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# How Do Environmental and Methodological Factors Influence Study Participants' Answers in Surveys on Risk Perception in the Context of Climate Change and Heat Stress?

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Manuscript submitted: 28 November 2022 / Accepted for publication: 24 September 2024 / Published online: 08 January 2025

#### **Abstract**

Research on climate change and impacts of natural hazards, such as heat waves, on human health has increased in recent years. Various approaches are used to study people's attitudes and actions in this context, but little is known about the extent to which different modes or other environmental variables influence the results. Therefore, we examined differences between surveys in three German cities, compared survey modes and investigated the influence of the temperature on the day of the survey and the previous days. We conducted two surveys on the topics of climate change risk perception and heat risk perception. In summer and autumn of 2019, in total 1,417 people from the three medium-sized German cities of Potsdam, Remscheid and Würzburg were surveyed via telephone or online. In summer of 2020, 280 people were surveyed face-to-face in public parks in Potsdam. Climate change risk perception, the perception of heat waves as a health threat and the knowledge of heat warnings differed depending on place of residence, survey mode and temperature. Participants of the online survey showed higher scores of risk perception than participants of the telephone and face-to-face surveys, indicating a self-selection bias. Increased temperature was associated with slightly higher levels of respondents' heat wave risk perception and, among participants surveyed outside, climate change risk perception. The finding that both survey mode and environmental factors can influence survey results should be heeded when planning or interpreting and comparing studies.

**Keywords** heat wave, risk awareness, health behavior, weather warning, multimethod research

Holzen, V., Heidenreich, A., & Thieken, A. H. (2024). How do environmental and methodological factors influence study participants' answers in surveys on risk perception in the context of climate change and heat stress? *DIE ERDE*, 155(2), 49–66.



https://doi.org/10.12854/erde-2024-647

#### 1. Introduction

# 1.1 Health Risks of Climate Change and Global Warming

Climate change has widespread impacts on human and natural systems (Intergovernmental Panel on Climate Change [IPCC], 2022). 2011 to 2020 was the warmest decade ever recorded (World Meteorological Organization, 2020) and climate models project further, significantly higher temperature extremes by the end of the 21<sup>st</sup> century (IPCC, 2022). Heat waves are likely to occur more often and at the same time last longer and be more intense (Fischer & Schär, 2010).

The rise in average global temperature and the related increasing frequency, intensity and duration of extreme heat is seen as the most immediate and direct impact of a changing climate on human health (Watts et al., 2019). Pathophysiological consequences of elevated temperatures include heat stress and heat exhaustion, which can develop into heat stroke and pose a serious threat to life (Hajat et al., 2010). In 2019, extreme heat waves with record-breaking temperatures in Western Europe led to up to 50% extra deaths above normal during the alert periods and caused excess mortality of several thousand people, for example, about 1,500 extra deaths in France alone (Vautard et al., 2020). In Germany, an estimated number of 6,900 heat-related deaths occurred in 2019 and 3,700 in the following year (Winklmayr et al., 2022). A heat wave in August 2020 caused an excess mortality of 6% for this month (and up to 20% in an especially hot week that month) compared to the previous four years (Deutscher Wetterdienst, 2020; Statistisches Bundesamt, 2020). Due to a reduced thermoregulatory function, elderly people and infants as well as chronically ill and physically impaired people are vulnerable groups (Hajat et al., 2010). However, prolonged exposure to high heat and heat waves causes impairment and discomfort in all people, although physiological adaptation may take place when people are frequently exposed to heat (Krummenauer et al., 2021; Raymond et al., 2020).

To reduce and manage the risk of climate change, mitigation and adaptation must be seen as complementary strategies (IPCC, 2022). Especially when it comes to heat, both structural and individual precautionary and adaptive measures are important to cope with the increased stress (Shooshtarian et al., 2018; World Health Organization, 2021). Different factors influ-

ence the implementation of such measures. An important one seems to be the perception of the problem itself, as could be shown for climate change adaptation behavior in general and adaptive behavior to heat in particular (Ban et al., 2019; Esplin et al., 2019; van Valkengoed & Steg, 2019). Therefore, it is important to analyze risk perception and examine underlying factors that influence risk perception and consequently adaptation behavior.

The aim of this research is to study the influence of different external factors on risk perception regarding climate change and heat. We chose three factors that play a relevant role in central research areas of environmental research and especially environmental psychology, but have been neglected in past research: place of residence, survey mode and temperature on the day of the survey and the previous days.

# 1.2 Climate Change and Heat Risk Perception

The earth's climate system and climate change are highly complex issues, which is why they are difficult to understand (Bruyninckx, 2018; Weber & Stern, 2011). Moreover, climate change is difficult for people to experience directly or even recognize on a purely perceptual or sensory level (Pawlik, 1991). Besides scientific results and evidence, there is a range of other factors, which influence people's attitude towards climate change and their perception of climate change as a risk (van der Linden, 2015). Hence, risk judgment of climate change varies greatly between individuals (Capstick et al., 2015; Metag et al., 2017; Poortinga et al., 2019).

Heat stress poses a serious health threat. However, many people do not adequately perceive heat phenomena as a health-threatening problem for themselves (Akompab et al., 2013; Howe et al., 2019). Especially elderly people which themselves are more vulnerable to suffering from heat stress are often not aware of the risks of heat stress (Abrahamson et al., 2009; Bittner & Stößel, 2012; Howe et al., 2019; Wolf et al., 2010). A review by Hass et al. (2021) shows that various environmental, social, personal, and structural factors have an impact on heat risk perception. Various studies for example state that women and younger people tend to show higher heat risk perception (Akompab et al., 2013; Beckmann et al., 2021; Howe et al., 2019; Kalkstein & Sheridan, 2007). Furthermore, belief in climate change is associated with increased heat risk perception (Cutler et al., 2018).

#### 1.3 Focus of This Research

This research aims to study the influence of different external factors, namely place of residence, survey mode and temperature during or before the survey on climate change risk perception and heat risk perception. When having a broader sample, people from different regions participate in a survey, when using multiple methods, different survey modes are being applied and when a survey is spread across different regions or runs over a longer period of time, participants take part while being exposed to varying temperatures. So, these factors are relevant in all areas of research, but the question arises whether and how much such methodological and environmental aspects influence the responses. We explore the following three research questions:

RQ 1: Does the place of residence have an impact on participants' climate change and heat risk perception?

