ENVIRONMENTAL RESEARCH
LETTERS

PERSPECTIVE • **OPEN ACCESS**

Dynamic model of climate action

To cite this article: Gabrielle Wong-Parodi *et al* 2024 *Environ. Res. Lett.* **19** 091007

View the article online for updates and enhancements.

You may also like

- Divergent response of energy exchange to heatwaves from flux tower observations among various vegetation types
Xiaohui Tian, Bo Qiu, Yueyang Ni et al.
- Interdecadal change in the relationship between the South China late rainy season rainfall and equatorial Pacific SSTs
Shaolei Tang, Zhiyuan Zhang and Jing-Jia Luo
- Hysteresis of Northern Hemisphere permafrost to carbon dioxide emissions
Ting Wei, Yueli Chen and Hui Wang

This content was downloaded from IP address 104.50.126.123 on 10/09/2024 at 18:00

ENVIRONMENTAL RESEARCH
LETTERS

OPEN ACCESS

RECEIVED
12 January 2024

REVISED
18 July 2024

ACCEPTED FOR PUBLICATION
30 July 2024

PUBLISHED
20 August 2024

Original content from this work may be used under the terms of the Creative Commons Attribution 4.0 licence.

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

PERSPECTIVE

Dynamic model of climate action

Gabrielle Wong-Parodi[1,*], Daniel P Relihan[2] and Dana Rose Garfin[3]

[1] Department of Earth System Science, Woods Institute for the Environment, and Department of Environmental Social Sciences, Stanford University, Stanford, CA 94305, United States of America
[2] Department of Psychological Science, University of California at Irvine, Irvine, CA 92697, United States of America
[3] Department of Community Health Sciences, Fielding School of Public Health, University of California at Los Angeles, Los Angeles, CA 90095, United States of America
[*] Author to whom any correspondence should be addressed.

E-mail: gwongpar@stanford.edu

Keywords: climate change, mitigation, adaptation, model, psychological processes, dynamic

1. Introduction

Climate change is occurring more rapidly than expected [1] and requires that people quickly and continually act [2] to reduce the most dire impacts on humans and the environment. Understanding the dynamic relationships among affective and cognitive processes (i.e. emotions like worry and fear, risk perceptions) and behaviors (i.e. adaptation, mitigation) that unfold in the context of the dynamic and increasing nature of climate change threats is essential. Assuming these relationships follow a one-directional path (e.g. high-risk perceptions result in more adaptation) may result in a less accurate picture. The reality of climate change demands a model of dynamic reciprocity: climate change-related threats like tropical cyclones, wildfires, or droughts are stochastic [3], thus adaptive or mitigative behavior must be performed continuously, even when threat saliency decreases. Importantly, bidirectional feedback loops likely occur: performing adaptation or mitigation behaviors may reduce an individual's perception of climate change risks and reduce their worry, even if those risks are stable or increasing, with unclear implications for future behavior. Yet climate change-related threats are also intensifying [3], thus new or more adaptive and mitigative behaviors must be performed over time. There is an urgent need to develop and test new dynamic models of behavior change that account for reciprocity among affective and cognitive processes and behaviors over time to better understand how to design behavioral interventions that promote sustained and effective adaptation and mitigation. To this end, our team has been employing innovative, longitudinal methods to test these processes using a theoretically derived approach across multiple climate-related threats, including tropical cyclones and wildfires [4–6]. In this perspective, we draw from this and other research to describe (1) the dynamic model of climate action (DMCA), (2) how to test it, (3) appropriate analytic strategies, and (4) a case study.

