

1 Evidence for three distinct climate change audience segments with varying belief
2 updating tendencies: Implications for climate change communication

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7 In 2016, the Paris Agreement was ratified. Parties to the agreement have
8 pledged to cooperate to keep global temperature increases well below 2°C above
9 pre-industrial levels (United Nations, 2015). The continued cooperation of democratic
10 countries is partly determined by public support. Yet, in America and Australia, public
11 concern for climate change often lags behind other social issues, such as strengthening
12 the economy (Markus, 2021; Pew Research Center, 2022).

13 Various interventions have been proposed to increase support for climate policy.
14 For example, telling people the proportion of climate scientists who believe in
15 anthropogenic climate change (97%) enhances concern about climate change and policy
16 support (van der Linden et al., 2015; van der Linden, in press). Such interventions treat
17 the public as a homogeneous entity. However, reception to climate change messages can
18 vary due to differences in motivation, ideology, and worldview (Feygina et al., 2010;
19 Kahan, 2012). For example, Hart and Nisbet (2012) exposed Americans to a news story
20 describing climate change risks, before measuring support for mitigation policies.
21 Compared to controls not exposed to an article, liberals who read the news story
22 showed greater support for mitigation policy, whereas conservatives showed reduced
23 support. Thus, when climate change messages clash with a person's pre-existing
24 political beliefs, they can backfire.

25 To improve interventions, communicators may use *audience segmentation* to
26 divide the public into homogeneous groups (W. R. Smith, 1956). Messages can then be
27 tailored to the characteristics of each group, which may enhance communication
28 effectiveness and mitigate backfire effects (Corner & Randall, 2011). A meta-analysis of
29 health communication suggests segmentation approaches are more effective than a
30 'one-size-fits-all' approach, particularly when psychological theory is used to understand
31 the segments (Noar et al., 2007).

32 The most established audience segmentation for climate change communication
33 is the *Six Americas* (Maibach et al., 2011; Yale Program on Climate Change

34 Communication, 2021). Six segments were developed from a nationally representative
35 survey of Americans. Although multidimensional, the Six Americas may be ordered on
36 continuous dimensions of belief and concern about climate change. The segments range
37 from the ‘alarmed’, the segment most accepting of climate change science; via the
38 ‘concerned’; the ‘cautious’; the ‘disengaged’; the ‘doubtful’; to the ‘dismissive’, a
39 segment which rejects climate science. Conceptual replications have revealed
40 comparable segments in other nations, such as Australia (Hine et al., 2013; Metag et al.,
41 2017; Morrison et al., 2013; Morrison et al., 2018; Neumann et al., 2021).

42 Most climate change audience segments, including the Six Americas, have been
43 developed using a *top-down* approach. Specifically, the audience is statistically grouped
44 across psychological characteristics known to correlate with climate change perceptions,
45 policy support, and pro-environmental behaviour (for a review, see Hine et al., 2014).
46 Alternatively, a *bottom-up* approach groups segments according to the audience’s views
47 of lay concepts of climate change, such as those found in social media discussions. This
48 overcomes a disadvantage of top-down approaches—they may omit features of climate
49 change salient to citizens, but not to researchers. However, bottom-up approaches are
50 sorely lacking in the climate change domain. Thus, it is unknown to what degree
51 current understandings of segmentation are limited by researchers’ preconceptions. Here
52 we addressed this shortcoming using a bottom-up audience segmentation approach.

53 We conducted bottom-up segmentation using the *Q methodology*—an analytical
54 approach to representing viewpoints (Brown, 1980). It uses a Q sort task whereby
55 participants rank statements about a topic, usually along a dimension of agreement.
56 Statements can be generated using a bottom-up approach, where statements capture
57 the breadth of conversational possibilities (Brown, 1980; Stephenson, 1986). Using
58 factor analysis, participants are then segmented based on ranks assigned to statements.
59 Applications of the Q methodology to climate change audiences are rare and limited to
60 small non-representative samples (e.g., Hobson & Niemeyer, 2012; Wolf et al., 2009).
61 The current research is the first to apply the Q methodology to nationally
62 representative samples. Our statements for the Q methodology were derived from

63 prevalent Australian social media discourse on climate change (Andreotta et al., 2019).

64 **The Current Paper**

65 We conducted two studies using representative samples of the Australian public.
66 Study 1 sought to derive audience segments using the Q methodology with statements
67 from social media, followed by measures of the above-mentioned psychological
68 characteristics. The study provided evidence for three different segments: Acceptors,
69 Fencesitters, and Sceptics. Analysis of psychological characteristics indicated segments
70 differed in their mental models, climate change concern and scepticism, political
71 ideology, and environmental worldviews. In Study 2, we replicated the three segments
72 and examined if they differed in their receptivity to climate science information.
73 Participants completed a belief-updating task in which they were asked for their beliefs
74 about the contribution of different causes to climate change, the likelihood climate
75 change will have specific impacts, and the effectiveness of Australia’s mitigation policy.
76 They were then given the actual scientific estimates for each event before submitting
77 their revised belief estimates. We found considerable heterogeneity across segments in
78 their belief-updating tendencies. These results provide insights into the effectiveness of
79 communicating scientific information to each segment.

80 **Study 1**

81 Climate change views may arise from the interaction of cognitive representations,
82 ideology, personality, and affect. Regarding cognitive representation, audience segments
83 typically vary in climate change scepticism (e.g., Yale Program on Climate Change
84 Communication, 2021), both epistemic (doubting climate science) and response
85 scepticism (doubting mitigation is possible, Capstick & Pidgeon, 2014). Beyond
86 general scepticism of human influence on climate, segments may hold specific causal
87 beliefs *mental models*—internalised representations used to generate descriptions,
88 explanations, and predictions (Granger et al., 2002; Jones et al., 2011; Rouse & Morris,
89 1986). Different causal beliefs can lead to different predictions. To illustrate, consider
90 two common mental models: one features greenhouse gas emissions as the predominant

91 cause of climate change, whereas the other features toxic air pollution as the
92 predominant cause (Fleming et al., 2021; Kempton et al., 1995; Reynolds et al., 2010).
93 Individuals with the second model may be most likely to suggest the ineffective strategy
94 of mitigating climate change by additional filtering of factory smokestacks (Kempton
95 et al., 1995). Thus, knowledge of segments' mental models provides insight into the
96 logic by which trusted information will be transformed into action or knowledge
97 (Granger et al., 2002), and which policies may be endorsed (Bostrom et al., 2012).

98 Deliberation through mental models and policy support may depend upon
99 cognitive styles. For example, individuals with a high *need for cognition* engage in, and
100 enjoy, effortful thinking (Cacioppo & Petty, 1982). Those high in need for cognition
101 tend to think openly and critically about issues, potentially leading to greater
102 acceptance of scientific perspectives on climate change (Sinatra et al., 2014).
103 Conversely, individuals with high self-perceived climate change knowledge may be
104 reluctant to seek out and accept scientific information (Stoutenborough & Vedlitz,
105 2014). Those with an elevated *considerations of future consequences* cognitive style are
106 predisposed to orient themselves to long-term over short-term goals (Strathman et al.,
107 1994), leading to higher support for mitigative policy (Wang, 2017).

108 Ideological characteristics may underscore the contents of mental models and
109 whether mental models are used in deliberation (Fleming et al., 2021). For example,
110 right-wing political ideologies de-emphasise climate change risks and concerns, thereby
111 legitimising mental models that represent climate change as a natural fluctuation in
112 climate (Campbell & Kay, 2014; Drews & van den Bergh, 2016; Leiserowitz, 2006; Zia
113 & Todd, 2010). Similarly, individuals with high *system justification*, a tendency to
114 perceive the prevailing social system as fair, legitimate, and justifiable (Kay & Jost,
115 2003), are motivated to deny the risks of climate change, as mitigative policies often
116 challenge the status quo (Feygina et al., 2010; van der Linden, 2017). Some sceptical of
117 climate change may demonstrate *conspiracist ideation* by believing climate change to be
118 a 'hoax' and therefore reject anthropogenic climate change (Lewandowsky, Gignac,
119 et al., 2013; Lewandowsky, Oberauer, et al., 2013; Sarathchandra & Haltinner, 2021).

120 Individuals differ in their environment worldviews, culturally shared values and beliefs
121 about the environment (Douglas & Wildavsky, 1983; Thompson et al., 1990). For
122 example, individuals may have an *environment-as-ductile* worldview that the
123 environment is unable to recover from human impacts or an *environment-as-elastic*
124 worldviews that the environment is readily able to recover from human impacts (Price
125 et al., 2014). Individuals with greater environment-as-ductile worldviews, or reduced
126 environment-as-elastic worldviews, demonstrate greater belief in anthropogenic climate
127 change, environmental concern, and pro-environmental behaviour (Price et al., 2014).
128 Lastly, values may influence climate change scepticism. Individuals with high
129 *conservation* values (the motivation to preserve the past, respect order, and resist
130 change) and low *self-transcendence* may be motivated to engage in climate change
131 denial (Corner et al., 2014; Drews & van den Bergh, 2016; Schwartz, 2012).