The place of residence can influence risk perception through different thermal experiences. Howe et al. (2019), for example, found that populations located in warmer climates have higher risk perceptions than those living in cooler climates. Different thermal experiences may be caused by geographical or structural differences of the studied areas. Urban areas, for example, get up to 10 °C hotter than their surroundings because of modification of land surfaces and other human activities (urban heat island effect; Oke, 1981). Structural aspects like the proportion of green, blue and grey (i.e. sealed) spaces do also influence heat stress (Li et al., 2020). Moreover, cultural contexts in different places of residence might also influence people's risk perception (Poortinga et al., 2019). In our study, we analyzed data from participants in three different German cities located in slightly different climates and studied the influence of different places of residence.

RQ 2: Does the survey mode have an impact on participants' climate change and heat risk perception?

Data can be collected in various forms; for surveys alone, there are many different approaches. Survey modes differ in the purposes they have been developed for and have their own advantages and disadvantages (Fouladi, 2014). The use of a mode should therefore be chosen carefully (Jones et al., 2013). Criteria are, for example, time- and cost-efficiency, representativeness of the sample, response rate, and complexity of

the survey (Bowling, 2005). Using mixed modes of data collection offers the possibility of offsetting the disadvantages of one mode with the advantages of another mode (Jäckle et al., 2010). It does, however, make it more difficult to merge data since different modes provide access to different types of people, attract different types of respondents and elicit different responses (Leeuw, 2005). Research regarding this mode effect shows different results, with some studies finding no and others substantial meaningful differences (Brener et al., 2006; Dodou & Winter, 2014; Szolnoki & Hoffmann, 2013; Zhang et al., 2017). Therefore, equivalence of measurements from different modes of administration cannot be assumed and effects of mode should be considered when comparing results from different sources (Fouladi, 2014). Reviewing the literature on the effects of questionnaire administration mode on data quality, Bowling (2005) states that many potentially biasing influences on the responses were found such as sample bias, social desirability bias or interviewer bias. Resulting differences seem to be stronger between interview and selfadministration modes, rather than within modes. In our study, we surveyed people via telephone, online and in person and analyzed whether these mode differences affect participants' risk perception.

RQ 3: Does the temperature have an impact on participants' climate change and heat risk perception?

Questions about the influence of weather and climate on humans were among the first research questions in environmental psychology and were already addressed by Hellpach (1977). Van der Linden (2018) stated that experiential factors, like temperature, are some of the most influential ones in driving public risk perception of climate change. Studies show that (perceived) experience with warm daily temperatures and heat waves, either during the survey or before, is associated with concern about global warming (Akerlof et al., 2013; Egan & Mullin, 2014; Hamilton & Stampone, 2013; Risen & Critcher, 2011). A meta-analysis on correlates of belief in climate change also showed that the experience of local weather changes and environmental cues have a significant effect (Hornsey et al., 2016). For heat risk perception as well, it was shown that people experiencing warmer temperatures in their everyday life have a higher risk perception (Howe et al., 2019). In line with that and extending to actual adaptive behavior, Kussel (2018) showed that the probability of heat-adaptation behavior also rose with increasing mean temperature during summer.

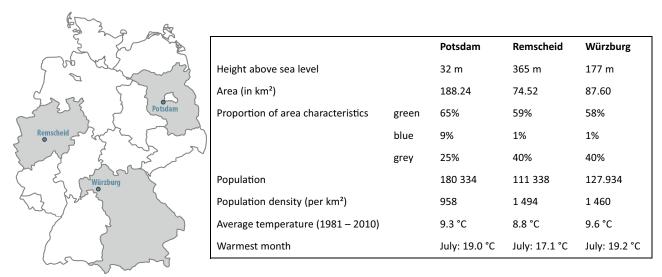
While many of the previous findings are based on laboratory studies, we took an approach that is more in the realm of field research and retrospectively determined the temperature. For our analyses, we used two different temperature measures: the average temperature on the day of the survey (T1) and the average temperature over the last seven days before the survey (including the day of the survey, T7). By doing so, we were able to compare different time horizons and follow up on the question if it is rather daily temperature or average temperature over a longer period of time that influences people's perception most (Deryugina, 2013; Hamilton & Stampone, 2013). According to the concept of visceral fit (Loewenstein, 1996), an experienced congruence between the current state (current temperature) and the visceral fit of an imagined state (global warming) should increase the estimated probability of that imagined state (Risen & Critcher, 2011). This explanation would suggest that it is rather temperature on the day of the survey that influences people's perception. One unusually hot day, however, is a natural part of day-to-day variation in weather and not representative of climate change. By including the average temperature over a longer period of time, we analyze, whether people take this into account and whether the temperature over a longer time span influences their risk perception more.

#### 2. Material and Methods

#### 2.1 Study Location

The surveys were carried out in the three mediumsized German cities of Potsdam (Brandenburg), Würzburg (Bavaria), and Remscheid (North Rhine-Westphalia). These cities represent a selection of cities from different federal states, geographical locations, and general economic situations. The different natural and urban conditions allow us to study a broad picture of different urban exposures to heat. Figure 1 gives an overview of various characteristics and differences of the cities. The climate of all cities can be classified as maritime climate (Cfb) according to the Köppen-Geiger climate classification system. However, there are slight differences in climate: Würzburg has the highest average temperature and the warmest month in the climatological norm from 1991–2020 (10.1 °C on average and 19.7 °C in July), followed by Potsdam (9.7 °C on average and 19.4 °C in July) and Remscheid (9.2 °C on average and 17.5 °C in July; DWD Climate Data Center, 2022). Since Watts et al. (2019) state that for every degree increase of Wet Bulb Globe Temperature beyond 24 °C, labor productivity loss ranges from 0.8% to 5%, the summer temperature differences between the three cities are meaningful.

Figure 1 Overview of the Study Locations and Relevant Characteristics



Note. Adapted from Heidenreich and Thieken, 2024.

