

Effects of atmospheric factors on daily intensive care unit cases in Germany: A Time Series Regression Study

Katharina Sasse¹, Christian Merckenschlager¹, Michael Jöhler¹, Till Baldenius², Patrik Dröge², Christian Günster², Thomas Ruhnke², Pablo Escrichuela Branz³, Lucas Pröll³, Bastian Wein³, Saskia Hettich⁴, Yevgeniia Ignatenko⁴, Taner Öksüz⁴, Iñaki Soto-Rey⁴, Elke Hertig¹

[affiliations]

¹Regional Climate Change and Health, Faculty of Medicine, University of Augsburg, Germany.

²AOK Research Institute (WIdO), Berlin, Germany

³Cardiology, Pneumology, Intensive Care Medicine and Endocrinology, University Hospital of Augsburg, Germany

⁴Digital Medicine, University Hospital of Augsburg, Germany

[corresponding author]

Katharina Sasse, katharina.sasse@med.uni-augsburg.de, Universitätsstraße 2, 86159 Augsburg, Germany

ABSTRACT

Introduction: Atmospheric conditions under climate change increase pressure on healthcare systems. Especially, the intensive care units (ICU) are vulnerable due to low buffer capacity and high utilization rates.

Methods: Daily ICU cases from 2009 to 2023 were derived from the German statutory health insurance data of eleven regional AOK insurances. Cases were stratified by age and sex. Generalized additive models were used to investigate the associations between daily ICU cases and lagged atmospheric variables. Thirteen intensive care relevant diseases were analyzed using disease-specific predictor sets. Analyses were conducted for regions derived from a human-biometeorological characterization of Germany. Model performance was assessed using (weighted) explained deviance.

Results: Over the 15-year study period, 9,970,548 ICU patients were recorded (44% women), 74.3% aged ≥ 60 years. Trauma was the most common ICU-related disease, followed by non-ST elevation myocardial infarction (NSTEMI), pneumonia and ischemic stroke. ICU demand was most sensitive ($p \leq 0.05$) to pressure-related factors, thermo-physiological parameters and ozone concentration. In terms of sex-age differences, atmospheric factors affected men more frequently, while women were more impacted by cold weather and particulate matter (PM_{10}). Heat was more relevant for patients aged ≥ 60 years. The NSTEMI model in Central Eastern Germany performed best (weighted explained deviance of 49.3%). In males ≥ 60 years, heatwaves were associated with a reduced risk of ICU cases (Relative Risk = 0.94, 95%-Confidence Interval 0.89 to 0.99).

Conclusion: The study identified key atmospheric factors for ICU, enabling the German healthcare system to prepare better for short-term impacts of meteorological and air quality factors.

Keywords: Environmental Health, Intensive Care Units, Health Care Sector, Regression Analysis, Atmosphere

43 KEY MESSAGES

44 What is already known on this topic:

- 45 • The atmospheric changes have a direct impact on public health and the inpatient care,
46 particularly in intensive care units.
- 47 • Consequently, there is a necessity to investigate the influence of atmospheric factors
48 on intensive care in order to prepare the healthcare system for the new circumstances.

49 What this study adds:

- 50 • The study provides evidence that atmospheric factors influence the intensive care in
51 Germany and describes age and sex-specific aspects.
- 52 • The results offer valuable insights into how different atmospheric factors affect the
53 demand for intensive care in hospitals.

54 How this study might affect research, practice or policy:

- 55 • The study enables the German healthcare system to better prepare for short-term
56 effects of atmospheric factors, and structural or resource-related adjustments could be
57 made in hospitals to anticipate for short-term fluctuations in intensive care demand.

INTRODUCTION

Urbanization, economic and industrial growth, have led to an increase in air pollutant emissions in recent decades, resulting in changes in environmental conditions. Projections show that climate change hazards will rise in both frequency and intensity in the future [1, 2]. Atmospheric hazards are important stressors that pose significant risks to public health including morbidity and mortality rates [3, 4]. These atmosphere-health relationships should be carefully monitored to assess the burden and adapt the healthcare sector, including climate-resilient health infrastructure [5].

Numerous studies have investigated the rising mortality and hospitalization rates associated with atmospheric stressors [2, 6]. However, the areas of inpatient care and Intensive Care Units (ICU) are generally highly affected by high-capacity usage. In Germany, the ICU-utilization rate of 81.6% allows only a low buffer capacity to deal with a growing demand in the face of atmospheric impacts [7]. This vulnerability is further exacerbated by the ongoing shortage of specialized medical personnel and leads to an urgent need to examine how atmospheric factors influence the use of intensive care [8]. In order to prepare the German healthcare system for the new circumstances and establish a climate-resilient intensive care structure, the lack of evidence-based assessments had to be addressed.

The ALERT-ITS study, funded by the Innovation Fund of the German Federal Joint Committee, aims to address this gap by linking region-specific daily ICU data with daily atmospheric data. The aim is to quantify the atmospheric impact on intensive care demand at a regional level in Germany, by evaluating regional meteorological and air pollution events with respect to the number of ICU cases. The atmospheric intensive care results serve as a basis for short-term predictions and will be integrated into daily clinical practice to enable resource-optimized and environmentally adapted inpatient care.

MATERIALS AND METHODS

Data and data preparation

The study constitutes a time series regression analysis, as it used daily aggregated health data collected over several years and incorporated multiple predictors with individual time lags to capture delayed effects [9, 10]. In order to guarantee optimal clinical practice and ethical standards of the Declaration of Helsinki, the RECORD guidelines for processing routine health data were adhered to (Supplementary, Table 1) [11].

Patient and public involvement

The ALERT-ITS study is comprised of several constituent elements, namely the statistical analysis and the implementation of the results in the form of a digital application. The present paper discusses statistical evaluation of the relationship between health and the atmosphere on intensive care, with patients not being involved in this step in the process. The results of the study will be integrated into daily clinical practice, and the application will be used by physicians for planning the intensive care resources. The physicians participated in the development of the application through an iterative user-centered design process, and will evaluate the digital tool after a pilot study [12]. Consequently, the target group of the ALERT-ITS study will be engaged, and this paper will serve as a basis to identify the health-atmospheric associations.

Study sample and health data

Information on intensive care cases was derived from anonymized, nationwide routine data from the German healthcare system. The 15-year routine data (2009-2023) were provided by the AOK Research Institute (WIdO), which were derived from statutory health insurance data of eleven regional AOK insurances. A subgroup division was done based on age and sex characteristics. The age of 60 was set as the threshold because many physiological changes occur at this age, including an increase of individuals' susceptibility to disease [13–15]. These

characteristics divided the sample into four subgroups: female ≥ 60 years (FE), male ≥ 60 years (ME), female < 60 years (FY), and male < 60 years (MY).