2. A Dynamic Model of Climate Action

We propose the DMCA (figure 1), which draws from prior empirical work and key theoretical models and frameworks, while embracing the dynamism and feedback processes inherent in decisions to act in response to climate change-related threats. This conceptual model is largely inspired and adapted from theoretical models such as the model of private proactive adaptation to climate change [7], climate change risk perception model [8], theoretical model of public-sphere climate action [9], and risk information seeking and processing model [10], which highlight the importance of cognitions, emotions, and socio-cultural context in shaping perceptions about climate change and motivating climate action. The DMCA also draws from a legacy of other theoretical models, such as the gateway belief model [11], underscoring the importance of the informational environment such as perceptions of scientific consensus and belief in human-caused climate change, and the protective action decision model [12], which suggests a feedback loop between behavior and information inputs such as environmental or social cues. The DMCA is also based on the framework of behavioral adaptation to climate change [13], developed in the context of wildfires, which proposes a feedback loop between biophysical drivers, outcomes, and psychosocial mediators including negative affect and adaptive behaviors. The DMCA provides a conceptual advance by bringing together key elements from

© 2024 The Author(s). Published by IOP Publishing Ltd

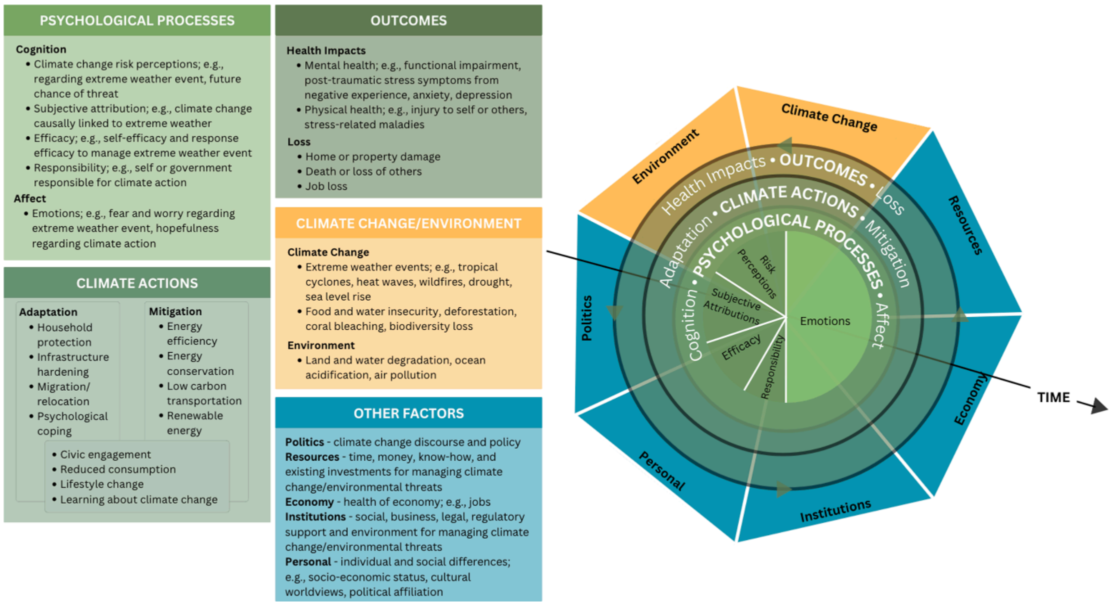

Figure 1. Dynamic model of climate action.

these theoretical models and frameworks, highlighting the reciprocity between psychological processes, climate action, and outcomes over time under the specter of evolving climate change threats.

The DMCA extends these existing models in two ways. First, it expands the idea of adaptation more broadly to include climate change mitigation [14], for example, using public transit and making green purchases, which we refer to more generally as 'climate action' [15]. Within this framework, the DMCA builds from the rich body of empirical and theoretical literature on climate mitigation that examines the role of factors such as experience, efficacy, risk perceptions, emotions, attributions, and responsibility on climate mitigation [7, 10, 11, 16–19]. Second, it embraces the idea that key psychological processes must include affective responses such as emotions, which are key drivers of decision-making. Importantly, when emotional responses diverge from cognitions, such as risk perceptions, they may supersede cognitions in driving behavior [20]. Hence, it is important to assess emotions alongside cognitions in response to climate change impacts, as they may play a central role in climate action.

