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Exploring associations between ambient temperatures and seizure occurrence

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ABSTRACT

Purpose: Environmental factors may influence seizure occurrence; however, the relationship between short- and medium-term temperature fluctuations and seizure occurrence remains unclear. This exploratory study investigated associations between daily ambient temperatures and seizure occurrence in patients with epilepsy.
Methods: A subset of patients from the RADAR-II cohort filled a seizure diary. Temperature information was obtained based on patients' home address postal codes. Four features were derived: diurnal temperature amplitude, day-to-day temperature change, deviation of the daily mean from the 7-day rolling mean, and deviation of the daily minimum from its 30-day rolling mean. Associations with seizure occurrence were evaluated using Generalized Estimating Equations with exchangeable correlation structure, adjusted for season, age, and sex. Robust sandwich variance estimation was applied; Benjamini-Hochberg FDR correction was used to account for multiple testing across four features.
Results: Twelve adults (mean age 38.7 years, SD 13.4, 50% female) documented seizures over 1884 days. Three of four temperature features were significantly associated with seizure occurrence after FDR correction: temperature amplitude (p_{FDR}=0.044), day-to-day temperature change (p_{FDR} =0.044), deviation of the daily minimum from its 30-day rolling mean (p_{FDR} =0.012). For the latter, the daily minimum lay 0.47 °C below its 30-day baseline on seizure days (β=−0.47 °C, 95%CI [−0.78, −0.16]).
Conclusion: Ambient temperature patterns at multiple timescales and seizure occurrence may be linked. It is likely that these associations are substantially influenced by both regional context and individual characteristics. While limited by sample size and regional focus, this associational and hypothesis-generating study underscores the relevance of environmental factors to seizure dynamics and warrants further investigation in larger populations.

1. Introduction

Understanding the environmental triggers of epileptic seizures is crucial for improving seizure monitoring and management. Temperature fluctuations have been associated with various health conditions, but their potential role in modulating seizure activity remains an open question [1–4]. Investigating the association between ambient temperature, here defined as current outside air temperature, and seizure occurrence could identify potential risk factors and inform seizure forecasting models.

Previous studies have explored the effects of meteorological variables on seizure occurrence, highlighting complex interactions between temperature, air pressure, and air pollution [5–8]. A 1 °C decrease in temperature was associated with a relative risk (RR) increase of 1.016 (95% CI: 1.008 - 1.024) for emergency visits due to epilepsy, with temperatures below 18 °C having the strongest predictive value (RR 1.12) [5]. Additionally, an increase in atmospheric pressure has been linked to an elevated seizure risk, although temperature remained the

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most substantial predictor in multivariate analyses [5]. Similarly, daily mean temperatures below the 2.5th percentile were significantly correlated with an increased likelihood of seizures [6]. In other studies, this association between low temperatures and seizure occurrence was also observed, although it was limited to febrile seizures [7].

Further analyses examined the relationships between ambient temperature, meteorological conditions, and epilepsy monitoring unit (EMU) admissions for seizures. The average daily number of hospital visits for epileptic seizures was significantly higher in January and February as compared to other months. Additionally, seizure frequency increased during periods of lower ambient temperature and larger within-day temperature changes. In one study, a 10 °C decrease in daily mean temperature was associated with a 6.37% (95% CI: 4.40% - 8.34%) increase in seizure-related medical visits [8]. Conversely, a study from Jena found that high ambient temperatures (>20 °C) decreased seizure risk by 46% (OR 0.54, 95% CI: 0.32 - 0.90) in the overall study population, with the strongest effect observed in male patients (OR 0.33, 95% CI: 0.14 - 0.74) [9]. This points to a potential nonlinear relationship between temperature and seizure risk. Further studies suggest a seasonal influence on seizure occurrence [10–12]. Seizure occurrence showed a significant seasonal pattern, with a peak in frequency in January and a low in August [10]. Unstable weather (defined here as rapid atmospheric pressure decreases of ≥10 hPa within several hours and temperature changes of ≥5 °C over two consecutive days) in spring, autumn, and winter led to increased seizure frequency for nearly half of epileptic patients, while only 7% of patients showed this association during summer [11]. Seizures were significantly more frequent in winter and fall, particularly for patients with generalized epilepsy. Lower temperatures and high air pressure were identified as risk factors, while high precipitation was associated with a protective effect on seizure admissions for generalized epilepsy [12].

In contrast to studies suggesting increased seizure risk in cold conditions, a 1 °C increase in temperature was associated with a higher risk of pediatric emergency department admissions for seizures in a study based in Turkey [13]. This apparently divergent finding highlights the complexity and potentially non-linear relationship between environmental influences and seizure occurrence, and the need for further research across diverse climatic regions [5–9,12,13]. Importantly, these contrasting results were derived from a pediatric cohort, in which age-related differences in neuronal excitability may influence temperature sensitivity [14–16]. Overall, temperature patterns appear to influence seizure susceptibility, yet their underlying mechanisms remain insufficiently understood and often underestimated [17]. Assuming that external temperature can modulate brain function, temperature-sensitive transient receptor potential (TRP) channels may provide a plausible mechanistic link, as their activation by heat or cold can influence neuronal excitability [18]. Nevertheless, this proposed mechanism remains hypothetical and should be regarded as a hypothesis for future research rather than an established explanation of the observed cold-night association.

