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QUANTITATIVE EEG CHARACTERIZATION OF NEURAL ALTERATIONS ASSOCIATED WITH ENVIRONMENTAL HEAT EXPOSURE IN URBAN HEAT ISLAND, A TIME-STAMP-LINKED HOSPITAL ARCHIVE STUDY.

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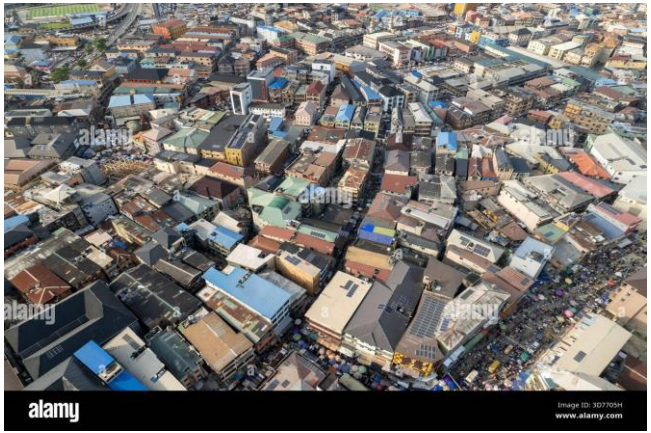
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Background of Study

URBAN HEAT ISLANDS

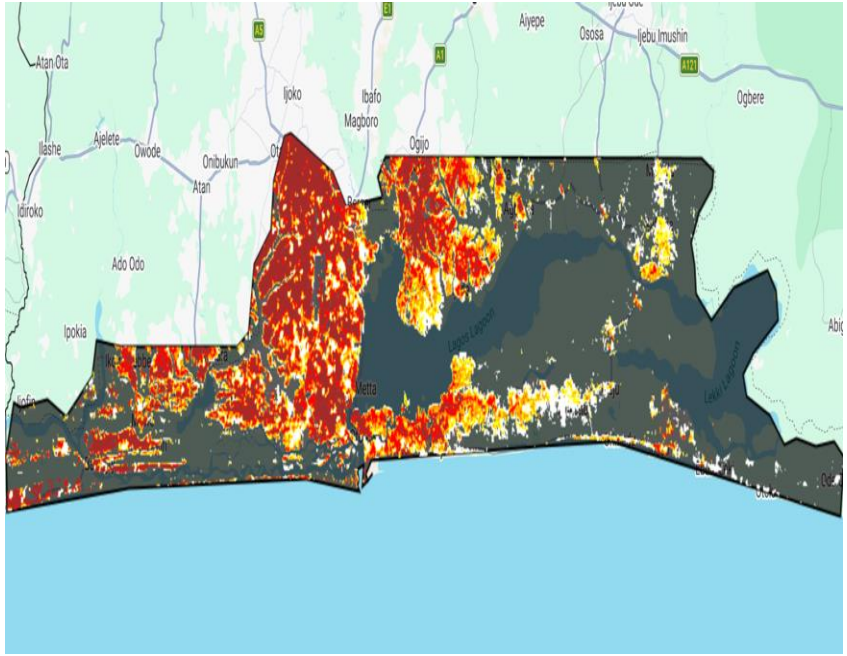
Urban Heat Island (UHI) is a condition that exposes the population to consistently elevated temperatures, which can significantly impair human physiological and neurological processes.





Features: Closely packed buildings, Heat producing engines, Lack of green space, Reduced wind speeds.