The DMCA also includes two dimensions not generally included in extant models and frameworks. First, we integrate emerging findings suggesting subjective attributions—making the cognitive connection between climate change and extreme weather events [21]—are key cognitive correlates for climate action [4], extending classic attribution theory [22]. Second, the DMCA explicitly includes time, indicating the importance of dynamic relationships among psychological processes, climate actions, outcomes, climate and environmental factors (i.e. extreme weather, water pollution), and other factors, and how they interact over time. For example, loss of property due to a wildfire may induce elevated wildfire risk perceptions and fear and worry, prompting climate action including the clearing of brush and purchase of additional wildfire insurance. When no wildfire occurs that season, lower wildfire risk perceptions and fewer climate actions are observed the following seasons, even if wildfire risk is elevated.

As shown in figure 1, the DMCA shows reciprocal relationships among psychological processes (e.g. cognitions and affect), climate actions (e.g. mitigation and adaptation behaviors), and action outcomes that arise, such as improved health (e.g. normal rather than dysregulated cortisol levels). This occurs in a social-ecological context, including direct exposures to climate change and its impacts (e.g. tropical cyclones, heatwaves, wildfires, and other environmental threats) among other environmental conditions. This also includes other contextual factors like political, resources, economic, institutional, and personal variables. This dynamic system has a temporal scale, where relationships and other factors fluctuate, change, and influence one another over time. For example, the experience of a tropical cyclone (a direct climate change impact) may be associated with elevated fear and worry about future events (affect), which in turn may be associated with stronger subjective attribution (cognition) and greater risk perceptions about tropical cyclones (cognitions). Those with stronger subjective attribution and risk perceptions about tropical cyclones may take steps to adapt (climate action), which are related to fewer negative health impacts (outcomes) when the next tropical cyclone occurs. This may subsequently be associated with lower personal tropical cyclone risk perceptions (cognitions) and lowered fear and worry about future events (affect) if fewer negative health impacts occur. For example, Wong-Parodi *et al* [23] found that as tropical cyclone adaptation behaviors increased over time, personal risk perceptions decreased, especially in the absence of storm activity. In another paper, Garfin and Wong-Parodi found exposure to tropical cyclones and perceived climate change experience positively correlated with climate actions [15]. Hence, this conceptualization of a dynamic system indicates that relationships co-evolve over time. Gaining a deeper understanding into the relationships between psychological processes and outcomes may yield insights into more effective ways to design interventions to encourage ongoing climate actions that promote sustainability and resiliency as climate-related events intensify.

3. Understanding dynamism

Clearly, it is important to understand the reciprocal relationships among psychological processes, climate actions, and outcomes. Yet how to do so is not straightforward. Experimental designs beyond hypothetical scenarios in controlled settings are logistically challenging or impossible and potentially unethical: testing the relationship would involve assigning participants to experience repeated exposure to climate change-related threats. There are three general approaches towards better understanding these dynamic relationships. First is through retrospective survey or interview studies; while informative, recall may be biased as people already know the outcome of decisions (e.g. taken protective adaptive action), memories fade, and processes like emotional responses are by their nature emphemeral [24]. Second is through simulation modeling, which is well-developed in the natural disaster literature with some models informed by behavioral science research [25] to model more realistic responses and potential outcomes. For example, scholars can model migration from coastal areas subject to sea level rise [26] or develop climate models informed by social and behavioral science [27]. Yet these methods fail to account for individual-level psychological processes, which are important for initiating and sustaining behaviors over time.

A third approach, longitudinal panel studies, particularly those that incorporate pre-event data, are a powerful way to examine the DCMA relationships with larger, representative samples in real-world settings to discern the dynamics among psychological processes, climate actions, and outcomes while accounting for other factors over time. Our team effectively leveraged such a design in a recent study that began in 2017 and assessed a probability-based, representative sample of U.S. Gulf Coast residents in the 60 h prior to the landfall of Hurricane Irma, which approached the U.S. Gulf Coast as a Category 5 tropical cyclone [15]. We then followed our sample over the next five years, assessing psychological (including attitudes, cognitions, and emotions) and behavioral (including climate actions and disaster mitigation efforts) responses to hurricanes and climate change-related threats over time [5, 15, 23]. This allowed us to explore the dynamic processes that occur between exposure and response to climate change-related threats over time.