Given these insights, this study explores the relationship between ambient temperature and seizure occurrence to assess its potential as an environmental risk factor. Previous research has largely focused on seasonal or long-term patterns, while the influence of short-term temperature dynamics on seizure risk remains insufficiently understood. By focusing on ambient temperature, our approach offers a sensitive means to capture temperature-related variations in seizure occurrence under real-world conditions. We hypothesized that seizure occurrence is higher during periods of seasonal extreme ambient temperatures and on days with larger temperature fluctuations.

2. Methods

2.1. Study design

This study was designed as a retrospective, single-center, observational and exploratory study analyzing recorded seizure events from patient data collected with the RADAR-II ambulatory study at the University Medical Center Freiburg between January 2021 and March 2022. See Supplementary Material S5 for more information. Ethical approval was obtained from the internal review board of the University Medical Center Freiburg (605/19). The study was conducted in accordance with the principles of the Declaration of Helsinki and all applicable local regulations. All patients provided informed consent before being enrolled into the study. Further details are provided in the Supplementary Material.

2.2. Data collection

Seizures were reported via a smartphone diary (the RADAR-base aRMT app [19]) over patient-specific observation periods. Temperature data were obtained for each patient based on their residential address' postal code. For each day, minimum (T_{min}), mean (T_{mean}), and maximum (T_{max}) temperatures were aggregated from 1 × 1 km modeled data to five-digit postal codes areas. Briefly, the 1 × 1 km modeled dataset was developed based on a multi-stage framework consisting of two linear mixed models and a thin plate spline interpolation, using data from multiple sources such as station observations and satellite-derived predictors. All models (T_{min}, T_{mean}, T_{max}) had high accuracy ($R^2 \geq 0.91$) and low errors (Root Mean Square Error ≤ 2.02 °C) [20]. More detailed information for the modeling approach and results is provided in the Supplementary Material S4. This allowed us to link daily seizure occurrences with corresponding ambient temperatures, in our study defined as the local temperature trends for each individual.

2.3. Data processing and statistical analysis

Based on the daily temperature data, we initially calculated six temperature features for each patient. Where a feature could be defined from either the daily mean or the daily minimum temperature, we retained one representative per timescale a priori to avoid redundancy. Collinearity among the four retained features was low (all VIF < 2.3; Supplementary Table S1). The candidate features were specified as a priori to capture distinct timescales of temperature variation: within-day variability, day-to-day change, weekly anomaly, and monthly nighttime anomaly. The four retained features included the diurnal temperature amplitude ($T_{amp} = T_{max} - T_{min}$) [21], day-to-day temperature changes (T_{chg}, calculated as the difference in T_{mean} between the current and previous day), the deviation of today's mean temperature from its 7-day rolling mean (T_{7dev}; causal; uses partial windows when fewer than 7 days are available), and the deviation of the daily minimum temperature from its 30-day rolling mean ($T_{min,dev}$; causal; uses partial windows when fewer than 30 days are available). See Fig. 1 for a visual overview.

These features were linked to each patient's seizure diary to allow comparison between seizure and non-seizure days. All features were computed causally, using only data up to and including the current day, from a continuous daily temperature series that preceded each recording period. Each window was extended one day at its start (uniformly, independent of seizure status) to capture boundary events, so all features are defined for the first analyzed day. Statistical analyses were restricted to days within each patient's observation period, ensuring that seizure status was known for all included days. Days with at least one reported seizure were classified as seizure days; all other days within the observation period were classified as seizure-free days.

Descriptive statistics were computed for the four temperature variables. To account for within-patient correlation of repeated observations, we used Generalized Estimating Equations (GEE) with a Gaussian family, identity link, and an exchangeable working correlation structure, clustered by patient ID (n = 12). For each feature, a separate GEE was fitted with the temperature feature as the continuous outcome and the binary seizure indicator (1 = day with ≥ 1 reported seizure, 0 = seizure-free day) as the predictor of interest, adjusting for season, age,

