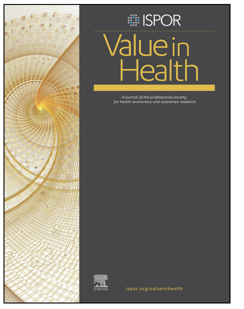
# Journal Pre-proof




Impact of heatwaves on health-related quality of life in older Chinese adults: A longitudinal cohort study

Yilin Zhang, MSc, Yan Lin, MSc, Zhihong Xiao, MSc, Yifeng Chen, PhD, Quan Zhou, PhD, Shuling Kang, PhD, Zhihao Yang, PhD, Fanni Rencz, PhD, Nan Luo, PhD, Jianjun Xiang, PhD

PII: S1098-3015(25)05691-8

DOI: https://doi.org/10.1016/j.jval.2025.11.005

Reference: JVAL 4513

To appear in: *Value in Health*

Received Date: 25 February 2025

Revised Date: 31 October 2025

Accepted Date: 12 November 2025

Please cite this article as: Zhang Y, Lin Y, Xiao Z, Chen Y, Zhou Q, Kang S, Yang Z, Rencz F, Luo N, Xiang J, Impact of heatwaves on health-related quality of life in older Chinese adults: A longitudinal cohort study, *Value in Health* (2026), doi: https://doi.org/10.1016/j.jval.2025.11.005.

**Target Journal:** Value in Health

# Title: Impact of heatwaves on health-related quality of life in older Chinese adults: A longitudinal cohort study

**Authors:** Yilin Zhang [a,†], MSc, Yan Lin [a,b,†], MSc, Zhihong Xiao [a,†], MSc, Yifeng Chen [a], PhD, Quan Zhou [b], PhD, Shuling Kang [b], PhD, Zhihao Yang [c], PhD, Fanni Rencz [d], PhD, Nan Luo [e,*], PhD, Jianjun Xiang [a,f,*], PhD

[a] Department of Preventive Medicine, School of Public Health, Fujian Medical University; and Key Laboratory of Environment and Health, Fujian Medical University, Fuzhou, Fujian Province, 350122, China

[b] Fuzhou Center for Disease Control and Prevention, Fuzhou, Fujian Province, 350122, China

[c] Health Services Management Department, Guizhou Medical University, Guiyang, China

[d] Department of Health Policy, Corvinus University of Budapest, Budapest, Hungary

[e] Saw Swee Hock School of Public Health, National University of Singapore, Singapore

[f] School of Public Health, The University of Adelaide, Adelaide, South Australia, 5005, Australia

**Corresponding author:**

Jianjun Xiang, jianjun.xiang@fjmu.edu.cn, School of Public Health, Fujian Medical University, Fuzhou, Fujian Province, 350122, China

Nan Luo, ephln@nus.edu.sg, Saw Swee Hock School of Public Health, National University of Singapore, Singapore.

**Precis:** Heatwaves significantly reduce health-related quality of life in older Chinese adults, with age, BMI, and humidity as key predictors, highlighting urgent need for targeted interventions.

**Word count:** 4500

**Number of pages:** 28

**Number of figures:** 4

**Number of tables:** 2

**Supplemental materials:** 1

Pages: 16

Figures: 6

Tables: 6

**Authorship Confirmation:** All authors certify that they meet the ICMJE criteria for authorship.

**Funding/Support:** This work was supported by the 2023 EuroQol Research Foundation (Project no.: 1599-RA), Minjiang Scholar Start-up Research Fund of

Fujian Province (Grant No. 2019-9202001001), and 2021 Natural Science Foundation of Fujian Province of China (2021J01722).

**Role of the Funders/Sponsors:** The funder had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication.

**Members of the Group:** Not applicable.

**Disclaimer:** The views of the authors expressed in this article do not necessarily reflect the views of the EuroQol Group.

**Ethical statement:** This study was approved by the Institutional Review Board of Fujian Medical University (2022-111). All participants provided written informed consent to participate in this study.

**Acknowledgements:** We thank all participants for participating in this survey during the hot summer and greatly appreciate their contributions. We also thank the two neighborhood committees, the key on-site organizer Ms. Maolan Chen for their generous support during the on-site survey.

**Data availability:** All data generated or analyzed during this study are included in this published article and its supplementary information files. The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Dr Luo is an editor for Value in Health and had no role in the peer-review process of this article.

# Impact of heatwaves on health-related quality of life in older Chinese adults: A longitudinal cohort study


## Abstract

***Objectives:*** Climate change has intensified heatwaves, posing significant health risks to older adults, yet their impact on health-related quality of life (HRQoL) in China's aging population remains underexplored. This study investigates the impact of heatwaves on HRQoL among older adults using the EQ-5D-5L.

***Methods:*** A cohort of community-dwelling Chinese adults aged≥60 years were followed up from spring to fall in 2023. Univariate regression and restricted cubic spline models analyzed linear and non-linear relationships between meteorological/demographic factors and EQ-5D-5L outcomes (utility values and EQ VAS scores). Machine learning models identified key predictors of heatwave-related HRQoL changes.

***Results*：** Among the 627 participants, both EQ-5D-5L utility values and EQ VAS scores followed a rise-and-fall pattern, initially increasing during the early heatwave period (T1) but subsequently declining significantly during the peak heatwave period (T2) (*P*<0.001). Underweight individuals had lower utility values ($\beta$=-0.394, *P*=0.006), while obese individuals had lower EQ VAS scores ($\beta$=-0.385, *P*=0.040). Age was negatively associated with both utility values ($\beta$=-0.003, *P*<0.001) and EQ VAS scores ($\beta$=-0.228, *P*<0.001). Meteorological factors, such as daily average relative humidity and temperature significantly affected both EQ-5D-5L utility values and EQ VAS scores (*P*<0.05). The Support Vector Machine model outperformed the other machine learning models, identifying body mass index as the most influential variable in predicting the EQ-5D-5L utility values, followed by age, pre-retirement occupation, education level, and daily average relative humidity.

***Conclusion:*** Heatwaves dynamically affect HRQoL in older adults in China, with an initial increase followed by a significant decline. Older, underweight, and less-educated adults are more vulnerable to the adverse impacts of heatwaves on HRQoL.

***Keywords:*** heatwaves, health-related quality of life, EQ-5D-5L, machine learning, restricted cubic spline

**Highlights:**

- This study fills the evidence gap in heatwave impacts on older adults' HRQoL, demonstrating a dynamic pattern: initial improvement in early heatwaves (T1), followed by significant decline during peak heatwaves (T2) using EQ-5D-5L.
- We identified adults ≥75 years, those underweight, or with low education as most vulnerable, with non-linear risks peaking at 27–33°C and humidity >78%.
- The findings inform targeted interventions (e.g., humidity-adjusted cooling strategies) for vulnerable subgroups, supporting climate adaptation in healthcare policy.

## Introduction

With the increasing frequency and intensity of extremely hot weather, climate change is posing a growing challenge to public health [1,2]. These risks disproportionately affect older adults due to diminished thermoregulation, chronic health conditions, and socio-economic vulnerabilities [3-6]. Heatwaves may exacerbate chronic illnesses and negatively affect the well-being of older adults [7,8]. To date, most research has focused on heat-sensitive morbidity and mortality outcomes, primarily utilizing health surveillance data such as ambulance call-out, emergency presentation, hospitalization, and death registry [9,10]. However, the broader impact of heatwaves on health-related quality of life (HRQoL) of older adults remains underexplored, which is an essential component of heat-attributed health burdens, particularly with improvements in heat adaptation and resilience [11].

HRQoL is an important multidimensional health status indicator, encompassing physical, psychological, social, and functional aspects of health [12]. The EQ-5D-5L instrument [13] is not only widely used to measure HRQoL in evaluating the impacts of health interventions (e.g., vaccines, drug therapies, medical devices, and clinical procedures), but also plays an important role in population health assessments. For example, it has been employed in large-scale surveys to assess health status across demographic groups and to monitor changes in population health over time [14]. In addition, the EQ-5D-5L has been applied to evaluate the health consequences of disasters and environmental changes [15-17]. However, its application in examining heatwaves and their effects on the HRQoL of older adults remains limited.

This study adopts a longitudinal approach to explore the extent to which heatwaves affect HRQoL, as measured by the EQ-5D-5L, in older adults across four distinct periods: pre-heatwave, early heatwave, peak heatwave, and post-heatwave. This dynamic follow-up approach aims to capture temporal variations in HRQoL and provide insights to inform potential preventive measures and response strategies to mitigate the sub-clinical effects of heatwaves on older adults.

