

Digital Heat Stress Monitoring in Outdoor Work Environments: Validation and Practical Implications of Mobile Application-Based WBGT Estimation

Oluwaseun Ibuife Oluwaniyi*

Received: 12 September 2025/Accepted: 9 December 2025 /Published: 13 December 2025

<https://dx.doi.org/10.4314/cps.v12i8.23>

Abstract: The growing availability of smartphone-based applications to monitor heat stress provides opportunities to democratize thermal risk assessment in workplaces where the use of the wet-bulb globe temperature instrumentation is economically or logistically expensive. This future field study confirmed the AIHA Heat Stress App 2.0 with calibrated 3M QUESTemp 34 reference monitoring in a range of outdoor thermal environments over an 18-day time span in a subtropical climate area. The 53 paired measurement sessions recorded a significant environmental variation with a reference WBGT between 19.8°C and 39.4°C. The mobile application displayed temporal concordance over reference measurements in tracing the patterns of heat stresses over the day but systematic negative bias with average of -1.7°C and standard deviation of 2.1°C. Differences became very large in the conditions of high solar radiation (1200-1500 hours) when reference WBGT was close to or above the regulations (up to 7.4 C) and single-session underestimation was at the highest point (7.4°C). The misclassification of the work-rest category was seen in 35.8 percent of the paired measurements in the majority of them being underscoring the risk. Findings are in favor of a hybridized monitoring system whereby smartphone applications offer the availability of preliminary screening and yet being anchored by calibrated instruments, precision-critical decisions in the form of compliance checks and high-risk exposures.

Keywords: Mobile health monitoring, occupational heat exposure, WBGT validation, smartphone applications, thermal risk assessment, workplace safety technology

Oluwaseun Ibuife Oluwaniyi

Department of Occupational Risk and Safety Sciences, University of Central Missouri, United States.

Email: seunibuife.oluwaniyi@gmail.com

<http://orcid.org/0009-0008-1960-8442>

1.0 Introduction

Global climate change is driving a clear increase in the frequency, intensity, and duration of extreme heat events worldwide.

Outdoor workers in sectors such as construction, agriculture, utility maintenance, transportation, and emergency services are particularly vulnerable to these changes, experiencing increased exposure to occupational heat stress. One of these in the form of increased occupational thermal stress exposures to health and productivity risks (Brimicombe et al., 2023; Alahmad et al., 2025). Heat-related illnesses remain a major and preventable cause of occupational morbidity and mortality, including conditions such as heat exhaustion, exertional heat stroke, and cardiovascular complications.

(Esmaeili et al., 2025).

The key issue of heat-related illness prevention lies in proper assessment of environmental risk through appropriate evaluation of environmental factors to ensure that protective measures are taken in time. The Wet-Bulb Globe Temperature (WBGT) is widely recognized as the global standard for occupational heat stress assessment due to its strong correlation with physiological heat strain (ISO 7243:2017; Budd, 2008). WBGT temperature is determined with the use of a composite index that is computed based on the natural wet-bulb temperature, black globe temperature and dry-bulb air temperature. The WBGT index is calculated using the following expression,

$$WBGT_{\square} = 0.7 \times T_{nwh} + 0.1 (T_g \times T_d)$$

where T_{nwb} , T_g , and T_d represent the natural wet-bulb, globe, and dry-bulb temperatures, respectively. (Kakaei et al., 2019).

The regulatory frameworks provided by OSHA, NIOSH, ACGIH, and international organizations constantly mention WBGT as the metric of choice when it comes to classifying thermal risks and determining the work-rest regimen (Bernard et al., 2023; Ioannou et al., 2022). The threshold values characterizing graduated risk ranges usually stratify: the values less than 26.7°C allow no changes in work plans; 26.7-29.4°C leads to the introduction of initial changes in activity; 29.5-31.0°C predetermines the necessity of significant work-rest cycles; 31.1-32.1°C approaches safe exposure limits; and the values more than 32.2 C often implies the need of stopping any activities (Golbabaie et al., 2021; Clark & Konrade, 2024)

Although WBGT has been proven valid and adopted by regulatory bodies, the practice has continued to suffer from challenges. Despite its validity, WBGT monitoring systems require substantial financial investment, making them inaccessible to many small-scale employers and organizations in developing regions. In addition to the expenses of acquisition, the implementation of the appropriate instruments entails technical skills such as the placement of sensors, maintenance guidelines, field calibration, and interpretation capabilities (Golbabaie et al., 2021). These working constraints limit the use of systematic WBGT surveillance to greater organizations with occupational health resources.

The widespread availability of smartphones, combined with advances in computational meteorology, has led to the development of digital heat stress monitoring tools. Location based meteorological data, radiant heat transfer algorithmic models, and user-specified contextual parameters are the keys to mobile heat stress applications where the real-time WBGT estimates are generated and made available to anyone with a smartphone (AIHA, 2024; Cannady et al., 2024). Such systems remove the cost of instrumentation,

make deployment easy and indicate risk information through user-friendly interfaces. It has been suggested that the adoption of mobile applications has the potential to revolutionize the concept of occupational heat protection by providing its services to hitherto undervalued groups of people such as agricultural workers, independent contractors, and workers in developing nations (Eggeling et al., 2023). Nonetheless, the potential systematic errors of estimating smartphone WBGT with the help of computational architecture are compared with the simple instrumentation. Mobile applications are based on the calculation of thermal indices using the output of gridded meteorological models or weather stations data reflecting the real conditions at the region averaged at tens of kilometers, unlike on-site monitors measuring actual environmental parameters (Clark & Konrad, 2024; Grundstein et al., 2025).