#### 2.2 Data Collection

## 2.2.1 Household Survey

Surveys on heat stress were conducted among residents of the cities of Potsdam, Würzburg, and Remscheid from 19 August to 19 October 2019 (see also Heidenreich & Thieken, 2024). Participants were either randomly contacted via telephone (Computer Aided Telephone Interviews—CATI) or voluntarily filled out an online questionnaire (Computer Aided Web Interviews—CAWI) that was advertised in the media. The survey comprised items on multiple topics including problem awareness, heat awareness and adaptation, and heat warnings. The relevant items for this paper are shown in Table 1. The time spans of the interviews varied strongly between participants in the household survey (HHS). Although both modes, CATI and CAWI, used the exact same questionnaire, CAWI participants needed less time to complete the survey (CATI: 18-79 min, median = 34 min; CAWI: 9-110 min, median = 25 min).

## 2.2.2 Green Space Survey

Face-to-face surveys (F2F) with people in public green spaces were conducted in Potsdam from 15 July to 22 August 2020. The surveys were carried out on 15 days, both during the week and at weekends, and took place in the well-known and popular parks Park Sanssouci, Volkspark and Neuer Garten. Two interviewers worked in parallel in different parks and rotated between parks on different study days to avoid biases. On each study day, six to 26 people were surveyed. The participants were surveyed face-to-face, and answers were captured with a tablet via the mobile application KoBoCollect. The questionnaire covered items on the rating of the park, the current well-being and weather perception, but also included the items from the HHS which are shown in Table 1. Since the green space survey (GSS) used only a part of the HHS questionnaire, survey time was shorter with time spans of 6-19 min (median = 8 min).

Table 1 Scales and Items From the Household and Green Space Survey (Own Translation of the German Questionnaire Items)

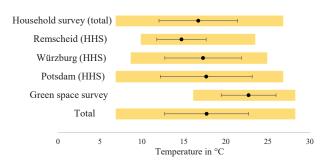
| Construct                         | Item(s)  | Answer options  | α    |
|-----------------------------------|--|---|------|
| Climate change<br>risk perception | <ol> <li>The climate is changing and it is increasingly getting hotter.</li> <li>Climate change will have an impact on my personal life.</li> <li>Climate change is greatly exaggerated in its significance by many. (r)</li> <li>In the coming years, there will be more and more heat waves in my city as well.</li> </ol>   | 1 = fully agree to<br>6 = do not agree at all                   | .747 |
| Heat wave risk perception         | Which of the following do you think are the three events that pose the greatest health threat to the population in your hometown?  - Storm, thunderstorm and hail  - UV radiation  - Heavy rain and flooding  - Fine dust pollution  - Snow and ice  - Pandemic influenzas and other epidemics  - Heat waves  - Allergies and diseases caused by non-native animal and plant species | 1 = heat waves<br>mentioned<br>0 = heat waves not<br>mentioned. |      |
| Awareness on heat warnings        | Were you aware of any heat warnings for your hometown in the current or last year?   | 1 = yes<br>0 = no   |      |

*Note.* (r) = recoded. The four items that represent the Climate Change Risk Perception were adapted from the New Ecological Paradigm Scale by Dunlap et al. (2000).

#### 2.2.3 Temperature Measures

The temperature on the respective survey days in the individual cities was determined retrospectively with daily temperature data from the German Weather Service (DWD Climate Data Center, 2021). We calculated the average daily temperature because it is considered having the most relevant impact on human health (Fenner et al., 2019). We additionally calculated the average over the last seven days before the survey. An overview of the temperature data for the survey days is displayed in Figure 2.

Figure 2 Overview of Temperature Data on the Survey Days for the Entire Dataset and Separated by Survey Type and City



*Note.* Black dots represent mean daily temperature and error bars represent standard deviation. Yellow shaded areas represent total measured temperature range.

# 2.3 Sample

#### 2.3.1 Household Survey

In total, 1,417 people were surveyed; thereof 900 via telephone and 517 online. The decision on the sample size for the telephone surveys (300 participants from each city) was based on budget constraints; for the online surveys, the aim was to attract 100 additional participants per city. The response rate of the telephone survey was 7%, due to sample-neutral (26%) and systematic dropouts (69%). Most of the respondents came from Würzburg (n = 583, 41.1%), followed by Potsdam (n = 455, 32.1%) and Remscheid (n = 379, 26.7%). The differences are mainly due to different numbers of online participants with most coming from Würzburg (n = 259) followed by Potsdam (n = 141) and Remscheid (n = 70). Of all participants, 818 (57.7%) were female and 598 (42.2%) male; one person (0.1%) stated their gender as diverse. Age ranged from 18 to 98 years (mean [M] = 57.81, standard deviation [SD] = 18.55). A more detailed description of the sample can be found in the appendix.

#### 2.3.2 Green Space Survey

We intended to interview a similar number of people as in the telephone interviews per city. In total, 280 people were successfully surveyed. The response rate was 70.6% (284 people), but four people were subsequently excluded, as they were either younger than 14 years or had dropped out of the survey at an early stage. The participants (58.9% female) were 14 to 87 years old (M = 43.74, SD = 16.53). 107 people (38.2%) came directly from Potsdam, the others were in the city for tourist purposes and came mainly from the surrounding area and in some cases from other parts of Germany. A more detailed description of the sample can be found in the appendix.

## 2.4. Statistical Analyses

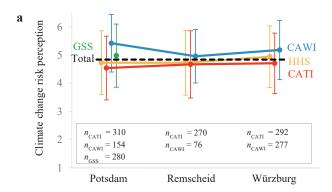
Statistical analyses were conducted using IBM SPSS version 27. Analyses of covariance (ANCOVA), binomial logistic regressions and hierarchical regressions were performed to determine the effects of place of residence, survey mode and temperature on climate change risk perception and heat risk perception. We consider both heat wave risk perception and awareness of heat warnings to reflect heat risk perception.

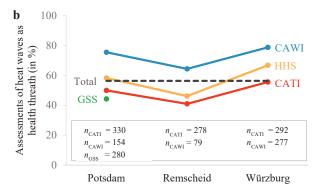
#### 3. Results

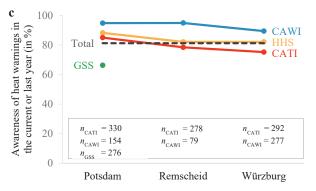
Participants displayed a high average climate change risk perception (M = 4.84, SD = 1.12; Figure 3a). Most respondents (56.4%) mentioned heat waves among their top three future health threats to their hometown citizens (Figure 3b). The vast majority of respondents (81.4%) stated that they had noticed at least one heat warning in the current or past year for their hometown (Figure 3c). During four days of the GSS, a heat warning was given. 16.9% of the respondents on that day (n = 65) reported having received a heat warning for that particular day.

