Master of Public Health

Master de Santé Publique

Short-Term Ambient Temperature Exposure and Momentary Depressive Symptoms in Older Adults: A GEMA Study Using Distributed Lag Models

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Table of content

Abstract

Background: As climate change intensifies, short-term exposure to ambient temperature has emerged as a key environmental determinant of mental health. Older adults are especially vulnerable to thermal stress due to physiological sensitivity and increased risk of mood disorders.

Objectives: This study investigates the relationship between short-term ambient temperature exposure and momentary depressive symptomatology in older adults, with a focus on temporal dynamics.

Methods: Using high-resolution GPS and ecological momentary assessment (EMA) data from 216 participants aged 60 and over in the Paris metropolitan area, we employed distributed lag linear models to estimate the effects of immediate and lagged temperature exposure (1–8 hours and 24 hours) on depressive symptomatology. Models were adjusted for questionnaire item, age, sex, education level, employment status, household income, baseline CES-D score, time of day, and season

Results

A total of 3,581 EMA questionnaires from 216 older adults yielded 7,197 depressive symptom items for analysis. Distributed lag linear models revealed a consistent positive association between ambient temperature and momentary depressive symptoms. Statistically significant associations were detected during the hour immediately preceding symptom assessment and from lag hours 6 through 24. The estimated effect of a 1°C increase in immediate temperature on depressive symptom scores peaked at lag 7 ($\beta = 0.014$; 95% CI: 0.003, 0.025), with slightly attenuated estimates at longer lags. Precision increased with longer exposure windows, reflected in narrower confidence intervals. Models using weighted lag structures yielded stronger and more precise associations than unweighted ones. Sensitivity analyses confirmed the robustness of findings: estimates were higher among participants with full lag coverage, and results remained directionally consistent when using maximum temperature or adjusting for humidity, though the latter showed no significant effects.

Conclusion

Our findings show a positive association between short-term temperature exposure and momentary depressive symptoms in older adults. These results suggest that even moderate ambient temperature increases—below heatwave thresholds—can influence subclinical

mood changes. This highlights the importance of integrating temperature-sensitive indicators into mental health surveillance and urban adaptation strategies. Future work should explore nonlinear exposure-response relationships, contextual modifiers such as season and indoor environments, and incorporate other environmental stressors like air pollution to enhance risk prediction and resilience planning.

Introduction

Climate change represents an escalating public health crisis, with rising global temperatures and an increase in heatwaves posing significant risks to mental health (Thompson et al., 2023). Several findings emphasize the need for climate-sensitive mental health strategies to mitigate these risks (Clery et al., 2024). Among the populations most affected by these environmental changes, older adults have been identified as particularly vulnerable due to their heightened sensitivity to temperature fluctuations and associated health risks.

White et al. (2023), after reviewing 104 articles on the topic of climate change and vulnerable populations, found that older adults are disproportionately impacted by elements like increased temperature; precipitation extremes; extreme weather events; and sea level rise, experiencing conditions such as solastalgia, depression, suicidality, PTSD, insomnia, and anxiety. This suggests that rising global temperatures may have persistent psychological consequences, particularly for aging populations. These findings have been corroborated by recent research showing that older adults exhibit increased sensitivity to heat, reporting greater thermal discomfort and perceiving higher ambient temperatures as more intense during summer conditions, specifically at temperatures above 22 °C (Meidenbauer et al., 2024). Furthermore, research has demonstrated that older adults have a higher mortality change rate (MCR = 1.11) at 35°C compared to younger individuals (MCR = 1.07), with elderly outdoor workers facing additional risks regardless of age or region (Park et al., 2019). Similarly, Noelke et al. (2016) observed that adults over 46 experience greater declines in emotional well-being compared to younger individuals when exposed to high temperatures. Additionally, Chen et al. (2019) found that the elderly, particularly men aged 65 and older, were the most vulnerable to heat-related depression, reinforcing the notion that climate change may have long-lasting psychological effects on this population.

While older adults are physiologically more vulnerable to extreme heat, studies suggest they may exhibit greater emotional resilience. Research in Chicago found that although they experience more discomfort at higher temperatures, older individuals regulate emotions more effectively than younger adults, who react more negatively to heat (Meidenbauer et al., 2024). Huang et al. (2023) similarly observed that distress levels generally decreased with age ($p < 0.01$), except for an increase among those aged 70–79 years.

These findings highlight the complexity of the relationship between aging, temperature sensitivity, and mental health outcomes, indicating that while older individuals are physically more vulnerable, their perception and emotional response to heat may differ from those of younger populations. Taken together, these studies suggest that although elderly individuals face higher hospitalization rates and physiological risks from heat exposure, they do not necessarily report the highest levels of negative emotions related to heat. This could be attributed to their more conservative and balanced perception of what constitutes a comfortable temperature, as well as potential adaptive mechanisms that allow them to better manage thermal discomfort. Nonetheless, the interplay between physiological vulnerability and emotional resilience warrants further investigation to develop targeted climate adaptation strategies that address both physical and psychological well-being in aging populations.

At the same time, the increase of temperature has been consistently associated with mental health issues, including increased suicide rates, hospitalizations, and the prevalence of depressive disorders. For example, Chen et al. (2019) examined the relationship between long-term exposure to high temperatures and major depressive disorder (MDD), revealing a non-linear association. Individuals residing in regions with average temperatures between 20–23°C had the lowest risk of developing MDD. However, in areas where temperatures exceeded 23°C, each 1°C increase was associated with a 7% higher risk of MDD.

Regarding hospitalizations, Bundo et al. (2021) found that in Switzerland, a 10°C increase in mean daily temperature led to a 4.0% rise in mental health hospitalization risk. A similar trend was observed in California, where a 5°C (10°F) increase in same-day mean apparent temperature correlated with a 4.8% increase in mental health-related ER visits, a 5.8% rise in self-injury/suicides, and a 7.9% increase in homicides during the warm season, with similar effects in colder months (Basu et al., 2017). Additionally, Thompson et al. (2023) reported a 9.7% increase in psychiatric hospitalizations during heatwaves.

For suicide rates, Bär et al. (2022) analyzed Swiss data (1995–2016) and found that suicide risk increased by 34% from the 10th to the 99th temperature percentile, with a lag of 0–2 days. This non-linear trend was consistent nationwide, highlighting rising temperatures as a significant suicide risk factor and emphasizing the need for targeted prevention strategies. Furthermore, evidence suggests a strong link between ambient temperature and adverse mental health outcomes, with each 1°C increase correlating with a 1.7% rise in suicides (Thompson et al., 2023).