The radiating heat element poses special difficulties to the algorithmic estimation. Black globe temperature is sensitively dependent on direct solar radiation and longwave thermal reradiation by heated surfaces which may increase the effective radiant temperature significantly higher than those obtained using solar geometry alone (Buzan, 2024). Mobile applications that do not have site specific globe temperature sensors will have to estimate mean radiant temperature based on theoretical calculations that might be too simplistic representations of complex three-dimensional radiant environments (Kong and Huber, 2024).

Previous validation studies have reported notable inconsistencies in smartphone-based WBGT estimation. Dillane and Balanay (2020) reported underestimation of the OSHA-NIOSH Heat Safety Tool to be systematic. WBGT in agricultural environments of averages 1.8°C and cases of 3°C. For example, Angol et al. (2025) reported an average underestimation of 2.4°C, which increased to 4–5°C under clear-sky midday conditions. Such discrepancies of measurements have direct operational implications. The 2-4°C underestimation in

cases where WBGT levels are close to regulatory levels may cause the movement of high risk where workers are supposed to do a lot of work-rest cycling to moderate levels where workers are subjected to less restrictive adjustments, leaving the workers under-protected. Despite these findings, significant gaps remain in the existing evidence base. Most validation studies focus on prototype tools rather than widely used commercial applications, and there is limited research evaluating performance across diverse environmental conditions or examining practical implications such as work-rest misclassification rates. The published validations are mainly on prototype research usage as opposed to commercial solutions. There are limited studies involving systematic research on the performance of the app over complete ranges of environmental conditions or operational effects measured in work-rest category misclassification rates. Furthermore, there is a lack of systematic field validation studies assessing the reliability of mobile applications under real-world occupational conditions.

The AIHA Heat Stress App is a rather topical object of validation because it is explicitly aimed at a workplace safety use, but effective peer-reviewed field tests in relation to WBGT reference values are little in number. The proposed research will fill these knowledge gaps by systematically comparing the AIHA Heat Stress App 2.0 with calibrated WBGT reference monitoring LTC in the variability of thermal conditions indicative of temperate climate outdoor occupational exposures. This study aims to (i) quantify the agreement between app-based and reference WBGT measurements, including systematic bias and random error (ii) evaluate operational implications by assessing the frequency of work-rest category misclassification and (iii) provide evidence-based recommendations on the appropriate use of mobile applications in occupational heat stress monitoring.

2.0 Methodology

2.1 Study Design and Environmental Context

This study adopted a prospective paired-measurement field design in which

smartphone-based WBGT estimates and reference WBGT measurements were collected simultaneously under identical environmental conditions.

The study was done in Warrensburg, Missouri, United States (38.8°N, 93.7°W; elevation: 256 m), a temperate continental climate region representative of outdoor working conditions in the U.S. Midwest and Great Plains. Data collection was conducted over 18 consecutive days (September 9–26, 2025), and the study period was selected to capture transitional early autumn conditions, including moderate temperatures and intermittent afternoon heat stress that could approach or exceed regulatory thresholds.

The measuring point was an outside area with concrete surface in such a way that it offered free access to sunlight during the day minimizing the influence of artificial heat sources and atypical surface features.

2.2 Instrumentation

2.2.1 Reference WBGT Monitoring System

A 3M QUESTemp 34 Thermal Environmental Monitor was used as the reference standard, which is a research-grade system that matched ISO 7243:2017 requirements. The instrument also has discrete dedicated sensors of each of the WBGT components: natural wet-bulb temperature measured using a precision thermistor with a wetted cotton wick; globe temperature through 150millimeter hollow sphere made of copper with an inbuilt thermistor, and shielded aspirated dry bulb thermistor. The manufacturer-reported measurement accuracy is $\pm 0.5^{\circ}\text{C}$, with a resolution of 0.1°C .

Pre-deployment calibration was verified using NIST-traceable temperature standards. Natural wet-bulb wick was changed at the beginning of the study and monitored on the daily basis. Battery charge was kept with more than 50% during the entire measurement sessions.

2.2.2 AIHA Heat Stress Application Platform

Concurrent WBGT estimates were obtained using an Apple iPhone 12 running Heat Stress App 2.0 on iOS 17. The computational

architecture of the application combines location-specific weather information of commercial meteorological data sources that integrate numerical weather prediction models, ground observations, and satellite data. The users set the geographic location, clothing ensemble and metabolic work rate. In this investigation, the parameters of the app configuration were unified: clothing was standardized as short-sleeved shirt and pants, the metabolic work rate was to be moderate work, and the automatic GPS positioning was turned on. All the readings were recorded with the same trained operator according to the same procedures.