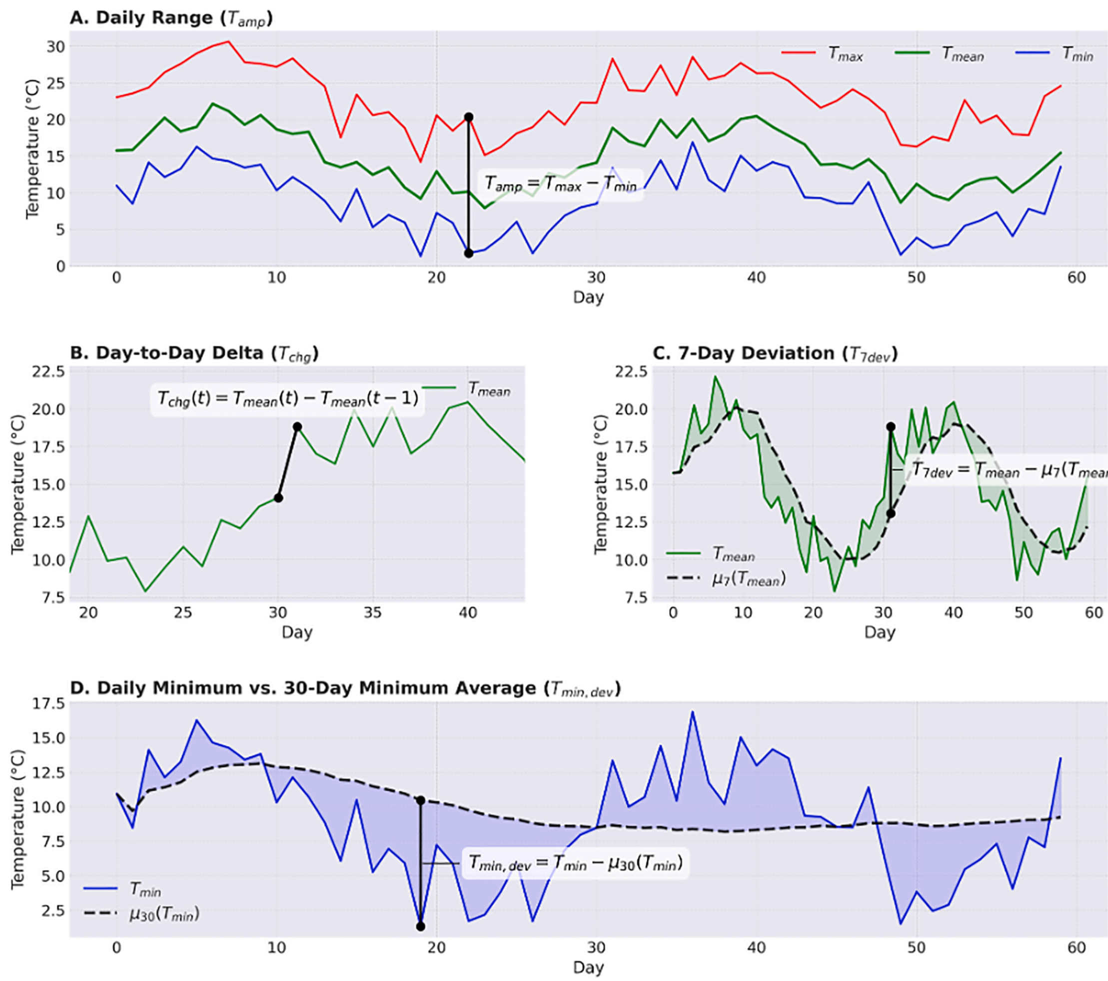

Fig. 1. Schematic illustration of calculated features: (A) Daily Range (T_{amp}): difference between daily maximum and minimum. (B) Day-to-Day Delta (T_{chg}): change in mean temperature between consecutive days. **(C)** 7-Day Deviation (T_{7dev}): deviation of today's mean temperature from the 7-day rolling mean of preceding days. **(D)** Daily Minimum vs. 30-Day Minimum Average ($T_{min,\ dev}$): deviation of the daily minimum temperature from its 30-day rolling mean. Temperatures in °C.

and sex: feature = $\beta_0 + \beta_1 \times$ seizure + $\gamma \times$ season + $\delta \times$ age + $\zeta \times$ sex, with season and sex as categorical terms. The coefficient β_1 represents the adjusted mean difference in the feature (in °C) between seizure and seizure-free days, with a positive β_1 indicating a higher feature value on seizure days. This specification reflects a group comparison (whether temperature conditions differ between seizure and seizure-free days) rather than prediction; the feature is therefore the outcome and seizure status the predictor, and the coefficient does not imply that seizures predict or cause temperature. Robust sandwich variance estimation was used. Small-sample corrections (e.g., Mancl–DeRouen) were evaluated but not adopted due to numerical instability (see Limitations). All analyses used a significance threshold of $p < 0.05$. To account for multiple testing across features, the Benjamini–Hochberg procedure was applied to control the false discovery rate. Data Processing, statistical analyses, and modeling were conducted using Python 3.11.9 (Python Software Foundation [22]), Numpy (v2.4.1; [23]), Pandas (v2.3.3; [24]), SciPy (v1.17.0; [25]), statsmodels (v0.14.6; [26]), Matplotlib (v3.10.8; [27]), and Seaborn (0.13.2; [28]).

3. Results

3.1. Clinical characteristics of patient population and dataset overview

Twelve patients were included in the study (mean age 38.7 years, SD 13.4, median 33.5, IQR 27.8–47.8), with 50% female. The flow of patient inclusion is presented in Fig. 2, and patient characteristics are summarized in Table 1. Over the study period, a total of 1886 days were documented, of which 1717 were seizure-free days and 179 were seizure days. Of the 179 seizure days, 147 had a single reported seizure, and 32 had more than one (21 with two, 9 with three, and 2 with four). Most patients resided in southern Germany (except patient 7), and daily temperature data were matched to each patient's postal code to reflect local environmental conditions. During the study period, temperatures ranged from around 0–5 °C in winter to 25–30 °C in summer, with intermediate values in spring and fall. Fig. 3 illustrates an overview of daily temperature values and seizure diary data. Seasonal patterns were apparent, with higher temperatures and greater within-day variability in summer, and lower temperatures with smaller day-to-day shifts in winter, providing context for interpreting the observed temperatures.