Understanding the impact of ambient temperature is essential not only for severe mental health outcomes such as morbidity and mortality but also for more subtle daily mood fluctuations. These variations can serve as early indicators of mental health deterioration, particularly in vulnerable populations (Bundo et al., 2023). For example extreme temperatures exacerbate stress, emotional distress, and social instability, further deteriorating community mental health and well-being (Thompson et al., 2023). A large-scale study analyzing data from 1.9 million U.S. respondents (2008–2013) found that increasing ambient temperatures significantly reduce emotional well-being (Noelke et al., 2016). Compared to a reference range of 50–60°F (10–16°C), daily temperatures above 70°F (21°C) led to a decline in well-being, with temperatures exceeding 90°F (32°C) reducing well-being by 4.4% of a standard deviation ($p < 0.01$) (Noelke et al., 2016). Similarly, Huang et al. (2023) found that temperatures above 32°C significantly increased emotional distress, with 33–35°C causing restlessness and anxiety ($p < 0.05$), 35–36°C leading to mood instability, and temperatures above 37°C resulting in extreme agitation and potential violence.

As shown before, different approaches have been taken to study the relationship between temperature and depression. One method increasingly used to obtain real-time, real-world data is ecological momentary assessment (EMA). For example, Meidenbauer et al. (2024) analyzed EMA data alongside high-resolution climate-modeled weather data to assess the effects of hot versus neutral days on emotional states at an individual time level. Their findings indicated that hot days increased thermal discomfort and lowered emotional well-being, with thermal discomfort being the key predictor of negative affect.

While several studies employing ecological momentary assessment (EMA) have explored the relationship between temperature and depressive symptoms, the evidence remains inconsistent. Although temperature appears to influence momentary depression, the precise pattern of this association is not yet clearly established. For instance, Bundo et al. (2023) reported that a 5°C increase in daily maximum temperature was associated with a 7% reduction in the likelihood of experiencing a bad mood in the general population. This effect remained significant, though attenuated (3%), after adjusting for sunshine duration (Bundo et al. 2023). On the other hand, Clery et al. (2024) found that higher temperatures were linked to a slight reduction in depressive symptoms (−0.2% per °C) and an increase in manic symptoms (+0.4% per °C), with marked seasonal variation: depressive symptoms decreased most in spring and summer, while manic symptoms increased in autumn. The authors attributed the lack of a stronger association with depressive symptoms to their inclusion of a broader temperature spectrum, contrasting with prior studies that focused predominantly on extreme heat or deviations from an optimal thermal range. Collectively, these findings suggest that moderate temperature increases may have mood-enhancing effects, whereas extreme heat could exacerbate depressive symptoms, contingent on whether the temperature is perceived as comfortable or excessive.

Expanding on the seasonal dimension, Zhang et al. (2023) found that higher winter temperatures were associated with better mood, whereas summer heat had adverse effects. Importantly, they also reported that relative humidity was not significantly associated with mood, highlighting the role of thermal perception over objective humidity metrics. Their findings underscore the context-dependent nature of temperature effects on mental health, which vary by season, individual sensitivity, and subjective experience of comfort. Regarding temporality, Zhang et al. 2023 observed that temperature was significantly and positively associated with mood only in models incorporating a 12-hour lag ($\beta = 0.180$, $p < 0.05$) and an 8-hour lag ($\beta = 0.181$, $p < 0.05$), suggesting that the psychological effects of ambient temperature may manifest with a delay rather than only a occurring immediately. This supports the use of lagged exposure windows in studies assessing short-term thermal effects on psychological states.

Given the complexity and context-dependence of the relationship between temperature and mental health, this study aims to assess how short-term ambient temperature exposure influences momentary depressive symptomatology in older adults. Using high-resolution GPS tracking and ecological momentary assessment (EMA) data, the analysis evaluates both immediate and delayed temperature exposure, compares meteorological indicators (e.g., mean, maximum temperature, and humidity), and tests the robustness of associations across model specifications. We hypothesize that temperature variability influences depressive symptoms, and that prolonged and delayed exposure may have stronger effects than immediate exposure.

This research was conducted as part of a Master’s internship within the Nemesis research team at the Pierre Louis Institute of Epidemiology and Public Health (IPLESP, UMR-S 1136). I contributed to all stages of data processing and modeling, including the cleaning and structuring of GPS and EMA data, integration of Météo-France hourly meteorological data, and implementation of distributed lag models (DLMs). This work aimed to generate fine-scale evidence on the mental health effects of short-term temperature variations, with relevance for climate-sensitive urban health strategies.

Methodology

Study Participants and data collection

A total of 216 participants aged 60 years and older were included in this study. All participants were drawn from the RECORD Cohort Study (Residential Environment and Coronary heart Disease), selected for the HANC (Healthy Aging and Networks in Cities) and MINDMAP sub-studies, a population-based cohort in the Paris metropolitan area (Chaix et al., 2019).

To assess daily mobility and mental health in real time, a GPS-based web mobility survey was conducted. This included a smartphone-based ecological momentary assessment (EMA) survey designed to capture depressive symptomatology throughout the day. Smartphones were provided to all participants, and a GPS receiver (BT-Q1000XT, QStarz, Taipei, Taiwan; 3-meter accuracy) was worn continuously during the 7-day observation period.

EMA questionnaires were delivered through the smartphone application at four fixed time slots each day: 9:00–12:00, 12:00–14:00, 14:00–16:00, and 16:00–18:00 (Fernandes et al., 2021). The study protocol allowed for the continuous collection of momentary psychological, spatial, and behavioral data over the course of the week.

CES -D questioners

The EMA questionnaires used in this study were a shortened version of the Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977), adapted to include eight items. This reduced format has been employed in prior research, including Karim et al. (2015) and Fancello et al. (2023). All original items were retained but reworded to capture momentary states, each introduced with the phrase “At the moment, I…”. Participants received four EMA questionnaires per day, each containing two items, ensuring that all eight items were assessed once daily. Given the focus on momentary depressive symptomatology, item scores were preserved in their original form—some reflecting negative emotions and others positive mood. The full list of items is provided in Annex 1.

Environmental data

Temperature and humidity data were obtained from the open-access platform provided by Météo-France (2023), specifically from the *Données Climatologiques de Base – Horaires* database. The collect data from 48 meteorological stations within the Île-de-France region between 2019 and 2021 were used. The temperature variable selected was the *température sous abri instantanée*, which corresponds to the air temperature measured at 1.5 meters above ground level in a ventilated shelter, protected from direct exposure to sunlight, wind, or precipitation (Météo-France, 2024). In addition, the *humidité relative* variable was used to represent the relative humidity, expressed as a percentage of the maximum amount of water vapor the air can hold at a given temperature. A total of 48 Météo-France weather stations across the region were included in the analysis. Their geographic distribution is shown in Figure 1.