## Methods

### *Study area and participant recruitment*

This longitudinal study was conducted in Fuzhou, the capital of Fujian Province, situated on the southeast coast of China. With a population of approximately 8 million, Fuzhou is experiencing significant demographic shifts, with 19.1% of its residents aged 60 years or older as of 2020 [18]. The city has a humid subtropical climate, characterized by long and hot summers [18].

Two representative communities in Fuzhou were selected to capture diverse socio-demographic and environmental conditions: (1) Champion Community (suburban): Lower housing density, proximity to preserved green spaces, and adjacency to the Min River; and (2) Yangqiao Henan Community (urban): Higher housing density, limited green space, and urban heat island effect. Both sites shared similar diurnal patterns (cooler mornings/evenings) but slightly differed in microclimates due to urbanization gradients. The geographical locations of the study communities are depicted in Figure

S1. The selection of these communities, differing in socioeconomic status, aimed to enhance the study's demographic diversity.

A team of ten trained interviewers administered the face-to-face survey and entered participants' responses directly into an online electronic questionnaire (WeChat Survey Star) using iPads. All interviewers were postgraduate students with academic backgrounds in preventive medicine, supervised by experienced field coordinators to ensure consistency and reliability, and were explicitly instructed not to make surrogate judgments during the survey. The questionnaire included the following sections: (a) Demographics: Age, gender, education level, and socioeconomic indicators (e.g., income and employment status); (b) Health status and well-being: the EQ-5D-5L, EQ-HWB [19] (not used in the current study), and Brief Inventory of Thriving (BIT) [20] (not used in the current study) questionnaires, as well as questions assessing self-reported physical and mental health, pre-existing chronic conditions, and current medication usage; and (c) Lifestyle factors: dietary habits, physical activity, smoking status, and alcohol consumption. Participants were recruited using a snowball sampling approach, facilitated by local neighborhood committees. Invitations were disseminated via social media (WeChat), mobile phone, and word of mouth. Eligibility criteria included being 60 years or older, having resided in the community for at least six months, proficiency in Mandarin or Foochow dialect, and cognitive and physical capability to participate in the interview. Individuals with cognitive impairments or those unwilling to participate were excluded. Participants were compensated with a small gift valued at \$5. To account for potential loss to follow-up, no new participants were recruited during the follow-up waves. Participation was entirely voluntary, with the option to withdraw at any time without any explanation. Ethical approval was obtained from the Biomedical Research Ethics Committee of Fujian Medical University (No. 2023-303).

Survey data were collected during four distinct periods in 2023, corresponding to various phases of heatwaves: (1) T0 (Pre-heatwave/Baseline): Spring (weeks 18–21), characterized by maximum daily temperatures <28°C; (2) T1 (Early heatwave): Early summer (weeks 27–30), onset of maximum daily temperatures first reached ⩾35°C for three consecutive days; (3) T2 (Peak heatwave): Conducted during the mid-summer, with sustained maximum daily temperatures ⩾35°C for at least three consecutive days; and (4) T3 (Post-heatwave/Recovery): Fall (weeks 39–42), marked by maximum daily temperatures <30°C. According to the China Meteorological Administration, a heatwave is defined as three or more consecutive days with maximum temperatures of 35°C or higher [21].

Meteorological data were obtained on a daily basis and linked to participants according to their interview dates. Specifically, daily maximum, minimum, and average temperatures, as well as relative humidity, were sourced from the Fuzhou Meteorological Station [22], a city-wide monitoring facility. Each participant's exposure was defined by the meteorological conditions on the interview date (i.e., concurrent daily conditions). Additionally, to assess potential lagged effects of heat exposure on HRQoL, we incorporated daily meteorological data from the 7 days preceding each interview (lag 1 to 7 days) in supplementary analyses. All meteorological data were synchronized with the four survey periods (T0 – T3) to examine the temporal relationship between weather conditions and health outcomes.

***Sample size***

This study employed a rigorous approach to calculating sample size, based on an expected minimal mean change of 0.03 in the utility value and a standard deviation of 0.20. Pre-survey data indicated the prevalence of health HRQoL impairment (defined as utility value <0.8) was 50% at baseline and increased to 53.5% during heatwaves, indicating a slight deterioration in HRQoL, which was consistent with the expected under heat stress conditions. Using a longitudinal design with repeated measurements, the required sample size was calculated with the following formula:

$$n = \left(\frac{Z_{1-2/\alpha}\sqrt{2\overline{p}\overline{q}}+Z_{\beta}\sqrt{p_0q_0+p_1q_1}}{p_1-p_0}\right)^2$$ [23]

Where: 'n' represents the sample size, '$Z_{1-2/\alpha}$' denotes the critical value for a two-tailed test, and '$Z_{\beta}$' signifies the critical value associated with the power of the test. The significance level ($\alpha$) is set at 0.05, the power ($\beta$) at 0.80 (since $\beta$=1-0.2). The effect size ($d$) is 0.03. The proportion under null hypothesis ($p_0$) is 0.50 and the proportion under alternative hypothesis ($p_1$) is 0.535. Considering a minimum follow-up rate of 70%, the required minimum sample size was adjusted to 337 participants to ensure sufficient statistical power.

***Instrument***

EQ-5D-5L is a generic preference-based measure that includes a descriptive system and a visual analogue scale (EQ VAS) [13]. The descriptive system measures HRQoL across five dimensions: mobility, self-care, usual activities, pain/discomfort, and anxiety/depression. Each dimension has five response levels: no problems, slight problems, moderate problems, severe problems, and extreme problems/unable to. Responses on these dimensions can be converted into a single utility value using a value set derived from public preference data. Utility values are expressed on a scale with anchors at 1 (full health) to 0 (a state equivalent to being dead), with scores below 0 representing health states deemed worse than dead. The EQ VAS enables individuals to provide a self-assessment of their health on a vertical scale, ranging from 0 (the worst health you can imagine) to 100 (the best health you can imagine). Both the descriptive system and EQ VAS use a 'today' recall period and we used the interviewer-administered Simplified Chinese version [24].

***Statistical analysis***

Descriptive statistical analyses were conducted on utility values, EQ VAS scores and the five dimensions of EQ-5D-5L. To assess changes in EQ-5D-5L dimensions across heatwave phases, the following approaches were used: (1) Weighted mean score calculation: Each response level was assigned an ordinal score (0=no problems, 1=slight problems, 2=moderate problems, 3=severe problems, 4=extreme problems/unable to) to quantify the overall severity of problems in each dimension. The weighted mean score for each dimension at each time point was calculated as: $\text{Weighted mean score} = \frac{\sum \text{Ordinal score} \times \text{Frequency}}{\text{Total participants at time point}}$ [25]; (2) Inferential tests for repeated measurements: Friedman tests assessed overall differences in weighted mean scores across the four time points (T0 to T3) for each dimension, given the ordinal nature of the data and repeated measurements. Post-hoc pairwise comparisons between each heatwave phase (T1, T2, T3) and baseline (T0) used Wilcoxon signed-rank tests, with Bonferroni correction ($\alpha$=0.017) to control Type I error; and (3) Effect size: Cohen's d quantified weighted mean scores difference between T2 and T0, with thresholds for small (0.2), medium (0.5), and large (0.8) effects. [26,27]

To assess group differences in the calculated EQ-5D-5L utility values and the self-rated EQ VAS scores, one-way analysis of variance (ANOVA) was first conducted, followed by Tukey's Honestly Significant Difference (HSD) test for post-hoc pairwise comparisons, with significance levels adjusted accordingly. Linear relationships were explored via univariate regression analysis, while a restricted cubic spline (RCS) model was developed to investigate potential non-linear associations between meteorological factors and HRQoL in older adults. RCS is particularly suitable for identifying and quantifying non-linear relationships, allowing for a more flexible and accurate representation of the complex interactions between meteorological factors (such as temperature and humidity) and HRQoL.

To identify influencing factors of the calculated EQ-5D-5L utility values and the self-rated EQ VAS scores, Lasso regression was utilized for variable selection to construct machine learning models. To predict and analyze the changes in HRQoL (defined as the reduction in EQ-5D-5L utility values/VAS scores from T0 to T2) among the older adults and their influencing factors, this study incorporated four distinct machine learning models: eXtreme Gradient Boosting (XGBoost), Random Forest (RF), Support Vector Machine (SVM), and K-nearest Neighbors (KNN).