$$UHI\ Index = \frac{LST_{pixel} - LST_{mean}}{LST_{mean}}$$

Mean LST (in Kelvin): 306.71406622037347

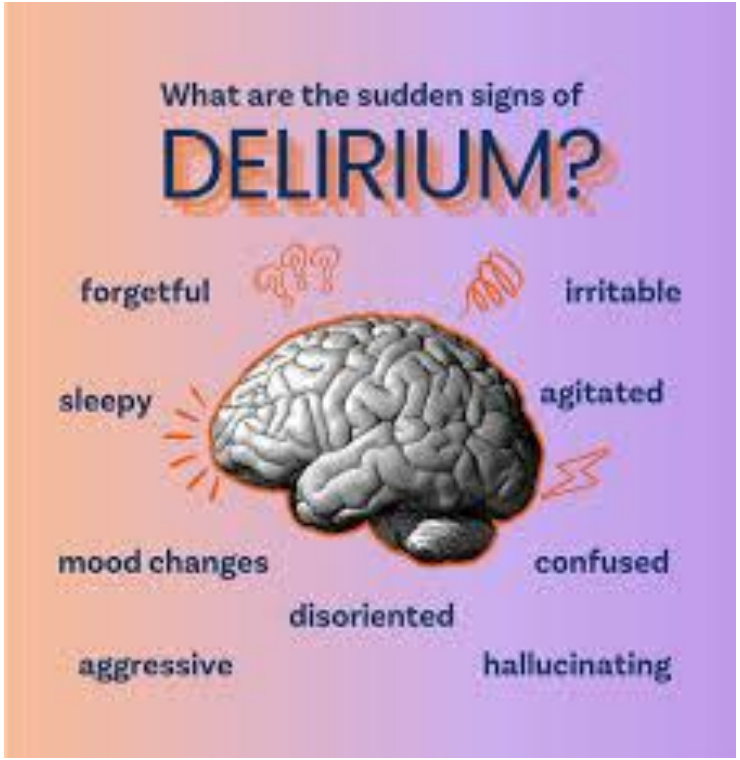
Yellow pixels → 35.1–36.6°C
Orange pixels → 36.6–38.2°C
Red pixels → 38.2–39.7°C

Background of Study

DELIRIUM

Delirium is a severe neuro-cognitive disorder characterized by a sudden disturbance in attention, awareness and cognitive function.

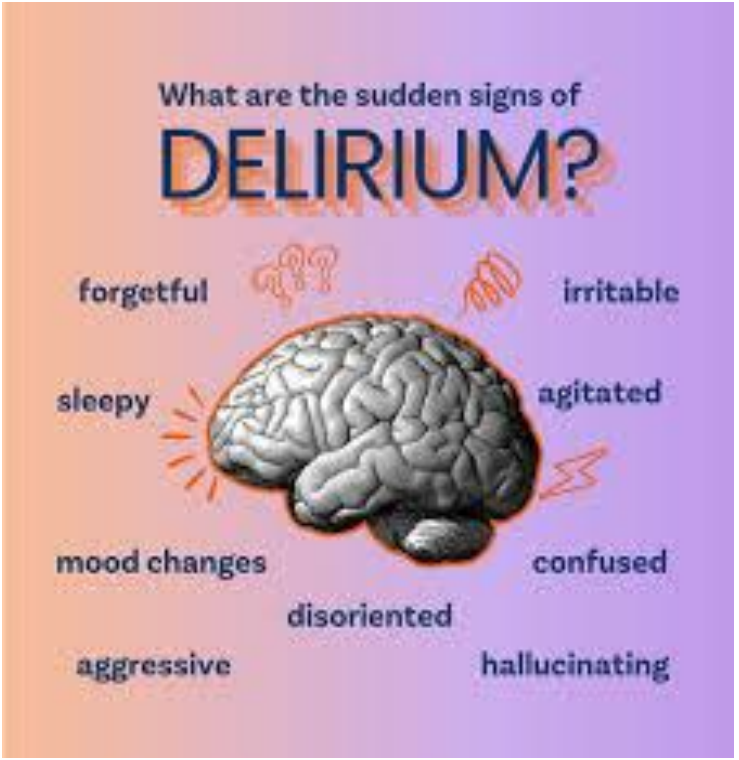
Individuals experiencing delirium often presents symptoms such as confusion, difficulty maintaining attention, disorganized thinking, memory impairment, and altered levels of consciousness