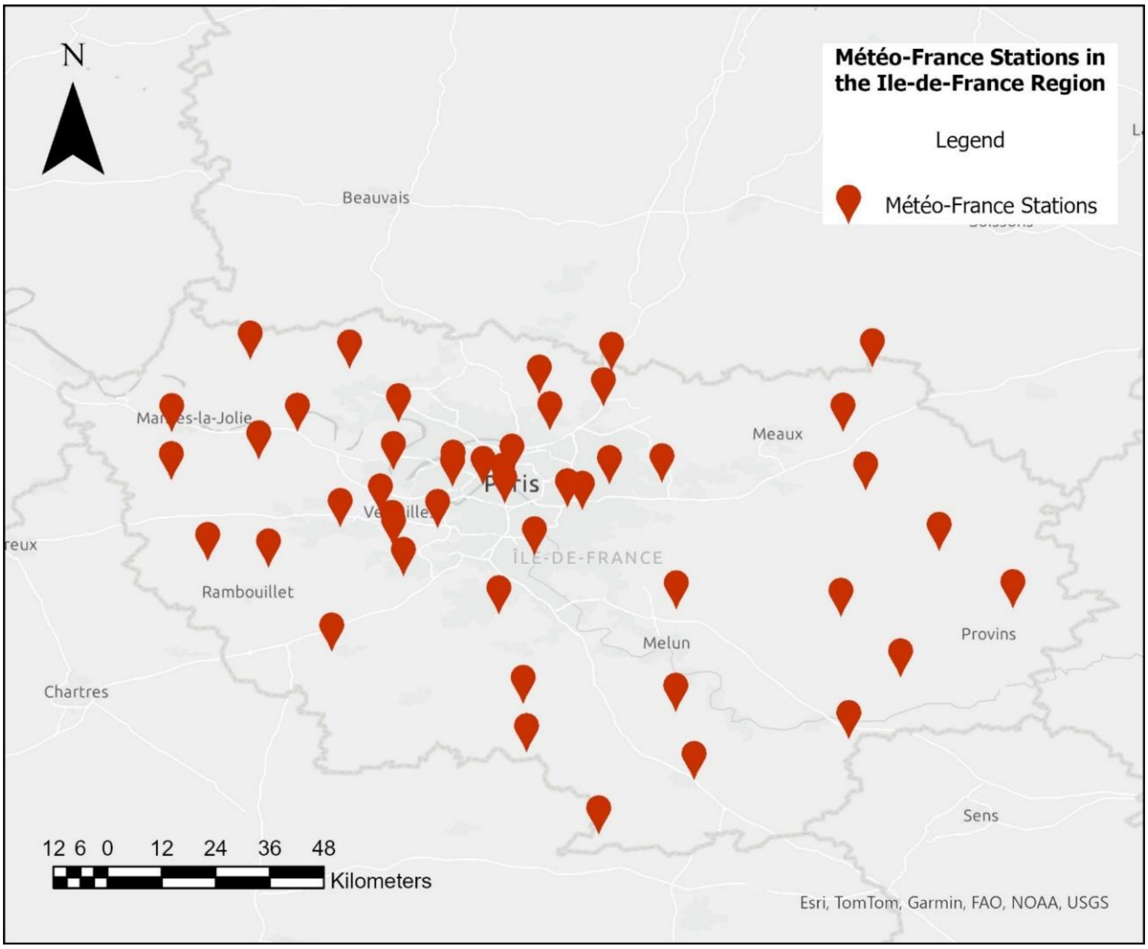

Fig 1. Geographic distribution of the 48 Météo-France meteorological stations included in the analysis across the Île-de-France region. These stations were continuously active during the study period (2019–2021) and are spread throughout central Paris and surrounding departments, providing comprehensive spatial coverage for environmental exposure assessment.

Mobility points and GEMA Data Processing and Dataset Assembly

Mobility data were collected using the TripBuilder application (Chaix et al., 2019), which integrates GPS points recorded through mobile devices. These GPS traces were uploaded to the TripBuilder web-mapping platform, which automatically identified visited places and trips based on spatial clustering. In addition to GPS data, three other types of geospatial points were used to improve trip reconstruction and exposure assessment:

1. **Google Directions API points**, which generated the shortest path along the street network when no GPS data were recorded for a trip;
2. **Manually drawn points**, used in cases where GPS data were missing and reconstruction was done manually by the research team;
3. **General Transit Feed Specification (GTFS) points**, which correspond to public transport segments, particularly underground trips (Fancello et al., 2021).

For the three non-GPS point types, interpolated points were generated every 20 meters using ArcgisPRO, and the corresponding imputed time was estimated using RStudio. After assembling the full mobility dataset, we selected the subset of points corresponding to the 24 and 8 hours prior to each EMA questionnaire response. This allowed us to measure the effects of maximum and minimum temperature over the previous day, as well as temperature exposure in the 8 hours preceding each response.

These exposure points were then matched to the nearest weather station using ArcgisPRO, considering the availability of Météo-France stations data at the response time. As illustrated in Fig. 1, each mobility point was matched to the nearest meteorological station in space and time, using a maximum distance threshold of 10 km—a criterion consistent with prior studies relying on spatial proximity for environmental exposure assignment (e.g., Bundo et al., 2023). Finally, in RStudio, each geolocated point was matched to the closest-in-time hourly weather observation from the assigned station, enabling the calculation of temperature and humidity exposures over the relevant pre-response periods for each participant.