Model performance was evaluated using metrics including R-squared, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The best-performing model was then utilized to assess the significance of the influencing factors in heatwave periods. All statistical analyses were performed using SPSS 25.0, R 4.1.3, and Python 3.11.

## Results

### *Demographic characteristics of the baseline survey*

A total of 638 older adults were invited to participate in the baseline survey. Of these, 627 completed valid questionnaires, yielding a response rate of 98.28%. There were no missing responses, as interviews were conducted face-to-face by trained personnel who ensured full completion. Three follow-up surveys were conducted during the initial heatwave, peak heatwave, and post-heatwave autumn period, with 499, 465, and 504 participants retained, respectively. Attrition was mainly due to travel (62%), difficulty contacting participants (e.g., returning to hometowns or invalid contact information), and other miscellaneous factors. No new participants were recruited after baseline. Attrition did not significantly alter the age, sex, education, BMI or chronic-disease profile of the retained sample (all $P > 0.05$, Table S1).

At baseline (Table 1), about two-thirds (65.87%) of participants were female. The participants' BMI ranged from underweight to obese, with the following distribution: 4.31% underweight (BMI<18.5), 50.40% normal weight (18.5≤BMI<24.0), 35.73% overweight (24.0≤BMI<28.0), and 9.57% obese (BMI≥28.0). Participants had a mean age of 70.34±6.90 years. Nearly all participants were of Han ethnicity (99.04%).

Educational attainment varied among the participants, with 10.37% being illiterate, 22.65% completing primary school, 26.79% junior high school, 27.91% high school, 6.86% college education, and 5.42% bachelor's degree or higher. Lifestyle behaviors indicated that most participants were non-smokers (88.84%) and non-drinkers (77.03%). More than two thirds (70.97%) of participants reported having chronic diseases.

***Descriptions of trends in utility values and EQ VAS scores***

Fig. 1 and Fig. S2 showed the temporal trends in utility values and EQ VAS scores over time, respectively. The utility values exhibited a distinct trajectory: an initial increase at the first follow-up (T1), followed by a decline at the second (T2), and partial recovery at the third (T3). Specifically, compared with baseline (T0), utility values were significantly higher at T1 but not at T2 or T3. However, both T2 and T3 showed significant decreases relative to T1. In terms of EQ VAS scores, a similar trend was observed. Scores at T1 were significantly higher than those at baseline, however, values at T3 were significantly lower than T1. No significant difference was observed between T2 and T3.

***Univariate linear regression analysis***

Univariate linear regression models were conducted using the pooled sample (data from all-time points) to examine associations between demographic, lifestyle, and meteorological factors and HRQoL outcomes. As shown in Table S2, the univariate linear regression models identified several significant associations. Utility values were significantly lower among underweight participants, widowed or single individuals, and alcohol drinkers. Higher values were observed among participants with at least junior secondary education, those living with both spouse and children, and former private business owners compared with agricultural workers.

As shown in the meteorological factors section of Table S2, current-day temperature had a positive impact on HRQoL, with higher temperatures correlating with better utility values and EQ VAS scores. Specifically, both maximum and minimum temperatures, as well as average daily temperature, were all positively related to HRQoL outcomes. In contrast, current-day humidity was negatively associated with HRQoL, with higher humidity levels linked to lower utility values and EQ VAS scores. Similar lagged effects were observed, with warmer temperatures in the preceding 1–3 days associated with improved HRQoL outcomes.

Table S3 summarizes the frequency and percentage distributions of each EQ-5D-5L dimension across all phases, while Table S4 presents the weighted mean scores for each EQ-5D-5L dimension across the four time points. The pain/discomfort dimension showed the most prominent changes (Table S4): its weighted mean score increased from 0.51 at baseline to 0.62 during the peak heatwave (a relative increase of 21.6%), with a significant difference compared to baseline ($P<0.001$, Cohen's d=0.32). This was accompanied by a notable shift in response distribution, with the proportion of participants reporting "no problems" in pain/discomfort decreased from 59.0% at baseline to 52.5% at peak heatwave, while those reporting "moderate problems" increased from 6.2% to 9.5%.

In contrast, other dimensions showed smaller fluctuations (Table S4). For example, mobility and usual activities exhibited modest increases in mean scores during the peak heatwave (0.36 and 0.22, respectively, vs. baseline scores of 0.29 and 0.15), with smaller effect sizes (Cohen's d=0.18 and 0.21). Self-care and anxiety/depression remained relatively stable across all time points, with mean score changes <0.02 ($P$>0.05 for all comparisons with baseline). These results indicate that pain/discomfort was the dimension most strongly affected by heatwaves, particularly during the peak phase.

***Non-linear analysis using RCS splines***

Fig. 2 and Fig. S3 illustrate the non-linear associations between temperature, humidity, and health-related utility values after adjusting for demographic and concomitant variables. Significant associations were observed between utility values and the same-day maximum, minimum, and average temperatures ($P$=0.015, 0.002, and 0.004, respectively), with each displaying non-linear effects ($P$ for non-linear=0.043, 0.020, and 0.021, respectively). Specifically, utility values decreased with maximum temperatures between 27°C and 33°C, however, followed an opposite trend outside this range. Similarly, minimum temperatures between 19°C and 22°C, and average temperatures between 22°C and 29°C, were associated with reductions in utility values.

Long-term metrics also affected utility values, such as daily minimum temperature on the 4th day preceding the survey ($P$<0.05, with a non-linear effect $P$=0.013). Elevated minimum temperatures above 22°C over this period were associated with improved utility values. However, the impact appears time-limited, as shown by the non-significant non-linear effect for minimum temperature over seven days (*P*=0.972), suggesting a diminishing influence over extended periods (Fig. 2 and Fig. S3).

Fig. 3 and Fig. S4 present the non-linear relationships between meteorological factors and EQ VAS scores, adjusted for demographic and other relevant variables. Significant correlations were identified with temperature and humidity across various time spans ($P<0.05$ overall). Non-linear effects were observed for current-day minimum and average temperatures (*P* for non-linear=0.002 and 0.012, respectively). Specifically, EQ VAS scores among older adults improved when minimum temperatures were between 20°C and 22°C. Conversely, average temperatures between 24°C and 29°C were associated with reduced scores.

Long-term temperature indices also displayed significant non-linear effects. Minimum temperatures 2-3 days prior significantly influenced EQ VAS scores (*P* for non-linear=0.021 and 0.002, respectively). When minimum temperatures exceeded 21°C two days prior, higher temperatures were associated with improved HRQoL. For temperatures three days prior, values within the range of 21°C–26°C were linked to improved scores, whereas temperatures above this range were linked to a decline in EQ VAS scores.

Humidity levels also influenced EQ VAS scores (Fig. S4). The average daily relative humidity over the preceding seven days showed a non-linear relationship with EQ VAS scores (*P* for non-linear=0.037). Specifically, EQ VAS scores increased when the relative humidity exceeded 78%, whereas they decreased as humidity levels rose below this threshold (Fig. 3 and Fig. S4). To verify the robustness of our findings on meteorological factors-HRQoL associations and address potential confounding by seasonality (e.g., duration of daylight, photoperiod), we conducted supplementary analyses using progressively adjusted regression models, with details summarized in Table S5.

***Construction of machine learning models***

During the heatwave periods, a Lasso regression model was constructed using utility values as the outcome variable. Fig. S5A illustrates the coefficient profile of the Lasso regression, and Fig. S5B displays the corresponding cross-validation curve. The analysis identified 14 significant predictors, such as BMI, age, education level, and marital status. Using these variables, multiple machine learning models were developed, among which the SVM model demonstrated the best predictive performance (Table 2).

When the EQ VAS was used as the outcome variable, the Lasso regression model analysis identified six significant predictors, including age, education level, alcohol consumption, chronic diseases, minimum temperature of the previous three days, and average daily temperature of the previous two days (Fig. S5C and Fig. S5D). Machine learning models were then developed based on these selected variables, with the SVM model again showing superior performance.