132 Personality may have wide-reading effects on engagement with, and views of,
133 climate change. Personality mediates the effects of risk perceptions, values, social
134 norms, and environmental concern on pro-environmental attitudes (Yu & Yu, 2017).
135 Emission-reducing behaviours are associated with the traits of openness (imaginative,
136 curious), conscientiousness (reliable, organised), and extraversion (sociability,
137 assertiveness; Brick & Lewis, 2014).

138 Affect, particularly worry about climate change, can influence climate change
139 views and support for action (Fleming et al., 2021; N. Smith & Leiserowitz, 2014; van
140 der Linden et al., 2019). For example, experimental and correlational research has
141 supported a Gateway Belief Model, where the influence of the perceived scientific
142 consensus on support for public action is mediated by cognitive (belief in climate
143 change and human causation) and affective (worry about climate change; van der
144 Linden et al., 2019). Worry about climate change is one the largest predictors of
145 mitigative policy support, surpassing the predictive capacity of other emotions
146 (N. Smith & Leiserowitz, 2014).

147 A complex myriad of psychological characteristics underpin tendencies to process
148 and seek information and engage in pro-environmental behaviour. This study aimed to

149 segment the audience using the Q methodology and examine segment differences in a
150 range of psychological characteristics. Although we used a bottom-up approach to
151 audience segmentation, we adopted a top-down approach to facilitate segment
152 interpretation by incorporating auxiliary measures of psychological characteristics that
153 may account for differences in segment membership. Critically, these auxiliary measures
154 were used to facilitate interpretation of audience segments after they had been
155 derived—they did not contribute to the segmentation process itself. We expected each
156 segment would be underscored by a unique signature of psychological characteristics.

157 **Method**

158 This study was pre-registered using the Open Science Framework
159 (https://osf.io/tc8v6/?view_only=c91a9e1cd22340378d13155129c804a6/).

160 **Participants.** Four-hundred and thirty-five Australian adults were recruited
161 online by Qualtrics. A targeted and stratified sampling process was used, whereby the
162 age ($M = 46.71$, $SD = 17.77$) and gender (female = 50.34%) were matched to the
163 general population of Australian adults reported in the national 2016 census. We did
164 not record the data of extremely fast responders, defined as those who completed the
165 study in less than 873 seconds (a preregistered criterion based on pilot testing).

166 **Materials and Procedure.** Participants completed the Q sort followed by an
167 inventory of psychological survey scales. Administration of scales was counterbalanced
168 to control order effects (see Supplementary Material). The median time taken to
169 complete the study was 26.17 minutes (interquartile range = 16.15 minutes).

170 **Q sort.** The Q sort requires a set of statements capturing the breadth of
171 conversational possibilities of an issue (Stephenson, 1986). Previous work has used an
172 inductive process to identify the structure of climate change commentary of Australian
173 tweets (Andreotta et al., 2019). This research revealed five enduring themes of public
174 discourse on climate change: climate change action, climate change consequences,
175 climate change conversations, climate change denial, and the legitimacy of climate
176 science and climate change. For each theme, we selected six tweets that captured the
177 heterogeneity of the theme (see Supplementary Materials). The resulting 30 tweets were

178 transcribed as statements that could be understood without the social context of the
179 original tweet. Where possible, language, sentiment, and tone were preserved.
180 Statements included: “it is important to vote for leaders who will combat climate
181 change” (climate change action), “climate change is a threat to the health and safety of
182 our children” (climate change consequences), “it is shameful that climate change, the
183 greatest problem of our time, is barely discussed in the media” (climate change
184 conversations), “climate change sceptics ignore basic climate science facts” (climate
185 change denial), and “scientists should stop falsely claiming that climate change is a
186 settled science” (legitimacy of climate science and climate change).

187 The Q sort comprised three phases. In phase 1, participants read each statement
188 and assigned it to one of three categories: (1) like their point of view; (2) unlike their
189 point of view; or (3) neutral or unsure. In phase 2, participants were required to rank
190 statements from “most unlike my point of view” (-4) to “most like my point of view”
191 (+4). The number of statements that could be placed at each rank was predetermined,
192 such that more statements could be placed at the midpoint rather than the extremes
193 (Figure 1). Thus, participants had to be selective in the statements used to represent
194 their most extreme views. In phase 3, participants responded to open-ended questions
195 prompting them to justify their placement of the statements ranked most extreme.

196 **Scales.** Twenty eight scales were used to measure cognitive, ideological,
197 personality, and affective psychological characteristics. For brevity, the scales are
198 summarised in Table 1.

Fig. 1. Schematic of the Q sort task. Participants progressed through a stack of
unsorted statements (A) by dragging the top-most statement into the grey box that
best corresponded to their point of view (B), as indicated by the blue solid line.
Participants could re-arrange statements at any time during the task. To facilitate this
process, statements could be placed in the orange temporary holding area (C), as
indicated by the pink dashed line

199 Results and Discussion

200 **Segments.** To identify segments, we conducted a factor analysis on the Q sort
201 data. Unlike traditional survey approaches which characterise factors of statements that
202 generate common response patterns across people, the Q methodology reverses this
203 statistical procedure to identify factors of people with common sorting styles (Brown,
204 1980; McKeown & Thomas, 2013; Watts & Stenner, 2012). We conducted a principal
205 components analysis using varimax rotation. We extracted a single factor, as the first
206 component accounted for a substantially larger proportion of variance (34.06% after
207 rotation) than the second component. Broadly, this extracted factor represents a
208 dimension of acceptance of anthropogenic climate change. We segmented individuals on
209 the basis of their factor loading: (1) *Acceptors* whose positive load onto the factor is
210 statistically significant ($n = 281$; 64.60%); (2) *Sceptics* whose negative load onto the
211 factor is statistically significant ($n = 36$; 8.28%); and (3) *Fencesitters* whose loading
212 onto the factor is not statistically significant ($n = 118$; 27.13%). Fencesitters are
213 necessarily less homogeneous in their climate change views than Acceptors and Sceptics,
214 otherwise Fencesitters would have emerged as a second factor.

215 To understand each segment's perspective, we constructed a 'representative' Q
216 sort (Brown, 1980; Watts & Stenner, 2012). For each segment, the average ranking
217 assigned to each statement by participants, weighted by participants' factor loading,
218 was calculated. The weighted-averages of statements were then mapped onto the
219 rankings enforced by the structure of the Q sort, known as factor scores (Table 2).
220 Factor scores were not calculated for Fencesitters, as the segment's sorting style was
221 necessarily heterogeneous. Next, we report the representative Q sorts for Acceptors and
222 Sceptics further elaborated on with the participants' text justification of their rankings.

223 Acceptors believe anthropogenic climate change is occurring (statements:
224 3, 10, 11, 13, 28), as indicated by an increased frequency of extreme weather and hotter
225 days (statements: 5, 10, 11). Acceptors reject the notion climate change is a hoax
226 (statements: 2, 6). Acceptors claim climate change will cause widespread changes:
227 physical changes in weather (statements: 9, 10, 11); biological changes to ecosystems,

228 such as damage to the Great Barrier Reef (statement: 4); and changes to human
229 systems, threatening agriculture (statement: 6), future generations (statement: 4), and
230 to a lesser degree, the poor (statement: 21). According to Acceptors, these impacts are
231 worse than scientists initially thought (statement: 8), though there are still
232 opportunities to mitigate and adapt (statements: 12, 15, 25, 26). Although Acceptors
233 believe action partly rests on collective society (statement: 27), they believe leaders
234 must take charge (statement: 1, 25) as “there are too many weak and idiot politicians in
235 parliament. we need to vote in people who will take action” otherwise “climate change
236 will spiral out of control”.

237 Sceptics reject the concept of anthropogenic climate change (statements:
238 3, 10, 11, 13, 28). According to Sceptics, there is conclusive evidence human activities do
239 not influence climate. Scientists who say otherwise are viewed by Sceptics to rely on
240 “dodgy modelling” and “bullshit thought up by some brain dead idiots in university”.
241 Thus, Sceptics claim climate scientists have overestimated the frequency and intensity
242 of current extreme weather events (statements: 10, 11), and will be incorrect in their
243 projections for the future (statements: 4, 7, 8). Consequently, Sceptics agree scientists
244 changed the name of their area of study from “global warming” to “climate change”, as
245 the world is not warming (statement: 5). As anthropogenic climate change “has nothing
246 to do with science and reality”, Sceptics question the motives of institutions that
247 endorse mitigative action (statements: 2, 5). For example, one Sceptic claimed “the
248 United Nations is hiding behind climate change to acquire money”. Similarly, Sceptics
249 argue against voting for leaders who will combat climate change (statements: 1) as such
250 leaders are only concerned “about what they can get”. These leaders are “going to
251 bankrupt Australia” by “chasing ghosts” as there is no way to “tame mother nature,
252 money can’t”. Citizens who demand solutions for climate change are the usual
253 ‘torch-and-pitchfork’ crowd (statement: 12).