3.2. Relative temperatures and temperature changes related to seizure occurrence

See Fig. 4 for the illustration of the results. Although distributions overlap substantially, daily temperature variables and derived features showed clear differences between seizure and non-seizure days. On a descriptive level (unadjusted, pooled across all patient-days), the diurnal temperature range (T_{amp}) was higher on seizure days (median 9.85 °C [7.07–12.97] vs. 9.00 °C [6.10–12.34]) and the daily minimum temperature deviation from the 30-day rolling mean ($T_{min,dev}$) was lower (−0.71 °C [−2.32, 0.98] vs. −0.05 °C [−1.84, 1.91]), suggesting colder-than-usual nights. Day-to-day temperature change (T_{chg}) showed similar

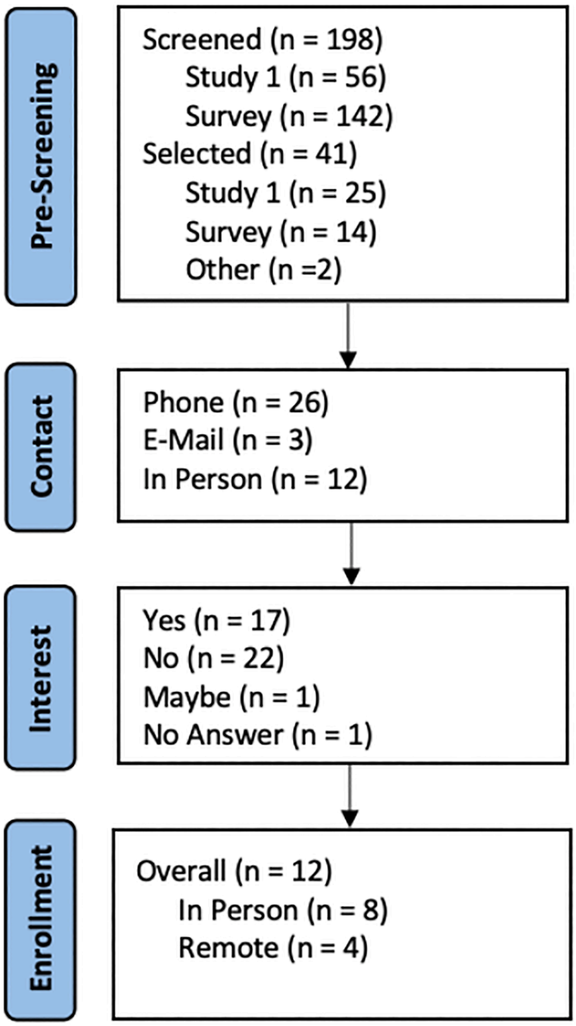

Fig. 2. Flow chart depicting patient inclusion across the different enrollment stages of the RADAR-II Study.

distributions between seizure and non-seizure days (0.12 °C [−0.74–1.10] vs. 0.03 °C [−1.12–1.15]), as did the 7-day deviation (T_{7dev}; −0.18 °C [−1.59–1.07] vs. −0.04 °C [−1.57–1.41]). Full descriptive statistics are provided in Supplementary Table S2.

In the GEE analysis, three of four temperature features were significantly associated with seizure occurrence after FDR correction (Table 2). Diurnal temperature range (T_{amp}, Fig.4A) was higher on seizure days than on seizure-free days (β=+0.73 °C). Day-to-day temperature change (T_{chg}, Fig.4B) was marginally lower on seizure days after adjustment (β=−0.07 °C). The deviation of the daily minimum temperature from its 30-day rolling mean ($T_{min,dev}$, Fig.4D) showed the largest adjusted difference. On seizure days, the minimum lay further below its recent baseline than on seizure-free days (β=−0.47 °C), i.e. colder-than-usual nights. The 7-day deviation feature (T_{7dev}, Fig.4C) did not differ significantly between seizure and seizure-free days. Sensitivity analyses are reported in Supplementary Table S3.

4. Discussion

This exploratory study compared temperature features between seizure and non-seizure days in a small cohort of patients with epilepsy in southern Germany. Unless stated otherwise, the associations discussed below refer to the adjusted GEE models (Table 2), which account for within-patient clustering and control for season, age, and sex; the pooled descriptive medians (Fig. 4, Table S2) are unadjusted and are reported only to illustrate the raw distributions. Seizure days differed from non-seizure days in short- and medium-term temperature fluctuations, suggesting a potential temporal link between ambient conditions and seizure risk.