***Assessment of the importance of features***

During heatwave periods, the feature importance assessment identified BMI as the most influential variable in the utility values model, followed by age, pre-retirement occupation, education level, and average daily relative humidity (Fig. 4). In the EQ VAS model, age was the most significant variable, followed by the minimum temperature of the preceding three days, average daily temperature of the preceding two days, education level, and alcohol consumption (Fig. S6). Further analysis of heatwave types revealed that humid heatwaves had a more pronounced negative impact on HRQoL compared to dry heatwaves (Table S6).

## Discussion

This longitudinal study examined the impact of heatwaves on HRQoL among older adults in Fuzhou, China. The novelty of this study lies in the longitudinal application of the EQ-5D-5L instrument to capture dynamic changes in HRQoL across heatwave phases, offering a nuanced assessment of subclinical heat-related health burdens that complement traditional mortality and morbidity metrics in climate-health research**.** As global warming intensifies, heatwaves pose significant health risks, particularly to vulnerable populations [28]. Our findings indicated a complex and nonlinear relationship between heatwaves and HRQoL, influenced by both demographic and meteorological factors. Notably, humidity emerged as a critical yet often underrecognized determinant of HRQoL, presenting unique challenges for adaptation given its strong dependence on regional climatic characteristics [29,30].

### *HRQoL trajectories during heatwaves*

Our results revealed a dynamic pattern in HRQoL during heatwaves, with an initial improvement followed by a decline, similar to findings by Ji et al. [31]. The initial improvement might be due to the body's adaptive mechanisms, which temporarily mask health declines [32]. However, prolonged heatwave exposure may overwhelm these adaptive capacities, leading to HRQoL decline, exacerbated by older adults' physiological frailty and cumulative heat-related strain [33].

Weather forecasts and proactive prevention measures such as hydration and air conditioning play crucial roles in mitigating the immediate impact of heatwaves [34]. At the individual/family level, targeted interventions, such as education on heat-humidity synergies, improving home ventilation, use of air conditioning/dehumidifiers, and consistent fluid intake, are critical for enhancing heat resilience among vulnerable subgroups (e.g., older adults with low education) [35,36]. However, vigilance may wane over time, leading to inadequate protective measures and a subsequent decline in HRQoL. Social-psychological factors also matter. Older adults may initially downplay heatwaves harms to preserve social image, however, accumulated strain eventually erodes HRQoL [37].

HRQoL decline during severe heatwaves primarily stems from pronounced physiological strain, particularly on the cardiovascular system [38-40], as short-term exposure to extreme heat has been linked to altered cardiovascular indicators (e.g., increased heart rate, systemic inflammation) that may indirectly impair overall well-being [40]. Behavioral restrictions such as reduced physical activity, constrained outdoor ventures, and curtailed social interactions during heatwaves further exacerbate psychological distress and negatively influence perceived HRQoL health [41]. Additionally, high temperatures disrupt appetite and sleep quality, thereby reducing functionality and overall wellness [42]. Although HRQoL improved after heatwaves, recovery was often incomplete, indicating persistent or recurring vulnerabilities [43]. Variations in individual resilience and coping strategies also play a role [44]. Our study underscores the need for tailored protective policies for older adults amid climate challenges. Enhancements in urban design, such as increased greenery and improved building insulation, are essential. Further research is needed to evaluate and develop interventions to meet individual needs and promote adaptive capacity.

***Dimension-specific vulnerability***

In this study, we examined which EQ-5D-5L dimensions were most susceptible to heatwave exposure. Pain/discomfort was identified as the dimension most consistently and markedly affected, particularly during the peak heatwave phase (T2). This finding suggests that subjective somatic distress may serve as an early and sensitive indicator of heat-related physiological strain, preceding detectable impairments in mobility, self-care, or usual activities [45]. The predominance of pain/discomfort aligns with established pathways through which heat stress exacerbates systemic inflammation, muscle ischaemia, and sleep disruption—mechanisms known to heighten nociceptive signaling [46]. Consequently, the observed decline in overall HRQoL during T2 appears to be driven primarily by worsening pain/discomfort scores, underscoring the value of dimension-level analyses for identifying mechanistic pathways and refining intervention targets in climate-health research [47].

***Demographic and health-related modifiers***

Linear regression analysis revealed significant associations between demographic factors and HRQoL. BMI showed a U-shaped relationship with HRQoL: underweight individuals (linked to frailty) and obese individuals (linked to comorbidities) reported poorer outcomes, consistent with broader evidence that extreme BMI phenotypes increase susceptibility to heat-related health impacts [36,48,49].

Age was negatively correlated with HRQoL, aligning with findings that older adults have reduced thermoregulatory capacity and higher vulnerability to heat stress [36,40]. This vulnerability is exacerbated by age-related physiological declines and social factors such as limited social support [50-52].

Higher educational attainment emerged as a protective factor and was associated with better HRQoL, probably because educated individuals are more likely to adopt heat-protective behaviors [53], consistent with evidence that health literacy reduces heat-related risk [36]. Living arrangements also influenced HRQoL, with individuals residing with family benefited from enhanced social support and greater resilience during extreme heat events [54,55]. Former private entrepreneurs reported better HRQoL during heatwaves, likely due to higher socioeconomic status and broader social networks [56-59]. The presence of chronic illnesses compounded vulnerability, as high temperatures exacerbate disease progression and compromise medication efficacy [60-62].

***Meteorological influences***

Our study revealed a nonlinear relationship between several meteorological factors and HRQoL. For instance, across the observed daily maximum temperature range of 27°C to 33°C, a temperature increase was positively associated with a higher risk of compromised HRQoL. Beyond this range, the risk diminished, possibly due to physiological regulatory mechanisms and heightened precautionary behaviors [63]. This aligns with broader observations that temperature effects on health are nonlinear and context-dependent [35].

Humidity exerted dual effects: high daily humidity appeared to reduce HRQoL, potentially due to impaired heat dissipation [64], whereas elevated 7-day average humidity (>78%) led to moderately improved HRQoL, possibly reflecting relief from dry-air discomfort [29,30]. Humidity emerged as an important but underexplored factor influencing HRQoL. Unlike ambient temperature, humidity is less easily mitigated with conventional cooling measures (e.g., air conditioning), as dehumidifiers are generally costlier, less accessible, and energy intensive [35], making it a harder-to-modify public health factor. Further research is needed to clarify its role and to inform feasible adaptation strategies.

Given these complexities, our findings suggest that both temperature and humidity should be considered when evaluating the health impacts of heatwaves. While this study was not designed to propose specific interventions, the results underscore the potential value of incorporating humidity-related indicators (e.g., wet-bulb temperature) into future research and early-warning frameworks [40].

Finally, we note that statistically significant HRQoL changes (e.g., utility decline at T2) were clinically meaningful. In this study, the observed reduction exceeded established minimally important difference (MID) thresholds for EQ-5D-5L utility values [65], indicating that heatwaves were associated with perceptible impairments in aspects of daily functioning (e.g., mobility limitations and increased pain or discomfort). These findings support the value of HRQoL as a sensitive endpoint for evaluating climate-related health burdens, while underscoring the need for further research to confirm these patterns and explore their broader implications.

***Strengths and limitations***

This study has several strengths, including a longitudinal design capturing temporal variations in HRQoL; use of a validated, multidimensional instrument; and analysis of nonlinear meteorological effects. However, limitations should be acknowledged. First, the findings are based on data collected from older adults of two urban communities in Fuzhou, China, and may not be generalizable to other populations or regions with different climates or socio-demographic structures. Second, the use of snowball sampling resulted in a higher proportion of women in our sample and may have favored the inclusion of healthier or more socially active participants. This selection bias may limit the representativeness of the study population and potentially overestimate HRQoL, compared with the general older adult population. Third, meteorological exposures in this study were estimated from city-level outdoor monitoring stations, while individual-level indoor conditions, microenvironments, and personal activity patterns were not captured. This may have introduced exposure misclassification and reduced the precision of assessing the true heatwave–HRQoL relationship. Nonetheless, rigorous interviewer training minimized data collection bias, ensuring participants independently reported HRQoL. Fourth, HRQoL is a subjective measure and may be influenced by reporting bias. Moreover, participants' awareness and use of weather forecasts were not assessed, which may be an important behavioral factor influencing adaptation to heatwaves. Finally, although we incorporated multiple socio-demographic, behavioral, and health-related variables (e.g., cooling measures, family living arrangements, chronic diseases, and hydration behaviors) into our analyses, it remains challenging to fully disentangle the independent and cumulative effects of temperature and humidity on HRQoL. Therefore, this study should be regarded as an initial step into this complex area, and future multi-site, longitudinal studies are warranted to validate and extend our findings.