254 **Predictors of Segment Membership.** Segments differed in their
255 psychological attributes (Table 3). To explore statistical differences, we constructed a
256 multinomial regression model that predicted segment membership as a function of the

257 z-scores of psychological characteristics. Due to the large number of related predictors,
258 we used a ridge regression. A ridge regression penalises the estimates of
259 highly-correlated terms to achieve greater reliability (a bias-variance tradeoff). For each
260 level of the penalty placed on highly-correlated terms (corresponding to a shrinkage
261 parameter λ), different coefficients are estimated. A cross-validation process (k -fold)
262 was used to determine the ideal penalty (λ). Confidence intervals of the coefficient were
263 calculated using a bootstrap procedure (Efron & Tibshirani, 1994). One thousand
264 samples were created by sampling participants (with replacement) from the study data.
265 For each sample, coefficients were estimated using the aforementioned ridge regression
266 and cross-validation processes. From the coefficient distributions, 95% confidence
267 intervals were identified.

268 Regression coefficients are presented in Figure 2. Acceptors (Sceptics) were
269 characterised by lower (greater) epistemic and response scepticism, greater (lower)
270 belief in anthropogenic climate change, greater (lower) worry about climate change,
271 lower (greater) endorsement of environment-as-elastic worldviews, less (more)
272 conservative political ideology, lower (greater) knowledge volume, and greater (lower)
273 belief carbon-emitting human activities cause climate change. High belief in societal
274 consequences of climate change reliably distinguished Acceptors only, whereas low belief
275 environmental harms causes of climate change and greater self-perceived climate change
276 knowledge reliably predicted Sceptics only. Fencesitters were distinguished by greater
277 levels of conspiratorial ideation. Fencesitters (Acceptors) were distinguished by higher
278 (lower) belief in the effectiveness of engineering policies, though this may be a result of
279 suppression via other predictors, as on average, Acceptors had numerically greater belief
280 in the effectiveness of engineering policies than Fencesitters. Likewise, the relatively low
281 coefficient of knowledge volume predicting Acceptor membership should also be
282 cautiously interpreted, as on average, Acceptors had greater knowledge volume than
283 Fencesitters. Personality, need for cognition, consideration of future consequences,
284 system justification, and values were not reliable predictors of segment membership.
285 Thus, each segment was associated with a unique pattern of psychological

286 characteristics.

287

Study 2

288 Study 1 provided evidence for three audience segments that differ in
289 psychological characteristics that transcend climate change (conspiratorial ideation,
290 environmental worldviews, and political ideology) and specific climate change beliefs
291 and mental models that may be more easily changed. However, the association between
292 climate change scepticism and ideological variables suggest some climate change beliefs
293 may be resistant to revision because of motivated reasoning (Bayes & Druckman, 2021).
294 For example, the association between climate change scepticism and right-leaning
295 ideology may be due to scepticism becoming a symbol of in-group membership for
296 conservatives—a process known as identity-protective cognition (Kahan et al., 2013). If
297 so, conservatives may be motivated to reject opposing beliefs as these would threaten
298 the material and emotional benefits gained from in-group membership. Thus, segments
299 may differ in their receptivity to climate science information.

300 To test this idea, in Study 2 we examined whether revision of climate change
301 beliefs differed across segments. We used a *belief-updating paradigm* (Garrett & Sharot,
302 2017). In this paradigm, in each trial, individuals generate numerical estimates of an
303 event or process, and then are shown an estimate and required to generate another
304 estimate. Although not commonly used in climate change communication research
305 (though, see Sunstein et al., 2017), the belief-updating paradigm allows researchers to
306 quantify belief-updating tendencies in a rigorous manner, that generalises across beliefs
307 and accounts for individual base rates (e.g., Garrett & Sharot, 2017; Ma et al., 2016).

Fig. 2. Ridge regression coefficients for each predictor of segment membership. The coefficients (dot) and 95% confidence intervals (error bars) are presented for Acceptors (blue), Fencesitters (yellow), and Sceptics (purple). Predictors are ordered by the magnitude of coefficients. The grey background highlights predictors where confidence intervals contains zero for all segments.

308 In the current study, we assessed updating across three mental model domains: climate
309 change causes, climate change consequences, and effective mitigation of climate change
310 (Bostrom et al., 2012). The dependent measure of interest was the direction and degree
311 of belief updating following receipt of scientific estimates.

312 Additionally, we explored two cognitive mechanisms which may account for a
313 relationship between segment membership and belief revision. The first is trust in the
314 source of incoming information. Acceptors may be more likely to trust scientific
315 institutions than Sceptics, due to observed differences in political ideology,
316 environmental worldviews, and climate change scepticism (Cook & Lewandowsky, 2016;
317 Sunstein et al., 2017). The second mechanism is optimism bias, where individuals tend
318 to revise their beliefs to a greater degree when receiving good news (e.g., initially
319 overestimating an event perceived as bad) than when receiving bad news (e.g., initially
320 overestimating an event perceived as good; Garrett & Sharot, 2017; Ma et al., 2016).
321 Sunstein et al. (2017) demonstrated that segments differ in their optimism bias—when
322 revising future-warming estimates, Sceptics updated optimistically, whereas Acceptors
323 updated pessimistically. Accordingly, we explored the possibility segment differences in
324 belief-updating can be explained by group differences in an optimism bias. To
325 determine which events were good or bad news, we included a sentiment inventory for
326 participants to indicate their feelings towards each climate change outcome.

327 Finally, Study 2 was an opportunity to replicate the three segment solution from
328 Study 1. However, the length of the belief-updating paradigm meant it was not
329 practical to include the psychological scales from Study 1.

330 Method

331 **Participants.** Qualtrics was used to recruit Australian adults ($N = 413$) using
332 the same targeted and stratified sampling process focussed on age ($M = 46.82$, $SD =$
333 18.04) and gender (female = 47.94%). Along these characteristics, the sample was
334 representative of the Australian population. We did not record the data of extremely
335 fast responders, defined as those who completed the study in less than 664 seconds (a

336 preregistered criterion based on pilot testing).

337 **Materials and Procedure.** All materials were presented to participants on a
338 computer screen via a web browser. After providing informed consent and demographic
339 data, participants completed the Q sort task used in Study 1. Next, participants
340 completed the trust inventory, belief-updating tasks (administered in a counterbalanced
341 order, see Supplementary Materials), and sentiment inventory. The median completion
342 time of the study was 25.02 minutes (interquartile range = 18.28 minutes).

343 **Trust inventory.** Participants were informed they would be shown
344 information from two sources: the peer-reviewed climate science literature and Climate
345 Action Tracker (an organisation that provides scientific analysis of government climate
346 action). For each source, participants read a lay description and indicated their trust of
347 the source on a seven-point Likert scale, ranging from “strongly distrust” (1) to
348 “strongly trust” (7).

349 **Belief-updating tasks.** We tested belief updating across three domains with
350 five belief-updating tasks: (1) belief in causes of climate change (three tasks); (2) belief
351 in consequences of climate change (one task); and (3) belief in effectiveness of mitigative
352 policies (one task). Each belief-updating task contained two stages. Firstly, participants
353 provided estimates for climate change drivers or outcomes (see Supplementary Materials
354 for more detail), by entering values from 0 to 100 into text boxes. Secondly, participants
355 were shown their initial estimates alongside the scientific estimate. Participants then
356 provided a new estimate. The presentation of belief-updating tasks was
357 counterbalanced across participants (see Supplementary Materials).

358 The first three belief-updating tasks concerned causal beliefs. For the first task,
359 participants estimated the percentage of human-driven and nature-driven causes of
360 climate change between 1980–2011, separately. For the second task, participants
361 estimated the percentage of climate change caused by each of six mechanisms (e.g.,
362 “carbon dioxide emissions” and “changes in solar activity”) between 1750–2011. For the
363 third task, participants estimated the percentage of warming caused by greenhouse gas
364 emissions from six human activities (e.g., “electricity use in residential buildings”).

365 Before supplying their estimates, participants were informed greenhouse gas emissions
366 drive most climate change.

367 Another belief-updating task concerned consequence beliefs. Participants
368 estimated the degree to which nine climate events (e.g., “the number of hot days
369 globally between 1901–2005”) occurred because of anthropogenic climate change.