Background of Study

DELIRIUM

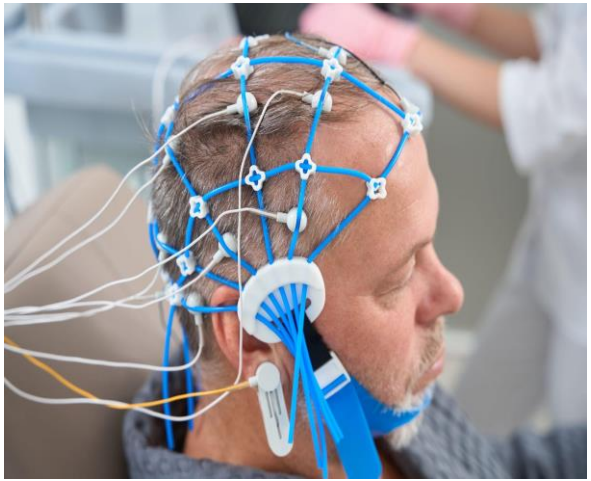
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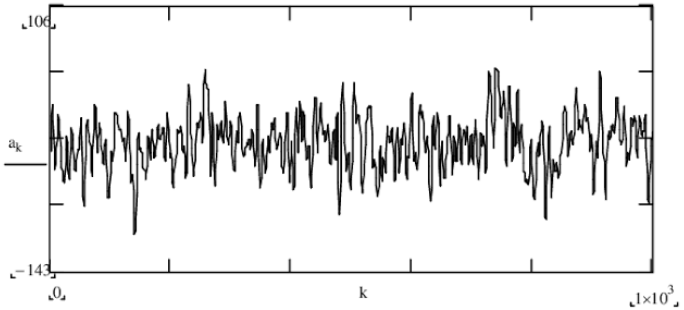


Background of Study

ELECTROENCEPHALOGRAPHY (EEG)

EEG is a safe, painless, non-invasive test that measures and records the electrical activity of the brain using small metal electrodes. In patients experiencing delirium, alterations in brain activity can be observed in EEG recordings.





LITERATURE REVIEW

S/N	Author(s) (Year)	Focus	Key Finding
1	Walter & Carraretto. 2016	Adverse effect of hyperthermia on cognitive performance.	Around 39°C, there is a plateau. Above ~39°C, there is decline.
2	Ondria Gleason (2003)	To help clinicians recognize, differentiate and manage delirium.	Delirium is common and frequent in high-risk groups.
3	Sirui et al (2025)	To evaluate how machine learning models can detect, predict, or monitor delirium using clinical and physiological data.	AI models perform well in delirium prediction and diagnosis.

Research Gap: There is little to no research examining the prevalence and impact of delirium among populations exposed to Urban Heat Island environments.

AIMS AND OBJECTIVES

Aims

To characterize quantitative EEG alterations associated with environmental heat exposure in a real-world clinical archive

Objectives

- Characterizes EEG Features associated with ambient heat exposure.
- Determines the strongest and most consistent associations across exposure definitions.
- Assess how robust these associations are given the confounders available (time of day, season).
- Combine heat responsive features into a candidate Thermal Index and test whether it generalizes to unseen data.

SIGNIFICANCE OF STUDY

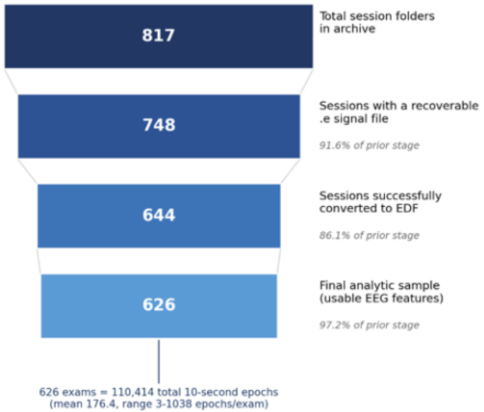
- Analyzes effect of Urban Heat Exposure on cognitive health.
- Supports SDG 3, Good Health and Well Being.
- Supports SDG 11 - Sustainable Cities and Communities.