Differences between survey settings, modes and cities are displayed in Figure 3 and will be further analyzed hereafter.

Figure 3 Overview of Scores for (a) Climate Change Risk Perception, (b) Heat Risk Perception and (c) Awareness of Heat Warnings (Separated by Survey Mode and Place)







Note. CATI = Computer Aided Telephone Interviews, CAWI = Computer Aided Web Interviews, HHS = household survey, GSS = green space survey. Error bars represent standard deviation.

#### 3.1 Influence of the Place of Residence

To focus on the place of residence as the factor of interest for this part of the study, only data from the CATI survey were included in the analyses. As this is the most representative sample, we report effects of age and gender in this section as well, but not in the following sections with other sample choices.

For climate change risk perception, an ANCOVA revealed significant differences for age and gender, F(1,829)=6.849, p=.009,  $\eta^2=.008$ , 95%-CI [-0.011; -0.002] and F(1,829)=10.111, p=.002,  $\eta^2=.012$ , 95%-CI [0.095; 0.403] respectively, but not for place of residence. Climate change risk perception decreased with increasing age and men indicated lower scores than women. After adjusting for age and gender, climate change risk perception did not differ statistically significant for the different cities, F(2,829)=1.619, p=.199, part.  $\eta^2=.004$ . Post-hoc analysis with G\*Power (Faul et al., 2009) yielded a power of 0.352.

Binominal logistic regressions indicated that participants from Remscheid had a significantly lower probability of mentioning heat waves among their top three future health threats to their hometown citizens than participants from Würzburg (OR = 0.550, 95% CI [0.392; 0.772]). Comparisons between Remscheid and Potsdam as well as Würzburg and Potsdam revealed no statistically significant differences (Table 2).

Participants from Potsdam had a significantly higher probability of having noticed at least one heat warning in the current or past year for their hometown than participants from both Würzburg (OR = 1.721, 95% CI [1.111; 2.660]) and Remscheid (OR = 2.044, 95% CI [1.333; 3.133]). Comparisons between Würzburg and Remscheid revealed no statistically significant differences. With increasing age, people had a significantly lower probability of being aware of heat warnings (Table 2).

Table 2 Binominal Logistic Regressions to Predict Heat Wave Risk Perception and Awareness of Heat Warnings Due to Different Places of Residence

|                             | Heat wave ris    | k perception             | Awareness of                      | heat warnings           |  |  |
|-----------------------------|------------------|--------------------------|-----------------------------------|-------------------------|--|--|
|                             | В                | OR [95% CI]              | В                                 | OR [95% CI]             |  |  |
| Remscheid<br>(vs. Potsdam)  | -0.318 (.170) †  | 0.727<br>[0.521; 1.015]  | -0.542 (.223) *                   | 0.581<br>[0.376; 0.900] |  |  |
| Potsdam<br>(vs. Würzburg)   | -0.279 (.168) †  | 0.757<br>[0.545; 1.0551] | 0.715 (.218) **                   | 2.044<br>[1.333; 3.133] |  |  |
| Remscheid<br>(vs. Würzburg) | -0.597 (.173) ** | 0.550<br>[0.392; 0.772]  | 0.172 (.207)                      | 1.188<br>[0.793; 1.781] |  |  |
| Age                         | 0.004 (.004)     | 1.004<br>[0.996; 1.013]  | -0.022 (.006) ***                 | 0.978<br>[0.966; 0.989] |  |  |
| Gender <sup>a</sup>         | -0.004 (.140)    | 0.996<br>[0.756; 1.311]  | -0.025 (.177)                     | 0.975<br>[0.689; 1.381] |  |  |
|                             | $R^2 = .002$ , C | ohens $f^2 = .02$        | $R^2 = .043$ , Cohens $f^2 = .04$ |                         |  |  |
|                             | Chi2(4)          | = 12.773*                | Chi2(4) = 23.454***               |                         |  |  |

*Note.* n = 859. Standard errors for B are presented in parentheses; a = 0 = 0 male, a = 0 = 0

# 3.2 Influence of the Survey Mode

To focus on survey mode and temperature as the factors of interest for this and the next part of the study, we included only data from Potsdam in the following analyses.

For climate change risk perception, an ANCOVA revealed significant differences between survey modes after adjusting for age and gender, F(2, 702) = 5.522, p = .004, part.  $\eta^2 = .015$ . Post-hoc analyses with G\*Power yielded a power of 0.841. Bonferroni-corrected post-hoc analyses revealed significantly lower scores for the CATI group compared to the CAWI group (p = .005,  $M_{\rm Diff} = -0.416$ , 95%-CI[-0.729; -0.103]) as well as the F2F group (p = .030,  $M_{\rm Diff} = -0.292$ , 95%-CI[-0.562; -0.021]). We found no significant differences between the CAWI and F2F groups (p = .828,  $M_{\rm Diff} = 0.124$ , 95%-CI[-0.149; 0.398]).

Binominal logistic regressions indicated that participants of the CAWI survey had a significantly higher probability of mentioning heat waves among their top three future health threats to their hometown citizens than participants of both the CATI (OR = 3.424, 95% CI [2.037; 5.756]) and the F2F (OR = 4.368, 95% CI [2.743; 6.957]) surveys. Comparisons between CATI and F2F revealed no statistically significant differences (Table 3).

Comparisons between survey modes showed significant differences in knowledge of heat warnings (Table 3). Participants from both the CAWI (OR = 9.463, 95% CI [4.229; 21.052]) and CATI (OR = 3.797, 95% CI [2.273; 6.343]) surveys had a significantly higher probability of having noticed at least one heat warning in the current or past year for their hometown than participants of the F2F survey. CAWI participants again had a significantly higher probability than CATI participants (OR = 2.485, 95% CI [1.033; 5.977]).