Such longitudinal panel studies involve asking the same individuals the same questions repeatedly over time. Commonly used in fields like public health, they have the advantage over repeated cross-sectional studies or retrospective studies. First, they can assess responses to specific exposures, especially with respect to the presence (or absence) of that exposure and its timing. Psychological and behavioral responses can be assessed before, during, and after climate events, providing richer data and avoiding recall bias often associated with cross-sectional, retrospective designs. Second, longitudinal panel studies allow statistical analyses to control for both current socio-demographic and historic individual characteristics, accounting for variability in the outcome due to potential confounding and alternative explanations. Third, longitudinal panel studies can be paired with probability-based sampling, avoiding biases of less rigorous sampling techniques by including those who tend to be under-represented and from hard-to-reach areas. Subsequently, evidence suggests using probability-based sampling to obtain a representative sample produces estimates with half the measurement error of opt-in samples commonly used by survey researchers [28].

Hence, data from probability-based longitudinal panel studies yield greater accuracy of psychological and behavioral estimates, which is important for informing policy, resource allocation, and scientific replicability. As part of a mixed-methods model, longitudinal panel modeling can be conducted in addition to other methods to 'triangulate' evidence connecting affect and cognitions to climate action. For example, longitudinal panel data can be merged with physical climate data (e.g. wind speed, estimated damage) using latitude and longitude data, news media broadcast coverage data, social vulnerability data, and text analysis of free-response questions or diaries.

However, longitudinal panel studies are not without their drawbacks. Limitations include sample attrition over time, high financial and logistical costs especially if using a probability-based sample, and reliance on self-report of behaviors. Assessing psychological processes and climate action at the time of potential acute exposure to climate change-related threats requires rapid ethics board approval, brief surveys, and low barriers to participation (e.g. online surveys). Despite this, longitudinal panel studies are a powerful way to examine the dynamism among psychological processes, climate actions, and outcomes over time.

4. Analyzing data from longitudinal panel studies

The complex nature of the DMCA necessitates several important statistical considerations when using a longitudinal panel approach. First, responses to the same questions from the same individual across surveys are likely to be correlated with each other (i.e. the data are dependent). For instance, a panelist's rating of climate change risk at one time is likely to be correlated with their rating of climate change risk at a subsequent time point, especially if they have remained in the same social and physical environments. Failing to account for this dependency in the data could lead to underestimated standard errors (increasing likelihood of statistical significance), lead to incorrect inferences, and violates a core assumption of common statistical techniques like analysis of variance and regression. A second statistical consideration is that the DMCA specifies several levels of analysis that may interact. For example, individual-level factors (like climate fears) may interact with macro-level factors (like storm damage per county) in predicting individuals' subsequent climate risk perceptions and behaviors. Mixed effects models (e.g. multilevel, hierarchical modeling), quantify and explain between- and within-person variability to address these concerns [29]. Mixed effects modeling accounts for multiple observations coming from the same individuals (i.e. non-independence) through the inclusion of random intercepts, and allows testing cross-level interactions like the interaction between individual climate change fears and county-level storm damage. By simultaneously testing within- and between-person variance over time and cross-level effects, mixed effects models provide a powerful tool for testing hypotheses derived from the DMCA. This is important for building a more comprehensive understanding of the dynamic ways individuals' interactions with their physical and social environments predict climate change-related emotions, cognitions, and behaviors over time.

A third statistical consideration in testing the DMCA is assessing indirect effects (i.e. mediation) and bidirectional effects, such as how higher climate change risk perceptions might predict more mitigation behaviors, which then may predict subsequent decreased climate change risk perceptions (due to having taken action to reduce those risks). Although mixed effects models can test mediation, the process is not straightforward as it requires conducting a series of models then bootstrapping to test the significance of the indirect effects. Moreover, mixed effects modeling is not suitable for testing bidirectional effects.