2.3 Field Measurement Protocols

Data were collected in the period between 0800-1700 hours local time on any study day. Measurement sessions were spread over at regular intervals throughout the day. Measurement sessions were distributed across four-time blocks: morning (0800–1000), late morning/midday (1000–1300), early afternoon (1300–1500), and late afternoon (1500–1700).

Every time the measurements were conducted, a standardized protocol was used: (I) Pre-measurement wet-bulb preparation: Before the experiment, a natural wet-bulb wick had to be pre-wetted with the use of carefully measured (0.20–0.25 mL) volumes of distilled water delivered using a calibrated pipette. Instrument positioning: The reference WBGT monitor was positioned on a level concrete surface at a height of 1.1 m. The smartphone was placed next to each other so that both systems would be exposing the same conditions.

(ii) Thermal equilibration: Both systems were activated and allowed to equilibrate. The time when all displayed values had stabilized with a fluctuation of less than 0.2 °C at 5 minutes was noted and readings were recorded.

(iii) Synchronized data capture: After stabilizing reference monitor parameters readings were recorded, then smart phone application readings were synchronized with reference monitor readings in under 60 seconds.

(iv) Metadata logging: Each of the sessions was recorded with date and time, observation person, description of the sky, estimation of the wind speed, and description of exceptional conditions. Every temperature was taken in degrees Celsius.

(v) Equipment verification: A daily check was performed like battery checking, self-test diagnostics of instruments and physical damage or sensor contamination check.

The quality control measures were duplicate measurements of selected 15% of the sessions randomly, systematic review of recorded data transcription errors, and the comparison of reference monitor dry-bulb temperature with those of nearby National Weather Service.

2.4 Data Management and Analytical Framework

Field data were entered into a structured electronic database using double-entry verification. Descriptive statistics were used to compute distributional parameters of the two measurement systems on all sessions and on the basis of time-of-day category.

Measurement agreement was determined by calculating paired differences (AIHA app WBGT – reference WBGT). Paired differences mean measures systematic bias and the standard deviation measures the random error.

The effects of operation were measured by categorizing every paired measurement based on categories of work-rest activity modification namely: low risk (≤ 26.7 °C), moderate risk (26.7–29.4°C), high risk (29.5–31.0°C), very high risk (31.1–32.1°C), and extreme risk (32.2°C). The category assignments were called independently between reference WBGT and app WBGT and misclassification was considered as discordant category assignment.

R version 4.3 was used to carry out the statistical analysis. Considering the applied nature of the study and small sample size. Given the applied nature of the study and the sample size, analysis focused on effect sizes and practical significance rather than formal hypothesis testing.

2.5 Ethical Considerations and Study Limitations

Since the study was an environmental measurement research that did not involve any human subject, it did not require institutional review board approval. The preventive measures towards heat illness were also used by the data collection personnel.

The study has several limitations, including restriction to a single geographic location, data collection during a limited seasonal window (September), absence of extreme heat conditions, reliance on a single reference instrument and mobile application, and standardized user inputs that may not reflect real-world variability.

3.0 Results and Discussion

3.1 Environmental Conditions and Descriptive Statistics

The study spanned 18 days and included 53 paired measurement sessions distributed across morning (n = 15), midday (n = 22), and afternoon (n = 16) time periods. Sky conditions were classified as clear (49%), partly cloudy (34%), and mostly cloudy or overcast (17%). Wind conditions were predominantly light to gentle breezes (53%), with occasional moderate breezes (8%).

Selected field measurements illustrating a range of thermal conditions and both concordant and discordant observations are presented in Table 1. Detailed descriptive statistics are provided in Table 2. Reference WBGT values ranged from 19.8°C to 39.4°C (range: 19.6°C), with a mean of 26.8°C (SD = 4.2°C). AIHA app estimates ranged from 16.0°C to 32.0°C (range: 16.0°C), with a mean of 25.1°C (SD = 3.6°C).

Table 1: Selected field measurements during September 2025 study period of data on paired WBGT reference monitor and AIHA Heat Stress App of various thermal conditions

Date	Time (hrs)	Reference WBGT (°C)	AIHA App (°C)	Difference (°C)	NIOSH Index (°C)
09/09/2025	14:15	23.2	21.0	-2.2	25.0
09/09/2025	16:15	23.5	21.0	-2.5	25.0
10/09/2025	13:00	24.4	25.0	+0.6	27.8
11/09/2025	09:41	23.1	25.0	+1.9	18.9
11/09/2025	13:54	28.3	28.0	-0.3	18.9
12/09/2025	10:45	27.7	26.0	-1.7	25.6
13/09/2025	11:00	29.4	27.0	-2.4	30.0
13/09/2025	16:07	36.2	28.0	-8.2	30.0
15/09/2025	12:27	39.4	32.0	-7.4	32.2
15/09/2025	14:37	26.9	28.0	+1.1	32.2
16/09/2025	10:44	25.2	28.0	+2.8	32.2
16/09/2025	12:50	32.2	28.0	-4.2	32.2
22/09/2025	09:05	22.7	21.0	-1.7	24.4
24/09/2025	16:15	23.1	22.0	-1.1	23.9

The narrowed range especially at the high end (app maximum 32.0 C against reference maximum 39.4°C) This narrower range—particularly the lower maximum value—

suggests that the application may impose algorithmic constraints that limit reported WBGT values under extreme conditions.