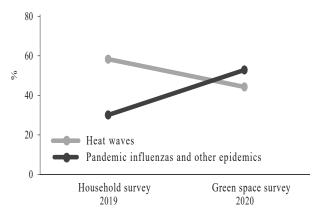
Regarding the differences in the probability of mentioning heat waves among the top three future health threats, the changed global situation with the COV-ID-19 pandemic, which was ongoing during the second survey period in 2020, may partly explain this difference. While the share of people who mentioned pandemic influenzas and other epidemics as one of the greatest health threats increased significantly from 2019 (30.1%) to 2020 (52.9%),  $\chi^2(1) = 38.50$ , p < .001,  $\phi = 0.23$ , the share of people who mentioned heat waves decreased (Figure 4). This shows that there has been a shift in the perceived relevance of various threats due to COVID-19.

Table 3 Binominal Logistic Regressions to Predict Heat Wave Risk Perception and Awareness of Heat Warnings Due to Different Survey Modes

|                           | Heat wave         | risk perception         | Awareness of                      | heat warnings            |  |  |
|---------------------------|-------------------|-------------------------|-----------------------------------|--------------------------|--|--|
|                           | В                 | OR [95% CI]             | В                                 | OR [95% CI]              |  |  |
| <b>CAWI</b><br>(vs. CATI) | 1.231 (.265) ***  | 3.424<br>[2.037; 5.756] | 0.910 (.448) *                    | 2.485<br>[1.033; 5.977]  |  |  |
| CATI<br>(vs. F2F)         | 0.243 (.208)      | 1.276<br>[0.849; 1.918] | 1.334 (.262) ***                  | 3.797<br>[2.273; 6.343]  |  |  |
| CAWI<br>(vs. F2F)         | 1.474 (.237) ***  | 4.368<br>[2.743; 6.957] | 2.244 (.409) ***                  | 9.436<br>[4.229; 21.052] |  |  |
| Age                       | -0.001 (.005)     | 0.999<br>[0.989; 1.009] | -0.001 (.006) †                   | 0.989<br>[0.976; 1.001]  |  |  |
| Gender <sup>a</sup>       | 0.120 (.159)      | 1.127<br>[0.825; 1.540] | 0.023 (.201)                      | 1.023<br>[0.689; 1.518]  |  |  |
|                           | $R^2 = .084$ , Co | whens $f^2 = .09$       | $R^2 = .130$ , Cohens $f^2 = .15$ |                          |  |  |
|                           | $Chi^2(4) =$      | 46.614***               | $Chi^2(4) = 60.909***$            |                          |  |  |

*Note.n* = 755. Standard errors for B are presented in parentheses; CATI = Computer Aided Telephone Interviews, CAWI = Computer Aided Web Interviews; F2F = face-to-face interviews;  $^a$  0 = male, 1 = female;  $^t$ p < .10,  $^*$ p < .05,  $^*$ \* $^t$ p < .01, and  $^*$ \*\* $^t$ p < .001

Figure 4 Share of Participants From the Potsdam Sample who Mentioned Heat Waves and Pandemic Influenzas and Other Epidemics as One of the Three Greatest Health Threats to the Population of Their Own Hometown



*Note.*  $n_{\text{HHS}} = 475$ ,  $n_{\text{GSS}} = 280$ .

# 3.3 Influence of the Temperature

We performed hierarchical regression analyses to predict climate change risk perception with the temperature of the day of the survey (T1) as well as the average temperature over the last seven days before the survey (T7). Setting (HHS vs. GSS) was included as a covariate as it was expected to make a difference if

participants experienced the temperature directly during the survey (which was the case for the GSS) or not (which was the case for the HHS). To assess the interaction between setting and temperature, a product term between these variables was added for analyses with T1. For T7 an interaction would not make sense because it was not considered relevant if people were indoors or outdoors during the survey when taking the average temperature over the last seven days into account.

In the regression analysis with T1, results show that temperature on the day of the survey was not a general predictor, but that setting moderated the effect between temperature and climate change risk perception significantly ( $\beta$  = .463, p = .045;  $\Delta R^2$  = .005, p = .045; Table 4). In the regression analysis T7, average temperature over the last seven days before the survey was a significant predictor for climate change risk perception ( $\beta$  = .099, p = .018; Table 4). Participants' climate change risk perception increased by .022 units on the scale with each additional degree Celsius. A post-hoc analysis using G\*Power suggests that a study with the mean of the currently observed effect sizes of the inclusion of temperature as an additional predictor and the sample size of our study would have a power of 0.541.

| Table 4 Hierarchical Regression Analysis to Predict Climate Change Risk Perception by Temperature on the Day of the Survey (T1) | ) |
|---|---|
| and Average Temperature Over the Last Seven Days Before the Survey (T7)   |   |

| Variable             | Model 1<br>B SEB β |      |       |          |      |                |        |                | Temperature T7  Model 2  B SEB β |        |      |      |
|----------------------|--------------------|------|-------|----------|------|----------------|--------|----------------|----------------------------------|--------|------|------|
| Age                  | 011***             | .002 | 184   | 011***   | .002 | 183            | 010*** | .002           | 180                              | 011*** | .002 | 179  |
| Gender <sup>a</sup>  | .090               | .086 | .039  | .084     | .086 | .036           | .091   | .085           | .039                             | .078   | .085 | .034 |
| Setting <sup>b</sup> | .087               | .093 | .038  | .010     | .104 | .004           | 999†   | .513           | 432                              | 014    | .102 | 006  |
| Temperature          |                    |      |       | .015†    | .009 | .071           | .007   | .010           | .033                             | .022*  | .009 | .099 |
| Setting* Temp.       |                    |      |       |          |      |                | .046*  | .023           | .463                             |        |      |      |
| $\Delta R^2$         |                    |      |       | .004†    |      | .005*          |        | .008*          |                                  |        |      |      |
| $R^2$ ( $R^2$ corr.) | .043*** (.039)     |      | .047* | *** (.04 | 1)   | .052*** (.045) |        | .050*** (.045) |                                  |        |      |      |

*Note.* Model 1 presents the basic model including age, gender and setting, Model 2 includes either T1 or T7 as an additional predictor and Model 3 includes the interaction term between setting and temperature for the regression analysis with T1; n = 707; a = male, b = male,

To further investigate the moderation between setting and temperature on the day of the survey, regression analyses were calculated separately for the HHS and the GSS (Table 5). Only within the GSS sample, the temperature proved to be a significant predictor and the temperature added significantly more explained variance ( $\beta$  = .159, p = .009;  $\Delta R^2$  = .025, p = .009). The participants' climate change risk perception increased by .055 units on the scale with each additional degree Celsius.