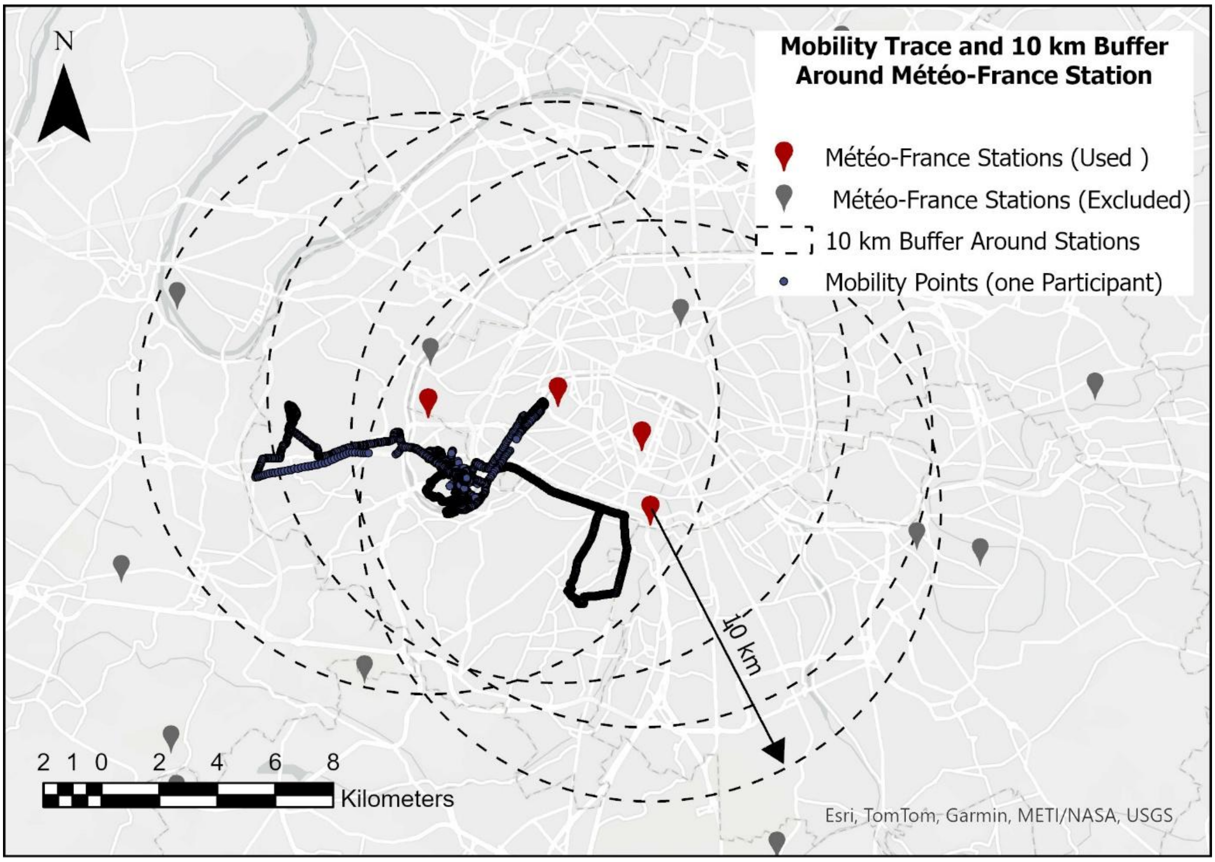

Fig.1 Participant mobility trace and 10 km buffer zones around Météo-France stations in the Île-de-France region.

The map displays the mobility points of one participant (in dark blue), derived from a combination of GPS tracks, street network alignment, GTFS data, and manually drawn segments. Red markers indicate the Météo-France stations used to assign environmental exposures to this specific participant, while gray markers show an example of the stations that were excluded in this case. Dashed circles represent 10 km buffers used to define the the maximal distance between participant locations and meteorological stations. This spatial configuration supported the integration of hourly meteorological data with fine-scale mobility trajectories.

Final data set and missing data

Participants completed a total of 6,532 EMA depression questionnaires, corresponding to 13,064 individual momentary depressive symptomatology items. Environmental exposure assessment was based on 13,564,539 spatial points. Of these, 1,130,088 points were excluded because they were located more than 10 kilometers from the nearest meteorological station, and an additional 39,805 points were excluded due to missing hourly meteorological data at the time of the observation. In total, 1,169,893 spatial points were excluded, resulting in 12,394,646 usable exposure points.

A total of 2,951 questionnaires were excluded due to the unavailability of temperature data for the corresponding time window and location. The final analytical dataset included 3,581 questionnaires, 7,197 depressive symptomatology items, and 216 participants.

Statistical methods

We aimed to assess how temperature exposure in the hours preceding each EMA response interacts with the association between time 0 temperature (i.e., the first hour before the response) in its association with momentary depressive symptomatology. To this end, we applied a distributed lag linear model (DLM) to estimate the association between temperature and momentary depressive symptoms across multiple lag periods. For each DLM, we calculated a weighted average temperature over the relevant lag windows, assigning greater weight to temperatures recorded closer in time to the EMA response. Weights were derived from the inverse of the time difference (in seconds) between each temperature observation and the questionnaire timestamp. The temperature in the hour immediately preceding the response (lag 0–1h) was modeled separately as the primary exposure, allowing us to examine its independent effect as well as its interaction with lagged exposure.

Exposure variables and covariates were assessed across multiple pre-response time windows, including 1- to 8-hour lags and a 24-hour window preceding each EMA response. We selected these lag structures based on previous studies indicating that the effect of temperature on mood may emerge several hours after exposure (Zhang et al., 2023; Bär et al., 2022), justifying the use of both immediate (lag 0–1) and delayed (e.g., lag 2–8 or lag 2–24) intervals. Mixed-effects models were adjusted for questionnaire item, age, sex, education level, employment status, household income, baseline CES-D score, time of day (morning, afternoon, night), and season. Covariate selection was guided by the Akaike Information Criterion (AIC) to ensure optimal model fit.

A continuous intraday covariate representing the time of the EMA response (in hours, with minutes expressed as fractions) was modeled using a natural cubic spline with 10 degrees of freedom. The optimal degrees of freedom were selected using the AIC. Random intercepts were specified at both the participant and participant-day levels to account for within-subject and within-day clustering in symptom responses. Also, in order to control for temporal autocorrelation a first-order autoregressive correlation structure was incorporated, using date time of the responses to define the temporal order of observations within each participant.

To estimate the total effect of temperature at each lag, we summed the beta coefficient of the immediate temperature exposure (first hour) and the coefficient of its interaction with the lag-specific weighted exposure. Corresponding standard errors and 95% confidence intervals were computed.

Sensitivity Analyses

To assess the robustness of the association between immediate temperature and depressive symptoms, a series of sensitivity analyses were conducted using four alternative model specifications. First, a restricted model was estimated on a subset of participants with complete exposure data across the full 8-hour window. Second, instead of using the average temperature across the lag window, the maximum temperature was used as the exposure variable to evaluate the sensitivity of the results to the temperature metric employed. Third, humidity was included as an additional covariate to examine whether it confounded or modified the association between temperature and depressive symptoms. For this model, only participants with complete humidity data were included.

Models 2 and 4 were estimated on reduced samples due to data availability. Model 2 included 195 participants, 1,273 questionnaires, and 2,531 EMA responses. Model 4 included 150 participants, 1,564 questionnaires, and 3,164 EMA responses. See Table 5 for detailed model specifications and corresponding results.

Results

Sociodemographic

Sociodemographic information included age (categorized as 60–70, 71–80, and >80 years), gender (female, male), education level [lower (30%), secondary (32%), higher (38%)], and household income per consumption unit (<2000€, 2000–4000€, >4000€). As shown in Table 1, the analytical sample (N = 216) comprised 49% of participants aged 60–70, 43% aged 71–80, and 7.9% aged over 80 years. Women represented 36% of the sample. Regarding household income, 15% of participants reported incomes below 2000€, 26% between 2000€ and 4000€, and 59% above 4000€. In terms of employment status, 85% of the participants were retired, while 13% were employed, 1.4% reported "other" status, and 0.5% were unemployed.