Table 2: The summary of WBGT reference monitor, AIHA Heat Stress App estimates and NIOSH Heat Stress Index during 53 paired sessions of measurement.

Parameter	Reference WBGT (°C)	AIHA App (°C)	NIOSH Index (°C)
Minimum	19.8	16.0	11.7
5th Percentile	21.2	19.5	16.8
25th Percentile	23.5	21.0	25.0
Median	26.4	26.0	27.8
75th Percentile	29.4	28.0	30.0
95th Percentile	34.8	31.2	32.2
Maximum	39.4	32.0	32.2
Mean	26.8	25.1	25.9
Standard Deviation	4.2	3.6	5.8
Interquartile Range	5.9	7.0	5.0
Coefficient of Variation	15.7%	14.3%	22.4%

3.2 Temporal Patterns and Direct Measurement Comparison

Fig. Figure 1 presents paired time-series data, showing strong agreement in diurnal patterns between the two systems, alongside systematic differences in absolute WBGT

values. Both systems exhibited expected solar-driven thermal cycles with minimum values during early morning, progressive warming through late morning, peak temperatures during 1200–1500 hours, and gradual afternoon cooling.

Time-Series Comparison of Reference WBGT and AIHA App Measurements Warrensburg, Missouri (September 9-26, 2025)

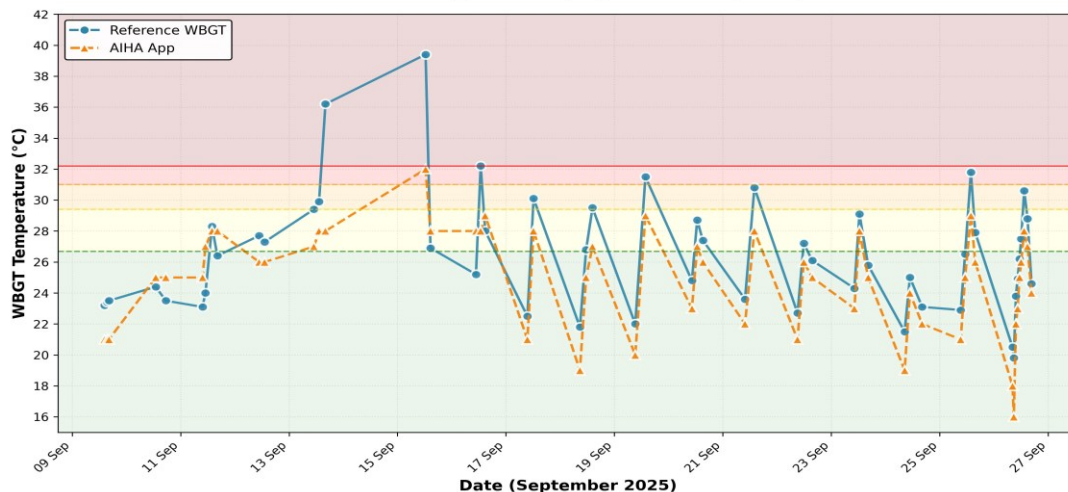


Fig. 1: Comparison of time-series of reference WBGT monitor (blue circles, solid line) and AIHA Heat Stress App estimates (orange triangles, dashed line) on each day of measurement. Categories of work and rest are indicated by horizontal dashed lines.

The observed temporal consistency indicates that the AIHA app effectively captures key environmental drivers of heat stress. However, the consistent vertical separation

between the curves indicates systematic underestimation, particularly during peak heat conditions. The highest recorded reference WBGT of 39.4 oC at 1227 hours on

September 15, 2025, was associated with an app estimate of 32.0 °C, representing the largest single-session underestimation (7.4°C). This happened in clear sky conditions when the solar elevation was high, wind low and the radiant loading high. There were also other significant discrepancies on September 13 at 1607 hours (reference 36.2°C versus app 28.0°C, underestimation of 8.2°C) and on September 16 at 12:50 hours (reference 32.2°C against app 28.0°C, underestimation of 4.2°C). These discrepancies consistently occurred under similar conditions, including afternoon hours, high solar radiation, and low wind speeds. In contrast, agreement between the two systems was higher during morning and late afternoon periods, when solar radiation was lower and WBGT values were below high-risk thresholds.

Paired difference analysis of all 53 sessions resulted in a mean bias of -1.7°C with a standard deviation of 2.1°C, indicating a consistent pattern of systematic underestimation. The standard deviation shows that despite eliminating the bias of the means, individual app estimates This suggests that individual app estimates may deviate by approximately ±4.2°C (two standard deviations), covering about 95% of observations. The distribution of paired differences as shown in Figure 2, paired differences stratified by WBGT risk category demonstrate that both bias magnitude and variability increase with environmental severity. Low-risk conditions had mean difference of -0.8°C (SD 1.2°C), moderate-risk conditions had mean difference of -1.6°C (SD 1.8°C) and high to extreme risk condition had mean difference of -3.2°C (SD 2.6°C).