To predict heat wave risk perception and awareness of heat warnings, binominal logistic regressions were calculated with T1 and T7 as predictors.

For heat wave risk perception, only T7 was a significant predictor (OR = 1. 040, 95% CI [1.005; 1.076]). With increasing temperatures over the previous seven days, the probability of considering heat as one of the greatest health threats increased. Besides temperature, setting was a significant predictor in all analyses, with a higher probability of mentioning heat as one of the greatest health threats among participants of the GSS (Table 6).

For awareness of heat warnings, temperature was no significant predictor. The setting however showed to be a significant predictor; participants of the GSS had a higher probability of being aware about heat warnings for their hometown in the current or last year than those of the HHS (Table 6).

Table 5 Hierarchical Regression Analysis to Predict Climate Change Risk Perception by Temperature (T1) Separated by Survey Setting

|                                     | Household survey <sup>a</sup> |             |      | Green space survey <sup>b</sup> |          |        |  |
|-------------------------------------|-------------------------------|-------------|------|---------------------------------|----------|--------|--|
|                                     | В                             | SE B        | β    | В                               | SE B     | β      |  |
| ge                                  | 014                           | .003        | .003 | 004                             | .004     | 061    |  |
| Gender <sup>c</sup>                 | .192                          | .110        | .110 | 032                             | .136     | 014    |  |
| emperature                          | .006                          | .010        | .010 | .055                            | .021     | .159** |  |
| R <sup>2</sup> (adding temperature) |                               | .001        |      | .025**                          |          |        |  |
| <sup>2</sup> (R <sup>2</sup> corr.) | .0                            | 60*** (.053 | )    | .03                             | 30* (.02 | 0)     |  |

*Note.* a n = 435; b n = 272; c 0 = male, 1 = female;  $\uparrow p < .10, *p < .05, **p < .01$ , and \*\*\*p < .001.

Table 6 Binominal Logistic Regressions to Predict Heat Wave Risk Perception and Knowledge of Heat Warnings by Temperature on the Day of the Survey (T1) and Average Temperature Over the Last Seven Days Before the Survey (T7)

|                      |  | Model 1                 |                    | Tempe<br>Model 2        | Temperature T1  Model 3   |                          |                    | perature T7<br>odel 2   |  |  |  |  |
|----------------------|--|-------------------------|--------------------|-------------------------|---------------------------|--------------------------|--------------------|-------------------------|--|--|--|--|
| Variable             | В                                      | OR [95% CI]             | В                  | OR [95% CI]             | В                         | OR [95% CI]              | В                  | OR [95% CI]             |  |  |  |  |
|                      | Heat wave risk perception <sup>a</sup> |                         |                    |                         |                           |                          |                    |                         |  |  |  |  |
| Age                  | 013<br>(.004)**                        | 0.987<br>[0.979; 0.996] | 013<br>(.004)**    | 0.987<br>[0.979; 0.996] | 013<br>(.004)**           | 0.987<br>[0.979; 0.996]  | 012<br>(.004)**    | 0.988<br>[0.979; 0.996] |  |  |  |  |
| Gender <sup>c</sup>  | .097<br>(.157)                         | 1.102<br>[0.810; 1.498] | 0.091<br>(.157)    | 1.096<br>[0.805; 1.491] | 0.096<br>(.157)           | 1.100<br>[0.809; 1.498]  | 0.080<br>(.158)    | 1.083<br>[0.795; 1.475] |  |  |  |  |
| Setting <sup>d</sup> | 0.795<br>(.175)***                     | 2.215<br>[1.573; 3.120] | 0.885<br>(.195)*** | 2.423<br>[1.654; 3.550] | 1.528<br>(.950)           | 4.611<br>[0.716; 29.696] | 0.979<br>(.194)*** | 2.661<br>[1.819; 3.893] |  |  |  |  |
| Temperature          | Temperature                            |                         | 0.017<br>(.016)    | 1.017<br>[0.986; 1.049] | 0.012<br>(.018)           | 1.012<br>[0.978; 1.047]  | 0.039<br>(.017)*   | 1.040<br>[1.005; 1.076] |  |  |  |  |
| Setting* Temp        | Setting* Temp.                         |                         |                    |                         | 0.029<br>(.043)           | 1.030<br>[0.947; 1.120]  |                    |                         |  |  |  |  |
| $R^2$                | .0                                     | 43                      | .04                | .045                    |                           | .046                     |                    | 52                      |  |  |  |  |
|                      |  |                         | 1                  | Knowledge of he         | eat warnin                | gs <sup>b</sup>          |                    |                         |  |  |  |  |
| Age                  | 017<br>(.006)**                        | 0.983<br>[0.977; 0.995] | 017<br>(.006)**    | 0.983<br>[0.972; 0.994] | 017<br>(.006)**           | 0.983<br>[0.972; 0.995]  | 017<br>(.006)**    | 0.983<br>[0.972; 0.995] |  |  |  |  |
| Gender <sup>c</sup>  | .005<br>(.202)                         | 1.005<br>[0.677; 1.492] | 0.08<br>(.202)     | 1.008<br>[0.679; 1.496] | 0.012<br>(.202)           | 1.012<br>[0.681; 1.503]  | 0.008<br>(.202)    | 1.008<br>[0.679; 1.496] |  |  |  |  |
| Setting <sup>d</sup> | 1.624<br>(.228)***                     | 5.075<br>[3.247; 7.932] | 1.553<br>(.253)*** | 4.723<br>[2.877; 7.756] | 2.063<br>(1.075) <i>†</i> | 7.871<br>[0.958; 64.681] | 1.597<br>(.254)*** | 4.938<br>[3.002; 8.124] |  |  |  |  |
| Temperature          |  |                         | -0.014<br>(.022)   | 0.986<br>[0.944; 1.030] | 0-0.021<br>(.027)         | 0.979<br>[0.929; 1.031]  | -0.006<br>(.024)   | 0.994<br>[0.948; 1.043] |  |  |  |  |
| Setting* Temp        |  |                         |                    |                         | 0.024<br>(.049)           | 1.024<br>[0.930; 1.128]  |                    |                         |  |  |  |  |
| R <sup>2</sup> .120  |  | .12                     | .121               |                         | 21                        | .120                     |                    |                         |  |  |  |  |

*Note.* Model 1 presents the basic model including age, gender and setting, Model 2 includes either T1 or T7 as an additional predictor and Model 3 includes the interaction term between setting and temperature for the regression analysis with T1. Standard errors for *B* are presented in parentheses. <sup>a</sup> n = 717; <sup>b</sup> n = 713; <sup>c</sup> 0 = male, 1 = female; <sup>d</sup> 0 = HHS, 1 = GSS; †p < .00, \*p < .05, \*\*p < .01, and \*\*\*p < .001.