370 The final belief-updating task concerned mitigation beliefs. Participants were
371 given information about the Paris Agreement and the Emissions Reduction Fund
372 (hereafter ‘ERF’), Australia’s central climate policy. Then, participants predicted the
373 change in Australia’s carbon dioxide emissions by the year 2030 (compared to 2005
374 levels) under Australia’s current climate policies. Unlike other tasks, participants
375 indicated the direction of change of emissions by using a drop-down menu (options:
376 increase, decrease, no change) and the amount of change by entering a percentage
377 (participants who indicated there would be no change had to enter “0”). Alongside both
378 their initial and revised estimates, participants indicated their approval of the ERF on a
379 seven-point Likert scale, ranging from “strongly disagree” (1) to “strongly agree” (7);
380 their level of approval of Australia’s climate policies on the same seven-point Likert
381 scale; and the likelihood Australia will meet the Paris Agreement (as a percentage, from
382 0 to 100).

383 ***Sentiment inventory.*** Participants indicated their feelings towards each
384 climate change event presented in the belief-updating tasks, on a five-point Likert scale,
385 ranging from “very negative” (1) to “very positive” (5). On the same scale, participants
386 were asked “If Australia met its commitment to the Paris Agreement, how positive or
387 negative would you feel about that?” Participants were not asked about their sentiment
388 towards climate change causes, as responses would be difficult to interpret.

389 **Results and Discussion**

390 **Segmentation Solution.** Following the analysis steps of Study 1, we
391 replicated the Acceptor, Fencesitter, and Sceptics segments. The factor scores of each
392 statement was near-identical for Acceptors and Sceptics (see Supplementary Material

393 for factor scores). Of the sample, 256 participants were Acceptors (61.99%), 114 were
394 Fencesitters (27.60%), and 43 were Sceptics (10.41%).

395 **Belief Updating.** The dependent variable of interest is *update*—the degree to
396 which a participant revised their estimate following exposure to scientific information,
397 as a proportion of their initial error. An update score was calculated for each
398 participant and for each belief. The magnitude of an update score is the difference
399 between the initial and revised estimate, divided by the magnitude of difference
400 between the initial and scientific estimate. The sign of the update score conveys
401 whether the update was towards (positive) or away (negative) from the scientific
402 estimate. Thus, an update score of one indicates a revision to match the scientific
403 estimate. Using this formula, update scores could not be defined when the initial
404 estimate equalled the scientific estimate (293 of 9888 updates; 2.96%) and such cases
405 were therefore excluded from further analysis.

406 Linear mixed-effects modelling was used to determine whether update varied as
407 a function of segment, trust in source information, or an optimism bias. Each domain of
408 belief (cause, consequence, and mitigation) was modelled separately. The general
409 strategy involved constructing several models, each with a different combination of
410 predictors (known as fixed effects). We then compared the consistency between data and
411 each model, via the Akaike Information Criterion (AIC), to determine the best fitting
412 models (detailed in the Supplementary Materials). For models of cause and consequence
413 beliefs, intercepts were assumed to randomly vary across participants, belief items, and
414 task administration orders (known as random effects). For mitigation beliefs, intercepts
415 were assumed to randomly vary across only task administration orders; as only a single
416 belief was measured, within-unit and between-unit variability cannot be partitioned. All
417 models were fit using maximum likelihood estimation. Predictor coefficients are
418 reported with a 95% confidence interval (CI), estimated using the Wald method. One
419 participant was excluded from analysis, as their data prevented model convergence due
420 to a belief update score several magnitudes higher than other participants.

421 Updating varied as a function of segment (Figure 3). Models with a main effect

422 of segment (and no other predictors) had better fit than models with no main effects.
 423 For cause beliefs, Acceptors updated more than Fencesitters (difference = 0.25,
 424 $CI = [0.12, 0.38]$), and Fencesitters updated more than Sceptics (difference = 0.39,
 425 $CI = [0.19, 0.59]$). For consequence beliefs, Acceptors again updated more than
 426 Fencesitters (difference = 0.25, $CI = [0.15, 0.34]$), who again updated more than
 427 Sceptics (difference = 0.24, $CI = [0.09, 0.40]$). For mitigation beliefs, Fencesitters
 428 updated the most, although they did not statistically differ from Acceptors (difference
 429 = 0.07, $CI = [-0.20, 0.34]$). However, Acceptors updated more than Sceptics (difference
 430 = 0.53, $CI = [0.13, 0.92]$). Thus, the patterns of segment updating for cause and
 431 consequence beliefs are not reflected in mitigation beliefs.

432 Segments may have differed in belief updating solely due to differences in trust
 433 in the source of information. However, this is not well supported by the evidence. For
 434 all domains, models with only a main effect of segment had considerably better fit than
 435 models with only a main effect of trust. Thus, trust alone cannot account for the effect
 436 of segment on belief update.

437 Generally, the best fitting models for update of cause and consequence beliefs
 438 were those including effects for both trust and segment membership. Additionally, there
 439 was substantial evidence for interactions. For cause beliefs, greater trust was associated
 440 with greater update for Acceptors (0.09 more update per point of trust,
 441 $CI = [0.01, 0.16]$) and Sceptics (0.18 more update per point of trust, $CI = [0.08, 0.28]$),
 442 but not for Fencesitters (0.02 less update per point of trust, $CI = [-0.06, 0.10]$). For
 443 consequence beliefs, greater trust was associated with greater update for Acceptors
 444 (0.10 more update per point of trust, $CI = [0.04, 0.16]$), but not for Sceptics (0.04 more
 445 update per point of trust, $CI = [-0.04, 0.12]$) or Fencesitters (0.04 more update per
 446 point of trust, $CI = [-0.02, 0.10]$). For mitigation beliefs, there was little evidence for

Fig. 3. Mean update for each domain and segment: Acceptor (blue), Fencesitter (yellow), and Sceptic (purple). Error bars represent one between-participants standard error of the mean

447 an interaction.

448 Segment differences in updating may be due to differences in optimistic
449 revisions. To explore this possibility, we determined which scientific messages were good
450 news and bad news on the basis of participants' emotional appraisals of events and their
451 first estimates. For example, if a participant indicated an event was negative and was
452 exposed to a scientific estimate greater than their first estimate, the event is bad news;
453 conversely, if this scientific estimate was instead less than a participant's first estimate,
454 the event is good news. Combinations of effects for segment and news type (coded as
455 good or bad) were entered into mixed-effects models. We did not model participant
456 update of neutral belief/news, which included 1420 of 3708 consequence belief updates
457 (38.30%) and 90 of 412 mitigation belief updates (21.84%). Of note, we did not model
458 optimistic updating for cause beliefs as we did not collect sentiment data for causes.

459 For consequence and mitigation beliefs, the best fitting models were those
460 containing main effects for segment and news type, but no interactions. There was a
461 tendency towards a pessimistic updating for all segments, such that updating is larger
462 for bad news than good news (Figure 4). As the best fitting models contained an effect
463 for segment, segment differences in update could not be solely accounted for by
464 differences in an optimism or pessimism bias.

465 **Change in Policy Support.** Additionally, we identified the predictors of
466 changes in policy support. To do so, we determined the fit of linear mixed-effects
467 models with combinations of main effects and interactions of: segment; change in
468 perceived mitigation effectiveness (positively-signed when policy perceived to be more
469 effective); and change in perceived likelihood of Australia satisfying the Paris
470 Agreement (positively-signed change when the Paris Agreement is perceived to be more
471 likely to be satisfied).

Fig. 4. Mean update for (a) consequence beliefs and (b) mitigation belief, as a function of news and segment: Acceptor (blue), Fencesitter (yellow), and Sceptic (purple). Error bars represent one between-participants standard error of the mean

472 For both support of the ERF and Australia's policy, two models had considerably
473 better fit. The first model contained a main effect of segment, a main effect of perceived
474 likelihood Australia will satisfy its Paris Agreement commitment, and an interaction
475 between these two variables. The second model contained the same effects as the first,
476 with an additional main effect of change in perceived mitigation effectiveness. For these
477 models, the coefficient for the interaction between segment and perceived likelihood of
478 meeting the Paris Agreement was only reliability signed (positive) for Acceptors (that
479 is, the confidence interval did not intersect zero). Additionally, participants who
480 updated towards greater perceived effectiveness of the ERF increased their support for
481 the ERF (0.00378 change on the scale per 1% increment of carbon dioxide reduction,
482 $CI = [0.00065, 0.00692]$), and their support for Australia's mitigation policies, although
483 not reliably (0.00185 change on the scale per 1% increment of carbon dioxide reduction,
484 $CI = [-0.00172, 0.00542]$). Overall, these models indicate participants of all segments
485 who reduce their belief in a policy's effectiveness also reduce their support for that
486 specific policy, but not general policy action. Additionally, Acceptors lowered their
487 support for specific policy to the degree that it harmed Australia's likelihood of meeting
488 the Paris Agreement. However, detrimental impacts on the Paris Agreement were
489 unrelated to changes in policy support of Fencesitters and Sceptics.