## Conclusions

This longitudinal study demonstrates that heatwaves substantially impair HRQoL in older adults, particularly those who are older, underweight, or have lower education attainment. HRQoL fluctuated across heatwave phases, reflecting nonlinear interactions between temperature, humidity, and demographic factors. The temperature range of 27–33°C is especially critical for HRQoL decline, while humidity is a key but underrecognized determinant. Future climate adaptation strategies should integrate both temperature- and humidity-specific interventions, prioritize vulnerable subgroups, and incorporate HRQoL measures as sensitive indicators of subclinical burden. Urban planning and public health policy should use meteorological/demographic data to design targeted, equitable interventions, such as enhanced early warning systems, heat-humidity risk communication, and community-based support networks, to protect older adults amid intensifying climate extremes.

## Abbreviations

| | |
|---|---|
| HRQoL | Health-Related Quality of Life |
| RCS | Restricted Cubic Spline |
| XGBoost | eXtreme Gradient Boosting |
| RF | Random Forest |
| SVM | Support Vector Machine |
| KNN | K-nearest Neighbors |



## References

1. Chambers J. Global and cross-country analysis of exposure of vulnerable populations to heatwaves from 1980 to 2018. *Climatic Change*. Nov 2020;163(1):539-558. doi:10.1007/s10584-020-02884-2
2. Somani R. Global Warming in Pakistan and Its Impact on Public Health as Viewed Through a Health Equity Lens. *International Journal of Social Determinants of Health and Health Services*. Apr 2023;53(2):154-157. doi:10.1177/27551938231154467
3. Romanello M, McGushin A, Di Napoli C, et al. The 2021 report of the Lancet Countdown on health and climate change: code red for a healthy future. *Lancet*. Oct 2021;398(10311):1619-1662.
4. Malmquist A, Hjerpe M, Glaas E, Karlsson H, Lassi T. Elderly People's Perceptions of Heat Stress and Adaptation to Heat: An Interview Study. *International Journal of Environmental Research and Public Health*. Apr 2022;19(7)3775. doi:10.3390/ijerph19073775
5. Lai ETC, Chau PH, Cheung K, Kwan M, Lau K, Woo J. Perception of extreme hot weather and the corresponding adaptations among older adults and service providers-A qualitative study in Hong Kong. *Front Public Health*. 2023;11:1056800. doi:10.3389/fpubh.2023.1056800

6. Cheng J, Xu ZW, Bambrick H, Su H, Tong SL, Hu WB. Heatwave and elderly mortality: An evaluation of death burden and health costs considering short-term mortality displacement. *Environment International*. Jun 2018;115:334-342. doi:10.1016/j.envint.2018.03.041

7. Brennan M, O'Shea PM, Mulkerrin EC. Preventative strategies and interventions to improve outcomes during heatwaves. *Age and Ageing*. Sep 2020;49(5):729-732. doi:10.1093/ageing/afaa125

8. Moon J. The effect of the heatwave on the morbidity and mortality of diabetes patients; a meta-analysis for the era of the climate crisis. *Environmental Research*. Apr 2021;195110762. doi:10.1016/j.envres.2021.110762

9. Liu JW, Varghese BM, Hansen A, et al. Heat exposure and cardiovascular health outcomes: a systematic review and meta-analysis. *Lancet Planetary Health*. Jun 2022;6(6):E484-E495.

10. Lin YK, Sung FC, Honda Y, Chen YJ, Wang YC. Comparative assessments of mortality from and morbidity of circulatory diseases in association with extreme temperatures. *Sci Total Environ*. Jun 25 2020;723:138012. doi:10.1016/j.scitotenv.2020.138012

11. Ji JS, Xia Y, Liu L, et al. China's public health initiatives for climate change adaptation. *Lancet Reg Health West Pac*. Nov 2023;40:100965. doi:10.1016/j.lanwpc.2023.100965

12. Otto C, Reiss F, Voss C, et al. Mental health and well-being from childhood to adulthood: design, methods and results of the 11-year follow-up of the BELLA study. *Eur Child Adolesc Psychiatry*. Oct 2021;30(10):1559-1577. doi:10.1007/s00787-020-01630-4

13. Herdman M, Gudex C, Lloyd A, et al. Development and preliminary testing of the new five-level version of EQ-5D (EQ-5D-5L). *Qual Life Res*. Dec 2011;20(10):1727-36. doi:10.1007/s11136-011-9903-x

14. Wang A, Rand K, Yang Z, Brooks R, Busschbach J. The remarkably frequent use of EQ-5D in non-economic research. *Eur J Health Econ*. Aug 2022;23(6):1007-1014. doi:10.1007/s10198-021-01411-z

15. Hugelius K, Gifford M, Örtenwall P, Adolfsson A. Health among disaster survivors and health professionals after the Haiyan Typhoon: a self-selected Internet-based web survey. *Int J Emerg Med*. Dec 2017;10(1):13. doi:10.1186/s12245-017-0139-6

16. Andrade MV, Noronha K, Santos AS, et al. Estimation of Health-Related Quality of Life Losses Owing to a Technological Disaster in Brazil Using EQ-5D-3L: A Cross-Sectional Study. *Value Health Reg Issues*. Dec 2021;26:66-74. doi:10.1016/j.vhri.2021.02.003

17. Yang F, Leon-Giraldo S, Moreno-Serra R. Health-related quality of life of a conflict-affected population in Colombia. *Qual Life Res*. Dec 2021;30(12):3559-3569. doi:10.1007/s11136-021-02805-5

18. National Bureau of Statistics. Population Census. 2020. https://www.stats.gov.cn/

19. Brazier J, Peasgood T, Mukuria C, et al. The EQ-HWB: Overview of the Development of a Measure of Health and Wellbeing and Key Results. *Value Health*. Apr 2022;25(4):482-491. doi:10.1016/j.jval.2022.01.009

20. Wiese CW, Tay L, Su R, Diener E. Measuring Thriving across Nations: Examining the Measurement Equivalence of the Comprehensive Inventory of Thriving (CIT) and the Brief Inventory of Thriving (BIT). *Appl Psychol Health Well Being*. Mar 2018;10(1):127-148. doi:10.1111/aphw.12119
21. Zhan LF, Wang YJ, Sun HM, Zhai JQ, Zhan MJ. Study on the Change Characteristics of and Population Exposure to Heatwave Events on the North China Plain. *Advances in Meteorology*. Aug 2019;20197069195. doi:10.1155/2019/7069195
22. Fuzhou Meteorological Station. http://fj.cma.gov.cn/fzsqxj/
23. Yang L. *Sample Size Calculation in Simple Linear Regression Under Two Scenarios*. 2024.
24. Luo N, Liu G, Li M, Guan H, Jin X, Rand-Hendriksen K. Estimating an EQ-5D-5L Value Set for China. *Value Health*. Apr 2017;20(4):662-669. doi:10.1016/j.jval.2016.11.016
25. Eom BW, Yoon HM, Kim YW, et al. Quality of Life and Nutritional Outcomes of Stomach-Preserving Surgery for Early Gastric Cancer: A Secondary Analysis of the SENORITA Randomized Clinical Trial. *JAMA Surg*. Aug 1 2024;159(8):900-908. doi:10.1001/jamasurg.2024.1210
26. Faul F, Erdfelder E, Lang AG, Buchner A. G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav Res Methods*. May 2007;39(2):175-91. doi:10.3758/bf03193146
27. Shafie AA, Vasan Thakumar A, Lim CJ, Luo N, Rand-Hendriksen K, Md Yusof FA. EQ-5D-5L Valuation for the Malaysian Population. *Pharmacoeconomics*. May 2019;37(5):715-725. doi:10.1007/s40273-018-0758-7
28. He RK, Tsoulou I, Thirumurugesan S, et al. Effect of heatwaves on PM2.5 levels in apartments of low-income elderly population. A case study using low-cost air quality monitors. *Atmospheric Environment*. May 2023;301119697. doi:10.1016/j.atmosenv.2023.119697
29. Haines SR, Hall EC, Marciniak K, et al. Microbial growth and volatile organic compound (VOC) emissions from carpet and drywall under elevated relative humidity conditions. *Microbiome*. Oct 2021;9(1)209. doi:10.1186/s40168-021-01158-y
30. Stefano De A, Luigi Pietro Maria C, Angelo F, Cesare Maria J. Feasibility study of a desiccant packed bed system for air humidification. Article. *Energy*. 0101 2021;doi:10.1016/j.energy.2020.119002
31. Ji SM, Zhou Q, Jiang Y, et al. The Interactive Effects between Particulate Matter and Heat Waves on Circulatory Mortality in Fuzhou, China. *International Journal of Environmental Research and Public Health*. Aug 2020;17(16)5979. doi:10.3390/ijerph17165979
32. Ahmed R, Ucci M, Mumovic D, Bagkeris E. Effects of thermal sensation and acclimatization on cognitive performance of adult female students in Saudi Arabia using multivariable-multilevel statistical modeling. *Indoor Air*. Feb 2022;32(2)e13005. doi:10.1111/ina.13005
33. Liu TT, Shi CX, Wei J, et al. Extreme temperature events and dementia mortality in Chinese adults: a population-based, case-crossover study. *International Journal of Epidemiology*. Feb 2024;53(1)doi:10.1093/ije/dyad119