Definition of Intensive Care Units (ICU)

The study focused on ICU cases in the inpatient sector. The operationalization of intensive care required a broader definition, given that not all hospitals have dedicated ICU or fulfil the billing criteria for complex intensive care treatment. The operation and procedure (OPS) code for intensive care complex treatment, the OPS code for intensive care patient monitoring, or the department code of ICU was used as a selection criterion (Supplementary, Table 2&3).

Definition of ICU-relevant diseases

The study only included cases of the 13 most common diagnoses in the ICU, providing a comprehensive overview [10, 16, 17]. The predefined diseases were classified using the International Statistical Classification Of Diseases And Related Health Problems, 10th revision, German Modification (ICD-10-GM) codes (Supplementary, Table 4). Neurological disorders (Transient Ischemic Attack (TIA), ischemic stroke, and non-subdural hemorrhage) were subdivided according to whether treatment was provided in an ICU or in a stroke unit (Supplementary, Table 5). In total, 16 disease-specific subdivisions were defined.

Regionalization

The classification of Germany into human-bioclimatic regions (HBC-regions) was based on seasonally resolved climatic variables. The climatic variables were derived from the ERA5-Land reanalysis dataset provided by the Copernicus Climate Data Store [18]. For the regionalization, a spatial principal component analysis was used to identify the optimal number of regions, and the grid boxes were assigned to the determined number of HBC-regions by means of a k-means cluster analysis. The regionalization identified six main regions, which were subdivided into up to three subregions using the aforementioned methods. Overall, the regionalization resulted in eleven HBC regions (Figure 1).

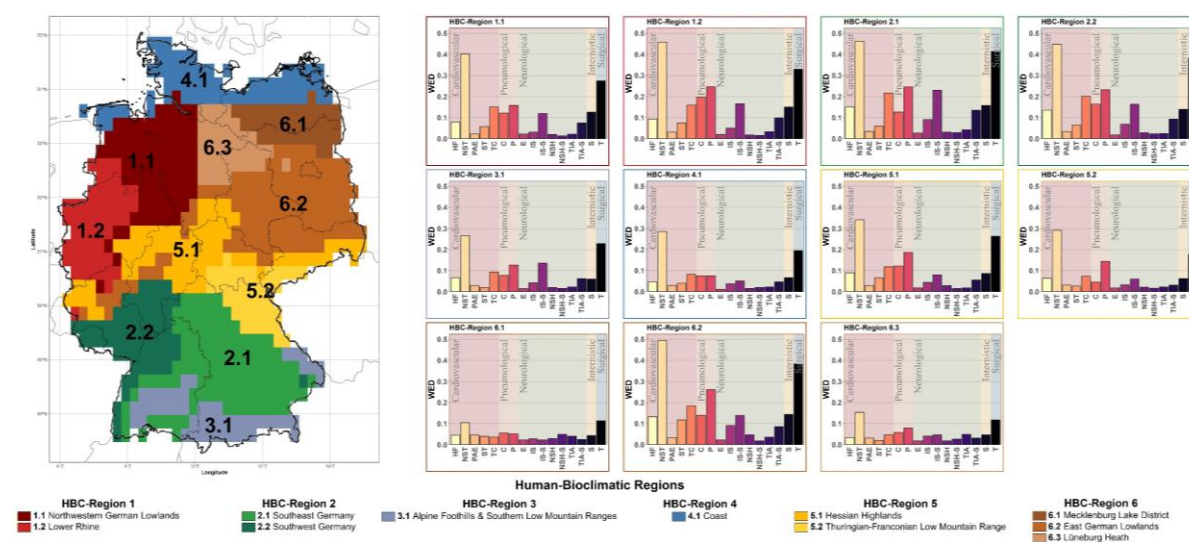


Figure 1. Regionalization across Germany and regional model performance (weighted explained deviance) per region and disease

Environmental factors

The study investigated atmospheric variables and indices associated with the selected intensive care diseases. Climatological data were represented by the ERA5 reanalysis data of the European Centre for Medium-Range Weather Forecasts (ECMWF), and air-hygienic data by the Copernicus Atmosphere Monitoring Service (CAMS) [18, 19]. 31 atmospheric variables and indices were extracted, aggregated and averaged to produce daily data for the region-specific models (Supplementary, Table 6).

Data quality assessment

Health data was checked for erroneous values within the ICD-10-GM coding system, and code definitions were checked to ensure internal validity [20, 21]. The health and atmospheric data set were checked regarding completeness, homogeneity, variability, outliers and trends. The quality of the atmospheric data was ensured by the Evaluation and Quality Control of the Copernicus Climate Change Service. The ERA5 and EAC4 data was already processed and checked for completeness by ECMWF and CAMS [22]. ECMWF performed data validation, anomaly checks, comparisons with other reanalysis products to ensure reliability and assessed for potential bias [23].

Statistical analyses

The aim was to identify relationships between daily inpatient and atmospheric data using regression analysis [9, 24]. All statistical analyses were performed using R (Version 4.5.1) and RStudio (Version 2025.05.1.513).

Data tests and basic statistics

The scale parameter was estimated to assess overdispersion ($\phi > 1$). Based on this, a quasi-Poisson distribution was applied to all regression analyses [24]. The generalized additive models (GAM) were used to account for nonlinear effects using the *R-package mgcv* [9, 26]. GAM are particularly useful for time series analyses that investigate the relationship between climate effects and health, and allow nonparametric adjustments for nonlinear effects [9, 14, 25, 26]. The atmospheric factors were divided into meteorological (up to ten lag days) and air quality predictors (up to seven days) [15, 26]. A disease-specific regression was performed, and the relative risk (RR) and its 95% confidence interval (CI) were calculated to select the optimal lag for each predictor [28]. In addition, several time variables were included in the GAM. The influence of the day of the week was included using a binary predictor in the model. Furthermore, the temporal trend was mapped in order to take the effects of long-term trends, e.g. from climate change into account [28]. The seasonality effects were analyzed with a sinusoidal and cosinusoidal component to consider seasonal fluctuations [29–32]. Sensitivity studies were conducted using cross-validation and tests for modifiers.

Statistical model

A specific set of atmospheric predictors per disease was created using the Bonferroni multiple testing strategy to counteract α -error accumulation ($\alpha \leq 0.05$) [33, 34]. Sensitivity studies using the Benjamini-Hochberg procedure were performed [35]. The daily ICU cases were assigned to the HBC-regions according to postal code. With this outcome data and predictor set, disease and subgroup-specific GAM were calculated for the eleven HBC-regions (Figure 1). In total, 704 different models (11 regions x 16 diseases x 4 subgroups) were created to detect

the regional association between the daily ICU cases per disease and atmospheric factors. Smoothed predictors were included in the models to represent nonlinear relationships. The thin plate regression splines with shrinkage were used as smoothing parameters [36, 37]. Splines captured the spatial relationships between patient data and weather variables in a flexible and adaptable way, and the smoothers were allocated wherever appropriate. If the smoothing effect was approximately linear, the smoother was removed [38]. The restricted maximum likelihood approach was used as it is optimal for smoothing and better suited for data with overdispersion [37]. Irrelevant terms were automatically shrunk to reduce the influence of these predictors (select = TRUE) [37]. Collinearity between the atmospheric variables was tested using the Spearman rank correlation coefficient to account for non-normally distributed data ($|\rho| \geq 0.7$) and the predictor with less significance was removed from the model [39].