In such situations, structural equation modeling (SEM) could be useful as it facilitates testing indirect and bidirectional effects, while also accounting for the non-independence of data from longitudinal panel designs. Specifically, dynamic structural equation models (DSEM) [30] integrate elements from several statistical approaches, including random intercept models, dynamic models, and SEM. This gives DSEM the flexibility to simultaneously model within- and between-person variance, mediation, bidirectional associations, and cross-level interactions. For example, a DSEM testing the DCMA could simultaneously assess change in the bidirectional association between individuals' climate-related risk perceptions and behaviors over time, how this change differs by different social groups, and what psychological or macro-level environmental factors may explain (i.e. mediate) this change. Moreover, like mixed effects models, DSEM treats time as continuous, which is consistent with the DMCA, and allows testing of non-normally distributed outcomes, which is important when assessing different types of psychological, social, and physical climate data together. Thus, the flexibility of DSEM allows a more complete way of statistically testing hypotheses derived from the DMCA by accounting for the multifaceted dynamism of interacting psychological, social, and environmental factors over time. Despite this advantage, major drawbacks to DSEM include its complexity, which can lead to more frequent convergence and model instability issues than other approaches (especially with small sample sizes), as well as higher computational demands and increased difficulty interpreting findings. Nonetheless DSEM is a promising avenue for illuminating the dynamic and interacting effects premised in the DMCA.

Another statistical approach to testing the DMCA is group-based trajectory modeling (GBTM), a type of discrete (finite) mixture modeling that identifies distinct unobserved (i.e. latent) groups or classes of individuals based on their trajectories of change in the outcome over time. For example, our team repeatedly surveyed a representative sample of Floridians and Texans in the United States about their climate change risk perceptions over five tropical cyclone seasons. Using GBTM, we found that people naturally grouped into three classes: those with (1) low/stable, (2) moderate/mostly stable, or (3) high/variable personal climate change risk perception trajectories, with differences between groups largest immediately after tropical cyclones and smallest in the absence of such storms [23]. This analysis allowed us to illustrate non-linear changes in climate-related cognitions, and test predictors of these changes, across multiple tropical cyclone seasons. However, GBTM does not directly allow testing of indirect effects nor directly models bidirectional effects, but may be combined with mixed effects modeling or DSEM to test different components of the DMCA.

5. Illustrative case study

Frontline communities experience the 'first and worst' impacts from climate change. In our longitudinal study of U.S. Gulf Coast tropical cyclones, we demonstrated the feasibility of conducting representative field research in advance of an approaching threat and following those who were exposed over time, documenting the dynamic processes that co-occur with respect to psychological and behavioral responses to climate change-related threats [5, 15, 23]. Extending this work in the context of wildfires on the U.S. West Coast, the Our Communities, Our Bay project is a longitudinal panel study in the San Francisco Bay Area [6] aiming to co-identify, co-develop, and co-test low-cost, affordable interventions such as air cleaners, which are small portable devices that remove indoor air pollutants during wildfires, and smartphone app-based messaging to reduce exposure to climate change-related hazards (e.g. wildfires) and to improve health over time through behavioral changes in frontline communities. This expands on the tropical cyclones project using mixed methods, including data collected through the Our Communities app on psychological processes (e.g. risk perceptions, emotions) and climate action (e.g. adaptation) as households are experiencing, for example, heat waves and wildfires. This further increases ecological validity and incorporates a more in-depth exploration of the lived experience of community members. Indoor and outdoor sensors collect air pollution and temperature data; mattress sensors collect health data; and energy meters collect energy consumption data. These quantitative data can be analyzed using mixed effects modeling to assess changes over time and the effectiveness of various interventions, while considering multiple levels of analysis simultaneously such as the interplay of individual, geographical, and ecological measurements. Moreover, GBTM can be used to understand naturally-occurring groups of people who behave in similar ways in their adaptations (or not) to climate change over time. This data-driven approach uses an algorithm to identify groupings of trends over time inherent in the data, as opposed to the researcher classifying participants into groups prior to analysis. DSEM can further elucidate insights by assessing potential explanatory mechanisms (i.e. mediation) and bidirectional effects. Findings can be used by community organizations and policymakers to better understand which interventions work best for whom and under what circumstances to better prepare frontline households for rapid climate change impacts.