3.3 Quantification of Measurement Bias and Random Error

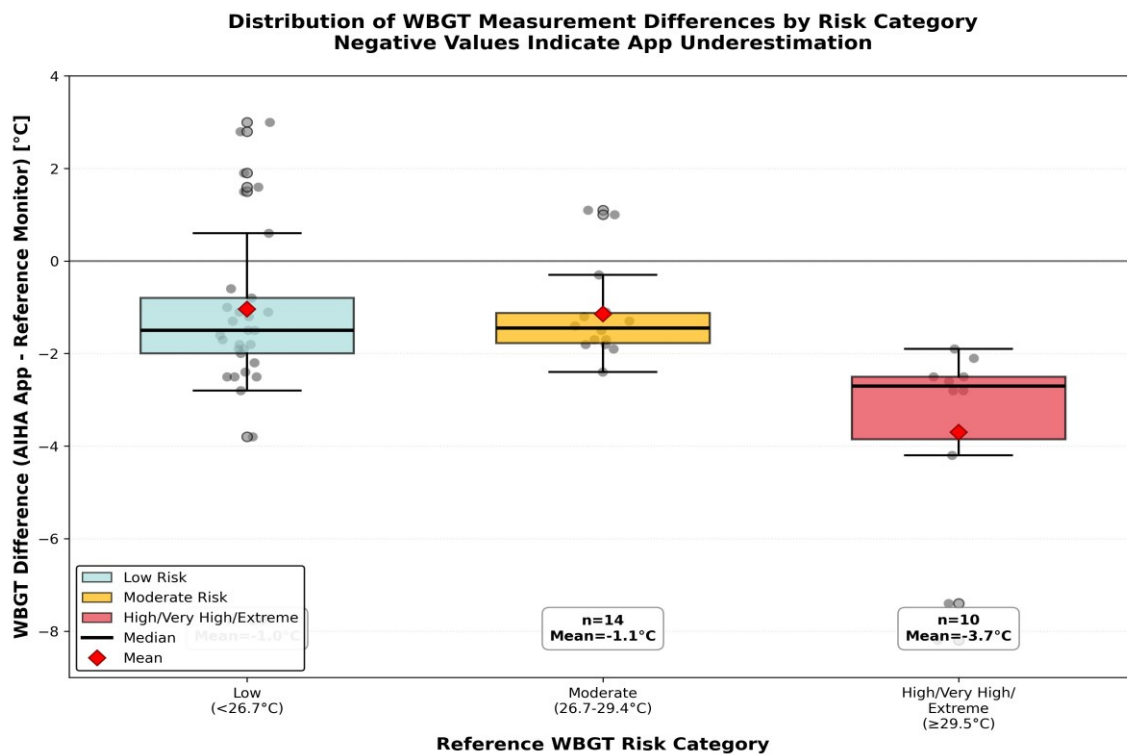


Figure 2: WBGT differences (AIHA app vs. a reference monitor) as a stratification by the reference WBGT risk category. Negative values depict underestimation of an app

A strong diurnal pattern was observed (Fig. 3). There was a difference of mean of -0.6°C (SD 1.0°C) between morning measurements, -0.9°C (SD

1.4°C) between late afternoon measurements and -2.8°C (SD 2.4°C) between midday measurements respectively.