Model performance

Explained deviance (ED) was used to evaluate the model performance and identify the best performing one. In order to assess the performance of the models independently of the subgroups, the disease-specific ED of the subgroups was weighted according to the proportion of the case numbers in the region and disease. A weighted mean was calculated, resulting in a weighted explained deviance (WED) value per disease. This allowed for comparing the models among individual diseases. For model validation and predictive quality, a blocked cross-validation for time series was performed.

RESULTS

Descriptive Results

Health data

The sample comprised 9,970,548 ICU patients (44% female, 74.3% persons ≥ 60 years). ME was the largest subgroup whereas the FY subgroup was the smallest one (Table 1). Regarding ventilation, clear differences between the subgroups were visible. People in the ME subgroup had around three times as many ventilation days and around five times as many daily ventilation hours compared to the FY subgroup (Table 1). The age distribution of obese ICU patients showed an inverse picture: Among ICU patients, the proportion of overweight individuals was higher in those under 60 compared to persons ≥ 60 years. Particularly for FY, a higher proportion of ICU patients were obese (Table 1).

Table 1. Descriptive statistics of the study sample and ranking of the most frequent intensive care related diseases, separated by subgroups

Subgroup	Distribution [%]	Diabetes [%]	Obese people [%]	Nursing home residents [%]	Proportion of days with ventilation [%]
ME	38.7	34.8	7.5	6.3	76.9
FE	35.6	33.9	8.6	10.9	67.6
MY	17.3	16.0	8.7	1.7	41.6
FY	8.4	14.1	10.0	1.7	27.2

Ranking of the most frequent intensive care relevant diseases, separated by subgroups

Subgroup	Ranking 1	Ranking 2	Ranking 3	Ranking 4	Ranking 5
ME	Trauma	Myocardial infarction (NSTEMI)	Ischemic stroke (stroke unit)	Sepsis	Pneumonia
FE	Trauma	Myocardial infarction (NSTEMI)	Ischemic stroke (stroke unit)	Sepsis	Heart failure
MY	Trauma	Myocardial infarction (NSTEMI)	Pneumonia	Myocardial infarction (STEMI)	Sepsis

FY	Trauma	Pneumonia	Myocardial infarction (NSTEMI)	Sepsis	Ischemic stroke (stroke unit)
----	--------	-----------	--------------------------------	--------	-------------------------------

Disease frequency

Due to its broad ICD-10-GM case definition, trauma accounted for the largest number of ICU cases. Ischemic strokes were common in the subgroups of people ≥ 60 years (Table 1). Among the respiratory diseases, pneumonia was the most frequent disease. During the 15-year period, the lowest ICU case numbers occurred in 2022–2023 for 10 of 16 diseases and in 2009 for the remaining six diseases. The most pronounced standardized increase in case numbers was observed for pneumonia, which may be attributable to the elevated incidence of pulmonary diseases during the COVID-19 pandemic.

Atmospheric data

A comparison of regional atmospheric characteristics revealed pronounced heterogeneity across the eleven HBC-regions (Figure 1). In Germany, HBC-region 5.2 was the coldest (mean: 27 ice days/year (daily $T_{\max} < 0^{\circ}\text{C}$), mean windchill index value (WCI): $5.4 \pm 7.4^{\circ}\text{C}$ (standard deviation, SD) and HBC-region 3.1 showed low temperatures (mean: 95.2 frost days/year (daily $T_{\min} < 0^{\circ}\text{C}$), no tropical nights (daily $T_{\min} > 20^{\circ}\text{C}$). In contrast, HBC-region 2.2 showed the highest heat burden (mean: 1.5 tropical nights/year, mean: 43.5 summer days/year (daily $T_{\max} > 25^{\circ}\text{C}$), mean: 9.6 hot days/year (daily $T_{\max} > 30^{\circ}\text{C}$), mean wet-bulb globe temperature (WBGT): $13.6 \pm 7.5^{\circ}\text{C}$ (SD)). The highest daily mean temperature ($10.7 \pm 6.8^{\circ}\text{C}$ (SD)) was observed in HBC-region 1.2 as well as the highest daily mean air pollutant levels for NO_2 ($8.2 \pm 3.7\text{ppb}$ (SD)) and PM_{10} ($19.5 \pm 6.6\mu\text{g}/\text{m}^3$ (SD)). HBC-region 2.2 had the highest daily mean $\text{PM}_{2.5}$ level ($13.5 \pm 6.5\mu\text{g}/\text{m}^3$ (SD)), while HBC-region 5.2 showed the highest daily mean ozone concentration (O_3 : $36.8 \pm 12.4\text{ppb}$ (SD)). Based on the health-atmosphere-regressions, the disease-specific predictor set included between six and 18 predictors (Table 2).

233 Table 2. Overview of the selected predictor set per disease

Disease	Predictor set
Myocardial infarction (STEMI)	Sea level pressure (SLP), Tropical night (TN), Coldwave Duration (CWDur), Hot day (HD), O ₃ , Summer day (SD)
Myocardial infarction (NSTEMI)	SLP, WCI, Wind day (WD), Frost day (FD), Heat stress wave duration (HSWDur), Heat stress wave intensity (HSWI), Heatwave (HW), PM ₁₀
Heart failure	SLP, Cold stress wave intensity (CSWI), SD, Cold stress wave day (CSWDay), Heatwave duration (HWDur), PM ₁₀ , Daily mean temperature (T), TN, Wet-bulb globe temperature (WBGT)
Pulmonary artery embolism	WD, O ₃ , TN, Heatwave intensity (HWI), Ice day (ID), SLP, Heat stress wave day (HSWDay), HSWI, HWDur, PM ₁₀ , sea level pressure difference (SLPD), SD, Wind chill index (WCI)
Tachycardia	TN, WD, CWDur, HD, Heatwave day (HWDur), HWI, O ₃ , SLP, WCI
Pneumonia	T, TN, WCI, O ₃ , Cold stress wave duration (CSWDur), CWDur, Coldwave intensity (CWI), NO ₂ , SLP, CSWI, Coldwave (CW), FD, HSWI, SLPD, WD
Chronic obstructive pulmonary disease (COPD)	O ₃ , Cold stress wave (CSW), PM ₁₀ , WBGT, CSWI, CW, CWDur, CWI, FD, Heat stress wave (HSW), HWI, ID, SLP, SLPD, T
Ischemic stroke	CWI, CSWDur, CSWI, HD, HSWI, O ₃ , PM ₁₀ , SLP, SD, T, TN, WD
Ischemic stroke (stroke unit)	SLPD, CSW, CSWDur, CSWI, CWDur, HSWDay, Heat stress wave intensity (HSWI), ID, TN, WBGT
Epilepsy	FD, O ₃ , CSW, CSWI, CWDur, HSWI, HWDur, PM _{2.5} , SLPD, WBGT, WD
Non subdural hemorrhage	T, WCI, WD, CSWDay, CWI, CSWI, HD, HW, HWDur, O ₃ , PM _{2.5} , SLP, SLPD, SD, TN, WBGT
Non subdural hemorrhage (stroke unit)	TN, O ₃ , WD, HD, HWI, WBGT, WCI
Transient ischemic attack	HW, SLPD, TN, CSW, CSWDay, CW, O ₃ , SD, WBGT
Transient ischemic attack (stroke unit)	NO ₂ , CSWDur, FD, HSW, PM ₁₀ , SLP, SD, WBGT, WCI, WD
Sepsis	CSWI, FD, WBGT, HWDur, SLP, SLPD, SD, T, WCI, WD