Table 1. Descriptive characteristics of study participants

Characteristic	Individuals (N=216)[1]
Age	
60-70	106 (49%)
71-80	93 (43%)
>80	17 (7.9%)
Gender	
Female	77 (36%)
Male	139 (64%)
Education level	
Lower_education	65 (30%)
secondary_education	70 (32%)
higer_education	81 (38%)
Household income per consumption unit	
<2000	32 (15%)
2000–4000	56 (26%)
>4000	128 (59%)
Employment status	
employed	29 (13%)
other	3 (1.4%)
retired	183 (85%)
unemployed	1 (0.5%)

[1] n (%)

Temperature, season and time of the day

Table 2 summarizes the temperature distributions across selected exposure windows, ranging from 1 hour to 24 hours prior to ecological momentary assessments. For each window, the table presents the average temperature (mean), its variability (standard deviation), and the corresponding maximum temperature. As shown, mean temperature values ranged from 15.13 °C (SD = 0.29) for the 1-hour window to 13.94 °C (SD = 1.86) for the 24-hour window. A gradual decrease in mean temperature and an increase in variability were observed as the exposure window extended, reflecting the temporal smoothing of temperature dynamics. These time-weighted metrics were used as primary exposure variables in the distributed lag models evaluating short-term associations between ambient temperature and depressive symptomatology.

Table 2: Summary of Temperature Metrics Across Exposure Windows in °C

Including Mean (SD) and Maximum Temperature

Exposure Window	Mean (SD)	Max
1h window	15.13 (0.29)	15.50
2h window	14.91 (0.31)	15.31
3h window	14.77 (0.49)	15.49
4h window	14.62 (0.64)	15.59
5h window	14.45 (0.76)	15.66
6h window	14.29 (0.87)	15.69
7h window	14.15 (0.97)	15.72
8h window	14.03 (1.06)	15.74
24h window	13.94 (1.86)	17.11

Table 3 displays the mean temperature (°C) across different exposure windows (from 1 to 24 hours) divided by season. Summer consistently shows the highest mean temperatures across all windows, with values ranging from 23.23°C at the 1-hour window to 21.41°C at the 24-hour window. In contrast, winter records the lowest values, with temperatures ranging from 8.20°C at 1 hour to 7.63°C at 24 hours. Autumn**,** which accounts for the largest share of observations (30**%**), and spring fall in between summer and winter, with autumn consistently warmer than spring across all exposure windows.

Table 3: Mean Temperature (°C) by Season Across Exposure Windows

Including unweighted averaged temperature values

Exposure Window	Autumn	Spring	Summer	Winter
1h window	16.16	12.41	23.23	8.20
2h window	15.91	12.25	22.95	8.04
3h window	15.77	12.10	22.76	7.94
4h window	15.62	11.93	22.55	7.84
5h window	15.47	11.73	22.34	7.72
6h window	15.32	11.52	22.14	7.63
7h window	15.20	11.33	21.95	7.57
8h window	15.09	11.17	21.77	7.53
24h window	15.10	10.93	21.41	7.63

Table 4 shows the mean temperature across exposure windows, now divided by time of day (morning, afternoon, and evening). Afternoon temperatures are the highest across all exposure windows, ranging from 15.71°C to 13.93°C. Morning temperatures are generally the lowest, with values from 13.90°C at 1 hour to 12.10°C at 8 hours. Evening temperatures fall in between but remain relatively stable across all windows, ranging from 14.05°C to 15.35°C. Overall, the highest mean temperature is observed in the 1-hour afternoon window (15.71°C), and the lowest in the 8-hour morning window (12.10°C).

Table 4: Mean Temperature (°C) by Season Across Exposure Windows

Including unweighted averaged temperature values

Exposure Window	Morning	Afternoon	Evening
1h window	13.90	15.71	14.05
2h window	12.97	15.51	14.72
3h window	12.68	15.33	14.97
4h window	12.47	15.11	15.18
5h window	12.30	14.88	15.31
6h window	12.22	14.66	15.35
7h window	12.15	14.48	15.33
8h window	12.10	14.33	15.27
24h window	14.03	13.93	13.84

Covariates

Across individual depressive symptom items, the direction and significance of associations were consistent across all time windows. In general, the reverse-coded questions — item 4 (“I don’t feel happy”) and item 6 (“I don’t enjoy life”) — showed the highest severity, with betas of approximately $\beta \approx 4.5$, when using item 2 (“I feel depressed”) as the reference. In contrast, item 2 and item 7 (“I feel sad”) exhibited the lowest severity. These results highlight that different item carry varying levels of momentary depression severity, suggesting that some symptoms may serve as more sensitive indicators of depressive states than others (see Appendix 1 for full item wording).

In addition, baseline depressive symptoms, as measured by the total CES-D score at baseline, were strongly and positively associated with momentary depressive symptom reports. The coefficient for the baseline score remained highly significant in all models ($\beta \approx 3.08$, $p < 0.001$), indicating that individuals with higher baseline depressive symptomatology were more likely to report elevated momentary symptoms throughout the study period.

Seasonality—specifically the summer period—showed a consistent trend toward higher depressive symptomatology relative to autumn, particularly in the initial lags. In models including lags 1 to 4, summer was significantly associated with increased depressive symptoms ($p = 0.044$ and $p = 0.0473$, respectively). In subsequent lags (lags 5 through 8 and lag 24), the association remained negative and of comparable magnitude but did not reach conventional levels of statistical significance (p-values ranging from 0.0509 to 0.0578).

Finally, time of day was not significantly associated with momentary depressive symptoms. Both afternoon and evening showed non-significant differences compared to the morning, suggesting no meaningful variation in symptoms across the day. These results may be explained by the relatively small temperature differences observed across time periods, as shown in Table 4.

Main model

A total of 3,581 EMA questionnaires, corresponding to 7,197 depressive symptom items, were analyzed from 216 older adults in the RECORD cohort. Distributed lag linear models (DLMs) were used to estimate the association between short-term temperature exposure and momentary depressive symptoms across time windows ranging from 1 to 8 hours, and 24 hours.