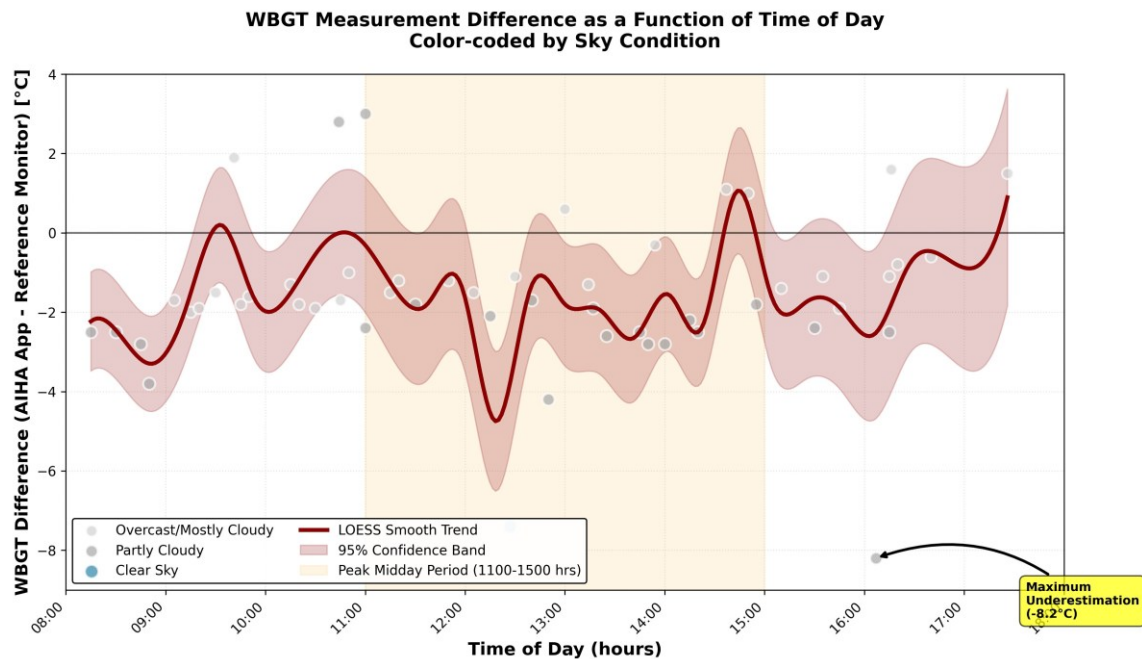


Figure 3: The difference between WBGT and the reference (app-reference) versus the time of the day. LOESS smoothed trend line has high diurnal pattern with highest underestimation in the peak radiation period as midday

In clear-sky sessions, the mean difference was found to be -2.3°C than in partially cloudy (-1.2°C) and mostly cloudy/overcast (-0.8°C). Light or calm air sessions revealed an average difference of -2.4°C against light to moderate winds (-1.3°C).

3.4 Work–Rest Category Misclassification Analysis

Table 3 presents a cross-tabulation of work–rest risk category classifications.

Out of 53 total paired measurements, 34 (64.2%) were correctly classified whereas 19 (35.8%) were misclassified

The level of performance decreased significantly at high risk levels. Out of 5 sessions with reference WBGT of extreme risk, the app correctly identified only 1 case (sensitivity = 20%), and the rest of the 4 cases were rated as high risk (n=3) or very high risk (n=1). In the case of high-risk conditions, the app made 6 of 10 correct predictions (sensitivity 60%) but false alarms with 4 (40%) of the cases labeled moderate-risk conditions. There was an improvement in sensitivity regarding moderate risk (80%) and low-risk (90%) conditions.

Table 3: Cross tabulation of the reference WBGT monitor (rows)-AIHA Heat Stress App estimates (columns) of the work-rest risk category assignments.

2*Reference Category	AIHA App Category					2*Total
	Low (≤ 26.7)	Moderate (26.7–29.4)	High (29.5–31.0)	V. High (31.1–32.1)	Extreme (32.2)	
Low ($\leq 26.7^{\circ}\text{C}$)	18	2	0	0	0	20
Moderate (26.7–29.4 $^{\circ}\text{C}$)	0	12	3	0	0	15
High (29.5–31.0 $^{\circ}\text{C}$)	0	4	6	0	0	10
Very High (31.1–32.1 $^{\circ}\text{C}$)	0	0	2	1	0	3
Extreme (32.2 $^{\circ}\text{C}$)	0	0	3	1	1	5

Total	18	18	14	2	1	53
-------	----	----	----	---	---	----

3.5 Integration with Published Literature

The present findings are consistent with results from previous field validation studies.

In the eastern North Carolina, Angol et al. (2025) found a mean WBGT underestimation of 2.4°C, and the single deviations got to almost 5°C at clear-sky noon times. Grundstein et al. (2025) recorded underestimation of 1.5°C to 4.2°C on average in six southeast locations of the U.S., and the error was worse in high absolute WBGT. Dillane and Balanay (2020) tested the OSHA-NIOSH Heat Safety Tool and found an average underestimation of 1.8°C with the highest differences in the middle of the afternoon to strong heat.

This agreement between numerous independent research teams, a variety of geographical environments, different mobile technologies, and diverse environmental conditions strongly suggests that systematic underestimation under high radiant heat conditions is a common limitation of current smartphone-based WBGT estimation methods. Mobile applications that do not have on-site sensors have to make predictions of black globe temperature based on computation models which are bound to simplify complicated three-dimensional radiant environments. In addition, meteorological models are run at spatial scales of kilometers which homogenize microclimate variability that control the real worker thermal exposure.

3.6 Integration with Published Literature

The operational recommendations that are supported by the empirical evidence are the following:

Place position apps as screening tools: Mobile heat stress applications are capable of valuable benefits in terms of initial thermal risk assessment, creating situational awareness, and determining times that merit careful examination. The reported systematic underestimation bias during high-heat conditions, combined with 35.8% false alarm rate, and poor performance at high risk levels prove that the apps cannot be used in

precision-sensitive applications such as checking compliance with regulatory requirements or managing exposure to high risks.

Use hybrid surveillance structures: Best practice involves a combination of real-time app monitoring and periodic verification that is conducted with portable WBGT monitors that are placed on designated locations or on designated time intervals. This intermediate solution uses app accessibility but guarantees measurement accuracy in the areas of greatest consequence. Use conservative safety factors: Where instrumentation is unavailable and decisions have to be based on app estimates only, good practice is to use express safety margins. The readings of app during midday under clear-sky and low-wind should be taken as a possibility of underestimating the actual exposure by 24 °C.

Prioritize instrumented surveillance of vulnerable populations: Some worker populations and exposure conditions are of priority in direct WBGT measurements such as unacclimatized workers, those with underlying medical conditions, workers in tasks involving high metabolic rate or wearing of vapor-impermeable protective clothing, and in operations during extraordinary events of heat.