Trauma	WBGT, O ₃ , CWDur, FD, SLP, T, CSWI, HD, HSWDay, HW, HWD, HWI, ID, NO ₂ , PM ₁₀ , PM _{2.5} , TN, WCI
--------	--

Model results

Given the large number of models, the effect sizes of the individual models were not discussed in detail. Instead, the best-performing model was examined more thoroughly as a representative example.

Atmospheric influence on the ICU

To gain a general understanding of the atmospheric influence on ICU in Germany, the proportion of the significance of the factors across all models was evaluated (Supplementary, Table 7). Daily sea level air pressure (SLP), sea level air pressure difference (SLPD) and wind days (WD) had a widespread significant influence ($p \leq 0.05$) on the number of daily ICU cases (SLP: 29.3% of all models, SLPD: 20.2%, WD: 24.9%). In addition, climatological reference days such as tropical nights (TN = 18.2%), summer days (SD = 17.8%) and frost days (FD = 14.8%) were relevant. Thermo-physiological parameters, whether for cold (WCI = 10.4%) or heat (WBGT = 11.1%), had a minor influence on the number of ICU cases. O₃ was the most important air pollution factor and played a significant role in approximately 16% of the models (PM₁₀ = 9.1%, PM_{2.5} = 5.3%, NO₂ = 3.8%).

The relevance of the predictors varied for the different diseases. No atmospheric factor significantly influenced all diseases, though each factor played a role in at least one. SLP, O₃, and TN most frequently played a significant role (Supplementary, Table 7). Pressure- and cold-related indices were primarily associated with respiratory diseases. Warm events (TN, SD) showed a strong association with neurological diseases, while cardiovascular disease were influenced by a variety of atmospheric factors (TN, SD, O₃, PM₁₀, SLP, WD).

Sex- and age-specific differences

Sex-specific differences were identified. A significant association between ICU and atmospheric factors was less frequent in women. However, for both sexes pressure-related

variables proved to be decisive for the number of ICU cases (Supplementary, Table 8&9). Heat-related factors were more likely to be significant for men, for example WBGT (men: 13.1%, women: 9.1%). Regarding air pollutants, PM₁₀ and O₃ played a more decisive role in the models for women. Further distinctions emerged when looking at disease-specific sex differences: A cold stress wave significantly influenced TIA in 14% of female models, but not in any of the male models. In contrast, NO₂ significantly affected the number of traumatic diseases in more than twice as many male models as female models.

Analysis of age-related differences showed that in both age groups, pressure-related factors were the most significant influencing factors (≥60 years: SLP = 31.8%; <60 years: WD = 29.0%). For persons aged ≥60 years, heat-related atmospheric factors were the most significant influencing factors (Supplementary, Table 10). In the younger subgroup, more cold-related factors were found to be significantly relevant for the number of daily ICU cases (Supplementary, Table 11). Similar to the sex-specific analysis, O₃ was the most important air pollutant (15.6% for persons ≥60 and <60 years), whereas PM₁₀ played a role only in the younger subgroup (11.9%). In the disease-specific analyses, significant associations with heat-related indices were more common in individuals aged ≥60 years. In this age group, myocardial infarction ICU cases were twice as likely to be associated with summer days (SD), and pneumonia was almost twice as often associated with tropical nights (TN), compared to persons <60 years. In the younger subgroup, a significant association with particulate matter was more frequently detectable for neurological disorders.

Model performance

Out of the 704 models, the best one was for non-ST elevation myocardial infarction (NSTEMI) in subgroup ME in HBC-region 2.1 (ED = 56.6%). The best disease-specific model performance (including all subgroups) was observed for NSTEMI in HBC-region 6.2 (WED = 49.3%, Figure 1). NSTEMI was the best-performing model in almost all HBC-regions. Only in the HBC-region 6.1 demonstrated trauma a better performance (WED = 11.4%). Figure 1

displays the WED of the models across Germany for each disease and shows that HBC-regions 6.2 and 2.1 performed best across most diseases.