# 4. Discussion

The aim of this research was to study the influence of three different external factors, namely place of residence, survey mode and temperature, on risk perception concerning climate change and heat. These factors play a relevant role in central research areas of environmental research but have often been neglected and only rarely considered as influencing factors or covariates in past research.

We found that the place of residence influenced heat risk perception (RQ1). Participants from Würzburg showed a higher heat wave risk perception than those from Remscheid and participants from Potsdam had a higher probability of being aware of past heat warnings than those from both Würzburg and Remscheid.

Participants from Remscheid being the ones with the lowest heat risk perception can be explained by the fact, that heat is not as big a problem in Remscheid as it is in the other cities (see Howe et al., 2019, for similar results). The temperature in the last 30-year refer-

ence period was lower in Remscheid, just as the average temperature in the hottest month was nearly 2 °C lower than in Potsdam and Würzburg (Figure 1). Another explanation, which is rather unlikely in this case but should not go unmentioned, is that people might also show a lower heat risk perception when they feel well prepared, for example through individual or structural adaptation measures to heat.

The survey mode influenced both climate change and heat risk perception (RQ2). Participants from Potsdam that were surveyed via CAWI or F2F showed a higher climate change risk perception than those surveyed via CATI. CAWI participants did also show a higher heat wave risk perception than those surveyed via CATI or F2F. Regarding awareness of heat warnings, CAWI participants had the highest likelihood of noticing past heat warnings, followed by those surveyed via CATI and F2F. While we used just data from Potsdam in the CATI and CAWI samples, there are people from elsewhere in the F2F sample due to the fact that tourists were included. Omitting tourists from the F2F sample would have considerably reduced sample size so that the statistical power of tests would not have been comparable anymore to the other samples. Since all people who were surveyed spoke German fluently, we can assume that the differences in awareness are neither due to misunderstandings nor to a different heat warning system.

Across all analyses, the survey mode had the biggest influence on both climate change and heat risk perception. People that participated via CAWI showed overall higher risk perception than the other participants. This illustrates the danger of public online surveys, which often produce a self-selection bias (Bethlehem, 2010). As the survey had been advertised as a survey on heat stress, especially people with increased sensitivity to or load from the topic might have participated. In our case, there might have been an additional selection bias through the freely chosen date of participation as people might have participated more frequently after experiencing high temperatures when their awareness of the topic was high. Following this argumentation, the participants of the GSS might have also self-selected themselves in the sense that people who are very sensitive to heat or had heard of heat warnings, might not have visited the parks on hot days (Kabisch et al., 2021). In line with Grandcolas et al. (2003), differences between the survey modes might hence be mainly attributable to sample bias rather than mode bias. The results are

nevertheless meaningful, as the subject of sample bias and especially self-selection is a potential fallacy in the wider environmental psychology research as well (Kaiser & Henn, 2017). It can lead to unreliable survey outcomes and challenges the validity of conclusions from behaviour research. In research that relies heavily on surveys, especially online surveys, this is a critical point that should be stronger addressed in the future and tried to be reduced by using a broader range of methods and ensuring a representative sample whenever possible and relevant. Additionally, when using different survey modes, the existence of mode effects should be tested and, if confirmed, survey mode should be treated as a control variable in the analyses.

Temperature during or before the survey was a significant predictor for both climate change and heat risk perception (RQ3). Across participants from the HHS and GSS, the average temperature over the last seven days before the survey (T7) was a significant predictor of climate change risk perception. The temperature on the day of the survey (T1) was a significant predictor of climate change risk perception only among the people of the GSS, not the HHS. T7 was a significant predictor of heat wave risk perception while T1 was not. Neither T1 nor T7 predicted awareness of heat warnings.

Our results confirm that temperature influences climate change risk perception and specify that it is rather the average temperature over a longer period of time that is relevant. By showing that the temperature on the day of the survey was a significant predictor of climate change risk perception only among the participants surveyed outdoors, it supports the idea of temperature influencing beliefs through a visceral fit (Risen & Critcher, 2011). In a study on predictors of health-related heat risk perception, Beckmann and Hiete (2020) limitatively state that the judgement of the participants could have been influenced by extreme heat at the moment of participation, which they did not control for. We showed that temperature did indeed influence participants' heat wave risk perception, but only the average temperature in the week before the survey (T7), not on the day of the survey (T1). The missing link between temperature and awareness of heat warnings is not surprising as we asked about any heat warnings over the past two years; thus recent heat warnings due to high temperatures before or during the survey should not be as decisive. Our results indicate that far more people were aware of heat warnings over the past two years than of heat warnings for the actual day. Only 16.9% of the respondents (n = 65) on days where heat warnings were issued reported having received such a warning for that particular day. These numbers are in line with findings by Heidenreich et al. (2021) who found that only 10.3% of the respondents surveyed at an open-air event in Würzburg, Germany, had heard of the heat warning for that particular day. This shows that official warnings have to be communicated more widely to reach more people. We found that awareness of heat warnings varied between respondents from different cities. This raises the question of whether the heat warnings were communicated and passed on differently in the cities and whether awareness varied as a result. In view of the increased development of heat protection plans, this is a question that should be pursued further. Additionally, we found that the probability of being aware of heat warnings decreased with increasing age. This is especially worrying, as the elderly are among the main vulnerable groups for heat stress (Hajat et al., 2010). Heat warnings should therefore specifically target this population group to allow for better adaptation.