34. Oertel A, Pickl M, Quinting JF, et al. Everything Hits at Once: How Remote Rainfall Matters for the Prediction of the 2021 North American Heat Wave. *Geophysical Research Letters*. Feb 2023;50(3)doi:10.1029/2022gl100958
35. Aunan K, Orru H, Sjödin H. Perspectives on connecting climate change and health. *Scand J Public Health*. Mar 2025;53(2):219-222. doi:10.1177/14034948241269748
36. Arsad FS, Hod R, Ahmad N, et al. The Impact of Heatwaves on Mortality and Morbidity and the Associated Vulnerability Factors: A Systematic Review. *Int J Environ Res Public Health*. Dec 6 2022;19(23)doi:10.3390/ijerph192316356
37. Da Hee K, Kyuho L. OLDER ADULTS' HEALTH AND SOCIAL ENGAGEMENT: THE MEDIATING ROLE OF SUBJECTIVE LIFE EXPECTANCY. Article. *Innovation in Aging*. 1101 2019;doi:10.1093/geroni/igz038.2555
38. Li YX, Gu Y, Li ZH, Zhang XY, Gao WJ, Xiao F. Study on the challenge and influence of the built thermal environment on elderly health in rural areas: Evidence from Shandong, China. *Building Simulation*. Aug 2023;16(8):1345-1360. doi:10.1007/s12273-023-1013-5
39. Yazdi MD, Wei YG, Di Q, et al. The effect of long-term exposure to air pollution and seasonal temperature on hospital admissions with cardiovascular and respiratory disease in the United States: A difference-in-differences analysis. *Science of the Total Environment*. Oct 2022;843156855. doi:10.1016/j.scitotenv.2022.156855
40. Cheng BJ, Li H, Meng K, et al. Short-term effects of heatwaves on clinical and subclinical cardiovascular indicators in Chinese adults: A distributed lag analysis. *Environ Int*. Jan 2024;183:108358. doi:10.1016/j.envint.2023.108358
41. Wang WQ, Li YH, Li L, Wang RS, Wang YQ. Study on thermal comfort of elderly in community parks: An exploration from the perspectives of different activities and ages. *Building and Environment*. Dec 2023;246111001. doi:10.1016/j.buildenv.2023.111001
42. Zheng GZ, Li K, Wang YJ. The Effects of High-Temperature Weather on Human Sleep Quality and Appetite. *International Journal of Environmental Research and Public Health*. Jan 2019;16(2)270. doi:10.3390/ijerph16020270
43. Todd P. Tropical storms and mortality under climate change. Article. *World Development*. 0501 2019;doi:10.1016/j.worlddev.2019.01.009
44. Bobb JF, Peng RD, Bell ML, Dominici F. Heat-Related Mortality and Adaptation to Heat in the United States. *Environmental Health Perspectives*. Aug 2014;122(8):811-816. doi:10.1289/ehp.1307392
45. 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*. Nov 2014;122(11):1187-92. doi:10.1289/ehp.1206132
46. Flouris AD, Dinas PC, Ioannou LG, et al. Workers' health and productivity under occupational heat strain: a systematic review and meta-analysis. *Lancet Planet Health*. Dec 2018;2(12):e521-e531. doi:10.1016/s2542-5196(18)30237-7
47. Janssen MF, Pickard AS, Golicki D, et al. Measurement properties of the EQ-5D-5L compared to the EQ-5D-3L across eight patient groups: a multi-country study. *Qual Life Res*. Sep 2013;22(7):1717-27. doi:10.1007/s11136-012-0322-4

48. Welch C. Age and frailty are independently associated with increased COVID-19 mortality and increased care needs in survivors: results of an international multi-centre study. *Age Ageing*. May 5 2021;50(3):617-630. doi:10.1093/ageing/afab026
49. Piya MK, Chimoriya R, Yu W, et al. Improvement in Eating Disorder Risk and Psychological Health in People with Class 3 Obesity: Effects of a Multidisciplinary Weight Management Program. *Nutrients*. Apr 23 2021;13(5)doi:10.3390/nu13051425
50. Wu YX, Zhang ZX, Liu H, et al. Age differences in thermal comfort and physiological responses in thermal environments with temperature ramp. *Building and Environment*. Jan 2023;228doi:10.1016/j.buildenv.2022.109887
51. Allemann MS, Lee PTT, Beer JH, Saravi SSS. Targeting the redox system for cardiovascular regeneration in aging. *Aging Cell*. 2023 Nov 2023;doi:10.1111/acel.14020
52. Hao R, Jin HY, Zuo JF, Wu YB, Sun XA, Hu J. The multiple mediating effect of family health and perceived social support on depressive symptoms in older adults: A cross-sectional national survey in China. *Journal of Affective Disorders*. Apr 2023;327:348-354. doi:10.1016/j.jad.2023.01.097
53. Reynolds A, Greenfield EA. Diminished Returns of Higher Parental Education on Cognition for Black Adults in Middle and Later Life. *Journals of Gerontology Series B-Psychological Sciences and Social Sciences*. Mar 2024;79(3)gbad181. doi:10.1093/geronb/gbad181
54. Ng N, Santosa A, Weinehall L, Malmberg G. Living alone and mortality among older people in Vasterbotten County in Sweden: a survey and register-based longitudinal study. *Bmc Geriatrics*. Jan 2020;20(1)7. doi:10.1186/s12877-019-1330-9
55. Zhang Y, Liu ZF, Zhang LL, Zhu PY, Wang X, Huang YX. Association of living arrangements with depressive symptoms among older adults in China: a cross-sectional study. *Bmc Public Health*. Jul 2019;191017. doi:10.1186/s12889-019-7350-8
56. Tetzlaff EJ, Goulet N, Gorman M, Ioannou LG, Kenny GP. Working under the 2021 Heat Dome: A Content Analysis of Occupational Impacts Mentioned in the Canadian Media. *Healthcare*. Sep 2023;11(17)2423. doi:10.3390/healthcare11172423
57. Park J, Chae Y, Choi SH. Analysis of Mortality Change Rate from Temperature in Summer by Age, Occupation, Household Type, and Chronic Diseases in 229 Korean Municipalities from 2007-2016. *International Journal of Environmental Research and Public Health*. May 2019;16(9)1561. doi:10.3390/ijerph16091561
58. Jens K, Thomas P, Niklas W. Collectors: Personality between consumption and investment. Article. *Journal of Behavioral and Experimental Finance*. 1201 2021;doi:10.1016/j.jbef.2021.100566
59. Wrana J, Diez JR. Multinational enterprises or the quality of regional institutions What drives the diffusion of global CSR certificates in a transition economy? Evidence from Vietnam. *Journal of Cleaner Production*. Jun 2018;186:168-179. doi:10.1016/j.jclepro.2018.03.113
60. Zanobetti A, O'Neill MS, Gronlund CJ, Schwartz JD. Summer temperature variability and long-term survival among elderly people with chronic disease. *Proceedings of the National Academy of Sciences of the United States of America*. Apr 2012;109(17):6608-6613. doi:10.1073/pnas.1113070109