Best-performing model

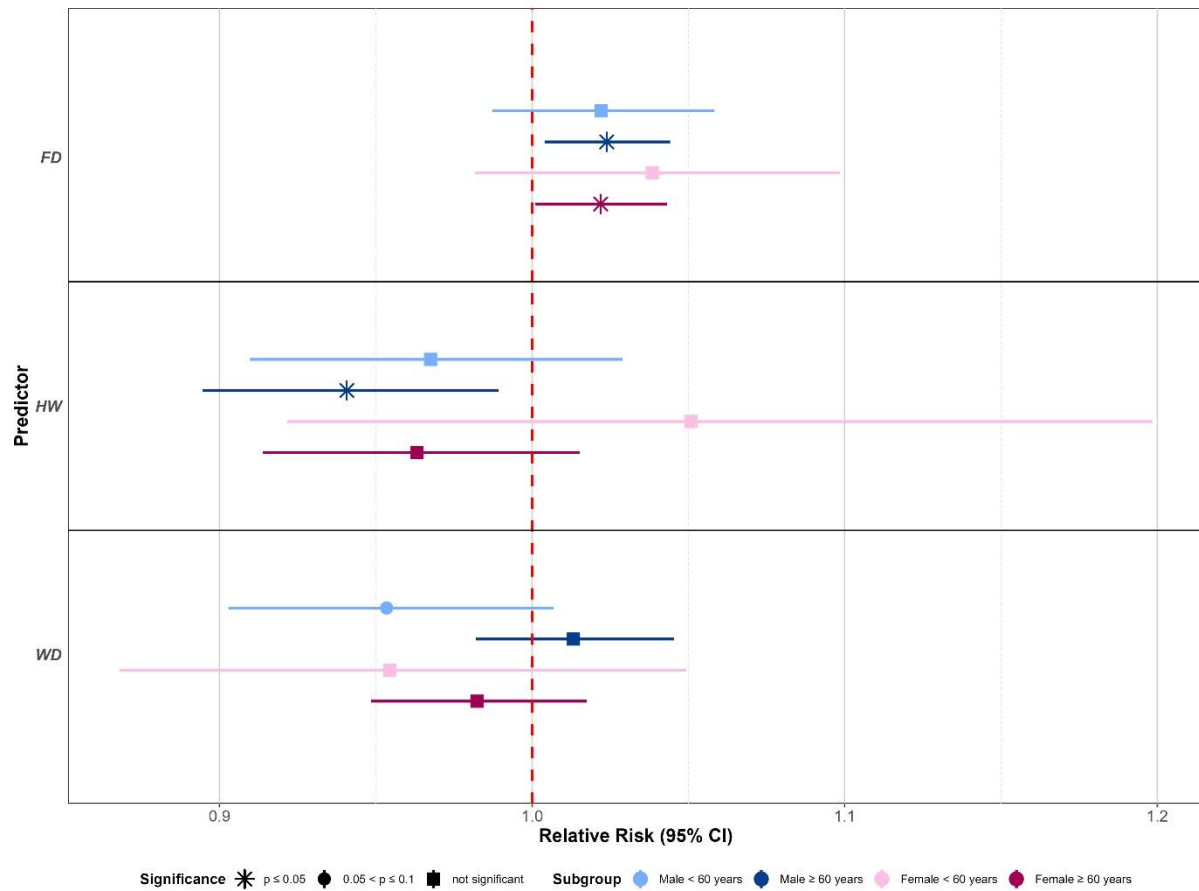
The model for NSTEMI in HBC-region 6.2 demonstrated the highest level of performance. Table 3 shows the statistical significance (p-value) and the type of association of all the atmospheric predictors. SLP played a significant role in the number of ICU cases of NSTEMI in all subgroups except for younger women ($p \leq 0.05$). Conversely, the intensity of a heat stress wave was found to be statistically significant for FY. WCI was only significant for men, and the duration of a heat stress wave had an influence on persons aged ≥ 60 years. PM_{10} showed no impact on the risk of developing a myocardial infarction across all models ($p > 0.1$).

Table 3. Significance and association table of NSTEMI models of all subgroups in HBC-region 6.2 (Orange = $p \leq 0.05$, green = $0.05 < p \leq 0.1$, blue = not significant, grey = not existent in the model set due to collinearity, + = positive association, - = negative association, ° = non-linear association)

Subgroup	Predictor							
	Wind day	Frost day	Heatwave	PM_{10}	Wind chill index	Sea level pressure	Heat stress wave duration	Heat stress wave intensity
FE	-	+	-	°	°	°	°	°
FY	-	+	+	°	°	°	°	°
ME	-	+	-	°	°	°	°	°
MY	-	+	-	°	°	°	°	°

Figure 2 represents a forest plot of the linear predictors. The statistical significance of RR was defined as the 95%-CI not including 1. FD increased the risk for ICU-relevant NSTEMI in persons ≥ 60 years by 2%, but with non-significant RR at 95%-CI (FE: RR = 1.02, 95%-CI [1.00-1.04]; ME: RR = 1.02, 95%-CI [1.00-1.04]). The occurrence of a heatwave exhibited a significant reduction of NSTEMI cases in ME by 6% (RR = 0.94, 95%-CI [0.89-0.99]). MY was the only subgroup influenced by WD ($0.05 < p \leq 0.1$, Table 3) and these days were

303 associated with a reduced risk of NSTEMI cases (Figure 2). However, the effect was not
304 statistically significant (RR = 0.95, 95%-CI [0.90-1.01]).



305 Figure 2. Forest plot of the linear predictors from NSTEMI models of all subgroups in HBC-region 6.2 (FD = frost
306 day, HW = heatwave, WD = wind day)

DISCUSSION

This study demonstrates that atmospheric factors influence intensive care utilization, with pronounced regional, age-, and sex-specific differences. The findings highlight the relevance of various atmospheric drivers for hospital intensive care demand.

Pressure-related factors had the greatest effect, even after controlling for collinearity among these factors and these results underscore the decisive role of air pressure on the ICU-demand. Another study confirms the link between air pressure and stroke incidence [40]. The influence of binary climatological reference days on ICU cases is consistent with literature: He et al. [28] demonstrated that nighttime temperature has a strong influence on stroke risk and other studies emphasize the link between temperature and mortality as well as cardiopulmonary diseases [4, 41]. Spell-length related indices (heat or cold stress waves) showed less frequent a significant association. However, earlier studies have reported an association between heatwaves and various diseases, but the inconsistent definitions of spell-length temperature-related indices as well as differences in the health outcome variables makes a comparison difficult [10, 42]. Thermo-physiological parameters played an important role in many models and supported the assumption that variables, which combine temperature, humidity and radiation are relevant for the demand of ICU treatments in Germany. The German Weather Service already uses perceived temperature to assess the thermal environment in terms of health and forwards warning levels to health authorities [43]. Future studies should consider thermo-physiological indices in order to describe thermal stress more accurately. The most important air pollutant in mapping the atmospheric-ICU-association was O_3 . The fact that O_3 is relevant to intensive care and thus influences healthcare provision structures is supported by the general effects of O_3 on health [44].

Sex-specific analyses revealed that particulate matter was associated with ICU cases in women and this increased vulnerability of women to air pollution has already been described in the literature [45]. At the same time, men in this study were more affected by heat-related

atmospheric factors. Overall, the male subgroups showed significant associations with atmospheric conditions more frequently and with more factors than the female subgroups. This may indicate a lower susceptibility of women to atmospheric influences, potentially related to higher health awareness and preventive care use [46]. Additionally, men are often more exposed to heat, noise, and air pollution at work, which could lead to higher stress levels and health risk [47]. Age-specific differences demonstrated that, heat events had the greatest impact on people ≥ 60 years. Gronlund et al. [48] investigated the impact of extreme heat and heatwaves on people ≥ 60 years of age. Other studies report increased hospital admissions and emergency room visits among elderly people during heatwaves. However, there are also protective effects depending on heatwave duration and the disease under consideration [10, 49].

