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Research article

Forecasting neurological emergency cases in relation to synoptic weather patterns: A suburban ER study

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ABSTRACT

Morbidity related to meteorological parameters is a significant public health concern in the context of global warming. While numerous studies have examined the effects of specific meteorological parameters on medical data, fewer have employed a synoptic climatological approach that considers the patterns of weather systems over a specific geographic area. This study utilizes Péczely Weather Patterns, a synoptic meteorological system that characterizes daily weather patterns across the entire Carpathian Basin. By utilizing Péczely synoptic classification, this study explores the correlation between weather patterns and emergency room (ER) visits due to neurological emergencies.

The analysis is grounded in medical data sourced from a prominent county hospital in Budapest. The data cover the period from 2015 to 2019, during which 34,560 patients were admitted to the ER with neurological problems. In this study, we mathematically modeled the relationships between synoptic weather types and neurological emergencies. We then analyzed the resulting probabilistic model to explore potential biometeorological correlations. On the basis of this model, we built a predictive simulation model to estimate the expected patient load. This approach has the potential to support the healthcare system from a human resource allocation perspective.

1. Background

The impact of global warming on public health has been a growing scientific concern in recent decades [1]. Several epidemiological studies have demonstrated the links among ambient temperature, air pressure and morbidity data [2–5]. The greatest amount of attention has been given to extreme heat waves, which have devastating effects on human health. The 2003 European heat wave is thought to have caused more than 70,000 deaths [6,7]. As the economic crisis looms, the hope for finding a responsible, satisfactory solution for future generations is fading. As extreme weather events are projected to increase in frequency, duration, and intensity due

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to climatic variability and change, it is imperative to elucidate the relationships between weather conditions and human health outcomes. This could help in the development of early warning systems and adequate adaptation strategies [8].

Weather is an extremely complex system. This complexity is patterned by macrosynoptic (synoptic) classification systems, which were developed with a focus on a series of stereotypic atmospheric conditions over a specific geographical region. The first actual classification of macrosynoptic positions was established more than 80 years ago by Bauer et al., in 1944 and revised by Hess and Brezowsky. The original 1952 manual Hess-Brezowsky system is still the standard in Germany, but recent publications focus on automating it to remove human error and applying it to climate models [9]. On the basis of the latter classification, specific macrosynoptic classifications have been developed in a growing number of countries. In Austria, Lauscher developed a system that collects the weather conditions of the Eastern Alps and Schüepp created such a classification in Switzerland [10]. The "Ostalpine Wetterlagen" (Eastern Alpine Weather Types) by Lauscher are still used, but recent publications often combine them with broader European scales to capture extreme events [11].In Switzerland, the Federal Office of Meteorology and Climatology (MeteoSwiss) has largely transitioned from the manual Schüepp system to automated classifications that mimic the original logic but are mathematically consistent [10].

The difficulty of classification is related to the fact that geographical location greatly influences weather conditions.

The “synoptic weather pattern and disease” assessment approach offers a distinct advantage over the evaluation of direct or derived meteorological parameter-based analyses, such as daily temperature, humidity, atmospheric pressure, wind conditions, and the wind chill index. This advantage lies in the ability of atmospheric weather patterns to represent complex spatial situations over the area under examination.

To the best of our knowledge, only a limited number of studies have explored the relationship between synoptic weather patterns and neurological disorders. This highlights the novelty and potential significance of our research in this underexplored field [12,13].

In Hungary, the first atmospheric macrocirculation classification was created by György Péczely (1929-1984), a Hungarian climatologist who described the different weather conditions across Hungary in his work published in 1957 [14].

After György Péczely's death in 1984, the classification work was continued by Csaba Károssy.

The Péczely scale is frequently used in modern research to analyze climate change trends, air pollution, and teleconnections. Recent studies have utilized the long timeframe of the Péczely dataset to detect shifts in atmospheric circulation. For instance, Mika et al. analyzed the full 140-year dataset and found significant changes in the frequency of specific types, such as an increase in anticyclonic dominance in summer, which correlates with warming trends in the Pannonian Basin [15].

Research has also linked Péczely types to broader European circulation patterns. Bartholy compared the Péczely system with the Hess-Brezowsky (Grosswetterlagen) system, demonstrating how the North Atlantic Oscillation (NAO) phases influence the frequency of specific Péczely types [16].

The classification is often used to assess precipitation drivers. Studies have compared subjective scales like Péczely's with objective computational classifications to better understand precipitation variability in Central Europe [17].

Péczely's classification system distinguishes 13 types of weather that characterize the Carpathian Basin, mainly on the basis of the air pressure values converted to sea level (see Fig. 1). He used 1015 hPa as the air pressure threshold and separated the cyclonic and anticyclonic pattern types. He also considered the wind directions by category and the orographic features of the Carpathian Basin. On the basis of this classification, each weather pattern is defined by a single code that represents the temperature, air pressure, air

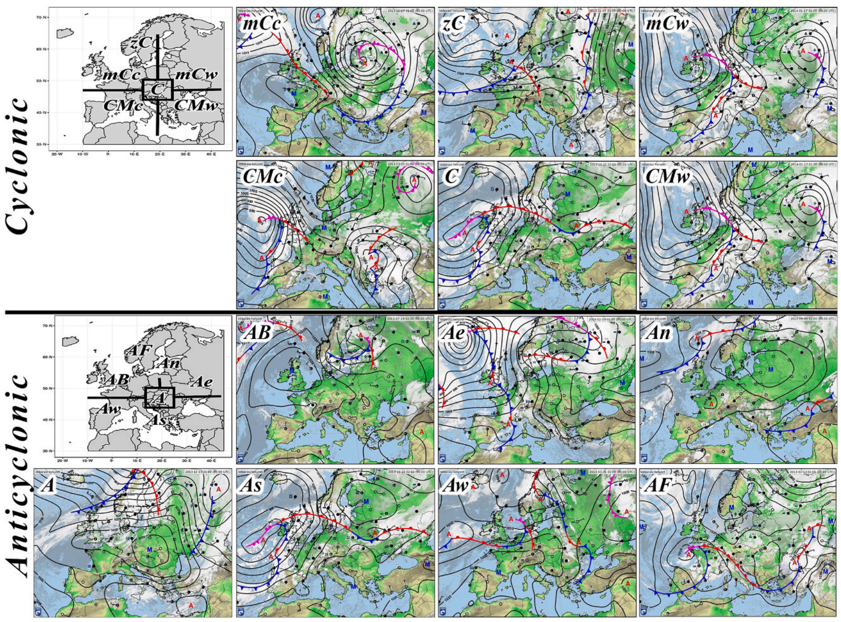

Fig. 1. Péczely weather pattern types. Péczely differentiated 13 cyclonic and anticyclonic patterns over Europe that determined the meteorological conditions over the Carpathian Basin.