490 General Discussion

491 We used a novel bottom-up approach to segment climate change views. Across
492 two studies, we find consistent evidence for three distinct audience segments: Acceptors,
493 Fencesitters, and Sceptics. In Study 1, we combined our bottom-up approach to
494 segmentation based on the Q sort with a top-down approach to segment interpretation
495 by incorporating auxiliary measures of potentially relevant psychological characteristics.
496 Importantly, these auxiliary measures were used to help interpret the segments once
497 they had been derived—they did not contribute to the segmentation process itself. This
498 combination of approaches revealed the three segments differ in their mental models of
499 climate change and other psychological characteristics. Study 2 demonstrated segments

500 differ in their belief-updating tendencies when exposed to scientific information.
501 Overall, our studies indicate the Australian public are divisible into three audience
502 segments with unique psychological characteristics and belief-updating tendencies.
503 Next, we summarise the characteristic differences between segments, how these can
504 inform communication strategies, and how our segmentation solution differs from
505 previous research.

506 **Characteristic Differences Between Segments**

507 Segment differences can be understood by referring to their sorting behaviour in
508 the Q sort task, responses on the psychological characteristics measures, and updating
509 tendencies in the belief-updating paradigm. From the Q sorts, it is apparent Acceptors
510 strongly believe in the urgency and reality of climate change. They recognise climate
511 change will have wide-ranging impacts on environment and society, and these impacts
512 may be worse than climate scientists expect. They reject conspiratorial notions of
513 climate change as a hoax, and they want to see political leadership and climate action.
514 By contrast, Sceptics have an alternative perception of reality—one where the science
515 suggests human actions are not influencing climate. Instead, climate change is a hoax
516 manufactured to serve a hidden agenda. Accordingly, climate scientists are thought to
517 use questionable research practices to create the illusion climate change is occurring.
518 They think climate scientists' forecasts of global warming have been proved wrong and
519 that, because of this, they deliberately changed the name of their field of study from
520 “global warming” to “climate change”. We cannot say anything specific about
521 Fencesitters other than that their sorting responses are more heterogeneous than the
522 other two segments.

523 Turning to psychological characteristics measures, Acceptors strongly believe
524 climate change is occurring and that carbon-emitting human activities cause climatic
525 changes. They are more worried about the issue than other segments and strongly
526 support climate action. This segment is politically liberal with an
527 environment-as-ductile worldview, meaning they think the natural environment has a

528 limited capacity to recover from damage. By contrast, Sceptics are less likely to believe
529 climate change is occurring and that carbon-emitting human activities cause climatic
530 changes—yet, Sceptics have the greatest self-confidence in their knowledge about
531 climate change. They are therefore sceptical of the need for climate action. This
532 segment is politically conservative with an environment-as-elastic worldview, meaning
533 they think the environment easily recovers from damage. Surprisingly, Sceptics did not
534 show the highest levels of dispositional conspiratorial ideation of all segments, despite
535 their strong endorsement of climate-conspiracy related items in the Q sort. Instead,
536 Fencesitters were the highest in dispositional conspiratorial ideation.

537 Our finding that dispositional conspiratorial ideation was elevated in
538 Fencesitters, but not Sceptics, seemingly contradicts an extensive literature showing
539 conspiratorial ideation predicts climate change scepticism (Hornsey et al., 2018; Kaiser
540 & Puschmann, 2017; Lewandowsky, Oberauer, et al., 2013). However, Lewandowsky
541 (2020) recently suggested individuals may deploy conspiratorial explanations for two
542 different reasons: (1) they have a general disposition towards engaging in conspiratorial
543 ideation; and/or (2) they seek to guard against worldview-incongruent information. In
544 the latter case, conspiracy theories may not reflect people’s real attitudes to climate
545 change but may instead be a pragmatic tool to indicate a person’s political stance on
546 the issue. Consistent with this, Fencesitters showed greater general disposition toward
547 conspiracism in the absence of a specific tendency toward climate change conspiracy
548 theorising, and have moderate political ideology and environmental worldviews. By
549 comparison, Sceptics do not show an increased general disposition toward conspiracism,
550 but they do show a specific tendency toward climate change conspiracy theorising,
551 accompanied by politically conservative ideology and environment-as-elastic worldviews.
552 Thus, unlike Fencesitters, Sceptics may be ideologically motivated to believe
553 conspiratorial accounts of climate change.

554 Finally, segments differed in the degree they revised their beliefs towards
555 scientific information. Specifically, for climate change causes and consequences,
556 Acceptors updated their beliefs more than Fencesitters, who in turn updated their

557 beliefs more than Sceptics. For mitigation, Acceptors and Fencesitters revised their
558 beliefs to a comparable degree, and more so than Sceptics. The segment differences in
559 belief updating could not be fully accounted for by trust in information source or an
560 optimism bias. In general, Acceptors and Fencesitters showed high degrees of
561 willingness to revise their beliefs, whereas Sceptics were highly resistant to revising their
562 beliefs. The willingness of Fencesitters but not Sceptics to update their beliefs in
563 response to scientific information confers further support for the notion the two
564 segments may deploy conspiracy theories for different reasons.

565 We found all segments updated optimistically, meaning their belief update in
566 response to scientific information was greater for good news than bad news. We do not
567 find evidence for a general pessimism bias in Acceptors, as suggested by previous
568 research (Sunstein et al., 2017). This discrepancy may be due to differences in the
569 classification of bad news. Unlike Sunstein et al. (2017) who assumed the belief of
570 interest (a change in temperature) was perceived by all participants to be equally
571 negative, we measured participant sentiment for each event and accounted for
572 individual differences in sentiment. Though, other factors could have accounted for
573 differences with previous research, such as the operationalisation of Acceptors or the
574 specific beliefs measured in studies.

575 **Communicating with the Different Segments**

576 To bolster public support for mitigative policies, our findings suggest
577 communicators should focus on Fencesitters. Acceptors already trust climate science
578 and support strong leadership to address climate change, whereas Sceptics are few in
579 number and politically-motivated to oppose mitigative policy, and are thereby resistant
580 to belief updating. In contrast, Fencesitters show potential for belief change, as they
581 update their beliefs in response to scientific findings and were not characterised by
582 extreme environmental worldviews or political ideology. However, just as Fencesitters
583 could be tipped towards greater climate change acceptance by exposure to scientific
584 information, they could be tipped toward scepticism by exposure to disinformation.

585 To protect Fencesitters from climate change disinformation, communicators
586 could preemptively use inoculation techniques to build psychological resistance to
587 disinformation before it is perceived (McGuire & Papageorgis, 1961). Inoculation
588 involves warning individuals they may be exposed to disinformation and explaining to
589 them the deceptive strategies and rhetorical techniques used by those that seek to
590 mislead (van der Linden et al., 2017). For example, Cook et al. (2017) found climate
591 change disinformation could be successfully inoculated by alerting individuals to the use
592 of ‘fake experts’ by the fossil fuel industry. Alternatively, if disinformation has already
593 informed belief, communicators may use various best-practice debunking strategies to
594 correct the disinformation (Lewandowsky et al., 2020; Lewandowsky et al., 2017). For
595 example, communicators could provide clear explanations for the established knowledge
596 that undermines the misinformation alongside an explanation of what is true instead
597 (Ecker et al., 2020; Lewandowsky et al., 2020; Paynter et al., 2019).

598 Although we emphasise Fencesitters, public support for mitigation policy can be
599 bolstered within Acceptors and potentially Sceptics. Despite worry about climate
600 change and having knowledge on its causes, many Acceptors fail to distinguish effective
601 and ineffective policies (Kempton et al., 1995; Read et al., 1994; Reynolds et al., 2010).
602 To reduce support for ineffective policies, communicators could encourage Acceptors to
603 apply their causal knowledge of greenhouse gases to the policy domain. Alternatively,
604 communicators could directly highlight the ineffectiveness of a policy and the adverse
605 impacts on international agreements. In contrast, changes in policy support of
606 Fencesitters and Sceptics was not associated with the consequences of ineffective policy
607 on international agreements. Lastly, messages from climate scientists could be
608 persuasive, as climate scientists are trusted by Acceptors.

609 Of all segments, Sceptics were most resistant to belief revision when contradicted
610 by science. Thus, communicators may need to deploy unique strategies to foster more
611 positive attitudes towards climate science and policy in this segment. One approach is
612 to leverage people’s motivations to maintain cognitive consistency in attitudes. For
613 example, Gehlbach et al. (2019) found conservatives asked to rate the generally

614 accepted contributions of science to society, such as discovering germs cause disease,
615 had more positive attitudes towards climate science than conservatives asked solely
616 about their climate science attitudes. Alternatively, communicators may avoid climate
617 science entirely by appealing to the benefits of mitigation policy to improve policy
618 endorsement, such as communicating the moral or economic co-benefits (Bain et al.,
619 2015). Though, communicators should be wary of Sceptics' aversion to commonly
620 discussed climate change mitigation policies, which may conflict with more conservative
621 political ideology (Campbell & Kay, 2014).