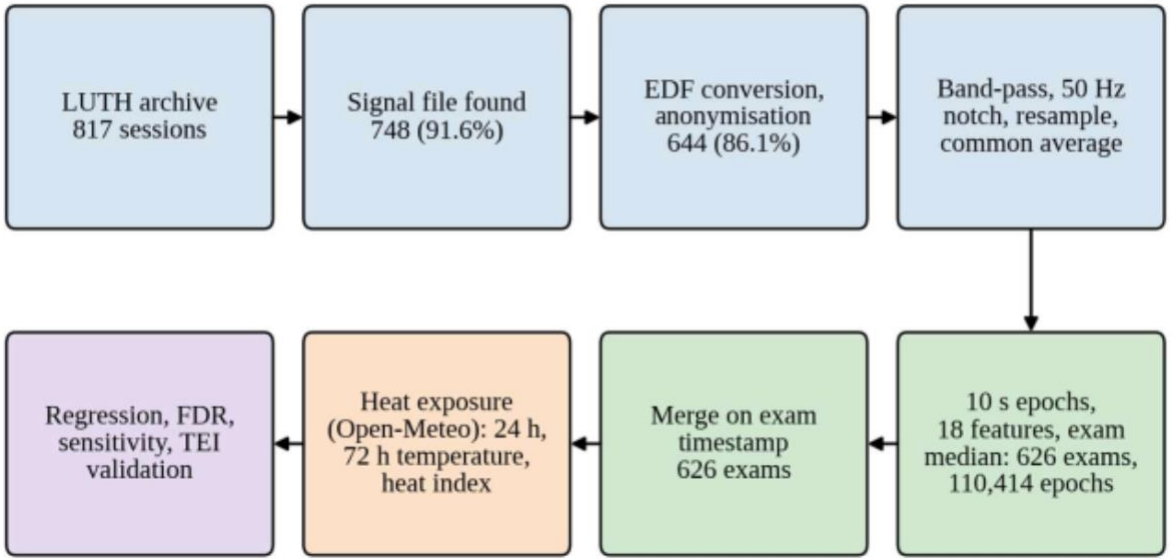
Methodology

- Collection of EEG data from Lagos University Teaching Hospital Luth.
- Redacting data collected of any relevant identifiers - name, date of birth.
- Data signal processing.
- Feature Extraction
- Generated the Secondary Thermal EEG Index combining both permutation entropy and gamma relative power

Methodology

Signal Processing





Statistical analysis: one model per EEG outcome

18 outcomes

9 core EEG features, 8 extended features (band ratios, spectral entropy, Hjorth), and 1 label-free abnormality score

One model each

EEG outcome ~ heat index (24 h) + exam hour + season, with a random intercept per patient (cluster-robust OLS if it fails to converge)

Multiple-test correction

Benjamini–Hochberg false discovery rate (FDR) across all 18 tests; threshold 0.05

Robustness check

Re-run with 4 exposure definitions: 24 h or 72 h window × temperature or heat index