movement, air humidity data, and air pollution conditions. Péczely's original work was designed for the Carpathian Basin and considered the basin characteristics and the modifying effects of the Mediterranean Sea and the Alps. He derived the individual types from the circulation systems of the temperate zone: meridional north, meridional south, zonal west, zonal east and central basic positions. The serial number of each type also corresponds to the code of the weather conditions in the catalog. The table below (Table 1) summarizes the typical weather parameters of each type. The gray fields indicate the days affected by the anticyclones, whereas the white fields indicate the days with cyclonic effects. Professor Péczely's work was continued by his former aspirant, Ákos Csaba Károssy, who depicted individual situations [18]. When separating the pressure systems, the value of 1015 hPa was considered the limit value. Altogether, 13 synoptic weather pattern situations can be divided into 6 cyclonic and 7 anticyclonic types (Fig. 1). One can assume that not only the meteorological and atmospheric parameters of the given day influence the occurrence of a medical event but also the preceding days, and the change in between might have an effect as well; in other words, the meteorologic effect might not exert an imminent effect.

2. Methods

2.1. The aim of the study

Our goal was to explore whether the daily Péczely synoptic weather patterns and their changes are related to the number of patients with acute neurological complaints coming to the Emergency Unit of the largest suburban hospital in Budapest.

2.2. Study population

Following the approval of the institutional ethical committee, we conducted a retrospective single-center study using anonymized patient admission data from the Emergency Unit of Budapesti Jahn Ferenc Hospital.

The dataset included 153,024 admissions recorded from January 1, 2015, to December 31, 2019. Among the 153,024 admissions, 34,560 cases were identified where the primary cause of admission to the emergency unit was an acute neurological problem, as indicated by the disease code for the primary reason for admission, according to the International Classification of Diseases, Tenth Revision (ICD-10). Fig. 3(A and B) presents a population pyramid of total neurology cases (A) and stroke-related ER admissions (B) for the examined time period.

2.3. The Inclusion/Exclusion criteria

The study included patients who fulfilled all the specified criteria for participation.

- The patients entered the Emergency Unit of Jahn Ferenc South-Pest Hospital and Clinic in Budapest during the period from 1 January 2015 through 31 December 2019.
- The study included all emergency visits which occurred as unscheduled cases at the Emergency Unit for triage assessment.
- The study included patients who were 18 years or older when they first visited the emergency room.
- The patient needed emergency hospital admission because their main neurological condition required immediate treatment according to the first ICD-10 code entered during their ER visit (Table 2 shows examples of acute cerebrovascular events and seizures/epilepsy and acute headache and neuromuscular crises).
- The analysis kept all emergency readmissions which involved the same patient because the five-year study duration provided enough time for patients to experience separate neurological events including seizures and headaches and vertigo and stroke.
- The study participants lived within the hospital service area which spanned app. 400,000 people to ensure their weather conditions matched the Péczely weather patterns.

Table 1
Macrosynaptic weather types of Hungary—the Peczely macrosynoptic classification types (1957).

Meridional Types	Zonal and Central Types
Types Connected with Northern Current:	***Types Connected with Western Current:***
1. mCc-Hu is in the rear of a West-European cyclone^{A}	***7. zC***-zonal flow, slightly cyclonic influence^{C}
2. AB-anticyclone over the British Isles^{C}	***8. Aw***-anticyclone extending from the west^{A}
3. CMc-Hu is in the rear of a Mediterranean cyclone^{A}	***9. As***-anticyclone to the south from Hungary^{A}
Types Connected with Southern Current:	***Types Connected with Eastern Current:***
4. mCw-Hu is in the fore of a West-European cyclone^{C}	***10. An***-anticyclone to the north from Hungary^{A}
5. Ae-anticyclone to the east from Hungary^{A}	***11. AF***-anticyclone over Fenno-Scandinavia^{A}
6. CMw-Hu is in the fore of a Mediterranean cyclone^{C}	
	Types of Pressure Centers:
	12. A-anticyclone center over Hungary^{A}
	13. C-cyclone center over Hungary^{C}
^{C}-Cyclonal, ^{A}-Anticyclonal	

Table 2
Subdivisions of strokes that occurred at the emergency unit between 2015 and 2019.

	Main categories	Subcategories	ICD-10 codes
Cerebrovascular Diseases	**Vascular occlusions**	Ischemic stroke	G4530, G4540, G4580, G4590, G4600, G4680, G8000, G8030, G8100, G8110, G8190, G8380, G8390, G9310, I6520, I6521, I6522, I6600, I6610, I6620, I6300, I6310, I6320, I6330, I6340, I6350, I6380, I6390, I64H0, I6590, I6640, I6680, I6690, I6780, I6790
		Ischemic stroke complication	I6940, I6980
		Sinus thrombosis	I6360, I6760
		Small vessel disease	G4670, I6720, I6740
		Thrombophylia	M3513
		Vascular malformation (Ischemic)	I6750
		Vertebrobasilar syndrome	G4640, I6500, I6510, I6630, G4500, G4630
	Intracranial bleedings	Intracerebral bleeding complication	I6910, I6920
		Ischemic stroke complication	I6930
		Parenchymal bleeding	I6100, I6110, I6120, I6130, I6140, I6150, I6160, I6180, I6190, I6290
		Subarachnoidal bleeding	I6000, I6010, I6020, I6040, I6060, I6070, I6080, I6090
		Subarachnoidal bleeding complicat.	I6900
		Subdural bleeding (non traumatic)	I6200
		Vascular malformation (bleeding)	I6081
	Vascular malf.	Vascular malformation	I6710, I6712, I6714, Q2820, Q2823, Q2830
	Dissections	Dissections	I6700

- The dataset contained all necessary information about admission dates and patient gender and age which enabled researchers to connect data with Péczely synoptic weather classifications for statistical evaluation.

Exclusion criteria

- The study excluded emergency hospital admissions which showed no acute neurological condition as their main diagnosis (the patients had either traumatic injuries without neurological symptoms or psychiatric conditions or internal medical conditions which became their primary admission reason).
- The research excluded all cases which entered the hospital through elective or planned admissions and all patients who transferred between hospitals.
- The modeling process required three essential variables which were absent from admissions records because they included admission date and primary ICD-10 code that prevented both time-based connection to Péczely weather patterns and proper neurological disease cluster identification.