622 **Comparison to Previous Segmentation Research**

623 Our studies found evidence for three segments, a number on the lower range of
624 segments reported in the literature (Hine et al., 2014). Though, the number of segments
625 derived in studies is an inherently subjective process. Therefore, the characteristics
626 underlying segments should be emphasised when comparing studies. Despite using a
627 bottom-up approach, our segmentation solution is broadly consistent with the literature
628 (e.g., Hine et al., 2016; Maibach et al., 2009; Morrison et al., 2013). Specifically, we
629 identified segments of Acceptors and Sceptics, consolidated on a continuum of climate
630 change scepticism, worry about climate change, and political ideology. We extend the
631 literature by identifying the conspiratorial disposition of Fencesitters and the typical
632 mental models held by each segment. Further, we identified the belief-updating
633 tendencies of segments, demonstrating that in some contexts, Fencesitters may be more
634 receptive to climate change science than Acceptors.

635 **Limitations**

636 The use of Internet panel services introduced methodological limitations to our
637 studies with effects for generalisation. The samples used in the study are not truly
638 representative of all Australians, as we sampled Australians who participated in panel
639 services, and matched the sample to Australian demographics only on gender and age.
640 Additionally, short-form scales were used in the first study to measure psychological
641 constructs. By virtue of minimal items, some scales had poor internal consistency (e.g.,

642 personality). However, we only selected short-form scales which had demonstrably good
643 psychometric properties, such as retest reliability (Rammstedt & John, 2007).

644 **Conclusion**

645 The predominant approach to segmentation of climate change audiences has
646 been top-down, which privileges researcher preconceptions over audience conceptions of
647 climate change. In contrast, we used a bottom-up approach to ensure segmentation
648 reflects lay views on climate change, as defined by the public. However, we did not
649 disregard theory—we complimented our segmentation by examining the psychological
650 characteristics of segments. We found the Australian public is composed of three
651 segments—Acceptors, Fencesitters, and Sceptics—with unique psychological
652 characteristics and belief-revision tendencies. Communication can be enhanced, our
653 results suggest, by conceptualising the public as relatively homogeneous segments,
654 rather than a heterogeneous whole. Yet, many communicators rely on a
655 ‘one-size-fits-all’ approach. For these communicators, our research outlines a
656 comprehensive profile of segments along with recommendations for communicating with
657 each. We suggest communicators should target Fencesitters who hold moderate views
658 and are receptive to belief revision. Care must nevertheless be taken since, although
659 Fencesitters are receptive to scientific information, they are also potentially vulnerable
660 to misinformation and conspiratorial thinking.

References

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- 662 Andreotta, M., Nugroho, R., Hurlstone, M. J., Boschetti, F., Farrell, S., Walker, I., &
663 Paris, C. (2019). Analyzing Social Media Data: A Mixed-Methods Framework
664 Combining Computational and Qualitative Text Analysis. *Behav. Res. Methods*,
665 *51*(4), 1766–1781. <https://doi.org/10.3758/s13428-019-01202-8>
- 666 Bain, P. G., Milfont, T. L., Kashima, Y., Bilewicz, M., Doron, G., Garðarsdóttir, R. B.,
667 Gouveia, V. V., Guan, Y., Johansson, L.-O., Pasquali, C., Corral-Verdugo, V.,
668 Aragonés, J. I., Utsugi, A., Demarque, C., Otto, S., Park, J., Soland, M.,
669 Steg, L., González, R., . . . Saviolidis, N. M. (2015). Co-Benefits of Addressing
670 Climate Change can Motivate Action Around the World. *Nat. Clim. Change*,
671 *6*(2), 154–157. <https://doi.org/10.1038/nclimate2814>
- 672 Bayes, R., & Druckman, J. N. (2021). Motivated Reasoning and Climate Change. *Curr.*
673 *Opin. Behav. Sci.*, *42*, 27–35. <https://doi.org/10.1016/j.cobeha.2021.02.009>
- 674 Bostrom, A., O'Connor, R. E., Böhm, G., Hanss, D., Bodi, O., Ekström, F., Halder, P.,
675 Jeschke, S., Mack, B., Qu, M., Rosentrater, L., Sandve, A., & Sælensminde, I.
676 (2012). Causal Thinking and Support for Climate Change Policies: International
677 Survey Findings. *Glob. Environ. Change*, *22*(1), 210–222.
678 <https://doi.org/10.1016/j.gloenvcha.2011.09.012>
- 679 Brick, C., & Lewis, G. J. (2014). Unearthing the “Green” Personality: Core Traits
680 Predict Environmentally Friendly Behavior. *Environment and Behavior*, *48*(5),
681 635–658. <https://doi.org/10.1177/0013916514554695>
- 682 Brown, S. R. (1980). *Political Subjectivity: Applications of Q Methodology in Political*
683 *Science*. Yale University Press.
- 684 Cacioppo, J. T., & Petty, R. E. (1982). The Need for Cognition. *J. Pers. Soc. Psychol.*,
685 *42*(1), 116–131.
- 686 Campbell, T. H., & Kay, A. C. (2014). Solution Aversion: On the Relation Between
687 Ideology and Motivated Disbelief. *J. Pers. Soc. Psychol.*, *107*(5), 809–824.
688 <https://doi.org/10.1037/a0037963>

- 689 Capstick, S. B., & Pidgeon, N. F. (2014). What is Climate Change Scepticism?
690 Examination of the Concept Using a Mixed Methods Study of the UK Public.
691 *Glob. Environ. Change*, *24*, 389–401.
692 <https://doi.org/10.1016/j.gloenvcha.2013.08.012>
- 693 Cook, J., & Lewandowsky, S. (2016). Rational Irrationality: Modeling Climate Change
694 Belief Polarization Using Bayesian Networks. *Top. Cogn. Sci.*, *8*(1), 160–179.
695 <https://doi.org/10.1111/tops.12186>
- 696 Cook, J., Lewandowsky, S., & Ecker, U. K. H. (2017). Neutralizing Misinformation
697 Through Inoculation: Exposing Misleading Argumentation Techniques Reduces
698 Their Influence. *PLOS ONE*, *12*(5), 1–21.
699 <https://doi.org/10.1371/journal.pone.0175799>
- 700 Corner, A., Markowitz, E., & Pidgeon, N. (2014). Public Engagement with Climate
701 Change: The Role of Human Values. *Wiley Interdiscip. Rev. Clim. Change*, *5*(3),
702 411–422. <https://doi.org/10.1002/wcc.269>
- 703 Corner, A., & Randall, A. (2011). Selling Climate change? The Limitations of Social
704 Marketing as a Strategy for Climate Change Public Engagement. *Glob. Environ.*
705 *Change*, *21*(3), 1005–1014. <https://doi.org/10.1016/j.gloenvcha.2011.05.002>
- 706 Douglas, M., & Wildavsky, A. (1983). *Risk and Culture: An Essay on the Selection of*
707 *Technological and Environmental Dangers*. University of California Press.
- 708 Drews, S., & van den Bergh, J. C. (2016). What Explains Public Support for Climate
709 Policies? A Review of Empirical and Experimental Studies. *Clim. Policy*, *16*(7),
710 855–876. <https://doi.org/10.1080/14693062.2015.1058240>
- 711 Ecker, U. K. H., O'Reilly, Z., Reid, J. S., & Chang, E. P. (2020). The Effectiveness of
712 Short-Format Refutational Fact-Checks. *Br J Psychol*, *111*(1), 36–54.
713 <https://doi.org/10.1111/bjop.12383>
- 714 Efron, B., & Tibshirani, R. (1994). *Introduction to the Bootstrap*. Chapman & Hall.
- 715 Enzler, H. B. (2015). Consideration of Future Consequences as a Predictor of
716 Environmentally Responsible Behavior: Evidence From a General Population