The association between seizure occurrence and lower minimum temperatures observed in our study is broadly consistent with previous reports linking cooler ambient conditions to an increased risk of seizures [5–8,12]. Although our analysis evaluated temperatures relative to each individual's recent 30-day baseline, the overall direction of the association agrees with earlier findings based on absolute ambient temperatures. Consistently, another studies have reported higher ambient temperatures to be associated with a reduced seizure risk, suggesting that the relationship between temperature exposure and seizure susceptibility may be non-linear or influenced by regional or climatic factors [9]. In addition, our finding that seizure occurrence was associated with greater daily temperature amplitudes is consistent with previous observations of increased seizure frequency during periods of larger within-day temperature fluctuations [8].

Beyond these established associations, our results provide evidence for a potentially novel temporal aspect of weather-related seizure risk. Specifically, seizure days were characterized not only by lower temperatures but also by more pronounced short- and medium-term deviations from recent baseline conditions. In particular, the nightly minimum temperature (T_min,dev) deviated more strongly below its 30-day rolling mean on seizure days than on seizure-free days. To our knowledge, this specific pattern, emphasizing the magnitude of deviation from recent local temperature conditions rather than absolute temperature alone, has not been reported previously and may indicate that short-term departures from an individual's recent thermal environment contribute to seizure susceptibility in adults.

This distinct temporal pattern may reflect circadian interactions between thermoregulation, sleep, and seizure threshold. Future studies should validate this phenomenon, ideally integrating continuous temperature sensing, not only for outdoor, but also for indoor and body temperature, tracking intercurrent illnesses and other factors that may be influenced by lower temperatures.

When interpreting associations between seizure occurrence and ambient temperature, it is important to consider these findings within the broader framework of weather-related health effects. Prior studies reported heterogeneous associations not only for temperature but also for other meteorological factors such as air pollution, humidity, and barometric pressure [5–9,29–36], likely reflecting regional variation, methodological differences, confounders, and complex interactions among environmental factors rather than a single dominant effect.

Evidence on air pollution illustrates this variability. Various pollutants, including particulate matter ($PM_{2.5}$, PM_{10} referring to particles with aerodynamic diameters smaller than 2.5 μm and 10 μm, respectively), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2) have been implicated as potential risk factors, with higher levels linked to increased prevalence of epilepsy-related emergency calls, outpatient visits, or hospitalizations in several studies, while other analyses reported inverse or null associations [8,29–32,37–40]. Interactions with seasonal temperature have also been observed, including stronger negative associations between ozone (O_3) and epilepsy visits during colder periods [13,41]. Findings for barometric pressure and humidity are similarly inconsistent. While an early study reported an increase in seizure frequency associated with daily pressure changes exceeding 5.5 hPa, subsequent studies yielded no risk association [5,33,34]; more recent data again suggest a positive relationship [12,35]. Humidity effects are likewise conflicting, with both protective and risk associations reported depending on context [9,35,36], potentially reflecting interactions with temperature [41,42]. In multi-variable environmental models, temperature emerged as the only meteorological factor significantly associated with seizure occurrence [5], underscoring its relevance as a primary exposure of interest in our study. Variability may also relate to seizure types or syndromes, including heat-sensitive epilepsy

Table 1
Patient characteristics and average exposure to air temperature.

Patient	Age	Sex	Epilepsy	Lobe	Onset Age	Seizure Type	Seizure Elements	Anti-Seizure-Medication	Observation period in days	Number of seizure days	Number of seizures	Seizure freq. / year
1	42	m	focal	frontal	9	focal	motor, bilateral-tonic-clonic	Oxcarbazepine, Levetiracetam, Cenobamate	190	41	47	90.3
2	31	f	focal	unknown	9	focal	motor, dyscognitive, bilateral-tonic-clonic	Perampanel, Oxcarbazepine, Zonisamide	182	8	8	16
3	33	f	focal	temporal	7	focal	dyscognitive, bilateral-tonic-clonic	Perampanel, Cenobamate, Brivaracetam	185	6	6	11.8
4	24	m	focal	temporal	8	focal	motor	Brivaracetam, Lamotrigine, Pregabalin	183	3	3	6
5	58	m	focal	frontal	46	focal	motor, autonomic	Perampanel, Brivaracetam	92	1	1	4
6	34	m	generalized	x	17	generalized	tonic-clonic	Lacosamide, Lamotrigine, Levetiracetam, Valproate	213	0	0	0
7	23	m	focal	frontal	5	focal	motor, bilateral-tonic-clonic	Cannabidiol, Oxcarbazepine, Rufinamide, Cenobamate	7	1	1	52.1
8	56	f	focal	frontal	9	focal	motor, autonomic, bilateral-tonic-clonic	Perampanel, Pregabalin, Lamotrigine, Eslicarbazepine acetate, Cenobamate	190	52	52	99.9
9	45	f	focal	unknown	10	focal	motor, bilateral-tonic-clonic	Brivaracetam, Lacosamide, Cenobamate, Perampanel	181	59	98	197.6
10	27	f	unknown	unknown	10	unknown	motor, dyscognitive, bilateral-tonic-clonic	Brivaracetam, Lamotrigine, Zonisamide	181	3	3	6
11	63	f	focal	frontal	22	focal	motor, dyscognitive, bilateral-tonic-clonic	Levetiracetam, Lacosamide, Cenobamate	181	5	5	10.1
12	28	m	focal	temporal	10	focal	motor, dyscognitive, bilateral-tonic-clonic	Lamotrigine, Zonisamide	111	0	0	0

such as Dravet syndrome or hot water epilepsy. Notably, prior studies have frequently reported links between ambient temperature and febrile seizures [7,43].