How to read the numbers that follow

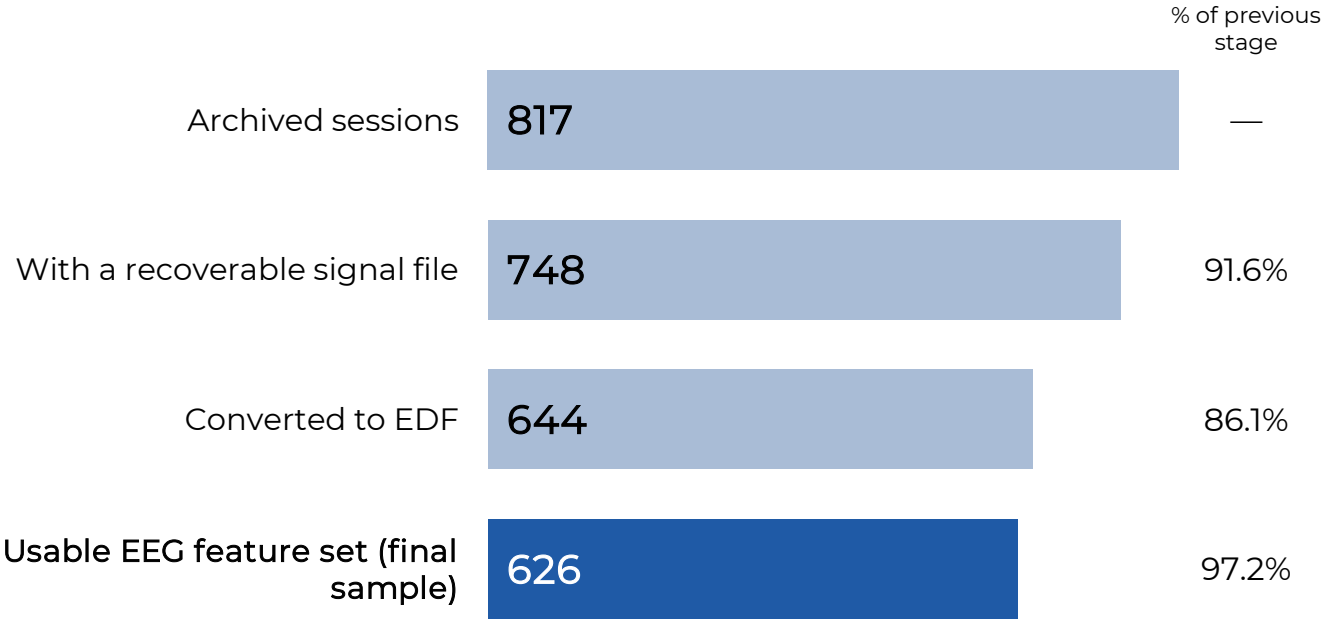
β (coefficient): change in the EEG outcome for each +1 °C of heat index

p: how surprising an association this strong would be if heat had no effect

FDR p: p adjusted for running 18 tests; this is the one to trust

r, R^2: (TEI only) correlation with real heat index on held-out exams, and the share of variation explained