- 717 Study. *Environ. Behav.*, *47*(6), 618–643.
718 <https://doi.org/10.1177/0013916513512204>
- 719 Feygina, I., Jost, J. T., & Goldsmith, R. E. (2010). System Justification, the Denial of
720 Global Warming, and the Possibility of “System-Sanctioned Change”. *Pers. Soc.*
721 *Psychol. Bull.*, *36*(3), 326–338. <https://doi.org/10.1177/0146167209351435>
- 722 Fleming, W., Hayes, A. L., Crosman, K. M., & Bostrom, A. (2021). Indiscriminate,
723 Irrelevant, and Sometimes Wrong: Causal Misconceptions about Climate
724 Change. *Risk Anal.*, *41*(1), 157–178. <https://doi.org/10.1111/risa.13587>
- 725 Garrett, N., & Sharot, T. (2017). Optimistic Update Bias Holds Firm: Three Tests of
726 Robustness Following Shah et al. *Conscious. Cogn.*, *50*, 12–22.
727 <https://doi.org/10.1016/j.concog.2016.10.013>
- 728 Gehlbach, H., Robinson, C. D., & Vriesema, C. C. (2019). Leveraging Cognitive
729 Consistency to Nudge Conservative Climate Change Beliefs. *J. Environ.*
730 *Psychol.*, *61*, 134–137. <https://doi.org/10.1016/j.jenvp.2018.12.004>
- 731 Granger, M. M., Fischhoff, B., Bostrom, A., & Atman, C. J. (2002). *Risk*
732 *Communication: A Mental Models Approach* (First). Cambridge University Press.
- 733 Hart, P. S., & Nisbet, E. C. (2012). Boomerang Effects in Science Communication: How
734 Motivated Reasoning and Identity Cues Amplify Opinion Polarization About
735 Climate Mitigation Policies. *Commun. Res.*, *39*(6), 701–723.
736 <https://doi.org/10.1177/0093650211416646>
- 737 Hine, D. W., Phillips, W. J., Cooksey, R., Reser, J. P., Nunn, P., Marks, A. D. G.,
738 Loi, N. M., & Watt, S. E. (2016). Preaching to Different Choirs: How to
739 Motivate dismissive, Uncommitted, and Alarmed audiences to Adapt to Climate
740 Change? *Glob. Environ. Change*, *36*, 1–11.
741 <https://doi.org/10.1016/j.gloenvcha.2015.11.002>
- 742 Hine, D. W., Reser, J. P., Morrison, M., Phillips, W. J., Nunn, P., & Cooksey, R.
743 (2014). Audience Segmentation and Climate Change Communication:
744 Conceptual and Methodological Considerations. *Wiley Interdiscip. Rev. Clim.*
745 *Change*, *5*(4), 441–459. <https://doi.org/10.1002/wcc.279>

- 746 Hine, D. W., Reser, J. P., Phillips, W. J., Cooksey, R., Marks, A. D. G., Nunn, P.,
747 Watt, S. E., Bradley, G. L., & Glendon, A. I. (2013). Identifying Climate Change
748 Interpretive Communities in a Large Australian Sample. *J. Environ. Psychol.*,
749 *36*, 229–239. <https://doi.org/10.1016/j.jenvp.2013.08.006>
- 750 Hobson, K., & Niemeyer, S. (2012). “What Sceptics Believe”: The Effects of
751 Information and Deliberation on Climate Change Scepticism. *Public Underst.*
752 *Sci.*, *22*(4), 1–17. <https://doi.org/10.1177/0963662511430459>
- 753 Hornsey, M. J., Harris, E. A., & Fielding, K. S. (2018). Relationships Among
754 Conspiratorial Beliefs, Conservatism and Climate Scepticism across Nations.
755 *Nat. Clim. Change*, *8*(7), 614–620. <https://doi.org/10.1038/s41558-018-0157-2>
- 756 Jones, N. A., Ross, H., Lynam, T., Perez, P., & Leitch, A. (2011). Mental Models: An
757 Interdisciplinary Synthesis of Theory and Methods. *Ecol. Soc.*, *16*(1).
- 758 Kahan, D. M. (2012). Cultural Cognition as a Conception of the Cultural Theory of
759 Risk. In S. Roeser (Ed.), *Handbook of Risk Theory* (pp. 725–759). Springer.
- 760 Kahan, D. M., Peters, E., Dawson, E. C., & Slovic, P. (2013). Motivated Numeracy and
761 Enlightened Self-Government. *Behav. Public Policy*, *1*(1), 54–86.
762 <https://doi.org/10.1017/bpp.2016.2>
- 763 Kaiser, J., & Puschmann, C. (2017). Alliance of Antagonism: Conunterpublics and
764 Polarization in Online Climate Change Communication. *Commun. Public*, *2*(4),
765 1–17. <https://doi.org/10.1177/2057047317732350>
- 766 Kay, A. C., & Jost, J. T. (2003). Complementary Justice: Effects of "Poor But Happy"
767 and "Poor but Honest" Stereotype Exemplars on System Justification and
768 Implicit Activation of the Justice Motive. *J Pers Soc Psychol*, *85*(5), 823–837.
769 <https://doi.org/10.1037/0022-3514.85.5.823>
- 770 Kempton, W., Boster, J. S., & Hartley, J. A. (1995). *Environmental Values in*
771 *American Culture*. MIT Press.
- 772 Leiserowitz, A. (2006). Climate Change Risk Perception and Policy Preferences: The
773 Role of Affect, Imagery, and Values. *Clim. Change*, *77*(1-2), 45–72.
774 <https://doi.org/10.1007/s10584-006-9059-9>

- 775 Lewandowsky, S. (2020). Hannah Arendt and the Contemporary Social Construction of
776 Conspiracy Theorists. *PsyArXiv*. <https://doi.org/10.31234/osf.io/fm8yg>
- 777 Lewandowsky, S., Cook, J., Ecker, U. K. H., Albarracín, D., Amazeen, M. A.,
778 Kendeou, P., Lombardi, D., Newman, E. J., Pennycook, G., Porter, E.,
779 Porter, E., Rapp, D. N., Reifler, J., Roozenbeek, J., Schmid, P., Seifert, C. M.,
780 Sinatra, G. M., Swire-Thompson, B., van der Linden, S., . . . Zaragoza, M. S.
781 (2020). *The Debunking Handbook 2020* (tech. rep.).
782 <https://doi.org/10.17910/b7.1182>
- 783 Lewandowsky, S., Ecker, U. K., & Cook, J. (2017). Beyond Misinformation:
784 Understanding and Coping with the “Post-Truth” Era. *J. Appl. Res. Mem.*
785 *Cogn.*, *6*(4), 353–369. <https://doi.org/10.1016/j.jarmac.2017.07.008>
- 786 Lewandowsky, S., Gignac, G. E., & Oberauer, K. (2013). The Role of Conspiracist
787 Ideation and Worldviews in Predicting Rejection of Science. *PLOS ONE*, *8*(10).
788 <https://doi.org/10.1371/journal.pone.0075637>
- 789 Lewandowsky, S., Oberauer, K., & Gignac, G. E. (2013). NASA Faked the Moon
790 Landing—Therefore, (Climate) Science Is a Hoax: An Anatomy of the Motivated
791 Rejection of Science. *Psychol. Sci.*, *24*(5), 622–633.
792 <https://doi.org/10.1177/0956797612457686>
- 793 Lindeman, M., & Verkasalo, M. (2005). Measuring Values With the Short Schwartz’s
794 Value Survey. *J. Pers. Assess.*, *85*(2), 170–178.
795 https://doi.org/10.1207/s15327752jpa8502_09
- 796 Lins de Holanda Coelho, G., Hanel, P. H., & Wolf, L. J. (2018). The Very Efficient
797 Assessment of Need for Cognition: Developing a Six-Item Version. *Assessment*,
798 *27*(8), 1870–1885. <https://doi.org/10.1177/1073191118793208>
- 799 Ma, Y., Li, S., Wang, C., Liu, Y., Li, W., Yan, X., Chen, Q., & Han, S. (2016). Distinct
800 Oxytocin Effects on Belief Updating in Response to Desirable and Undesirable
801 Feedback. *PNAS*, *113*(33), 9256–9261. <https://doi.org/10.1073/pnas.1604285113>
- 802 Maibach, E. W., Leiserowitz, A., Roser-Renouf, C., & Mertz, C. K. (2011). Identifying
803 Like-Minded Audiences for Global Warming Public Engagement Campaigns: An

- 804 Audience Segmentation Analysis and Tool Development. *PLOS ONE*, 6(3).
805 <https://doi.org/10.1371/journal.pone.0017571>
- 806 Maibach, E. W., Roser-Renouf, C., & Leiserowitz, A. (2009). Global Warming's Six
807 Americas 2009.
- 808 Malka, A., Krosnick, J. A., & Langer, G. (2009). The Association of Knowledge with
809 Concern about Global Warming: Trusted Information Sources Shape Public
810 Thinking. *Risk Anal.*, 29(5), 633–647.
811 <https://doi.org/10.1111/j.1539-6924.2009.01220.x>
- 812 Markus, A. (2021). *Mapping Social Cohension* (tech. rep.).
- 813 McGuire, W. J., & Papageorgis, D. (1961). The Relative Efficacy of Various Types of
814 Prior Belief-Defense in Producing Immunity Against Persuasion. *J. Abnorm.*
815 *Soc. Psychol.*, 62(2), 327–337.
- 816 McKeown, B., & Thomas, D. B. (2013). *Q Methodology* (Second). SAGE Publications
817 Ltd.
- 818 Metag, J., Füchslin, T., & Schäfer, M. S. (2017). Global Warming's Five Germanys: A
819 Typology of Germans' Views on Climate Change and Patterns of Media Use and
820 Information. *Public Underst Sci*, 26(4), 434–451.
821 <https://doi.org/10.1177/0963662515592558>
- 822 Morrison, M., Duncan, R., Sherley, C., & Parton, K. (2013). A Comparison Between
823 Attitudes to Climate Change in Australia and the United States. *Australas. J.*
824 *Environ. Manag.*, 20(2), 87–100. <https://doi.org/10.1080/14486563.2012.762946>
- 825 Morrison, M., Parton, K., & Hine, D. W. (2018). Increasing belief but Issue Fatigue:
826 Changes in Australian Household Climate Change Segments Between 2011 and
827 2016. *PLOS ONE*, 13(6), 1–18. <https://doi.org/10.1371/journal.pone.0197988>
- 828 Neumann, C., Stanley, S. K., Leviston, Z., & Walker, I. (2021). *The Six Australias:*
829 *Concern About Climate Change (and Global Warming) is Rising* (Unpublished
830 Manuscript).