61. Gu SM, Wang XF, Mao GM, et al. The effects of temperature variability on mortality in patients with chronic obstructive pulmonary disease: a time-series analysis in Hangzhou, China. *Environmental Science and Pollution Research*. Oct 2022;29(47):71502-71510. doi:10.1007/s11356-022-20588-1
62. Fu J, Liu YB, Zhao YK, et al. Association between the temperature difference and acute exacerbations of chronic obstructive pulmonary disease: A time-series analysis with 143,318 hospital admissions in Beijing, China. *Frontiers in Public Health*. Jan 2023;111112926. doi:10.3389/fpubh.2023.1112926
63. Manchanda M, Leishman E, Sangani K, Alamri A, Bradshaw HB. Activation of TRPV1 by Capsaicin or Heat Drives Changes in 2-Acyl Glycerols and N-Acyl Ethanolamines in a Time, Dose, and Temperature Dependent Manner. *Front Cell Dev Biol*. 2021;9:611952. doi:10.3389/fcell.2021.611952
64. Kivimaki M, Batty GD, Pentti J, et al. Climate Change, Summer Temperature, and Heat -Related Mortality in Finland: Multicohort Study with Projections for a Sustainable vs. Fossil -Fueled Future to 2050. *Environmental Health Perspectives*. Dec 2023;131(12)doi:10.1289/ehp12080
65. Cheng LJ, Chen LA, Cheng JY, Herdman M, Luo N. Systematic review reveals that EQ-5D minimally important differences vary with treatment type and may decrease with increasing baseline score. *J Clin Epidemiol*. Oct 2024;174:111487. doi:10.1016/j.jclinepi.2024.111487

**Figure Legends:**

Figure 1. Forest plot for statistical assessment of EQ-5D-5L utility value trends. Note: T0-T1 represents a comparison between baseline and first follow-up. P is from Tukey's HSD test.

Figure 2. RCS analysis of the relationship between EQ-5D-5L utility values and meteorological factors. The analysis was performed at wind speeds of 3 knots across the 10th, 50th, and 90th percentiles. Statistical significance was set with a threshold of p-overall<0.05. ORs are indicated by solid lines, while 95% CIs are represented by shaded areas.

Figure 3. RCS analysis of the relationship between EQ VAS scores and meteorological factors.

Figure 4. Feature importance analysis for predictors of EQ-5D-5L utility values during heatwaves.

**Supplementary material legends**

**Figure S1.** Geographical locations of the two residential communities surveyed in Fuzhou, China: (A) Champion Community, Cangshan District; and (B) Yangqiao Henan Community, Gulou District. The left panel shows the position of Fuzhou within Fujian Province, and the right panel illustrates the urban districts of Fuzhou with the two study sites marked.

**Figure S2.** Forest plot for statistical assessment of EQ VAS score trends. **Note:** T0-T1 represents a comparison between baseline and first follow-up. *P* is from Tukey's HSD test.

**Figure S3.** RCS analysis of the relationship between utility scores and meteorological factors.

**Figure S4.** RCS analysis of the relationship between EQ VAS scores and meteorological factors.

**Figure S5.** Variable selection and model validation through Lasso regression for assessing utility values and EQ VAS scores in older adults during heatwave period. Panels A and C illustrate the coefficient profile plots for utility values and EQ VAS scores respectively, where each line represents the trajectory of a variable's coefficient as the regularization parameter is varied. Panels B and D show the cross-validation curves for utility values and EQ VAS scores accordingly, with each point on the line indicating the model's performance at a specific value of the regularization parameter during the cross-validation process. These plots elucidate the feature selection efficacy of the Lasso regression and affirm the predictive stability of the resultant models.

**Figure S6**. Feature importance analysis for predictors of EQ VAS scores during heatwaves.

**Table S1.** Baseline demographic characteristics and attrition analysis of the longitudinal cohort.

**Table S2.** Univariate regression analysis.

**Table S3**. Frequency and percentage distribution of EQ-5D-5L dimensions across heatwave phases.

**Table S4.** Weighted mean scores of EQ-5D-5L dimensions at baseline and during heatwave phases.

**Table S5.** Sensitivity analysis of seasonal confounding effects on heatwave-HRQoL associations: comparison of models adjusting for daylight and photoperiod.

**Table S6.** Dry vs. humid heatwave effects on HRQoL (complete cases, n=432).

# Tables

**Table 1.** Demographic characteristics of the baseline survey.

| Variables | | N (%)/Mean (SD) |
|---|---|---|
| Gender | Male | 214(34.13) |
| | Female | 413(65.87) |
| BMI (kg/m$^2$) | Underweight (BMI< 18.5) | 27(4.30) |
| | Normal weight (18.5≤BMI<24.0) | 316(50.40) |
| | Overweight (24.0≤BMI<28.0) | 224(35.73) |
| | Obese (BMI≥28.0) | 60(9.57) |
| Age (years) | | 70.34(6.90) |
| Nationality | Han | 621(99.04) |
| | Minorities | 6(0.96) |
| Education level | Illiteracy | 65(10.37) |
| | Primary school | 142(22.65) |
| | Junior high school | 168(26.79) |
| | Senior high school | 175(27.91) |
| | Associate degree | 43(6.86) |
| | Bachelor's degree or higher | 34(5.42) |
| Marital status | Married | 509(81.18) |
| | Separated/divorced | 21(3.35) |
| | Widowed/single | 97(15.47) |
| Living arrangement | With children only | 173(27.59) |
| | With spouse only | 199(31.74) |
| | Living alone | 54(8.61) |
| | With spouse and children | 183(29.19) |
| | Other | 18(2.87) |
| Current employment | Employed | 27(4.31) |
| | Retired | 600(95.69) |
| Current workplace location | Indoor | 17(62.96) |
| | Outdoor | 10(37.04) |
| Cooling measures at workplace | None | 6(22.22) |
| | Electric fans only | 19(70.37) |
| | Air conditioning only | 2(7.41) |
| Pre-retirement occupation | Agriculture/forestry/fishing workers | 116(18.50) |
| | Factory workers | 172(27.43) |
| | Administrative/managerial staff | 105(16.75) |
| | Professionals/technicians | 116(18.50) |
| | Sales/service workers | 10(1.60) |
| | Private business owners | 27(4.31) |
| | Homemakers | 31(4.94) |
| | Other | 50(7.98) |

| | | |
|---|---|---|
| Personal annual income (10,000 RMB) | <3 | 188(29.98) |
| | 3-5.99 | 279(44.50) |
| | ≥6 | 142(22.65) |
| | Prefer not to say | 18(2.87) |
| Smoking status | Non-smoker | 557(88.84) |
| | Smoker | 70(11.16) |
| Alcohol consumption | Non-drinker | 483(77.03) |
| | Drinker | 116(22.97) |
| Chronic diseases | Yes | 445(70.97) |
| | No | 182(29.03) |
| Type I diabetes | Yes | 7(1.12) |
| | No | 620(98.88) |
| Type II diabetes | Yes | 127(20.26) |
| | No | 500(79.74) |
| Coronary heart disease | Yes | 42(6.70) |
| | No | 585(93.30) |
| Stroke/Transient ischemic attack | Yes | 7(1.12) |
| | No | 620(98.88) |
| Hypertension | Yes | 275(43.86) |
| | No | 352(56.14) |
| Chronic obstructive pulmonary disease | Yes | 6(0.96) |
| | No | 621(99.04) |
| Gastritis/Gastric ulcer | Yes | 38(6.06) |
| | No | 589(93.94) |
| Nephritis | Yes | 12(1.91) |
| | No | 615(98.09) |
| Nephrolithiasis | Yes | 7(1.12) |
| | No | 620(98.88) |
| Renal failure | Yes | 3(0.48) |
| | No | 624(99.52) |
| Adoption of cooling measures in recent days | Yes | 290(46.25) |
| | No | 337(53.75) |
| Drink water only when feeling thirsty | Yes | 211(33.65) |
| | No | 416(66.35) |
| Schedule outdoor activities for cooler times of the day | Yes | 583(92.98) |
| | No | 44(7.02) |
| Take sun-protective measures when going outdoors. | Yes | 466(74.32) |
| | No | 161(25.68) |