2.4. Data collection period

External validation of our predictive model was not possible due to the profound impact of the COVID-19 pandemic on healthcare utilization patterns immediately after our study period (2015–2019), which would have introduced significant confounding.

Therefore, the COVID period (March 2020–May 2023) was excluded from the analysis. Healthcare systems worldwide underwent severe disruption during this time. Hospitals restructured departments, redeployed staff, and diverted resources to manage the respiratory crisis. Patient pathways changed. Access shifted. The clinical routine that had operated for decades broke down at multiple levels.

These structural upheavals created statistical bias that could not be separated from the actual relationship between weather and neurological emergencies. We could not distinguish the effects of synoptic patterns from the effects of a collapsing healthcare infrastructure. That made the data unusable for our purposes.

The WHO formally declared the end of the COVID-19 pandemic phase on May 5, 2023. Even after that date, recovery was slow. Normal healthcare operations returned gradually, not suddenly. Rather than attempt to model through the transition period—when some wards reopened, staffing remained fractured, and referral patterns had yet to stabilize—we chose to keep the study window clean: 2015–2019, plus the post-recovery period if external validation becomes possible.

2.5. Clustering of ICD-10 categories

The current version of the International Classification of Diseases, Tenth Revision (ICD-10) was endorsed in May 1990 and was adopted by more than 100 countries worldwide, including Hungary, in 1996. Consequently, all coding in Hungary is based on the ICD-

10 system. For this study, we selected patients whose primary diagnosis was a neurological disorder. Proper and thorough coding of concomitant diseases might not be feasible upon admission because of factors such as a lack of precise information, limited patient–medical staff communication, and the rush that allows the clinician's attention to the main cause of admission. Therefore, our analyses were conducted solely on cases where the primary cause of emergency room (ER) admission was a neurological problem.

Given that the ICD-10 aims to define individual diseases, it was necessary to establish clusters of major neurological diseases for a comprehensive analysis. Neurological disorders are grouped into multiple levels on the basis of the underlying pathophysiology to define larger sets of major disorders (e.g., stroke, headache, and epilepsy). Grouping near-identical features into a single term is indispensable for ensuring reproducibility and maintaining statistical power. Subcategories were also defined where necessary (e.g., hemorrhagic stroke, ischemic stroke, subarachnoid bleeding, etc., within the stroke group); refer to Table 2 for the ICD-10 clustering of neurological disorders.

2.6. Meteorological data

Detailed meteorological data were sourced from the Hungarian Meteorological Service (see Acknowledgments).

2.7. Applied mathematical methods

The Péczely style macrosynoptic classification, which encapsulates the meteorological-atmospheric parameters under investigation, was examined. The focus of the analysis was on the relative frequencies and their deviation from the distribution observed between 1881 and 2019. Considering the significant impact of extreme weather events on human health, a comparison was also made of the prevalence of cyclone and anticyclone days between the periods 2015-2019 and 1881-2019. Péczely day switches that occurred less frequently than 3 times within the specified timeframe were removed from the analysis.

The relationship between Péczely style macrosynoptic classification and daily ER visits was explored next. To uncover this relationship, we employ a Poisson regression model, a widely used statistical technique for modeling count data, which is particularly well suited for our data because of its discrete nature and the presence of overdispersion. Poisson regression allows the estimation of the expected number of occurrences of the dependent variable for a given set of independent variables, enabling the investigation of the impact of these variables on the outcome of interest and the extraction of meaningful insights into the underlying relationships.

By using this model, the daily ER visits can be estimated, and the underlying causal relationship between the macrosynoptic weather patterns and the load on the emergency room can be determined.

To evaluate potential overfitting, we employed cross-validation and analyzed the discrepancy between the mean squared error (MSE) of the training and test datasets. Furthermore, we assessed the model assumptions by examining overdispersion using the Pearson chi-squared statistic relative to the residual degrees of freedom. The resulting ratio indicated moderate overdispersion, suggesting that the variance in the data exceeded what is expected under the standard Poisson distribution. To address this, we applied a Poisson model with robust (sandwich) standard errors and calculated quasi-Poisson-adjusted standard errors, ensuring more reliable inference despite the presence of overdispersion.

In the quantitative analysis of neurology patient admissions correlated with Péczely weather classifications, we implemented a robust Poisson regression framework to address the count nature of the data. The dataset was initially stratified by admission date and corresponding Péczely Pattern value, yielding an aggregated count of cases per category, which served as our response variable.

To accommodate the temporal progression inherent in the dataset, we employed a smoothing spline technique. By fitting a spline, we were able to attenuate the impact of short-term fluctuations while preserving the overall trend. The resulting smoothed values were denoted as 'spine' and integrated into the dataset as a new feature.

In preparation for the Poisson regression, we encoded the Péczely classification values into a series of binary variables through one-hot encoding, extracting the final 13 categorical features. The design matrix ‘X’ was thus composed of these dummy variables, alongside an intercept term to account for the model's baseline level of admissions. Missing data were imputed with zeroes to maintain numerical stability and to allow for meaningful model estimation. Similarly, any infinite values were sanitized to ensure the integrity of the regression analysis.

The dependent variable ‘y’, representing the number of neurology patient admissions, was derived directly from the original count data. Given the nature of the data, the Poisson distribution was deemed the appropriate model choice; thus, a generalized linear model (GLM) with a Poisson family was fitted.

$$Log(\lambda_{\mathrm{i}}) = \beta_0 + \beta_1 X_{\mathrm{i}1} + \beta_2 X_{\mathrm{i}2} + \ldots + \beta_n X_{\mathrm{i}n} + \delta S_{\mathrm{i}}$$

where

λ_i: Expected number of neurology patient admissions (i-th observation)

Log: Natural logarithm

β_0: Intercept term

β_1, β_2, …, β_n: Coefficients for the dummy variables of the Péczely classification

X_{i1}, X_{i2}, …, X_{in}: Dummy variables for the Péczely classification (for i-th observation)

δ: Coefficient for the spline-smoothed feature (S)

S_i: Spline-smoothed value for the i-th observation

The statistical analyses were conducted via Python version 3.9.12 and executed within the Visual Studio Code - Insiders integrated development environment, version 1.80.0-Insider, developed by Microsoft Corporation in 2023. The analysis leveraged various libraries, such as Pandas (version 1.4.2), Plotly (version 5.18.0), and Statsmodels (version 0.13.2).