- 831 Noar, S. M., Benac, C. N., & Harris, M. S. (2007). Does Tailoring Matter?
832 Meta-Analytic Review of Tailored Print Health Behavior Change Interventions.
833 *Psychol. Bull.*, *133*(4), 673–693. <https://doi.org/10.1037/0033-2909.133.4.673>
- 834 Paynter, J., Luskin-Saxby, S., Keen, D., Fordyce, K., Frost, G., Imms, C., Miller, S.,
835 Trembath, D., Tucker, M., & Ecker, U. (2019). Evaluation of a Template for
836 Countering MisinformationReal-World Autism Treatment Myth Debunking.
837 *PLOS ONE*, *14*(1), 1–13. <https://doi.org/10.1371/journal.pone.0210746>
- 838 Pew Research Center. (2022). *Public’s Top Priority for 2022: Strengthening the*
839 *Nation’s Economy* (tech. rep.). Pew Research Center.
- 840 Price, J. C., Walker, I. A., & Boschetti, F. (2014). Measuring Cultural Values and
841 Beliefs about Environment to Identify their Role in Climate Change Responses.
842 *J. Environ. Psychol.*, *37*, 8–20. <https://doi.org/10.1016/j.jenvp.2013.10.001>
- 843 Rammstedt, B., & John, O. P. (2007). Measuring Personality in One Minute or Less: A
844 10-Item Short Version of the Big Five Inventory in English and German. *J. Res.*
845 *Personal.*, *41*(1), 203–212. <https://doi.org/10.1016/j.jrp.2006.02.001>
- 846 Read, D., Bostrom, A., Morgan, M. G., Fischhoff, B., & Smuts, T. (1994). What Do
847 People Know About Global Climate Change? 2. Survey Studies of Educated
848 Laypeople. *Risk Anal.*, *14*(6), 971–982.
849 <https://doi.org/10.1111/j.1539-6924.1994.tb00066.x>
- 850 Reynolds, T. W., Bostrom, A., Read, D., & Morgan, M. G. (2010). Now What Do
851 People Know About Global Climate Change? Survey Studies of Educated
852 Laypeople. *Risk Anal.*, *30*(10), 1520–1538.
853 <https://doi.org/10.1111/j.1539-6924.2010.01448.x>
- 854 Rouse, W. B., & Morris, N. M. (1986). On Looking into the Black Box: Prospects and
855 Limits in the Search for Mental Models. *Psychol. Bull.*, *100*(3), 349–363.
856 <https://doi.org/10.1037/0033-2909.100.3.349>
- 857 Sarathchandra, D., & Haltinner, K. (2021). How Believing Climate Change is a “Hoax”
858 Shapes Climate Skepticism in the United States. *Environ. Sociol.*, *7*(3), 225–238.
859 <https://doi.org/10.1080/23251042.2020.1855884>

- 860 Schwartz, S. H. (2012). An Overview of the Schwartz Theory of Basic Values. *Online*
861 *Read. Psychol. Cult.*, 2(1), 1–20.
- 862 Sinatra, G. M., Kienhues, D., & Hofer, B. K. (2014). Addressing Challenges to Public
863 Understanding of Science: Epistemic Cognition, Motivated Reasoning, and
864 Conceptual Change. *Educ. Psychol.*, 49(2), 123–138.
865 <https://doi.org/10.1080/00461520.2014.916216>
- 866 Smith, N., & Leiserowitz, A. (2014). The Role of Emotion in Global Warming Policy
867 Support and Opposition. *Risk Anal.*, 34(5), 937–948.
868 <https://doi.org/10.1111/risa.12140>
- 869 Smith, W. R. (1956). Product Differentiation and Market Segmentation as Alternative
870 Marketing Strategies. *J. Mark.*, 21(1), 3–8. <https://doi.org/10.2307/1247695>
- 871 Stephenson, W. (1986). Protoconcurus: The Concourse Theory of Communication.
872 *Operant Subj.*, 9(2), 37–58.
- 873 Stoutenborough, J. W., & Vedlitz, A. (2014). The Effect of Perceived and Assessed
874 Knowledge of Climate Change on Public Policy Concerns: An Empirical
875 Comparison. *Environ. Sci. Policy*, 37, 23–33.
876 <https://doi.org/10.1016/j.envsci.2013.08.002>
- 877 Strathman, A., Gleicher, F., Boninger, D. S., & Edwards, C. S. (1994). The
878 Consideration of Future Consequences: Weighing Immediate and Distant
879 Outcomes of Behavior. *J. Pers. Soc. Psychol.*, 66(4), 742–752.
880 <https://doi.org/10.1037/0022-3514.66.4.742>
- 881 Sunstein, C. R., Bobadilla-Suarez, S., Lazzaro, S. C., & Sharot, T. (2017). How People
882 Update Beliefs about Climate Change: Good News and Bad News. *Cornell Law*
883 *Rev.*, 102(6), 1431–1444.
- 884 Thompson, M., Ellis, R., & Wildavsky, A. (1990). *Cultural Theory*. Westview Press.
- 885 United Nations. (2015). *Paris Agreement* (tech. rep.).
- 886 van der Linden, S., Leiserowitz, A. A., Feinberg, G. D., & Maibach, E. W. (2015). The
887 Scientific Consensus on Climate Change as a Gateway Belief: Experimental
888 Evidence. *PLOS ONE*, 10(2), 1–8. <https://doi.org/10.1371/journal.pone.0118489>

- 889 van der Linden, S. (2017). Determinants and Measurement of Climate Change Risk
890 Perception, Worry, and Concern. In M. C. Nisbet, M. Schafer, S. Markowitz,
891 S. O'Neill, & J. Thaker (Eds.), *The Oxford Encyclopedia of Climate Change*
892 *Communication*. Oxford University Press, Oxford. Oxford University Press.
- 893 van der Linden, S. (in press). The Gateway Belief Model (GBM): A Review and
894 Research Agenda for Communicating the Scientific Consensus on Climate
895 Change. *Curr. Opin. Psychol.* <https://doi.org/10.1016/j.copsyc.2021.01.005>
- 896 van der Linden, S., Leiserowitz, A., & Maibach, E. (2019). The Gateway Belief Model:
897 A Large-Scale Replication. *J. Environ. Psychol.*, *62*, 49–58.
898 <https://doi.org/10.1016/j.jenvp.2019.01.009>
- 899 van der Linden, S., Leiserowitz, A., Rosenthal, S., & Maibach, E. (2017). Inoculating
900 the Public Against Misinformation about Climate Change. *Glob. Chall.*, *1*(2),
901 1600008. <https://doi.org/10.1002/gch2.201600008>
- 902 Wang, X. (2017). Understanding Climate Change Risk Perceptions in China: Media
903 Use, Personal Experience, and Cultural Worldviews. *Sci. Commun.*, *39*(3),
904 291–312. <https://doi.org/10.1177/1075547017707320>
- 905 Watts, S., & Stenner, P. (2012). *Doing Q Methodological Research Theory, Method and*
906 *Interpretation*. SAGE Publications Ltd.
- 907 Wolf, J., Brown, K., & Conway, D. (2009). Ecological Citizenship and Climate Change:
908 Perceptions and Practice. *Environ. Polit.*, *18*(4), 503–521.
909 <https://doi.org/10.1080/09644010903007377>
- 910 Yale Program on Climate Change Communication. (2021). Global Warming's Six
911 Americas.
- 912 Yu, T.-Y., & Yu, T.-K. (2017). The Moderating Effects of Students' Personality Traits
913 on Pro-Environmental Behavioral Intentions in Response to Climate Change.
914 *Int. J. Environ. Res. Public Health*, *14*(12), 1–20.
915 <https://doi.org/10.3390/ijerph14121472>
- 916 Zia, A., & Todd, A. M. (2010). Evaluating the Effects of Ideology on Public
917 Understanding of Climate Change Science: How to Improve Communication

- 918 Across Ideological Divides? *Public Underst. Sci.*, 19(6), 743–761.
- 919 <https://doi.org/10.1177/0963662509357871>