Temperature likely contributes to a complex set of environmental and physiological influences on seizure susceptibility. It directly affects human physiology, with elevated body temperature impairing sleep quality, increasing fatigue, and possibly influencing neuronal excitability [1]. This observation may help contextualize our finding that days with comparably low minimum temperatures were associated with increased seizure risk, possibly indicating a shared physiological stress mechanism linking acute cold exposure and seizure susceptibility. In line with this, studies on neuronal excitability have shown that high temperatures increase excitability and alter synchronization, leading to stronger coupling and a higher firing rate [44]. Overall, meteorological influences on epilepsy are multifactorial and context dependent. Understanding how temperature interacts with environmental exposures and individual susceptibility remains a key challenge for future research.

4.1. Limitations

Results need to be interpreted in the setting of data acquisition. While our exploratory study provides valuable insights into the association between ambient temperatures and seizures, certain limitations must be acknowledged. A key limitation is that all features were computed causally, using only data up to and including the current day. This analysis is correlational in nature since the seizure day itself contributes to the feature computation (e.g., T_{min} on a seizure day is included in the rolling mean), the features are therefore not suitable for prospective forecasting without modification. A strictly causal implementation, where features are derived exclusively from days prior to the seizure, would be required for deployment in a prediction system. Moreover, the observational nature of the study prevents causal conclusions, and potential confounders, such as medication adherence or individual health conditions, as well as secondary factors, as respiratory seasonal illnesses or fluctuations in immune-response based on ambient temperature, cannot be controlled in this dataset. Additional factors such as weekday patterns, holidays, major events (e.g., elections or sports events), or patient travel outside respective postal code areas were also not accounted for. The small sample size, reliance on postal