The models for NSTEMI and trauma showed the best model performances. Both diseases were among the diagnoses with the highest number of cases. This large database may in turn have favored model performance, as it allowed for more stable associations to be calculated. A similar effect should be considered when looking at the regional differences: HBC-regions 6.2 and 2.1 accounted for the highest number of cases, which could explain the greater statistical significance in these regions. In the best-performing model (myocardial infarction, HBC-region 6.2), heatwave occurrence was associated with a reduced risk of ICU-relevant NSTEMI among men, while heat stress wave duration and intensity were associated with elderly and women. These findings could be supported by previous studies, which have established associations between heatwaves and cardiovascular outcomes [17, 50]. Fine particulate matter has been linked to vascular damage and myocardial infarction, whereas PM_{10} showed in this study no significant association with NSTEMI [51]. These findings should be interpreted with caution, as air pollution was assessed using regional averages, which may obscure localized exposure effects. In HBC-region 6.2, cold temperatures were identified as a risk factor for NSTEMI among individuals ≥ 60 years, which may be facilitated by increased blood viscosity and arterial pressure [52].

The study used routine data, which is more suitable for reflecting the actual reality of healthcare provision. Compared to studies with primary data collection, secondary data is cost-effective and comparatively faster to obtain. Another advantage is the high number of cases and the possibility of analyzing subgroups [20]. Changes in the ICD-10-GM coding were checked and incorporated into the case selection. An a priori assessment of the most important ICU-relevant diseases was conducted, and the consideration of the different HBC-regions in Germany led to diverse results. In addition, analyzing atmospheric-health effects separately by age and sex may help medical personnel to address the specific needs of different population groups more effectively. Nevertheless, the study was limited in scope because the sample consisted exclusively of AOK-insured individuals. The age and sex structure of the inhabitants in Germany differ from the AOK population and this selection bias leads to a limited external validity. However, AOK patients account for almost one third of the German population [53]. The AOK routine data represents claims data and coding biases may occur due to monetary disincentives, which could affect the validity of routine data [20]. During the study period, a decline in ICU-utilization was observed, with a significant decrease during the period of the coronavirus pandemic. Levels of patient treatments did not return to those seen in 2019. Based on this, the pandemic years were not excluded as there had been a lasting change in healthcare structures [54].

In conclusion, this study introduces an innovative environmental modelling approach that combines atmospheric factors with ICU data across Germany using human-biometeorological regions. This region-specific framework enables new insights into how distinct climatic conditions affect ICU admissions, by incorporating a variety of weather and air pollution variables. The atmosphere-health association showed regional, age and sex heterogeneity in the intensive care demand. Therefore, the healthcare system needs to be better prepared. All study results will serve as the basis for atmospheric short-term demand forecasts for ICU. These projections can then be integrated into daily clinical practice to facilitate resource-optimized inpatient care.

Acknowledgements

The abbreviation ALERT-ITS is based on the complete name of the study, “Development of a prediction and monitoring model for regional forecasting of intensive care and ventilation needs based on atmospheric factors”.

Competing Interests

The authors declare no competing interests.

Funding

Research reported in this publication was supported by the German Innovation Fund (grant number 01VSF23015).

Author Contributions

Conceptualization: EH, KS, CM. Literature search: KS, PB. Disease and intensive care medicine definition: PB, BW, TB, TR. Data preparation – Health data: TR, TB, PD. Data preparation – atmospheric data and regionalization: MJ, CM, KS. Data analysis and model selection: KS, CM, EH. Writing – original draft preparation: KS, CM, EH. Writing – review and editing: all authors.

Ethical Approval

This study protocol was approved by the local ethics committee in Munich and registered in the German clinical trials register (DRKS00034441). The analysis was anonymized secondary data and informed consent was not required. A data protection concept was adopted in collaboration with the AOK Research Institute. A license agreement and declarations of commitment were signed by the scientists conducting the analysis. All methods were performed in accordance with the relevant guidelines and regulations.

Data sharing statement

The authors confirm that the health data utilized in this study cannot be made available in the manuscript, the supplemental files, or in a public repository due to German data protection laws ('Bundesdatenschutzgesetz', BDSG). Therefore, they are stored on a secure drive in the WIdO, to facilitate replication of the results. Generally, access to data of statutory health insurance funds for research purposes is possible only under the conditions defined in German Social Law (SGB V § 287). Requests for data access can be sent as a formal proposal specifying the recipient and purpose of the data transfer to the appropriate data protection agency. Access to the data used in this study can only be provided to external parties under the conditions of the cooperation contract of this research project and after written approval by the sickness fund. For assistance in obtaining access to the data, please contact wido@wido.bv.aok.de. The atmospheric data sets are available in a public, open access repository. The reanalysis data for the atmospheric conditions is available on the ECMWF website (<https://cds.climate.copernicus.eu/datasets/reanalysis-era5-pressure-levels?tab=overview>) and the air hygiene data on the CAMS website (<https://ads.atmosphere.copernicus.eu/datasets/cams-global-reanalysis-eac4?tab=download>).

REFERENCES

1. Abed Al Ahad M, Chalak A, Fares S, Mardigian P, Habib RR. Decentralization of solid waste management services in rural Lebanon: Barriers and opportunities. *Waste management & research : The Journal for a Sustainable Circular Economy*. 2020;38:639–48. doi:10.1177/0734242X20905115.
2. Abed Al Ahad M, Sullivan F, Demšar U, Melhem M, Kulu H. The effect of air-pollution and weather exposure on mortality and hospital admission and implications for further research: A systematic scoping review. *PLoS One* 2020. doi:10.1371/journal.pone.0241415.
3. Rus A-A, Mornoş C. The Impact of Meteorological Factors and Air Pollutants on Acute Coronary Syndrome. *Curr Cardiol Rep*. 2022 Oct;24:1337–49. doi:10.1007/s11886-022-01759-5.
4. García-León D, Masselot P, Mistry MN, Gasparrini A, Motta C, Feyen L, Ciscar J-C. Temperature-related mortality burden and projected change in 1368 European regions: a modelling study. *The Lancet Public Health*. 2024;9:e644-e653. doi:10.1016/S2468-2667(24)00179-8.
5. Golden CD, Childs ML, Mudele OE, Andriamizarasoa FA, Bouley TA, Nicola G de, et al. Climate-smart public health for global health resilience. *The Lancet Planetary Health*. 2025;9:101293. doi:10.1016/j.lanplh.2025.101293.
6. Masselot P, Mistry M, Vanoli J, Schneider R, lungman T, Garcia-Leon D, et al. Excess mortality attributed to heat and cold: a health impact assessment study in 854 cities in Europe. 2023;7:e271-e281. doi:10.1016/S2542-5196(23)00023-2.
7. Intensivregister DIVI. Zeitreihen: Gesamtzahl gemeldeter Intensivbetten (Betreibbare Betten und Notfallreserve). 2025. <https://www.intensivregister.de/#/aktuelle-lage/zeitreihen>. Accessed 31 Jul 2025.
8. Karagiannidis C, Janssens U, Kluge S, Walcher F, Marx G. Intensivstationen: Ein Drittel der Betten ist gesperrt. *Deutsches Ärzteblatt*. 2021;118:A1908-1909.