6. Conclusions

The DMCA provides a conceptual advance embracing the dynamism and feedback among psychological processes, climate actions, and outcomes in real-world settings. Longitudinal panel designs are best suited to testing this dynamism, although careful consideration needs to be paid to ensure that designs are sensitive to the needs and lived realities of people.

Data availability statement

No new data were created or analysed in this study.

Acknowledgments

The authors would like to thank Drs. Roxane Cohen Silver, E Alison Holman, and Baruch Fischhoff for their guidance and intellectual contributions to projects that informed this perspective. The authors would also like to thank Drs. Natalie Herbert, Seung-Hyun Cho, and Jenny Suckale, as well as Mr. ShihMing Huang, Ms. Ortensia Lopez, Ms. Violet Wulf-Saena, Ms. Caroline Beckman, Mr. Cade Cannedy, Ms. Samantha J Kramer, and Mr. Derek Ouyang for their intellectual collaboration and partnership on the Our Communities, Our Bay project described in this perspective.

Author contributions

Gabrielle Wong-Parodi: Conceptualization, Writing—Original Draft, Writing—Review & Editing, Visualization, Supervision, Project administration, Funding acquisition. Dana Rose Garfin: Conceptualization, Writing—Review & Editing, Supervision, Project administration, Funding acquisition. Daniel P Relihan: Conceptualization, Writing—Review & Editing.

Funding

The research that informed this perspective was supported by funding from the National Science Foundation (SBE-1760764 to Roxane Cohen Silver, E Alison Holman, and Mansour Fahimi, SES-1811883 to Gabrielle Wong-Parodi, Roxane Cohen Silver, and Joshua Wurman, BCS-1902925 to Roxane Cohen Silver, E Alison Holman, and Mansour Fahimi, SES-2030139 to Gabrielle Wong-Parodi and Dana Rose Garfin, Cooperative Agreement with the National Center for Atmospheric Research 1755088). Our Communities, Our Bay was developed under assistance Agreement No. 84024001 awarded by the US Environmental Protection Agency (EPA) to Gabrielle

Wong-Parodi (Stanford University) and Seung-Hyun Cho (RTI International). This manuscript has not been formally reviewed by the EPA. The views expressed in this manuscript are solely those of the authors and do not necessarily reflect those of the agency. The EPA does not endorse any products or commercial services mentioned in this manuscript. Our Communities, Our Bay is also supported by a National Science Foundation CAREER award (SES-2045129), a Stanford Center for Population Health Sciences award, and a United States Parcel Service Endowment Fund at Stanford award to Gabrielle Wong-Parodi. Our Communities, Our Bay is additionally supported by a Stanford Impact Labs award to Jenny Suckale.

Conflict of interest

The authors have no competing interests nor financial disclosures.

ORCID iDs

Gabrielle Wong-Parodi https://orcid.org/0000-0001-5207-7489
Daniel P Relihan https://orcid.org/0000-0003-3674-4290
Dana Rose Garfin https://orcid.org/0000-0002-0435-9307