In our analyses, we took particular care to ensure that the methods we used did not yield estimates based only on daily values, as this could easily lead to false results due to the variation in daily case numbers, which is why we fitted distributions and used probability models for our analysis. This approach minimizes the effect of the high variance in daily event numbers and enables the exploration of the true causal relationship between weather and neurological problems.

3. Results

3.1. Distribution of consecutive Péczely Patterns of the examined period

As an initial step, we compared the frequency of days with different Péczely patterns both within the examined five-year period (2015-2019) and the overall historical data covering the period between 1881 and 2019 (see Fig. 2).

The frequencies of days 1, 3, 4, 5 and 7 differ significantly. While the frequency of Péczely pattern 1 day more than doubled, the frequencies of patterns 3, 4, 5 and 7 days decreased significantly. Patterns 1, 3, 4 and 7 are cyclonic, and the only difference lies in the location of the cyclone relative to the Carpathian Basin. In the last four years, more than twice as many cyclones have formed over the Baltic region and Ukraine as in previous decades, and their circulation pattern has influenced the weather in Hungary.

As the next step, neighboring day analysis was performed, as the change from one pattern to the other is an important factor in health-related conditions. To present this, a 13x13 matrix was created to visualize the frequencies of these changes (see Fig. 3). The frequencies are color-coded for clarity. The matrix also highlights that certain rare variations did not occur during the study period (marked in white). During the examined period of 2015-2019, the proportion of adjacent day pairs classified as Péczely 1-1 was significantly greater than that in the overall historical data. Specifically, the number of days classified as Péczely 1 occurred more than twice as often as the average of 138 years (represented in yellow). Fig. 3(A and B) also demonstrates that the overall frequency of Pattern 3 is rare.

Cyclones and anticyclones play pivotal roles in weather variability. Given their significant impact on life, we conducted an investigation to ascertain whether the cyclone–anticyclone ratio diverges between the period under study and the total known period. The proportion of days characterized by anticyclonic conditions is 67.04% for the total period and 63.04% for the period under study. Thus, there is no significant difference between the two periods in this regard.

3.2. The population of the study

Out of the 153,024 ER admissions, 34,560 (22.58 %) cases were identified where the primary cause of admission to the emergency unit was an acute neurological problem. The patients' average age was 55.37 years with a standard deviation of 19.05. The median age was 57, ranging from 40 (25th percentile) to 71 (75th percentile). Over a span of 1806 days, an average of approximately 19 neurological cases were reported daily. The size of the population covered by this hospital is app. 400.000 people.

The dataset included 16,882 (48.85 %) male patients, with 5320 (31.51 %) aged over 65 years, and 17,678 (51.15 %) female patients, with 7149 (40.44 %) aged over 65 years. The mean age was 56.63 years (SD 20.03) for women and 54.06 years (SD 19.05) for men.

Neither ethnicity data not or socioeconomic indicators were available for analyses.

Fig. 4(A and B) shows the population distribution of total neurological admissions from 2015 to 2019.

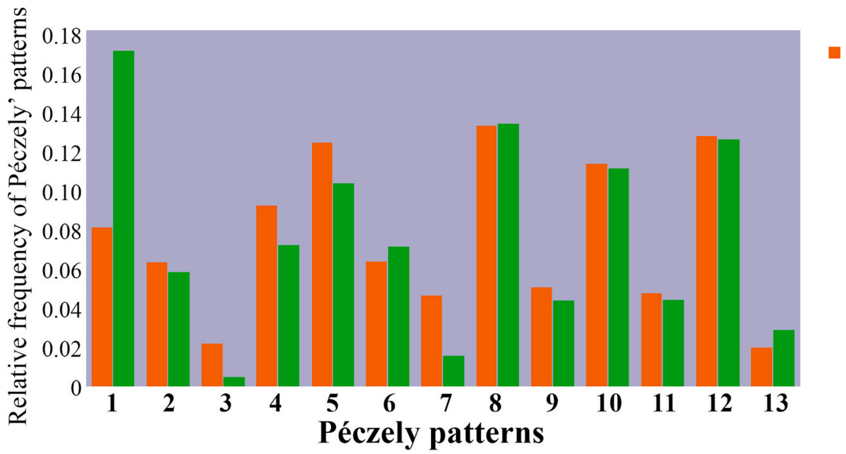

Fig. 2. Comparison of the relative frequencies of Péczely pattern types between the examined period from 2015 to 2019 and the historical date from 1881 to 2019.

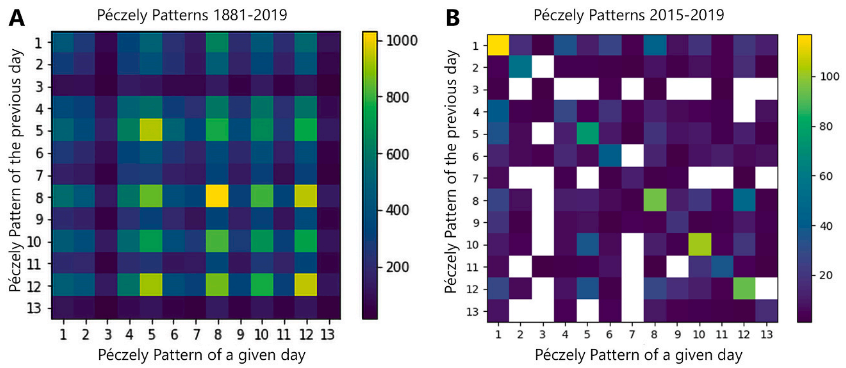

Fig. 3. Frequency of Péczely pattern changes on adjacent days between 1991–2019 and 2015–2019.

3.3. Exploring the effects of synoptic weather types on neurological ER admission

Fig. 5 shows the number of neurological admissions for each different Péczely class. One can observe that Types 4, 7 and 10 come with higher patient numbers, whereas Types 3, 6 and 11 features fewer admissions. For type 4 and type 7 days, cyclones in different parts of Europe and the weather fronts associated with cyclones have an impact on the Carpathian Basin. For type 10, the weather in Hungary is influenced by an anticyclone over the Baltic or Polish plain, which results in essentially dry sunny weather but often results in the appearance of characteristic orographic occlusion fronts due to the modifying influence of the Carpathian Mountains. Pulses 4, 7 and 10 are characterized by variable, windy weather accompanied by precipitation, which is also associated with high atmospheric pollution in the cases of days 4 and 10. On days 3 and 11, the incidence rates were lower. These day types are spatially very different atmospheric formations, but they influence the weather of the Carpathian Basin in a similar way, as both bring cooling, lower than the seasonal average temperatures and low air pollution. However, type 3 brings almost the same amount of precipitation to the Carpathian Basin each month, whereas type 11 comes with dry weather.