626 of 817 archived EEG sessions were usable



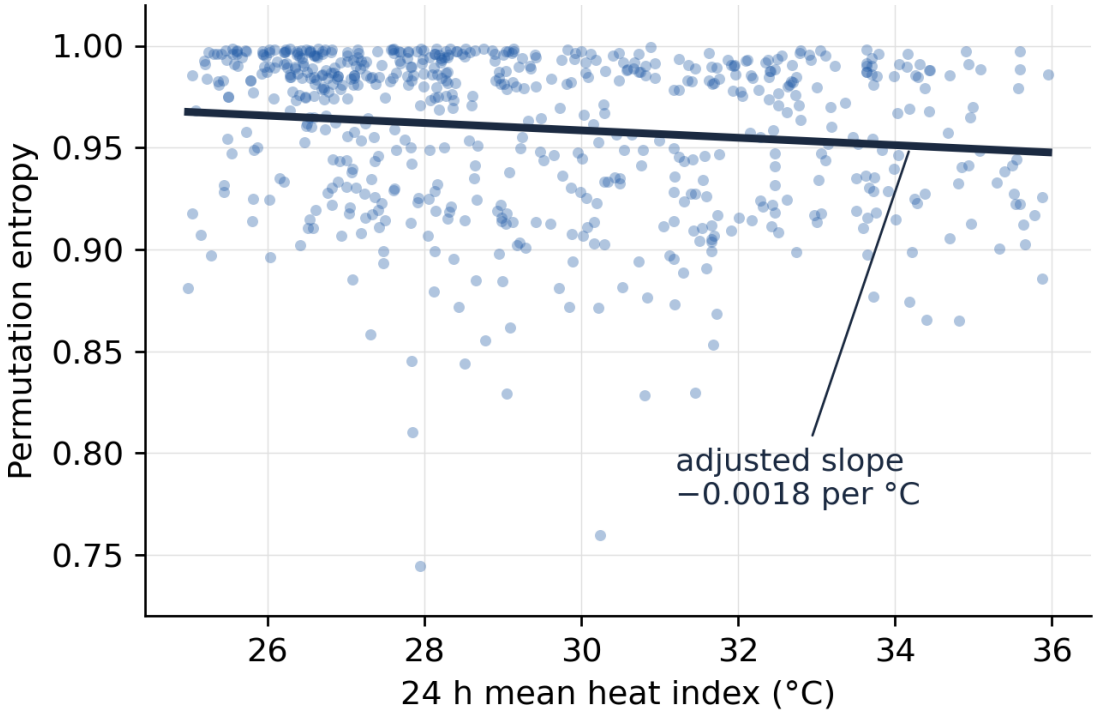
110,414
usable 10-second epochs

619
patients (n = 626 exams)

421 / 205
wet-season / dry-season exams

76.6% of the original 817 sessions retained. All 104 conversion failures share one documented file-format error (not data quality). Every final exam had a complete 24 h of weather data.

Permutation entropy falls as heat rises (FDR p = 0.03)



n = 626 exams. Line: slope adjusted for exam hour and season, drawn through the sample mean. Permutation entropy = how unpredictable the EEG is (0–1).

−0.0018

change in entropy per +1 °C heat index (adjusted)

FDR p = 0.0298

the only 1 of 18 outcomes that survives correction (raw p = 0.0017)

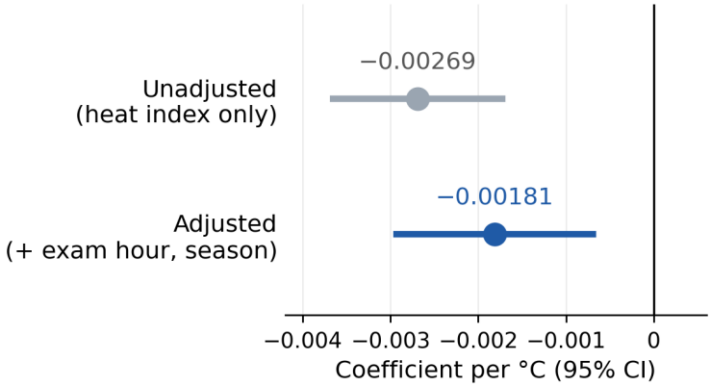
≈ −0.13 SD

small effect: ~0.02 entropy over the 25–36 °C range, vs SD = 0.039

The association holds across heat definitions and after adjustment

Outcome (p-value)	Heat index 24 h	Heat index 72 h	Temp. 24 h	Temp. 72 h
Permutation entropy	0.002	0.002	< 0.001	< 0.001
Gamma relative power	0.011	0.001	0.010	0.001
Hjorth activity	0.072	0.072	0.076	0.083
Other 15 outcomes (smallest p)	0.224	0.313	0.222	0.296

Four heat measures correlate at r ≥ 0.93: one result seen four ways, not four replications.