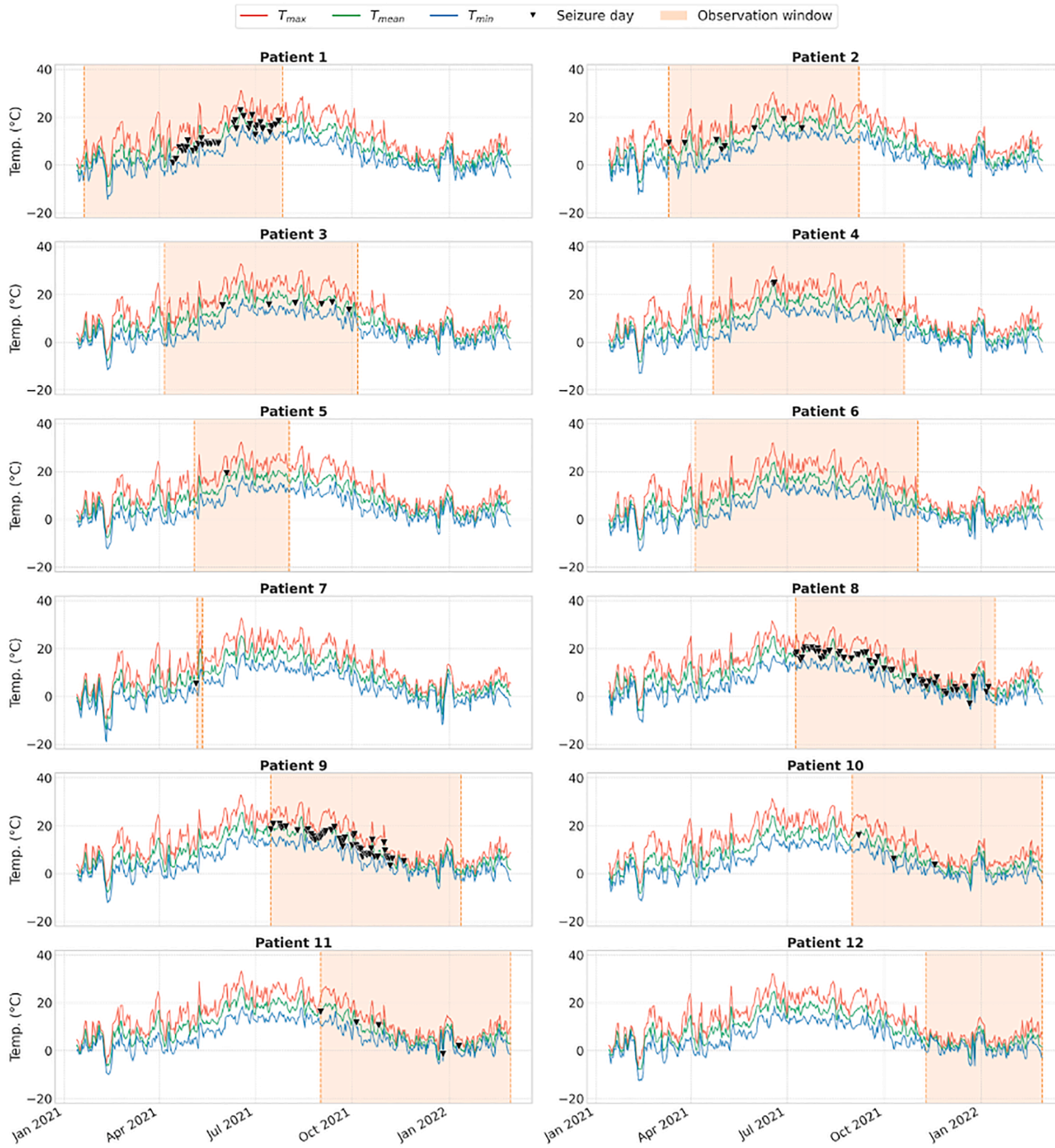

Fig. 3. Temperature trends and Seizure timings by patient. For each patient, daily maximum (red), minimum (blue), and mean (green) temperatures are shown over time. Study observation periods are highlighted in orange. Seizures occurring within these observation windows are indicated by black triangles. Seizures were reported during the respective observation windows only. Note that observation periods vary across patients and may not overlap.

codes rather than live locations and potential inaccuracies in self-reported seizure diaries may introduce biases or inconsistencies. Additionally, our data included a higher proportion of recordings from fall, which may limit seasonal representation, and seizure data were pooled across patients, meaning that individuals with higher seizure frequency contributed disproportionately to the overall results (three patients contributed 31.31% of data), though sensitivity analyses showed similar results when excluding these dominant contributors (see Table S3 in supplement). The small sample size allowed for long recordings. Weather encompasses more than just temperature, and other factors may play a role. In this context, the generalizability to other regions, such as those with widespread air-conditioning or different temperature fluctuations, remains to be analyzed. GEE models accounted for within-patient correlation but not between-patient correlation from shared weather patterns; however, robust variance estimation enables conservative interpretation of our data. Additionally, with only 12 clusters, standard sandwich standard errors may be slightly optimistic; small-sample corrections (Mancl-DeRouen) were considered but showed numerical instability due to heterogeneous within-cluster variance. This small number of GEE clusters from only 12 individuals with unevenly distributed seizure burden constrains the stability and generalizability of the estimates. Furthermore, because participants unwilling to use an Android device were excluded, potential selection bias cannot be fully ruled out. Despite these constraints, our findings highlight promising avenues for future research with more controlled methodologies.

4.2. Clinical implications, future directions and research needs

Extreme ambient temperatures and sudden temperature changes may contribute to an increased seizure frequency, highlighting the need for greater awareness among clinicians and patients. If confirmed in larger studies, integrating temperature-related risk factors into seizure management plans could help improve patient counseling and preventive strategies, such as lifestyle adjustments or remote monitoring