Across all models, the coefficient for immediate temperature was positive. Statistically significant associations were observed within the first hour preceding the response, as well as from the 6th through the 24th hour windows prior to the response. The magnitude of the total effect including the interaction term, increased progressively from the 1-hour to the 8-hour exposure window. For example, in the lag 6 model, a 1°C increase in immediate temperature was associated with a 0.013 -point increase in depressive symptom scores (95% CI: 0.002 to 0.025). The highest effect estimate was observed in the 7-hour lag window model, showing a 0.014-point increase in depressive symptomatology (95% CI: 0.003 to 0.025) per 1 °C increase in average temperature exposure during the preceding 7 hours, followed by a slight decline in effect estimates for longer lag windows. The direction of the association was positive across all time windows from 1 hour to 24 hours, with all point estimates lying to the right of zero. Precision tended to improve in the longer time windows, as indicated by narrower confidence intervals (Figure 3).

The results were highly consistent across models using both weighted and unweighted lagged temperature averages. In both cases, effect estimates for immediate temperature remained positive and consistently higher than the effect estimates of previous hours. Slightly stronger associations and narrower confidence intervals were observed in the weighted.

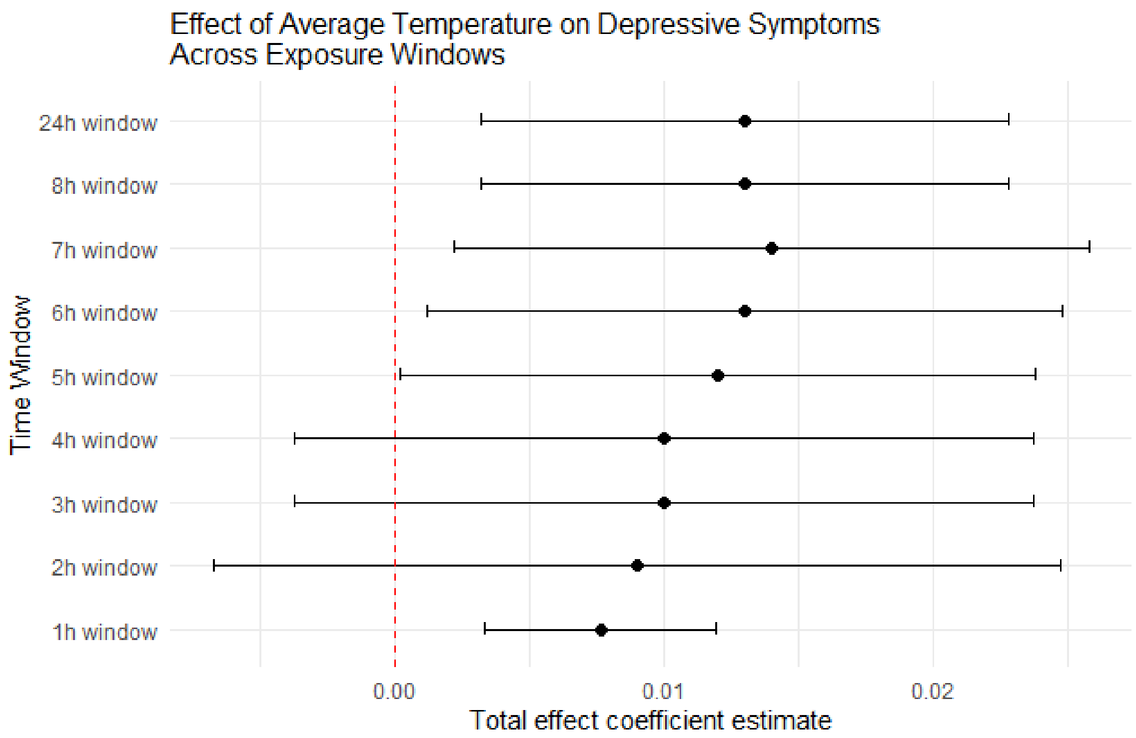

Fig. 3 Estimated total effect of the weighted average temperature on depressive symptoms across different pre-response exposure windows. Each point represents the total effect coefficient (sum of the

immediate and interaction terms) from distributed lag linear models (DLMs), with horizontal lines indicating 95% confidence intervals. The red dashed line marks the null effect (β = 0).

Sensitivity Analyses

Table 5 presents the total effect estimates of the depressive symptoms across several distributed lag models (DLMs) using weighted exposures. Four model specifications are included: (1) the standard model using the full sample and lag structure; (2) a restricted model including only participants with complete exposure data across all eight lag periods; (3) a model using maximum temperature instead of mean temperature; and (4) a model adjusting for humidity. Results are shown for the 2-hour, 8-hour, and 24-hour exposure windows, with beta coefficients and 95% confidence intervals.

In the standard model, the association between temperature and depressive symptoms became statistically significant starting at the 6-hour window, as previously described. In the restricted model with full lag coverage, the effect estimates were generally larger but followed the same temporal pattern; for instance, at the 8-hour window, the total effect was β = 0.021 (95% CI: 0.003 to 0.039). The estimate at 2 hours remained non-significant, similar to the main model. The model based on maximum temperature yielded a statistically significant effect only at 24 hours (β = 0.010; 95% CI: 0.001 to 0.019), but showed higher effect estimates at earlier lags, even though their confidence intervals slightly crossed the null. Finally, the model adjusting for humidity did not show significant associations at any time window, with estimates close to zero and confidence intervals consistently including the null. Across all models and exposure durations, the direction of the effect remained positive, though statistical significance and magnitude varied depending on model specification.

Table 5. Total effect coefficient of the different models

Distributed Lag Models with Weighted Exposures

Exposure Model	Beta Coefficient	95% Confidence Interval
Model 1. Standar model		
2h window	0.009	[-0.007, 0.025]
8h window	0.013	[0.003, 0.024]
24h window	0.013	[0.003, 0.023]
Model 2. Full 8 hours model		
2h window	0.020	[-0.010, 0.049]

Table 5. Total effect coefficient of the different models

Distributed Lag Models with Weighted Exposures

Exposure Model	Beta Coefficient	95% Confidence Interval
8h window	0.021	[0.003, 0.039]
Model 3. Maximum temperature model		
2h window	0.014	[-0.001, 0.029]
8h window	0.012	[-0.000, 0.024]
24h window	0.010	[0.001, 0.019]
Model 4. Adjusting for humidity		
2h window	0.007	[-0.019, 0.032]
8h window	0.009	[-0.008, 0.027]
24h window	0.009	[-0.007, 0.025]

The analyses included data from the HANC and MINDMAP studies, comprising 216 participants over a 7-day period, with a total of 3,581 questionnaires. Of these, 3,650 questionnaires were linked to outdoor temperature exposures, and 7,197 momentary depressive symptom reports were analyzed. Models 2 and 4 were estimated on slightly smaller subsets due to data availability. Distributed Lag Linear Models (DLMs) were fitted, incorporating random effects at the participant and day levels, along with an autoregressive structure to account for the temporal ordering of observations within each participant, based on date-time. A continuous intraday covariate representing time at the hourly level (with minutes as fractional values) was included in all models and modeled using a natural cubic spline with 10 degrees of freedom. All models were adjusted for questionnaire item, age, sex, education, employment status, household income, baseline depressive symptom score, time of day, and season. Full results are presented in the annexes.