9. Bont J de, Krishna B, Stafoggia M, Banerjee T, Dholakia H, Garg A, et al. Ambient air pollution and daily mortality in ten cities of India: a causal modelling study. *The Lancet Planetary Health*. 2024;8:e433-e440. doi:10.1016/S2542-5196(24)00114-1.
10. Sohail H, Kollanus V, Tiittanen P, Schneider A, Lanki T. Heat, Heatwaves and Cardiorespiratory Hospital Admissions in Helsinki, Finland. *Int J Environ Res Public Health*. 2020;17:7892. doi:10.3390/ijerph17217892.
11. Benchimol EI, Smeeth L, Guttman A, Harron K, Moher D, Petersen I, et al. The REporting of studies Conducted using Observational Routinely-collected health Data (RECORD) statement. *PLoS Med*. 2015;12:e1001885. doi:10.1371/journal.pmed.1001885.
12. Ignatenko Y, Cramer S, Meyer P, Schaumann M, Pröll L, Hinske LC, et al. User-Centered Design of ALERT-ITS: An ICU Bed Forecasting Monitoring System. In: Andrikopoulou E, Gallos P, Arvanitis TN, Austin R, Benis A, Cornet R, et al., editors. *Intelligent Health Systems – From technology to data and knowledge*: IOS Press; 2025. p. 522–526. doi:10.3233/shti250392.
13. Peng RD, Bobb JF, Tebaldi C, McDaniel L, Bell ML, Dominici F. Toward a quantitative estimate of future heat wave mortality under global climate change. *Environ Health Perspect*. 2011 May;119:701–6. doi:10.1289/ehp.1002430.
14. Li Y, Wang X-L, Zheng X. Impact of weather factors on influenza hospitalization across different age groups in subtropical Hong Kong. *Int J Biometeorol*. 2018;62:1615–24. doi:10.1007/s00484-018-1561-z.
15. Chen K, Breitner S, Wolf K, Hampel R, Meisinger C, Heier M, et al. Temporal variations in the triggering of myocardial infarction by air temperature in Augsburg, Germany, 1987-2014. *Eur Heart J*. 2019;40:1600–8. doi:10.1093/eurheartj/ehz116.
16. Bai L, Li Q, Wang J, Lavigne E, Gasparrini A, Copes R, et al. Hospitalizations from hypertensive diseases, diabetes, and arrhythmia in relation to low and high temperatures: population-based study. *Sci. Rep*. 2016 Jul;6:30283. doi:10.1038/srep30283.

17. Bein T, Karagiannidis C, Gründling M, Quintel M. Neue intensivmedizinische Herausforderungen durch Klimawandel und globale Erderwärmung. *Der Anaesthesist*. 2020;69:463–9. doi:10.1007/s00101-020-00783-w.
18. Muñoz-Sabater J. ERA5-Land hourly data from 1950 to present: Copernicus Climate Change Service (C3S) Climate Data Store (CDS). 2019. DOI: 10.24381/cds.e2161bac. Accessed 13 Mar 2024.
19. Inness A, Ades M, Agustí-Panareda A, Barré J, Benedictow A, Blechschmidt A-M, et al. The CAMS reanalysis of atmospheric composition. *Atmospheric Chemistry and Physics*. 2019;19:3515–56. doi:10.5194/acp-19-3515-2019.
20. Slagman A, Hoffmann F, Horenkamp-Sonntag D, Swart E, Vogt V, Herrmann WJ. Analyse von Routinedaten in der Gesundheitsforschung: Validität, Generalisierbarkeit und Herausforderungen. *Z Allg Med*. 2023;99:86–92. doi:10.1007/s44266-022-00004-0.
21. Horenkamp-Sonntag D, Schneider U, Engel S, Linder R, Gerste B, Ihle P. Validität von GKV-Routinedaten: In welchem Umfang muss bei der wissenschaftlichen Nutzung von Sekundärdaten die Daten-Qualität geprüft werden? *Zeitschrift für Palliativmedizin*. 2014;15:1615–2921. doi:10.1055/s-0034-1374464.
22. Isaksen I, Bonavita M, Buizza R, Fisher M, Haseler J, Leutbecher M, Raynaud L. Ensemble of Data Assimilations at ECMWF: ECMWF Technical Memoranda. ECMWF 2010 Dec. doi:10.21957/obke4k60.
23. Hersbach H, Bell B, Berrisford P, Hirahara S, Horányi A, Muñoz-Sabater J, et al. The ERA5 global reanalysis. *Quart J Royal Meteorol Soc*. 2020 May;146:1999–2049. doi:10.1002/qj.3803.
24. Cameron A, Trivedi PK. Regression-based tests for overdispersion in the Poisson model. *Journal of Econometrics*. 1990;46:347–64. doi:10.1016/0304-4076(90)90014-K.
25. Ravindra K, Rattan P, Mor S, Aggarwal AN. Generalized additive models: Building evidence of air pollution, climate change and human health. *Environment International*. 2019 Nov;132:104987. doi:10.1016/j.envint.2019.104987.

26. Kuźma Ł, Dąbrowski EJ, Kurasz A, Święczkowski M, Jemielita P, Dobrzycki S, Lip GYH. Short and mid-term impact of ozone on myocardial infarction incidence in Poland. *Lancet Reg Health Eur*. 2024 Jun 22;43:100982. doi:10.1016/j.lanepe.2024.100982.
27. He Y, Zhang X, Gao J, Gao H, Cheng J, Xu Z, et al. The impact of cold spells on schizophrenia admissions and the synergistic effect with the air quality index. *Environ Res*. 2022 Sep;212:113243. doi:10.1016/j.envres.2022.113243.
28. Hertig E, Meisinger C, Schneider A, Peters A, Scheidt W von, Kuch B. Meteorologische Faktoren gesundheitsrelevanter troposphärischer Ozonkonzentrationen am Beispiel täglicher Herzinfarktfälle in der Region Augsburg. In: Soentgen J, Gassner UM, Hayek J von, Manzei A, editors. *Umwelt und Gesundheit*. Baden-Baden: Nomos; 2020. p. 305–322.
29. Bhaskaran K, Gasparrini A, Hajat S, Smeeth L, Armstrong B. Time series regression studies in environmental epidemiology. *Int J Epidemiol*. 2013 Aug;42:1187–95. doi:10.1093/ije/dyt092.
30. Nyoka R, Omony J, Mwalili SM, Achia TNO, Gichangi A, Mwambi H. Effect of climate on incidence of respiratory syncytial virus infections in a refugee camp in Kenya: A non-Gaussian time-series analysis. *PLoS One*. 2017 Jun 1;12:e0178323. doi:10.1371/journal.pone.0178323.
31. Touloumi G, Samoli E, Pipikou M, Le Tertre A, Atkinson R, Katsouyanni K. Seasonal confounding in air pollution and health time-series studies: effect on air pollution effect estimates. *Stat Med*. 2006 Dec;25:4164–78. doi:10.1002/sim.2681.
32. Colón-González FJ, Fezzi C, Lake IR, Hunter PR. The effects of weather and climate change on dengue. *PLOS Neglected Tropical Diseases*. 2013 Nov 14;7:e2503. doi:10.1371/journal.pntd.0002503.
33. Bland JM, Altman DG. Multiple significance tests: the Bonferroni method. *BMJ*. 1995 Jan 21;310:170. doi:10.1136/bmj.310.6973.170.
34. Bender R, Lange S, Ziegler A. Multiples Testen. *Dtsch Med Wochenschr*. 2007;132 Suppl 1:e26-9. doi:10.1055/s-2007-959035.