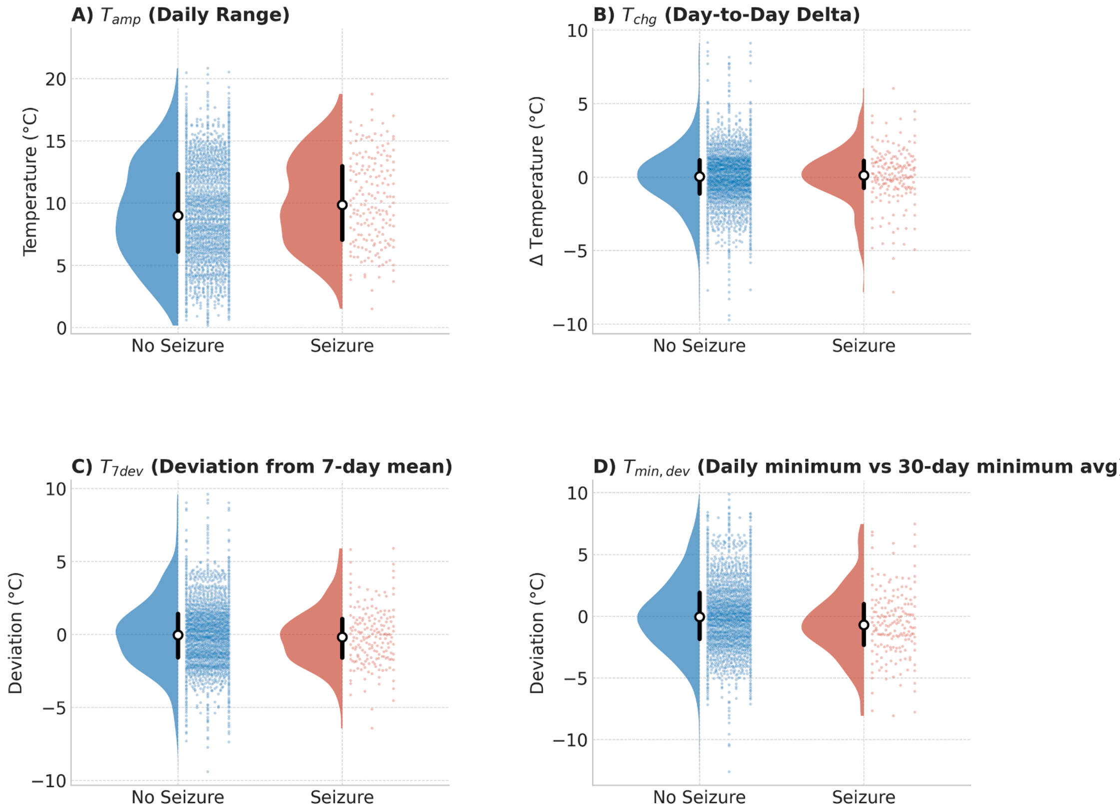

Fig. 4. Temperature metrics of seizure (red) and non-seizure days (blue). (A) Daily range (T_{amp}), (B) day-to-day variability (T_{chg}), (C) deviation from 7-day mean (T_{7dev}), (D) deviation of daily min from 30-day min. average ($T_{min,dev}$). Rainclouds show the kernel density estimate, individual observations, and the median with the interquartile range. Distributions are unadjusted and pooled across patient-days; adjusted group comparisons accounting for within-patient correlation, season, age, and sex are reported in Table 2.

Table 2
GEE analysis: association of temperature features with seizure occurrence.

Feature	β (°C)	95% CI	p	p_{FDR}
Daily Range (T_{amp})	0.73	[0.06, 1.40]	0.033	**0.044** *
Day-to-Day Delta (T_{chg})	−0.07	[−0.14, −0.01]	0.028	**0.044** *
7-Day Deviation (T_{7dev})	0.02	[−0.23, 0.26]	0.905	0.905
Daily Min. Deviation ($T_{min,dev}$)	−0.47	[−0.78, −0.16]	0.003	**0.012** *

Models adjusted for season, age, and sex; clustered by patient ID; robust sandwich variance estimation. Each feature tested in a separate model. β = regression coefficient; CI = confidence interval; p_{FDR} = Benjamini-Hochberg FDR-corrected p-value. * $p_{FDR} < 0.05$. Sensitivity analyses are reported in Supplementary Table S3. Analysed n = 1896 days (179 seizure, 1717 seizure-free) for all four models.

during extreme weather conditions. Additionally, these insights could inform the development of personalized interventions, including adaptive medication strategies and wearable seizure-detection devices that account for environmental triggers.

Our findings suggest a potential link between temperature changes at multiple time scales and increased seizure occurrence, supporting the hypothesis that temperature fluctuations may act, in certain conditions, as a trigger for epileptic seizures. However, given the limited sample size, larger, multicenter studies are needed to confirm this association and account for potential confounding factors. Future studies should ideally incorporate accurate GPS data for each patient to properly assess ambient temperature, taking patients' mobility into account. Furthermore, including individual on-body temperature data, which could be obtained via wearable devices, would enable a more detailed examination of this potential association, especially given that air-conditioning systems may be major confounders. Moreover, wearable sensors could be used to capture potential mediators of a temperature effect, such as sleep quality. In this context, an ideal setup combining ultra-long-term subcutaneous EEG monitoring with wearables and continuous temperature measurements is outlined in the Ultra-Long-Term Sleep (ULTS) study [45]. Additionally, continuous data collection from a large cohort across all seasons would be essential for validating potential seasonal impacts. Future investigations should also explore the underlying physiological mechanisms and assess whether personalized climate-adaptive strategies could help mitigate seizure risk in vulnerable patients.

5. Conclusion

Exploratory analysis in this small cohort suggests that ambient temperature patterns at multiple timescales differ between seizure and seizure-free days, particularly regarding stronger nightly minimum deviations in comparison to the recent 30-day mean. These findings highlight the potential value of incorporating environmental context into personalized seizure prediction models and warrant further investigation in larger, more diverse populations.

Declarations

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Author contributions

Conceptualization: DG, NZ, AS, SV; Methodology: DG, NZ, NS, CG, TL, AS, SV; Formal Analysis / Data Curation: DG, NZ, NS, CG; Investigation: NZ, MD, NN, MD, AS; Writing – Original Draft: DG, SV; Writing –

Review & Editing: all authors; Visualization: DG, NS, CG; Supervision: ASB, TL, AS, SV; Project Administration: DG, NZ, AS, SV; Funding Acquisition: SV.

Declaration of competing interest

SV, TL and CG are part of unlicensed patent applications and patents covering seizure-monitoring technology.

TL received grant support from investigator-initiated grants by Epitel and Liva Nova, NIH/NINDS, Epilepsy Research Fund, Patricia B Terwilliger Chair in Epilepsy Research, and Epilepsy Research Fund. He received device loans from Empatica and Epitel. He holds unlicensed patents pending and approved for seizure detection, prediction, and epilepsy and neurological management. He received travel support for lectures by non-profit organizations and academic centers.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.seizure.2026.08.009.

Data availability

Data that support the findings of this study are available upon reasonable request. Requests should be directed to MD for seizure data and AS for temperature data and will be evaluated in accordance with the study's ethical approval and applicable data protection regulations. The analysis code is publicly available at https://github.com/AIBAT-LMU/seizure-temperature.

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