Discussion

The findings indicate a significant and positive association between ambient temperature and momentary depressive symptoms among older adults. This relationship was observed both in the immediate term—specifically in the hour preceding the questionnaire response—and also when considering later periods, particularly from hour 6 to 24. Notably**,** as shown in Fig. 3, the models for the preceding hours display wider confidence intervals compared to the first-hour window. This, along with the smaller effect estimates for earlier lag temperatures, suggests a weaker association with these previous time intervals and indicates that the relationship between temperature and depressive symptoms is primarily driven by immediate exposure — even though previous lags still present a weak effect on their own. On the other hand, the lack of significant associations between lag 2 and lag 5 may be explained by relatively small temperature variations during these time windows. That is, the similarity between immediate and early lagged temperatures may have limited the model's ability to detect distinguishable effects.

Nevertheless, our results clearly show a positive relationship between temperature and momentary depressive symptomatology, both at the time of exposure and considering prior hours. This effect persisted even after adjusting for temporal trends, seasonality, and sociodemographic covariates. These results support our initial hypothesis and are consistent with those of Meidenbauer et al. (2024), who used a similar EMA-based approach, and large-scale studies such as Noelke et al. (2016), which reported that increasing ambient temperatures significantly reduce emotional well-being. They also align with the broader literature indicating a positive association between heat and suicidality and psychiatric admissions (Chen et al., 2019; Bundo et al., 2021; Basu et al., 2017; Bär et al., 2022).

At the same time, other short-term EMA studies, such as those by Bundo et al. (2023) and Cléry et al. (2024), reported inverse associations, indicating that higher temperatures were linked to fewer depressive symptoms. These discrepancies may be attributable to seasonal or contextual differences, including variations in thermal comfort across settings. In our analysis, seasonality—particularly summer—emerged as a significant effect modifier in the relationship between temperature and depressive symptoms. However, further investigation is warranted to better understand the ways seasonality affects this relationship.

Regarding the variation across time windows, our findings show a strong effect of immediate temperature on depressive symptoms, with a weak but notable influence of previous exposures. This pattern aligns with previous literature, including studies by Bundo et al. (2021) and Zhang et al. (2023).

Sensitivity analyses supported the robustness of the results. When restricting the sample to participants with complete lag exposure data, the findings remained consistent with the primary models. In the third model**,** even though the confidence intervals for some of the earlier lags slightly cross the null, the estimated effects remain present and are larger than those observed for mid-range lags. This reinforces the relevance of immediate and short-term thermal exposure. These findings are consistent with those of Meidenbauer et al. (2024)**,** who also reported significant associations between maximum temperature and mood.

Conversely, models adjusting for humidity yielded null results across all lags, indicating that relative humidity may be less predictive of depressive symptoms than objective temperature. This is in line with Zhang et al. (2023), who also found no significant relationship with humidity, although it contrasts with other studies that have suggested that humidity contributes to thermal discomfort and psychological stress (Chen, et al. 2017). The inconsistency in the literature may reflect the complex interplay between humidity and thermal perception. It is also possible that our null results stem from limitations such as reduced sample size in the humidity models or the presence of comfortable temperature levels that moderated humidity's impact. Further research is needed to clarify humidity’s role.

Seasonality also played a notable role in our findings. Specifically, summer was significantly associated with increased depressive symptoms. These observations support the growing recognition of the importance of temporally-resolved exposure modeling when assessing environmental determinants of mental health (Basu et al., 2017). However, as I mentioned already, further research is needed to more fully understand the seasonal effects, including the role of acclimatization, which may moderate the psychological impact of temperature.

Unlike previous research linking extreme heat to hospitalizations or suicidality, this study focused on subclinical, moment-to-moment mood fluctuations. This more granular approach demonstrates that even moderate increases in ambient temperature—well below heatwave thresholds—can elevate depressive symptomatology. These findings advocate for the inclusion of temperature variability in psychological risk assessments, even in the absence of extreme weather events.

This study has several limitations. Although the use of high-resolution EMA and GPS data represents a significant methodological advance over traditional time-series designs, limitations in environmental data resolution persist. Exposure assignment was based on the nearest meteorological station within a 10-kilometer buffer, which may not accurately capture local microclimatic variation, especially in urban environments. Moreover, since most weather stations were located near the city center, participants in peripheral or less densely monitored areas may have been excluded due to lack of nearby data, introducing spatial bias and reducing the generalizability of results beyond central Paris. Temperature and humidity data were only available at hourly intervals, which may overlook rapid fluctuations in thermal exposure. Indoor temperature was not measured, limiting the ability to account for differences between indoor and outdoor environments—an important factor for older adults. Key environmental covariates such as air pollution and solar radiation were not included, and humidity data were limited to a subset of participants, reducing statistical power to detect modifying effects. The models assumed linear relationships between temperature and depressive symptoms, despite evidence suggesting potential nonlinear or threshold effects; future studies should employ distributed lag nonlinear models (DLNM) to better capture these dynamics. Finally, residual confounding from unmeasured behavioral or contextual factors (e.g., medication use, hydration, physical activity) cannot be ruled out, and environmental data missingness was not random, further reinforcing the need for finer-scale, more comprehensive exposure assessment in future research.

Finally, from a public health perspective, the findings suggest that temperature-sensitive mental health interventions—such as behavioral guidance during hot periods or urban cooling strategies—may benefit vulnerable populations, especially older adults. Policy recommendations include expanding green infrastructure, promoting heat-resilient urban design, and implementing early warning systems that account for mental health risks associated with heat. These strategies are essential for mitigating the psychological consequences of rising temperatures in a changing climate (Rony & Alamgir, 2023).

Conclusion

Using high-resolution GPS-linked EMA data, we identified a significant association between ambient temperature and momentary depressive symptomatology, contributing to the growing body of evidence that rising temperatures can exacerbate depressive symptoms. Moreover, our findings refine existing knowledge by exploring the temporally dynamic aspects of this relationship. These insights have important implications for mental health risk forecasting and the strategic timing of public health interventions. The psychological vulnerability of older populations to heat may call for anticipatory and targeted adaptation strategies.

In the context of accelerating climate change and increasing urban heat burden, these findings underscore the urgency of integrating thermal exposure into mental health early warning systems and climate adaptation strategies. Policies should aim not only to mitigate rising temperatures but also to adapt urban environments to growing thermal stress. Future research should investigate nonlinear lag structures, seasonal variations, and additional environmental indicators or composite measures that better capture perceived thermal comfort.