3.4. Mathematical model to forecast daily case numbers on the basis of Péczely patterns

A mathematical model based on the Poisson distribution was created and compared with the source data.

Table 3 provides quantitative data on neurological incidents for each daily pattern. Péczely patterns 7 and 4 present high case numbers, whereas days 6 and 11 present low numbers, with lower number of occurrences for days 7 and 11. The model's fit parameters indicate a good description of patient admission numbers.

The model accurately forecasted that weather patterns 7 and 4, characterized by variable, rainy, and windy conditions, would correlate with a high incidence of cases. Conversely, patterns 11 and 6 were associated with the lowest case numbers. The forecast simulation precisely estimated the number of patients admitted corresponding to a given pattern, with no discrepancy of up to three

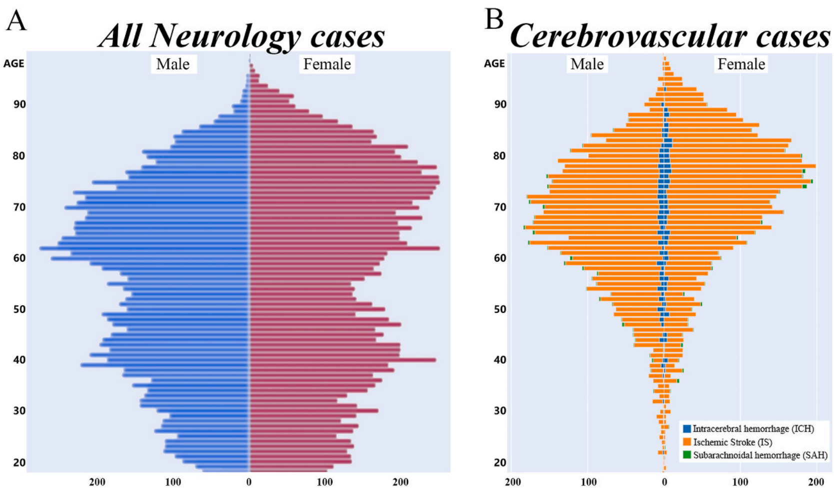

Fig. 4. P population pyramid of total neurology (A) and stroke-related (B) ER admissions between 2015 and 2019. Stroke-related admissions constitute the majority of acute neurological emergencies in individuals over the age of 55. Earlier onset of ischemic stroke (yellow in panel B) is evident in the male population, whereas instances of intracerebral hemorrhage (blue in panel B) are rare in individuals younger than 45 years.

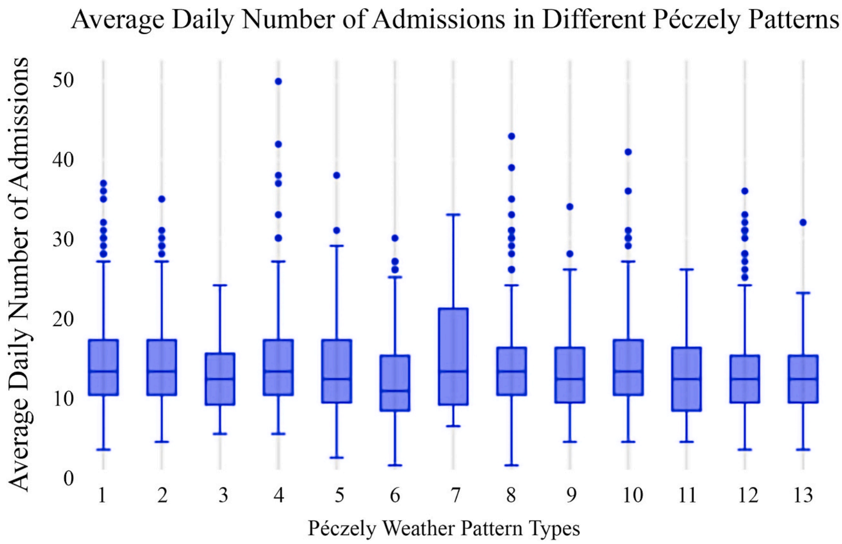

Fig. 5. Average daily admissions of neurological ER cases on different Péczely days.

Table 3
The means and standard deviations of the observed daily incidence rates and model-estimated patient volumes for different Péczely patterns.

Péczely Patterns	Number of occurences	Source Data		Forecast simulation				Comparison
		Mean	STD	Mean	STD	CI (0.025)	CI (0.975)	P-Value
Pattern 1	316	19.17	6.29	19.17	3.68	10.15	28.18	<0.0001
Pattern 2	108	19.57	5.95	19.57	4.58	8.36	30.79	<0.0001
Pattern 3	9	18.44	6.77	18.44	0.64	16.89	20.00	0.04100
Pattern 4	134	20.16	8.08	20.16	3.83	10.78	29.55	<0.0001
Pattern 5	192	18.54	6.04	18.54	3.09	10.97	26.10	<0.0001
Pattern 6	132	17.40	6.27	17.40	3.15	9.68	25.13	0.00200
Pattern 7	29	20.97	7.67	20.97	5.43	7.68	34.25	0.00300
Pattern 8	247	19.30	6.71	19.30	3.17	11.54	27.06	<0.0001
Pattern 9	87	18.68	6.65	18.68	3.22	10.81	26.55	<0.0001
Pattern 10	206	19.54	6.34	19.54	3.93	9.93	29.15	<0.0001
Pattern 11	82	17.26	5.89	17.26	2.75	10.52	23.99	<0.0001
Pattern 12	233	18.52	6.31	18.52	2.86	11.52	25.51	<0.0001
Pattern 13	53	18.34	5.84	18.34	2.44	12.37	24.31	0.01000

decimal places between the calculated and model-predicted values.

However, the calculated standard deviations were larger than the predicted standard deviations, indicating that our model may underestimate outliers, thus being ‘more rigid than reality’. The final two columns present the 95% confidence intervals predicted by the model for each day type. The first column indicates the frequency of days corresponding to that type. The p values demonstrate that even for relatively rare days, our model was able to provide a reasonably accurate estimate."