35. Benjamini Y, Hochberg Y. Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society: Series B (Methodological)*. January 1995;57:289–300. doi:10.1111/j.2517-6161.1995.tb02031.x.
36. Peng RD, Dominici F, Louis TA. Model Choice in Time Series Studies of Air Pollution and Mortality. *Journal of the Royal Statistical Society Series A: Statistics in Society*. 2006 Mar;169:179–203. doi:10.1111/j.1467-985X.2006.00410.x.
37. Wood SN. *Generalized Additive Models: An introduction with R*. Second Edition. CRC Press 2017. doi:10.1201/9781315370279.
38. Amin R, Ar Salan MS, Hossain MM. Measuring the impact of responsible factors on CO2 emission using generalized additive model (GAM). *Heliyon*. 2024;10:e25416. doi:10.1016/j.heliyon.2024.e25416.
39. Yildizhan H, Udriștioiu MT, Pekdogan T, Ameen A. Observational study of ground-level ozone and climatic factors in Craiova, Romania, based on one-year high-resolution data. *Scientific reports*. 2024 Nov 5;14:26733. doi:10.1038/s41598-024-77989-0.
40. Ertl M, Beck C, Kühlbach B, Hartmann J, Hammel G, Straub A, et al. New Insights into Weather and Stroke: Influences of Specific Air Masses and Temperature Changes on Stroke Incidence. *Cerebrovasc Dis*. 2019;47:275–84. doi:10.1159/000501843.
41. Zhang S, Breitner S, Donato F de', Stafoggia M, Nikolaou N, Aunan K, et al. Heat and cause-specific cardiopulmonary mortality in Germany: a case-crossover study using small-area assessment. *Lancet Reg Health Eur*. 2024 Sep 6;46:101049. doi:10.1016/j.lanepe.2024.101049.
42. Xu Z, FitzGerald G, Guo Y, Jalaludin B, Tong S. Impact of heatwave on mortality under different heatwave definitions: A systematic review and meta-analysis. *Environment International*. 2016 Apr-May;89-90:193–203. doi:10.1016/j.envint.2016.02.007.
43. Matzarakis A. Das Hitzewarnsystem des Deutschen Wetterdienstes (DWD) und seine Relevanz für die menschliche Gesundheit. *Gefahrstoffe-Reinhaltung der Luft*. 2016;76:457–60.

44. Turner MC, Jerrett M, Pope CA, Krewski D, Gapstur SM, Diver WR, et al. Long-Term Ozone Exposure and Mortality in a Large Prospective Study. *Am J Respir Crit Care Med*. 2016 May 15;193:1134–42. doi:10.1164/rccm.201508-1633OC.
45. Su B, Liu C, Chen L, Wu Y, Li J, Zheng X. Long-term exposure to PM_{2.5} and O₃ with cardiometabolic multimorbidity: Evidence among Chinese elderly population from 462 cities. *Ecotoxicology and Environmental Safety*. 2023;255:114790. doi:10.1016/j.ecoenv.2023.114790.
46. Jordan S. Inanspruchnahme präventiver Maßnahmen. Eine Analyse von Einflussfaktoren auf die Nutzung von Verhaltensprävention bei Erwachsenen. Bielefeld: Universität Bielefeld; 2020.
47. Keller D, Hornberg C, Niggemann H, Neuhann HF, Ranft U, Dott W, Wiesmüller GA. Geschlechterassoziierte Expositionen bei Patienten einer umweltmedizinischen Beratungsstelle. *Arbeitsmed. Sozialmed. Umweltmed*. 2005;40:342–53.
48. Gronlund CJ, Zanobetti A, Schwartz JD, Wellenius GA, O'Neill MS. Heat, heat waves, and hospital admissions among the elderly in the United States, 1992-2006. *Environ Health Perspect*. 2014 Nov;122:1187–92. doi:10.1289/ehp.1206132.
49. Bobb JF, Obermeyer Z, Wang Y, Dominici F. Cause-specific risk of hospital admission related to extreme heat in older adults. *JAMA*. 2014 Dec 24-31;312:2659–67. doi:10.1001/jama.2014.15715.
50. Mason H, C King J, E Peden A, C Franklin R. Systematic review of the impact of heatwaves on health service demand in Australia. *BMC Health Serv Res*. 2022 Jul 28;22:960. doi:10.1186/s12913-022-08341-3.
51. Münzel T, Sørensen M, Gori T, Schmidt FP, Rao X, Brook FR, et al. Environmental stressors and cardio-metabolic disease: part II—mechanistic insights. *European heart journal*. 2017 Feb;38:557–64. doi:10.1093/eurheartj/ehw294.
52. Analitis A, Katsouyanni K, Biggeri A, Baccini M, Forsberg B, Bisanti L, et al. Effects of cold weather on mortality: results from 15 European cities within the PHEWE project. *Am J Epidemiol*. 2008 Dec 15;168:1397–408. doi:10.1093/aje/kwn266.

- 591 53. Schmuker C, Polte C, Beydoun G, Günster C. Diagnosehäufigkeit und Inanspruchnahme
592 von Gesundheitsleistungen. In: Günster C, Klauber J, Klemperer D, Nothacker M, Robra
593 B-P, Schmuker C, editors. Versorgungs-Report Leitlinien: Evidenz für die Praxis. Berlin:
594 Medizinisch Wissenschaftliche Verlagsgesellschaft; 2023. p. 257–289.
595 doi:10.32745/9783954668007-21.
- 596 54. Hentschker C, Mostert C, Klauber J. Auswirkungen der Covid-19-Pandemie im
597 Krankenhaus: Fallzahlentwicklung und Charakteristika der Covid-19-Patienten. In:
598 Klauber J, Wasem J, Beivers A, Mostert C, editors. Krankenhaus-Report 2023. Berlin,
599 Heidelberg: Springer; 2023. doi:10.1007/978-3-662-66881-8_19.