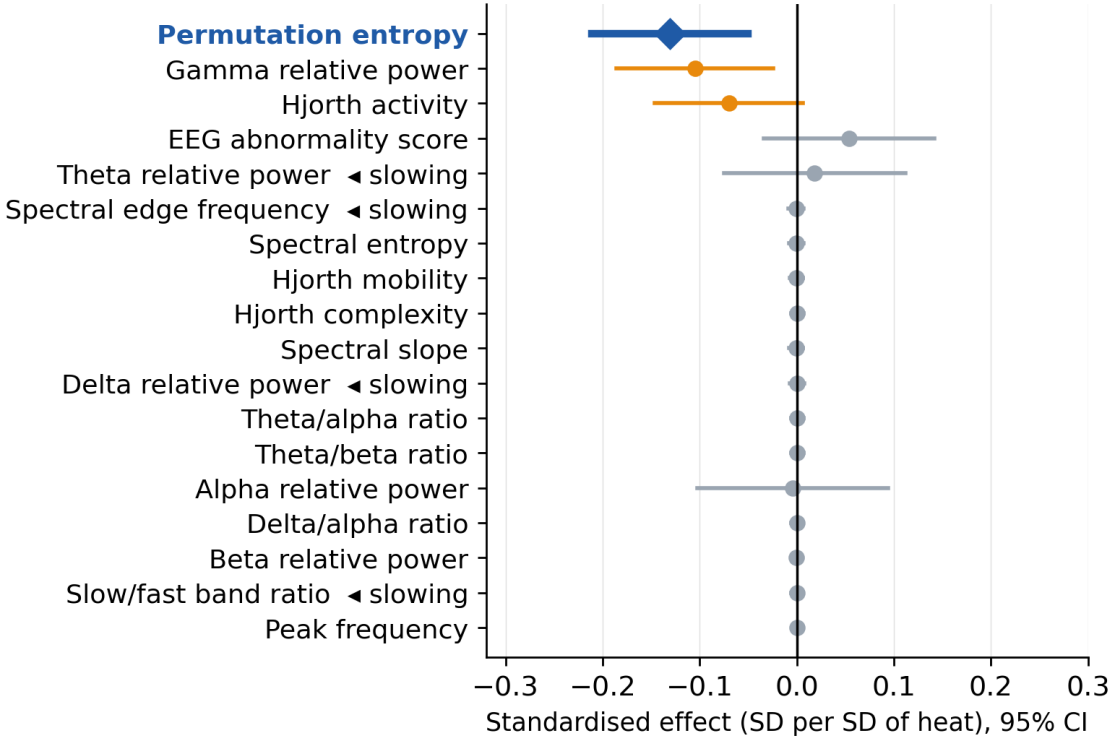


Adjustment shrank the slope by about a third, but it stays clearly below zero (p = 0.0017).

Read as: permutation entropy is consistent under every heat definition tested. Gamma is consistent in direction but does not survive FDR (0.1007). Hjorth activity stays near threshold without crossing it.

Not controlled: medication, age, sex (not available in the archive).

Only permutation entropy moved: 15 of 18 outcomes show no association



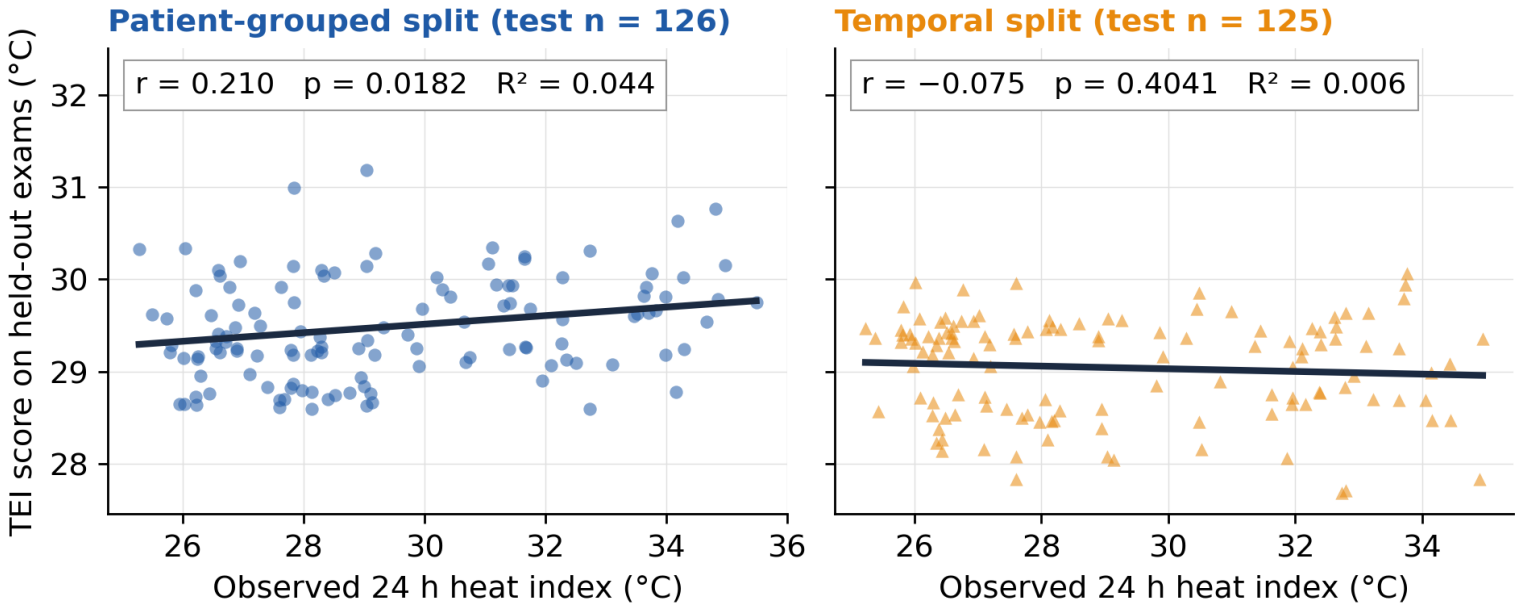
Slowing markers: flat. Delta, theta, slow/fast ratio and spectral edge frequency show no association ($p > 0.29$ under all four definitions).