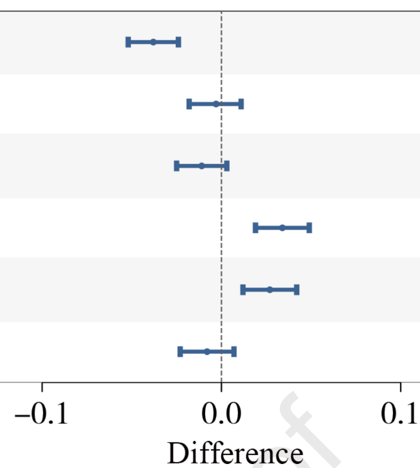
| | |
|---|---|
| No | 161(25.68) |

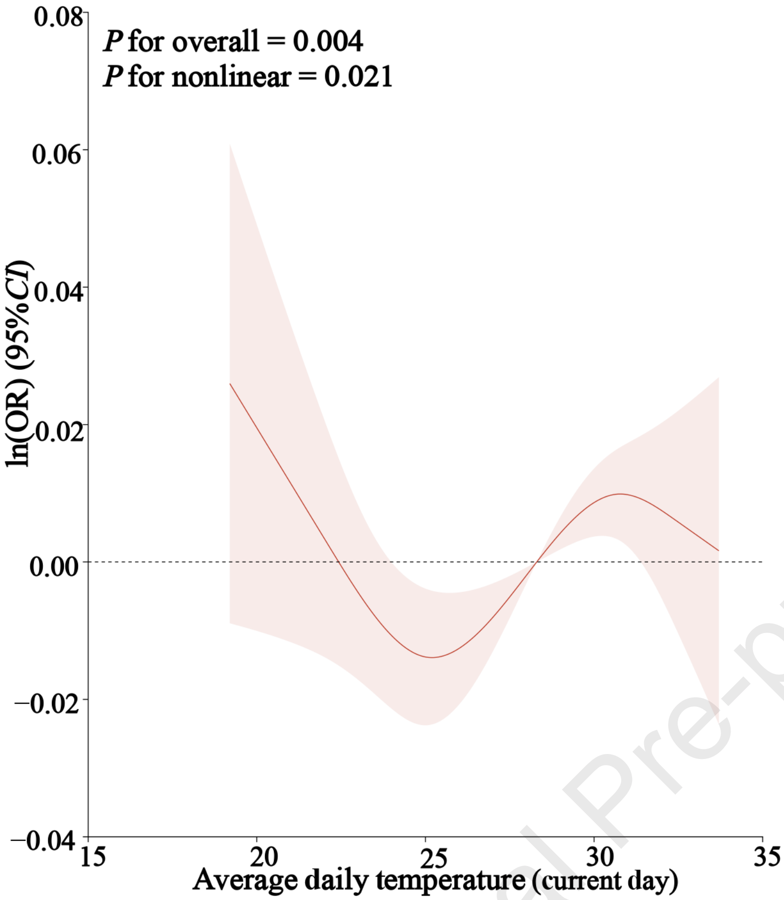
**Table 2.** Construction and evaluation of machine learning models during heatwave periods.

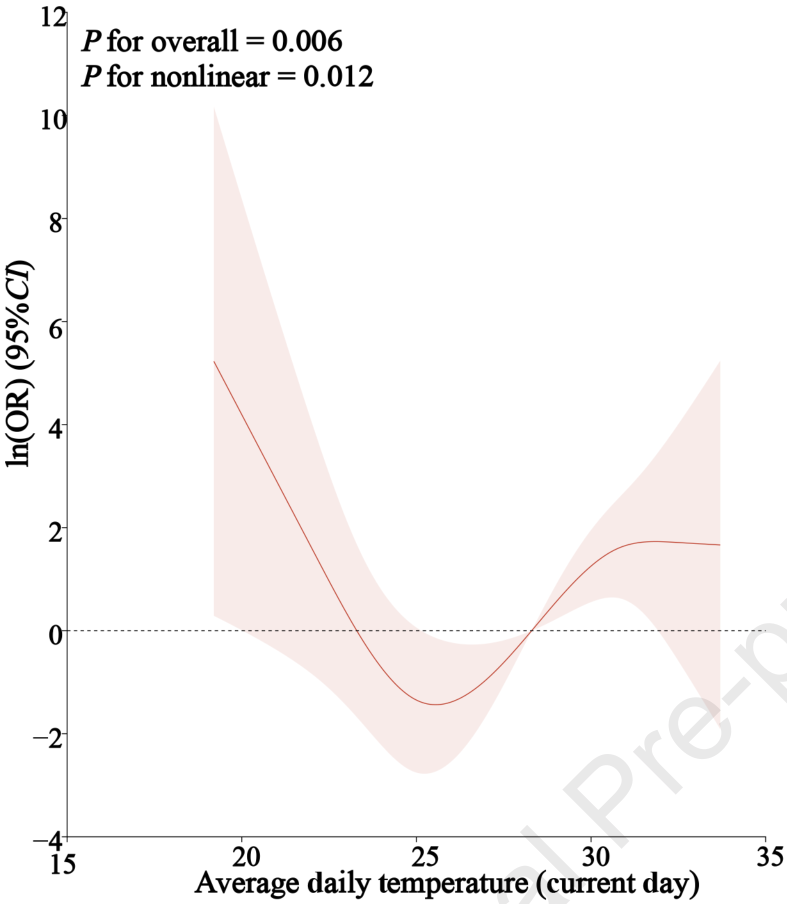
| Models | Utility Values | | | | | | EQ VAS | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Validation set | | | Test set | | | Validation set | | | Test set | | |
| | $R^2$ | RMAE | MAE | $R^2$ | RMAE | MAE | $R^2$ | RMAE | MAE | $R^2$ | RMAE | MAE |
| **XGBoost** | 0.102 | 0.014 | 0.087 | 0.16 | 0.019 | 0.176 | 0.017 | 3.028 | 0.020 | 0.024 | 3.332 | 0.200 |
| **RF** | 0.278 | 0.019 | 0.048 | 0.148 | 0.031 | 0.152 | 0.345 | 3.905 | 0.342 | 0.080 | 6.602 | 0.046 |
| **SVM** | 0.508 | 0.002 | 0.003 | 0.387 | 0.019 | 0.029 | 0.650 | 2.172 | 0.240 | 0.010 | 3.000 | 0.017 |
| **KNN** | 0.198 | 0.015 | 0.184 | 0.130 | 0.025 | 0.111 | 0.167 | 2.515 | 0.165 | 0.364 | 3.017 | 0.339 |

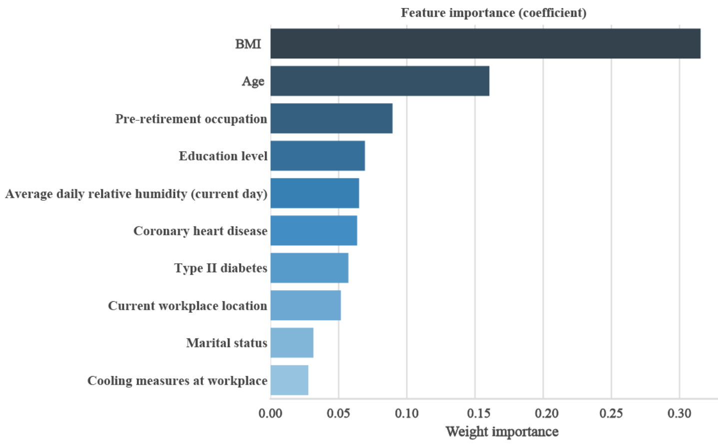
**Note:** $R^2$ represents the coefficient of determination, RMAE denotes the relative mean absolute error, and MAE stands for the mean absolute error.

| Time | Difference | | *P* |
|---|---|---|---|
| T0 – T1 | –0.038 (–0.052, –0.024) | | <0.001 |
| T0 – T2 | –0.003 (–0.018, 0.011) | | 0.646 |
| T0 – T3 | –0.011 (–0.025, 0.003) | | 0.124 |
| T1 – T2 | 0.034 (0.019, 0.049) | | <0.001 |
| T1 – T3 | 0.027 (0.012, 0.042) | | <0.001 |
| T2 – T3 | –0.008 (–0.023, 0.007) | | 0.321 |




P for overall = 0.004
P for nonlinear = 0.021
0.08
0.06
0.04
0.02
0.00
−0.02
−0.04
ln(OR) (95%CI)
15
20
25
30
35
Average daily temperature (current day)


P for overall = 0.006
P for nonlinear = 0.012
ln(OR) (95%CI)
12
10
8
6
4
2
0
−2
−4
15
20
25
30
35
Average daily temperature (current day)


Feature importance (coefficient)
BMI
Age
Pre-retirement occupation
Education level
Average daily relative humidity (current day)
Coronary heart disease
Type II diabetes
Current workplace location
Marital status
Cooling measures at workplace
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Weight importance