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List of Appendices

Appendix 1. CES-D transformed questionnaires

Q1. A l'instant présent, je suis contrarié(e) par des choses qui d'habitude ne me dérangent pas.

○ Oui tout à fait ○ Oui plutôt ○ Non pas vraiment ○ Non pas du tout

Q2. A l'instant présent, je me sens déprimé(e).

○ Oui tout à fait ○ Oui plutôt ○ Non pas vraiment ○ Non pas du tout

Q3. A l'instant présent, j'ai l'impression que toute action me demande un effort.

○ Oui tout à fait ○ Oui plutôt ○ Non pas vraiment ○ Non pas du tout

Q4. A l'instant présent, je suis heureux(se).

○ Oui tout à fait ○ Oui plutôt ○ Non pas vraiment ○ Non pas du tout

Q5. A l'instant présent, je me sens seul(e).

○ Oui tout à fait ○ Oui plutôt ○ Non pas vraiment ○ Non pas du tout

Q6. A l'instant présent, je profite de la vie.

○ Oui tout à fait ○ Oui plutôt ○ Non pas vraiment ○ Non pas du tout

Q7. A l'instant présent, je me sens triste.

○ Oui tout à fait ○ Oui plutôt ○ Non pas vraiment ○ Non pas du tout

Q8. A l'instant présent, je manque d'entrain.

○ Oui tout à fait ○ Oui plutôt ○ Non pas vraiment ○ Non pas du tout

Appendix 2. Full results for all the models

Table 4. All total effect coefficient for each model

Distributed Lag Models with Weighted Exposures

Exposure Model	Beta Coefficient	95% Confidence Interval
Model 1. Standar model		
1h window*	0.008	[0.003, 0.012]
2h window	0.009	[-0.007, 0.025]
3h window	0.010	[-0.004, 0.023]
4h window	0.010	[-0.002, 0.023]
5h window	0.012	[-0.000, 0.024]
6h window	0.013	[0.002, 0.025]
7h window	0.014	[0.003, 0.025]
8h window	0.013	[0.003, 0.024]
24h window	0.013	[0.003, 0.023]
Model 2. Full 8 hours model		
2h window	0.020	[-0.010, 0.049]
3h window	0.022	[-0.004, 0.047]
4h window	0.021	[-0.002, 0.044]
5h window	0.020	[-0.001, 0.041]
6h window	0.020	[0.001, 0.040]
7h window	0.021	[0.002, 0.040]
8h window	0.021	[0.003, 0.039]
Model 3. Maximum temperature model		
2h window	0.014	[-0.001, 0.029]
3h window	0.010	[-0.003, 0.023]
4h window	0.012	[-0.000, 0.025]
5h window	0.012	[-0.000, 0.024]
6h window	0.012	[-0.001, 0.024]
7h window	0.011	[-0.001, 0.023]
8h window	0.012	[-0.000, 0.024]
24h window	0.010	[0.001, 0.019]
Model 4. Adjusting for humidity		
2h window	0.007	[-0.019, 0.032]

Table 4. All total effect coefficient for each model

Distributed Lag Models with Weighted Exposures

Exposure Model	Beta Coefficient	95% Confidence Interval
3h window	0.011	[-0.011, 0.034]
4h window	0.011	[-0.010, 0.031]
5h window	0.012	[-0.008, 0.031]
6h window	0.011	[-0.007, 0.030]
7h window	0.010	[-0.008, 0.028]
8h window	0.009	[-0.008, 0.027]
24h window	0.009	[-0.007, 0.025]

*The 1h window model was computed using unweighted average exposure values.

Résumé (Français)

Contexte : Avec l'intensification du changement climatique, l'exposition à court terme à la température ambiante est devenue un facteur environnemental majeur influençant la santé mentale. Les personnes âgées sont particulièrement vulnérables au stress thermique en raison de leur sensibilité physiologique et d'un risque accru de troubles de l'humeur.

Objectifs : Cette étude vise à évaluer l'association entre l'exposition à la température ambiante à court terme et les symptômes dépressifs momentanés chez les personnes âgées.

Méthodes : À partir de données GPS haute résolution et d'évaluations écologiques momentanées (EMA) recueillies auprès de 216 participants âgés de 60 ans et plus dans la région parisienne, nous avons utilisé des modèles linéaires à retards distribués pour analyser les effets de l'exposition immédiate et différée à la température (1 à 8 heures et 24 heures) sur les symptômes dépressifs. Les modèles ont été ajustés pour les covariables sociodémographiques, l'heure de la journée et la saison.

Résultats

Un total de 3 581 questionnaires EMA provenant de 216 personnes âgées ont permis d'obtenir 7 197 observations de symptômes dépressifs. Les modèles linéaires à retards distribués ont révélé une association positive constante entre la température ambiante et les symptômes dépressifs momentanés. Des associations statistiquement significatives ont été observées pendant l'heure précédant immédiatement l'évaluation des symptômes, ainsi

qu’entre les heures de retard 6 à 24. L’effet estimé d’une augmentation de 1 °C de la température immédiate sur les scores de symptômes dépressifs atteignait un maximum au retard 7 ($\beta = 0{,}014$; IC 95 % : 0,003 à 0,025), avec des estimations légèrement atténuées pour les retards plus longs. La précision augmentait avec l’élargissement des fenêtres d’exposition, comme en témoignent des intervalles de confiance plus étroits. Les modèles utilisant des structures de retards pondérés ont montré des associations plus fortes et plus précises que ceux utilisant des retards non pondérés. Les analyses de sensibilité ont confirmé la robustesse des résultats : les estimations étaient plus élevées chez les participants ayant une couverture complète des retards, et les résultats restaient cohérents lorsqu’on utilisait la température maximale ou un ajustement pour l’humidité, bien que cette dernière n’ait pas montré d’effet significatif.

Conclusion

Nos résultats mettent en évidence une association positive entre l’exposition à court terme à la température et les symptômes dépressifs momentanés chez les personnes âgées. Ces résultats suggèrent que même des augmentations modérées de la température ambiante – en deçà des seuils de canicule – peuvent influencer des variations subcliniques de l’humeur. Cela souligne l’importance d’intégrer des indicateurs sensibles à la température dans les systèmes de surveillance en santé mentale et les stratégies d’adaptation urbaine. Les recherches futures devraient explorer les relations non linéaires entre exposition et réponse, les modificateurs contextuels tels que la saison ou l’environnement intérieur, ainsi que l’intégration d’autres facteurs environnementaux comme la pollution de l’air afin d’améliorer la prédiction des risques et la planification de la résilience.