Fig. 6 shows the density functions corresponding to each pattern. For each function, the area beneath the curve is proportional to the probability of the number of arrivals being influenced by the day type, ranging from 1 to negative infinity, and from negative infinity to a specified value x. The abscissa (horizontal coordinate) of the maxima indicates the impact of the day type: the abscissae of the maxima for days 7, 4, and 2 are the largest, indicating a high number of cases on these days. Conversely, the abscissae of the extremes for days 6 and 11 are the smallest, indicating a low number of cases.

3.5. Overall neurology case numbers – sequential combinations of Péczely's patterns

A correlation analysis was conducted between consecutive Péczely day types and case numbers. Péczely day changes that occurred fewer than three times within the specified timeframe were excluded from the analysis. The graph represents the average number of patients for each day type throughout the study period, using a color scale where lighter colors correspond to higher values and black indicates the absence of data for that day combination. Importantly, the impact of weather on disease patterns can extend to the previous day and often manifests early in the day, attributing the majority of weather-related effects to the conditions of the preceding day. A matrix representation (Fig. 7) was used to depict the volume of acute neurological patients in the ER on successive days. The Péczely weather type on the day of ER admission was compared with the Péczely weather type of the previous day. Each cell of the matrix signifies the frequency of each shift, offering a comprehensive view of daily changes. This methodology considers the influence

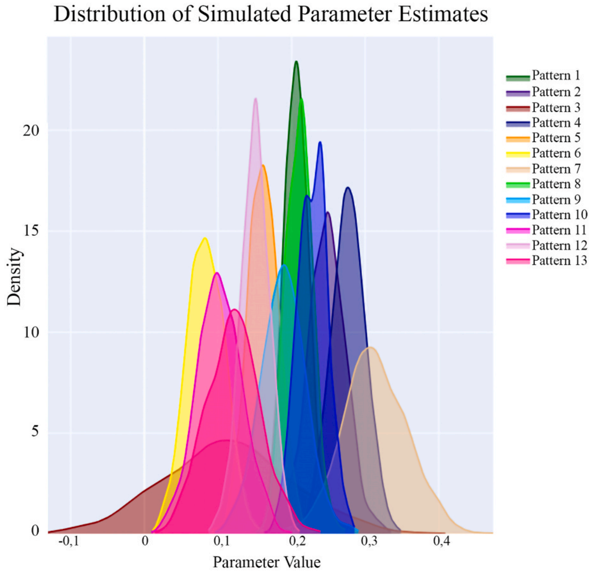

Fig. 6. Average daily admissions of neurological ER cases for different Péczely patterns based on the model.

of both the current and previous days' weather on the occurrence of events.

The highest number of patients treated for neurological problems were 7-4 (29 patients on average), 7-8 and 9-10 days (both app. 27 cases on average). Given that the average patient load is between 15 and 19 patients per day, these peak periods may necessitate the presence of an additional neurologist, as the workload increases by 50–80%. Systemic thrombolysis in stroke care requires undivided attention, which presents a challenge during these peak periods. There is a high probability that multiple thrombolysis candidates may arrive simultaneously, potentially impacting the timing of patient care and resulting in treatment delays on such days.

4. Modeling the overall acute neurology case load

We identified day combinations that yield extreme case numbers. While mathematically there are 169 (13*13) combinations,

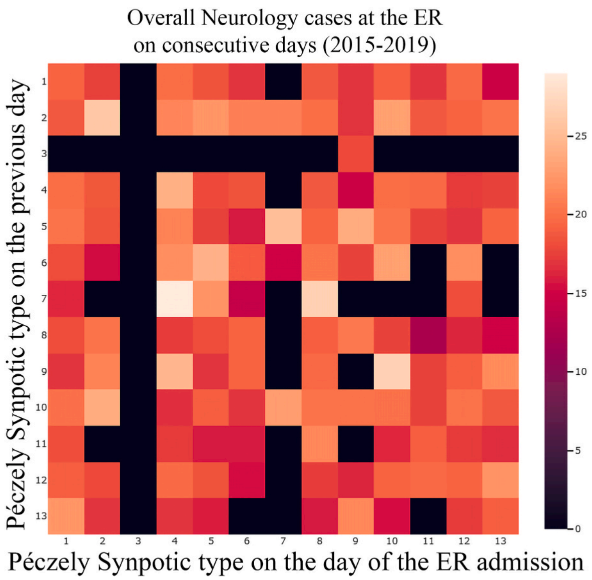

Fig. 7. The impact of weather on disease patterns can extend to the day before an event. We used a matrix representation to illustrate the neurological patient volume on the ER on successive days. Péczely weather type on the day of ER admission compared with the previous day Péczely type. Each cell of the matrix represents the frequency of each shift, providing a detailed view of day-to-day changes. This approach accounts for the influence of both the current and previous days' weather on the event occurrence. Consecutive days with low frequency (fewer than three days during the 2015-2019 period) are represented in black.

atmospheric laws render some impossible, reducing the actual number analyzed.

To examine the effect of the pattern changes, we utilized a similar model to the previous model. However, instead of using the patterns themselves, we used the combinations as the inputs of the model. Given that the case rates are affected by several days, the table below collects the combinations of days that occur at least ten times and have the greatest influence (increase or decrease) on the case rates. As in the previous table, the frequency, calculated and predicted case numbers, standard deviations, 95% confidence intervals and p values are shown (Table 4). As much less data are available, the model is more uncertain, with fewer cases reaching the level of significance. The first five rows of the table give the five transitions with the smallest number of cases, whereas the last five rows give the transitions with the largest number of cases. The predicted and calculated values are now the same, and the estimated variances are also lower.

Our model enables the prediction of the impact of weather on patient admissions across subgroups. Notably, there are distinct differences in case numbers between individuals under 65 and those aged 65 or over. For the younger demographic, our model forecasts a high incidence of cases on Péczely days 7, 3, and 4, whereas for the older demographic, case numbers are lower on days.

4.1. Stroke patients

We examined the influence of the Péczely patterns on the largest subgroups, with stroke identified as the subgroup with the highest incidence (see Fig. 4). Considering the time-critical nature of stroke care, we investigated the associations between changes in Péczely types and the major forms of stroke, including ischemic stroke, intracerebral hemorrhage, and subarachnoid bleeding (see Fig. 8). This investigation offers important insights into the temporal patterns of neurological emergencies, with implications for resource allocation and patient care.