Using a multi-method approach allowed us to study a broad sample; for example, by conducting a representative telephone survey and an interview survey among visitors of green spaces. However, this study also presented some challenges. The biggest might be the different periods of data collection. The one-year lag between the HHS and the GSS is particularly relevant because of the outbreak of the COVID-19 pandemic in the interim, which has led to huge disruptions in everyday life and might have been responsible for a shift in people's priorities and risk assessments. We showed that participants of the survey in 2019 more often considered heat waves than pandemic influenzas and other epidemics as one of the three greatest health threats, while this trend had reversed in the survey in 2020. Furthermore, even though both surveys were conducted in Potsdam, the samples of the HHS and GSS are not necessarily comparable with each other as the sample in the parks included a high share of tourists while the HHS targeted residents of the city. This composition of the sample might also be an explanation for the lower probability of awareness of past heat warnings among the participants surveyed F2F in the parks. The tourists in this sample may have come from regions where there were fewer heat warnings (although there were frequent heat warnings across all of Germany in 2018 and 2019),

or might not have wanted to think about these topics during their holidays. This still underlines that sampling is important. Another limitation concerns the temperature measurement. We have taken the average day temperature in the respective city as the reference temperature; an even more precise recording of the temperature actually experienced at the time of the survey would be possible through an individual temperature measurement during the survey; in addition, sun/shade, wind and humidity could also be included. However, measuring and recording all these variables requires more capacities than were available. Nevertheless, our results offer a valuable addition to the previous sparse literature on the influence of temperature on heat risk perception, but do not claim to be an exact record of all measurable parameters that potentially influence thermal well-being.

#### 5. Conclusion

This study showed that both survey mode and environmental factors influence survey results with regard to climate change and heat risk perception. This should be heeded when planning or interpreting and comparing studies on these topics. Survey mode, in particular, was shown to be a crucial factor; we highlighted the relevance of self-selection bias in particular for the online survey and reiterate the control of this in future research. Besides that, we argue for the use of a broader range of methods and data collection in the relevant setting itself. When comparing different studies on the same subject, the possible effect of different modes used should be considered but also the setting and situation in which the study had taken place. We recommend including information on the temperature during the survey period in future surveys which include questions related to climate change and/or heat. Some indications for future risk communication can be derived from our research. Based on the finding that the perception of risk is decisive for the initiation of action, risk communication and information campaigns should start when people are more aware of the risk, which is, as our results show, during periods with higher temperatures. Besides that, risk perception should meet people where risks can be experienced and provide information for suitable adaptation as well.

#### Acknowledgements

We thank Lara Deppermann for her contribution to the data collection as well as Dr. Antje Otto and Lisa Dillenardt for their support in designing the questionnaire.

#### **Funding**

This research was conducted within the framework of the research project "Urban resilience against extreme weather events - typologies and transfer of adaptation strategies in small metropolises and medium-sized cities" (ExTrass) funded by Germany's Federal Ministry of Education and Research (BMBF, contract numbers 01LR1709A1 and 01LR2014A) and the European Union NextGenerationEU.

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#### Appendix

Table A1 Survey Characteristics for the Entire Dataset and Separately by Survey Type and Place, Compared to the German Population

|                    |       |      | Sex (%) |      | Age |       |       |
|--------------------|-------|------|---------|------|-----|-------|-------|
|                    |       | n    | f       | m    | d   | Μ     | SD    |
| Household survey   | CATI  | 900  | 59.1    | 40.9 | 0.0 | 64.75 | 16.16 |
|                    | CAWI  | 517  | 55.3    | 44.5 | 0.2 | 45.13 | 15.72 |
|                    | total | 1417 | 57.7    | 42.2 | 0.1 | 57.81 | 18.55 |
| Potsdam            | CATI  | 320  | 62.8    | 37.2 | 0.0 | 68.02 | 14.39 |
|                    | CAWI  | 155  | 64.5    | 34.8 | 0.6 | 43.00 | 14.87 |
|                    | total | 475  | 63.4    | 36.4 | 0.2 | 60.11 | 18.62 |
| Remscheid          | CATI  | 278  | 58.3    | 41.7 | 0.0 | 64.34 | 16.00 |
|                    | CAWI  | 79   | 36.7    | 63.3 | 0.0 | 57.13 | 12.77 |
|                    | total | 357  | 53.2    | 46.5 | 0.0 | 62.83 | 15.64 |
| Würzburg           | CATI  | 302  | 56.0    | 44.0 | 0.0 | 61.67 | 17.43 |
|                    | CAWI  | 283  | 55.5    | 44.5 | 0.0 | 43.04 | 15.49 |
|                    | total | 585  | 55.7    | 44.3 | 0.0 | 52.87 | 18.97 |
| Green space survey |       | 280  | 58.9    | 41.1 | 0.0 | 43.74 | 16.53 |
| Total              |       | 1697 | 57.9    | 42.0 | 0.1 | 55.42 | 18.97 |
| German population  |       |      | 50.7    | 49.3 | 0.0 | 44.5  |       |

*Note.* German population at the reporting date 31.12.2019 (Statistische Ämter des Bundes und der Länder 2019a, 2019b). CATI = Computer Aided Telephone Interviews, CAWI = Computer Aided Web Interviews.

#### Sample Differences

Participants of the household survey (M=57.81, SD=18.55) were significantly older those of the green space survey (M=43.74, SD=16.53), t(1599)=11.602, p<.001. Within the household survey sample, age differed significantly between the cities; with respondents from Würzburg being the youngest, followed at a great distance by Potsdam and Remscheid, F(2,1326)=37.058, p<.001. This results partly from the different shares in telephone and online surveys. Within each city and over all cities, CATI participants (M=64.75, SD=16.16) were older than CAWI participants (M=45.13, SD=15.72), t(1327)=21.367, p<.001.

No differences were found for the distribution of gender between the household survey and the green space survey. Women were slightly overrepresented in both samples (57.7% and 58.9% respectively) with no difference between the samples,  $\chi^2(1) = 0.129$ , p = .719 (Cramer's V = .009). Distribution of gender

differed between the cities of the household survey with the highest share of women in Potsdam followed by Würzburg and Remscheid,  $\chi^2(2) = 10.051$ , p = .007 (Cramer's V = .084). Over all cities there were no differences between the distribution of gender between the survey methods,  $\chi^2(1) = 1.825$ , p = .177 (Cramer's V = .036).

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