Improve knowledge about technology constraints: To be effectively used, users must know that application outputs are approximate and liable to error, that the apps are not as predictable in situations that present the highest thermal risk and that employees must have the authority to raise the alarm when the app-readings are not consistent with their perceived thermal exposure.

3.7 Study Limitations

Geographic confinement to one temperate continental climate site precludes the area of tropical or desert conditions. The 18 day September observation window was able to capture a large portion of variability, but failed to include extreme events, which are rare, or more than one month of warm season. Contrary to comparative breadth is

concentration on one commercial instance and reference monitor model. The standardization of the inputs in apps reduced confounding, but might not represent the variability in the application in the real world. The focus of the study was on measurement congruency and not on the actual health outcomes.

3.7.1 Future Research Directions

Future research should focus on multi-site validation across diverse climatic regions, including extreme heat conditions; comparative evaluation of multiple mobile platforms; development of hybrid sensor–smartphone systems; improvement of predictive algorithms using large datasets; and longitudinal studies examining the relationship between measurement discrepancies and heat-related health outcomes.

This field study provides empirical evidence that the AIHA Heat Stress App 2.0 is effective in capturing temporal patterns of outdoor thermal stress but exhibits systematic underestimation of absolute WBGT values when compared with calibrated reference instruments. The app demonstrated a mean negative bias of -1.7°C ($\text{SD} = 2.1^{\circ}\text{C}$), with extreme underestimation reaching 7.4°C during periods of peak solar radiation. Measurement discrepancies increased markedly under high-heat conditions, particularly near regulatory thresholds and during clear-sky, midday, and low-wind environments.

These measurement limitations translated into meaningful operational consequences. A misclassification rate of 35.8% was observed in work–rest risk category assignments, with a strong directional bias toward underestimation (non-conservative error). Performance degradation was most pronounced at higher risk levels, where the app demonstrated low sensitivity—20% under extreme heat conditions and 60% under high-risk exposures—raising concerns about its reliability in critical decision-making contexts. Comparison with existing literature reveals strong consistency across studies conducted in different geographic and environmental

settings. This convergence suggests that the observed limitations are not application-specific but instead reflect inherent challenges in estimating radiant heat and microclimate variability using meteorological data-driven models.

The findings support a hybrid approach to occupational heat stress monitoring. Smartphone applications can play a valuable role in preliminary risk screening, enhancing situational awareness, and enabling broad surveillance across distributed work environments. However, their use should be limited in contexts requiring high accuracy, such as regulatory compliance, high-risk exposure management, and formal occupational health assessments.

Organizations seeking to implement evidence-based heat stress management should integrate mobile technologies with periodic verification using calibrated WBGT instruments, particularly during high-risk conditions. Interim risk mitigation strategies should include the application of conservative safety margins when interpreting app-based estimates and targeted worker training to ensure awareness of technological limitations. As climate change continues to intensify occupational heat exposure globally, the integration of digital innovations with established measurement standards represents a practical and scalable pathway for improving thermal risk management. *Line spacing not uniform*

Acknowledgments

The author owes a debt of gratitude to the Department of Occupational Risk and Safety Sciences at the University of Central Missouri who provided instrumentation, field support, and technical expertise, which made this investigation possible.

4.0 References

American Industrial Hygiene Association (2024). AIHA launches enhanced heat stress mobile app 2.0 to protect indoor workers, employers from indoor occupational heat hazards. Press Release. <https://www.aiha.org/press/aiha-launches-enhanced-heat-stress-mobile-app-v2>