The general distribution of ischemic strokes appears to be relatively uniform. However, a notable increase in case numbers—nearly twice the average—is associated with the 12-to-11-day change. Intracerebral hemorrhage (ICH) is known to occur less frequently than ischemia. Péczely synoptic weather changes from day types 7-12, 8-2, 11-4, and 9-11 have been linked to a doubling of ICH cases in the emergency room. An increase in subarachnoid hemorrhage (SAH) was observed during the 6-to-10 and 7-to-12 changes (see Fig. 8). The high daily averages for most cases are attributable primarily to a few extreme days, resulting in a low frequency of occurrence yet a significant impact on the average. This phenomenon underscores the notion that extreme outlier days can exert a substantial influence on average outcomes.

Despite the lower case numbers for ICH and SAH, these patients often require more extensive care, frequently necessitating further transfer to a neurosurgery department. This underscores the importance of understanding these temporal patterns for effective resource allocation and patient management.

4.2. Differences between age and sex groups

The data were divided into four distinct categories on the basis of sex and age. The first category included male patients under the age of 65, with a total of 10,515 cases. The second category included female patients under the age of 65, with a total of 11,544 cases. The third category included female patients over the age of 65, with a total of 7139 cases. The fourth category included male patients over the age of 65, with a total of 5362 cases.

A new mathematical model was fitted for each group, and the parameters obtained were compared. The results are presented in Fig. 9. The largest discrepancies were consistently observed in the male age group, with significant differences evident in the models for patterns 6, 7 and 13.

For those under 65, patterns 11 and 6 are characterized by low case rates, whereas for those over 65, days 3, 11, and 9 present low case rates. Days 9 and 6 present average case rates.

Our model also reveals gender-based differences in patient attendance at the ER. For men, high case numbers are associated with days 7, 4, and 10, whereas for women, day 2 appears alongside days 7 and 4. Péczely day 2 is associated with a low case rate in men, whereas day 10 is associated with an average case rate in women. Péczely days 11 and 6 had a low incidence in both sexes. Day 13 has the lowest case rate in men and is relatively high in women, whereas day 3 has a low incidence in women and is average for men.

Table 4
Shows the accuracy of the forecasting model for sequential Péczely patterns.

Sequential Péczely' patterns	Number of occurences	Source Data		Forecast simulation				Comparison
		Mean	STD	Mean	STD	CI (0.025)	CI (0.975)	P-Value
Pattern 8 to11	10	12.30	3.86	12.30	2.09	7.40	17.20	0.0146
Pattern 12 to 6	14	15.50	4.43	15.50	2.18	10.38	20.62	0.2076
Pattern 1 to 9	14	17.00	5.91	17.00	2.57	10.98	23.02	0.2153
Pattern 6 to 1	28	18.07	6.27	18.07	4.71	7.02	29.12	0.1363
Pattern 1 to 2	14	17.43	5.71	17.43	4.78	6.22	28.64	0.3708
Pattern 5 to 1	31	20.13	4.92	20.13	3.00	13.08	27.17	0.0404
Pattern 5 to 4	11	21.09	10.31	21.09	4.72	10.03	32.16	0.1724
Pattern 10 to 2	15	23.93	6.69	23.93	7.07	7.35	40.52	0.0782
Pattern 2 to 11	10	18.80	5.77	18.80	1.44	15.43	22.17	0.1736
Pattern 6 to 10	20	23.00	6.47	23.00	4.47	12.51	33.49	0.0065

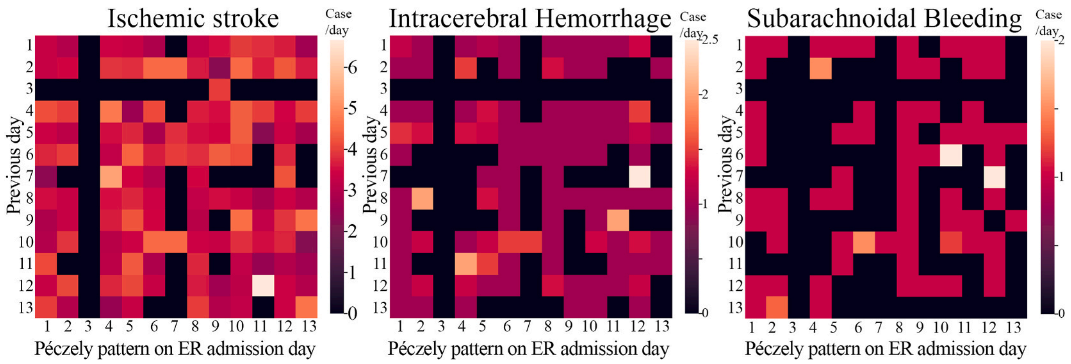

Fig. 8. The average daily frequency (case/day) of different stroke types at the Emergency Unit based on Péczely weather type on admission day and a day before. The dark elements of the matrix show very low case numbers or days when a certain Péczely type switch is rare.

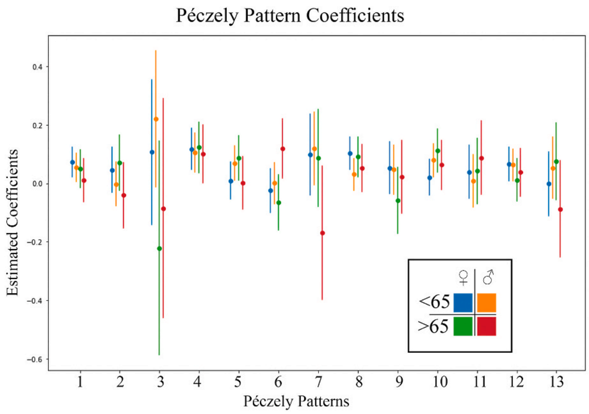

Fig. 9. Model parameter outputs for the age and sex groups.

5. Discussion

In the realm of neurology, specific meteorological parameters have been identified as factors contributing to the increased prevalence of certain disorders. These parameters encompass average daily temperature, humidity levels, atmospheric pressure, and prevailing wind conditions, among others. Observations have also indicated that seasonal variations play a significant role in the occurrence of certain disorders. These disorders are often characterized by a sudden, or 'paroxysmal', onset and primarily include conditions stemming from diseases of the cerebrovascular system. These conditions include hemorrhagic and ischemic strokes, as well as subarachnoid hemorrhages [19–21].

However, notably, the results of various studies investigating these associations have been inconsistent and sometimes contradictory. This inconsistency underscores the complexity inherent in these relationships and points to the need for more comprehensive and nuanced research in this area. The exploration of these relationships holds significant potential for enhancing our understanding of these disorders and could lead to more effective strategies for prediction and management.