Suggestive only. Gamma (FDR 0.10) and Hjorth activity (p 0.07–0.08).

What this means. Heat is associated with lower EEG complexity, not with the diffuse slowing typical of delirium.

Dots = standardised effect; bars = 95% CI. Blue: passes FDR. Orange: suggestive. Grey: no association.

Exploratory: the Thermal EEG Index passed one split and failed the stricter one



TEI = 29.44 − 0.446·z(PE) − 0.216·z(gamma)

Predicted heat index from two z-scored EEG features, weights fit on the training fold only (full-sample weights shown).

Not validated. The temporal split, the harder test, shows no association; the other split explains only 4.4% of variation. Entropy does nearly all the work (p = 0.001 vs gamma p = 0.287).

What these results can and cannot say

Association, not cause

Cross-sectional design, one row per exam. No causal claim is supported.

Medication, age, sex not controlled

Medication fields were empty in 740 of 741 files; age and sex were not available. Adjusted only for exam hour and season.

Exposure is outdoor weather

One reanalysis series for the hospital location, not indoor, personal or satellite land-surface exposure.

No delirium label

Findings describe EEG complexity, not a delirium diagnosis or a validated clinical marker.

One hospital, some data lost

Single archive; 104 of 748 sessions (13.9%) could not be converted and were not checked for bias.

Gamma artifact unverified

Direction (falls with heat) argues against muscle artifact, but recordings were not inspected directly.

DISCUSSION

- The Thermal EEG Index generalized under a patient-grouped held-out split ($r = 0.210$, $p = 0.0182$) but failed under a stricter, temporal split ($r = -0.075$, $p = 0.4041$).
- This study presents both and treats the index as unvalidated, but considers it a specific target for prospective follow-up work.

CONCLUSION

- This Study provides quantitative evidence that ambient heat exposure is measurably associated with EEG complexity anchored by permutation entropy.
- A secondary thermal index showed promise under one validation but didn’t generalise consistently.

DIRECTION FOR FUTURE RESEARCH

- Ongoing collection of location based EEG data at LUTH and FMC.
- Utilization of this data to get better informed results.

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Lv, S., Li, J., He, H., Zhao, Q., & Jiang, Y. (2025). Artificial intelligence applications in delirium prediction, diagnosis, and management: A systematic review. Artificial Intelligence Review, 58, 269. https://doi.org/10.1007/s10462-025-11264-0

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Walter, E. J., & Carraretto, M. (2016). The neurological and cognitive consequences of hyperthermia. Critical Care, 20, 199. https://doi.org/10.1186/s13054-016-1376-4