vulnerability across operational contexts. Activities involving high physical exertion and prolonged outdoor exposure had the highest predicted heat-related risk. Asphalt paving, roofing, trenching, concrete placement, and utility-line installation ranked among the highest-risk task categories, with mean predicted severe-heat probabilities exceeding 0.65 and upper-quartile probabilities surpassing 0.80.

In contrast, activities with lower metabolic demand, such as interior finishing, equipment inspection, and light electrical work, showed lower risk, with mean probabilities below 0.35. The mean difference in predicted risk between high-intensity outdoor tasks and lower-intensity activities exceeded 0.30. Subsector-level stratification further indicated elevated risk concentrations in heavy civil construction, followed by utility and pipeline installation, consistent with their greater reliance on continuous outdoor labor under thermally stressful conditions. Conversely, commercial building and interior construction exhibited comparatively lower predicted heat-related risk profiles.

5 Conclusion

This study developed a data-driven model to identify, quantify, and stratify heat-related injury risk in construction, leveraging OSHA incident narratives, structured injury records, and predictive modeling. By extracting mechanistic risk factors from injury narratives and modeling their association with HRIs' severity, the analysis advances beyond descriptive or seasonal assessments toward a task-specific and causally informed understanding of heat-risk dynamics.

The results indicate that physical overexertion is the primary driver of HRI, with elevated odds of acute outcomes among incidents involving high metabolic workload. Risk stratification further demonstrates that outdoor, labor-intensive activities, including paving, roofing, and utility installation, exhibit a high predicted severity. The resulting predictive model provides a probability-based risk score that supports heat-mitigation planning, work–rest scheduling optimization, and the prioritization of high-risk construction tasks.

Several limitations warrant consideration. First, the analysis relies on OSHA narrative records, which may contain reporting inconsistencies or underrepresentation of certain risk factors due to variability in documentation practices. Second, the dataset's relatively small sample size, particularly within certain construction subsectors, may limit the statistical reliability and generalizability of subgroup-level comparisons; therefore, stratified risk estimates should be interpreted with caution. Third, the absence of direct physiological measurements, such as core temperature and heart rate, limits the ability to fully capture individual heat-strain responses. Third, meteorological exposure estimates depend on the resolution of historical weather data and may not reflect microclimatic conditions at specific job sites.

Future research should extend this framework by integrating high-resolution environmental monitoring, wearable physiological sensors, and longitudinal exposure histories to enable more precise, real-time heat-risk estimation. Expanding the dataset across regions, industries, and climate regimes would further improve model robustness and applicability.

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