The ability to accurately predict patient volume in the emergency room (ER) has several advantages. Dependable forecasts of ER admissions aid healthcare providers and policymakers in the optimal allocation of human resources. An accurate estimation of patient volume allows providers to foresee surges in demand and adjust staffing levels as needed. Furthermore, data from ER visits serve as a crucial resource for monitoring the quality of care, as they enable the tracking and analysis of metrics such as patient wait times, types of treatment administered, and visit outcomes.

Meteorological conditions, shaped by interconnected factors such as air temperature, wind patterns, and humidity, exhibit a complex interplay where alterations in one can potentially influence the others. To consider these climatic parameters holistically while considering regional weather conditions, we employed the Péczely macrosynoptic classification. This methodology facilitated an effective characterization of the meteorological environment at the investigated time points on a daily scale.

We observed a significant surge in emergency room (ER) visits on days classified as Péczely types 4 and 7. The meteorological conditions on these days are driven primarily by cyclonic and frontal activities, typified by increased precipitation rates, strong winds, and fluctuating weather patterns. Notably, type 4 days during the summer season are associated with oppressive conditions and elevated pollutant concentrations. In contrast, Péczely type 6 and 11 days were correlated with below-average case rates, despite high standard deviations.

Given that the majority of neurological ER admissions are stroke related, we paid particular attention to exploring its relationship with Péczely patterns. To develop a predictive model, the change in weather from one day to the next is of paramount importance. As outlined above, we were able to identify days with changes in synoptic weather conditions when the patient load increased by 50–80%.

The strengths of our study lie in the evaluation of a substantial number of ER visits over a five-year period and the application of sophisticated mathematical modeling. Synoptic classification provides the advantage of representing daily weather via a single code, thereby eliminating the need to analyze multiple variables. This approach enhances the efficiency and comprehensibility of our analysis, making our findings more accessible to the scientific community.

To the best of our knowledge, this inaugural study explored the relationships between ER visit rates associated with neurological disorders and weather pattern types. Previous studies have examined synoptic weather classifications in relation to specific neurological diseases, such as epilepsy [13,22–24]. Our study stands out because it provides crucial data that enable healthcare providers to rationalize neurological ER care in relation to synoptic meteorological phenomena. The observed effect size is significant because of the universal nature of the risk factor and the prevalence of neurological cases in ER wards.

Accounting for weather variations allows us to gain a more accurate understanding of the true demand for emergency care and identify areas requiring improvement in care delivery. This information is invaluable in our ongoing efforts to increase the quality of care we provide and effectively allocate resources. Knowledge of ER visit numbers can aid healthcare organizations in cost management by pinpointing areas for improvement in patient care and resource utilization. ER visit data can also track disease incidence and prevalence within a population, providing valuable insights for public health initiatives and resource allocation.

As such, further research in this area is not only warranted but could prove pivotal in our ongoing efforts to combat these conditions.

6. Conclusion

Synoptic weather classification, such as Péczely's classification, provides a significant advantage by reducing the complexity of numerous weather parameters. This is achieved by defining specific meteorological constellations over a certain geographical area. Although our data are derived from Hungary, our methodology can be applied to various regions where atmospheric constellations can be defined.

The analysis of neurological emergencies in the context of synoptic meteorological conditions has laid the groundwork for predictive modeling. The developed model demonstrated the ability to predict the volume of neurological patients arriving at the emergency unit based on Péczely's weather classifications.

Notably, it can accommodate less frequent day types, which conventional statistical methods often struggle with or are unable to address properly. This research underscores the potential of synoptic weather classifications in enhancing our understanding and prediction of emergencies.

6.1. Limitations of the study

This study is based on data from a single emergency department, which may limit the generalizability of our findings to other populations or healthcare settings. However, the homogeneity of the study sample enhances internal validity, and our primary aim was to assess whether synoptic meteorological patterns could inform healthcare workload planning in this context.

While we incorporated both long-term and short-term temporal effects using smoothing splines and lagged analyses, reliable estimation was not feasible for lags of two days or more.

External validation of our predictive model was not possible due to the profound impact of the COVID-19 pandemic on healthcare utilization patterns immediately after our study period (2015–2019), which would have introduced significant confounding. We acknowledge these limitations and recommend that future research include multicenter, demographically diverse data and pursue external validation once healthcare operations stabilize to pre-pandemic conditions.

The COVID period (March 2020–May 2023) was excluded because healthcare systems worldwide underwent severe disruption—departments restructured, staff redeployed, patient pathways altered—creating statistical bias impossible to disentangle from the actual relationship between weather and neurological emergencies. The WHO declared the pandemic phase over on May 5, 2023, yet recovery was gradual; normal operations did not snap back instantly. We kept the study window clean at 2015–2019 rather than attempt to model through a fractured transition periodOverall, while these limitations should be considered when interpreting our findings, the study offers an important step toward integrating synoptic meteorological information into healthcare resource planning, and provides a foundation for future, broader investigations.

CRediT authorship contribution statement

Bence Sipos: Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation. **Brigitta Szilágyi:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Péter Sótonyi:** Writing – review & editing, Resources, Conceptualization. **Kata Kreinicker:** Writing – review & editing, Data curation. **Krisztián Kása:** Writing – review & editing, Data curation. **Lajos Szabó:** Writing – review & editing, Data curation. **Gábor Lovas:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization.

Ethics approval

The study and use of the data were approved by the Medical Directorship of Jahn Ferenc South-Pest Hospital and Clinic and the Institutional Ethical Committee.

Consent for publication

No individual patient record was used in any form in the study.

Availability of data and materials

The medical datasets generated and/or analyzed during the current study are not publicly available as it is the medical data of Jahn Ferenc Hospital, Budapest, Hungary, but are available from the corresponding author on reasonable request. The meteorological datasets were made available for the authors by the Hungarian Meteorological Service (see Acknowledgements) are available from the corresponding author on reasonable request.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this manuscript, the authors used Perplexity AI for the following specific tasks: (1) literature search support and summarization of relevant sources; (2) refinement of text, prose structure, and readability; and (3) grammar and style checking on human-generated content. All AI-generated outputs were thoroughly reviewed, edited, and verified by the authors for accuracy and alignment with the study's scientific content and conclusions. No AI tool was used for idea generation, data interpretation, statistical analysis, or formulation of scientific conclusions. All core research findings, study design decisions, eligibility criteria development, and analytical interpretation represent the independent work and critical evaluation of the authors. The authors take full responsibility for the accuracy and integrity of the content in this manuscript.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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List of abbreviations

ICD-10 International Classification of Diseases, Tenth Revision
ER – Emergency Room
ICH – intracerebral hemorrhage
SAH – subarachnoidal hemorrhage

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