- Alahmad, B., Kessler, W., Alwadi, Y., Schwartz, J., Wagner, G. R. & Micheals, D. (2025). A nationwide analysis of heat and workplace injuries in the United States. *Environmental Health*, 24, 65, pp. 1–10. <https://doi.org/10.1186/s12940-025-01231-1>
- Alahmad, B., Al-Hemoud, A., Al-Bouwarthan, M., Khraishah, H., Kamel, M., Akrouf, Q., Wegman, D.H., Bernstein, A.S., Koutrakis, P. (2023). Extreme heat and work injuries in Kuwait's hot summers. *Occupational and Environmental Medicine*, 80, 6, pp. 347–352. <https://doi.org/10.1136/oemed-2022-108488>
- Angol, B., Sousan, S. & Balanay, J. A. G. (2025). Comparison between WBGT app prototype and WBGT monitor to assess heat stress risk in an Eastern North Carolina outdoor setting. *Journal of Occupational and Environmental Hygiene*, 22, 4, pp. 274–287. <https://doi.org/10.1080/15459624.2024.2444415>
- Bernard, T. E., Flash, J. W. & Ashley, C. D. (2023). Group outcomes for time-weighted averaging in WBGT-based heat stress exposure assessments. *Annals of Work Exposures and Health*, 67(3), 345–353. <https://doi.org/10.1093/annweh/wxac083>
- Brimicombe, C., Lo, C. H. B., Pappenberger, F., Di Napoli, C., Maciel, P., Quintino, T., Cornforth, R. & Cloke, H. L. (2023). Wet Bulb Globe Temperature: Indicating extreme heat risk on a global grid. *GeoHealth*, 7(2), e2022GH000701. <https://doi.org/10.1029/2022GH000701>
- Budd, G. M. (2008). Wet-bulb globe temperature (WBGT)—its history and limitations. *Journal of Science and Medicine in Sport*, 11, 1, pp. 20–32. doi.org/10.1016/j.jsams.2007.07.003
- Buzan, J. R. (2024). Implementation and evaluation of wet bulb globe temperature within non-urban environments in the community land model version 5. *Journal of Advances in Modelling Earth Systems*, 16, 2, e2023MS003704. <https://doi.org/10.1029/2023MS03704>
- Cannady, R., Warner, C., Yoder, A., Miller, J., Crosby, K., Elswick, D. & Kintziger, K.W. (2024). The implications of real-time and wearable technology use for occupational heat stress: A scoping review. *Safety Science*, 177, 106600. <https://doi.org/10.1016/j.ssci.2024.106609>
- Cannady, R.T., Yoder, A., Miller, J., Crosby, K. & Kintziger, K. W. (2025). Understanding and perceiving heat stress risk control: Critical insights from agricultural workers. *Journal of Occupational and Environmental Hygiene*, 22, 3, pp. 203–213. <https://doi.org/10.1080/15459624.2024.2439812>
- Clark, J. & Konrad, C. E. (2024). Observations and estimates of wet bulb globe temperature in varied microclimates. *Journal of Applied Meteorology and Climatology*, 63(2), 305–319. <https://doi.org/10.1175/JAMC-D-23-0078.1>
- Dillane, D. & Balanay, J. A. G. (2020). Comparison between OSHA-NIOSH Heat Safety Tool app and WBGT monitor to assess heat stress risk in agriculture. *Journal of Occupational and Environmental Hygiene*, 17, 4, pp. 181–192. doi.org/10.1080/15459624.2020.1721512
- Eggeling, J., Rydenfalt, C., Halder, A., Toftum, J., Nybo, L., Kingma, B. & Gao, C. (2023). Validating an advanced smartphone application for thermal advising in cold environments. *International Journal of Biometeorology*, 67, 12, pp. 1957–1964. <https://doi.org/10.1007/s00484-023-02553-w>
- Esmaili, S.V., Fatemeh, P., Amirreza, S., Ali, M. & Habibollah, D. (2025). Improving heat stress prevention through targeted education in hot and humid workplaces: a study in a foundry industry. *BMC Public Health*, 25, 2613. <https://doi.org/10.1186/s12889-025-23851-5>
- Golbabaee, F., Asour, A. A., Keyvani, S., Kolahdouzi, M., Mohammadiyan, M. & FasihRamandi, M. (2021). Limitations of WBGT Index for application in

Industries: A systematic review. *International Journal of Occupational Hygiene*, 13, 4, pp. 366–380.

Grundstein, A.J., Yeargin, S.W., Cooper, E.R., Cargile, L., Clark, J., Lopez, R.M., Miller, K.C., Montalvo, A.M., Scarneo-Miller, S., Stearns, R.L. (2025). Evaluating Heat Risk: Comparing on-site WBGT measurements versus smartphone application estimates. *GeoHealth*, 9, 3, e2025GH001347. <https://doi.org/10.1029/2025GH001347>

Ioannou, L. G., Tsoutsoubi, L., Mantzios, K., Vliora, M., Nintou, E., Piil, J. F., Notley, S. R., Dinas, P.C., Gourzoulidis, G. A., Havenith, G., Brearley, M., Mekjavic, I. B., Kenny, G. P., Nybo, L. & Flouris, A. D. (2022). Indicators to assess physiological heat strain. Part 3: Multi-country field evaluation and consensus recommendations. *Temperature*, 9, 3, pp. 274–291. <https://doi.org/10.1080/23328940.2022.2044739>

Kakaei, H., Omidi, F., Ghasemi, R., Sabet, M. R. & Golbabaei, F. (2019). Changes of WBGT as a heat stress index over time: Systematic review and meta-analysis. *Urban Climate*, 27, pp. 284–292. <https://doi.org/10.1016/j.uclim.2018.12.009>

Kjellstrom, T., Briggs, D., Freyberg, C., Lemke, B., Otto, M., Hyatt, O. (2016). Heat, human performance and occupational health: A key issue for the assessment of global climate change impacts. *Annual Review of Public Health*, 37, pp. 97–112. <https://doi.org/10.1146/annurev-publhealth-032315-021740>

Kong, Q. & Huber, M. (2024). Evaluation of WBGT as a heat stress index using energy balance modelling. *International Journal of Biometeorology*, 68, 5, pp. 911–925. <https://doi.org/10.1007/s00484-024-02627-5>

Declarations

Conflict of Interest

The authors declared no conflict of interest

Funding

No funding was obtained for this work

Ethical consideration

Not applicable

Data Availability.

All data generated or analysed during this study are included in this published article and its supplementary information files.

Author Contributions

All components of the work were written by the author