References

[1] Tollefson J 2022 Climate change is hitting the planet faster than scientists originally thought *Nature* **28**
[2] IPCC 2022 *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge University Press)
[3] IPCC 2021 *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge University Press)
[4] Wong-Parodi G and Rubin N B 2022 Exploring how climate change subjective attribution, personal experience with extremes, concern, and subjective knowledge relate to pro-environmental attitudes and behavioral intentions in the United States *J. Environ. Psychol.* **79** 101728
[5] Garfin D R, Thompson R R, Holman E A, Wong-Parodi G and Silver R C 2022 Association between repeated exposure to hurricanes and mental health in a representative sample of Florida residents *JAMA Netw. Open* **5** e2217251
[6] Herbert N *et al* 2023 Improving adaptation to wildfire smoke and extreme heat in frontline communities: evidence from a community-engaged pilot study in the San Francisco Bay Area *Environ. Res. Lett.* **18** 074026
[7] Grothmann T and Patt A 2005 Adaptive capacity and human cognition: the process of individual adaptation to climate change *Glob. Environ. Change* **15** 199–213
[8] van der Linden S 2015 The social-psychological determinants of climate change risk perceptions: towards a comprehensive model *J. Environ. Psychol.* **41** 112–24
[9] Doherty K L and Webler T N 2016 Social norms and efficacy beliefs drive the alarmed segment's public-sphere climate actions *Nat. Clim. Change* **6** 879–84
[10] Kahlor L A 2007 An augmented risk information seeking model: the case of global warming *Media Psychol.* **10** 414–35
[11] van der Linden S, Leiserowitz A and Maibach E 2019 The gateway belief model: a large-scale replication *J. Environ. Psychol.* **62** 49–58
[12] Lindell M K and Perry R W 2012 The protective action decision model: theoretical modifications and additional evidence *Risk Anal.* **32** 616–32
[13] Hamilton M, Fischer A P, Guikema S D and Keppel-Aleks G 2018 Behavioral adaptation to climate change in wildfire-prone forests *WIREs Clim. Change* **9** e553
[14] Carman J P and Zint M T 2020 Defining and classifying personal and household climate change adaptation behaviors *Glob. Environ. Change* **61** 102062
[15] Garfin D R and Wong-Parodi G 2024 Climate change anxiety, hurricane exposure, and climate change actions and attitudes: results from a representative, probability-based survey of US Gulf Coast residents *Lancet Planet. Health* **8** e378–90
[16] Xie B, Brewer M B, Hayes B K, McDonald R I and Newell B R 2019 Predicting climate change risk perception and willingness to act *J. Environ. Psychol.* **65** 101331
[17] Doherty T J and Clayton S 2011 The psychological impacts of global climate change *Am. Psychol.* **66** 265–76
[18] Tian J, Sun M, Gong Y, Chen X and Sun Y 2022 Chinese residents' attitudes toward consumption-side climate policy: the role of climate change perception and environmental topic involvement *Resour. Conserv. Recycling* **182** 106294
[19] van der Linden S 2017 Determinants and measurement of climate change risk perception, worry, and concern *SSRN Electron. J.* 1–53
[20] Wong-Parodi G and Feygina I 2021 Engaging people on climate change: the role of emotional responses *Environ. Commun.* **15** 571–93
[21] Ogunbode C A, Demski C, Capstick S B and Sposato R G 2019 Attribution matters: revisiting the link between extreme weather experience and climate change mitigation responses *Glob. Environ. Change* **54** 31–39
[22] Weiner B 1985 An attributional theory of achievement motivation and emotion *Psychol. Rev.* **92** 548–73
[23] Wong-Parodi G, Relihan D P and Garfin D R 2024 A longitudinal investigation of risk perceptions and adaptation behavior in the US gulf coast *PNAS Nexus* **3** 099
[24] Coughlin S S 1990 Recall bias in epidemiologic studies *J. Clin. Epidemiol.* **43** 87–91
[25] Wang Y, Kyriakidis M and Dang V N 2021 Incorporating human factors in emergency evacuation—An overview of behavioral factors and models *Int. J. Disaster Risk Reduct.* **60** 102254
[26] Hauer M E, Fussell E, Mueller V, Burkett M, Call M, Abel K, McLeman R and Wrathall D 2020 Sea-level rise and human migration *Nat. Rev. Earth Environ.* **1** 28–39
[27] Stern P C, Dietz T, Nielsen K S, Peng W and Vandenbergh M P 2023 Feasible climate mitigation *Nat. Clim. Change* **13** 6–8
[28] Beshay 2023 Comparing two types of online survey samples *Pew Research Center Methods* (available at: www.pewresearch.org/methods/2023/09/07/comparing-two-types-of-online-survey-samples/)
[29] Hoffman L 2015 *Longitudinal Analysis: Modeling Within-Person Fluctuation and Change* (Routledge)
[30] Asparouhov T, Hamaker E L and Muthén B 2018 Dynamic structural equation models *Struct. Equ. Modeling* **25** 359–88