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Abstract:
A central challenge for climate policy is to select effective climate mitigation measures that maintain prosperity and wellbeing. To picture and reason about such complex problems, cognitive psychology shows that people use 'mental models'. Thus, if citizens possess mental models of the climate policy problem, this will affect how they view climate policies. This study reveals that people do, indeed, have mental models that connect the main elements of the problem. Using a nationally representative public sample (n=1,200), we measure patterns of causal relationships that people perceive between four main elements: climate change, climate policy, economic growth, and health and wellbeing. We find that people not only perceive coherent relationships between these elements, they report confidence in their answers and will give high accuracy ratings when shown diagrams of their model constructed from their responses. However, mental models vary substantially across participants, with disagreement on most relationships. Association tests and cluster analysis do not identify recognisable patterns. Hence, while the results reveal an average mental model of the climate policy problem, there is neither a dominant model nor a clear set of contrasting models. These findings challenge common assumptions about how citizens will evaluate proposed policies, while suggesting opportunities to influence mental models through evidence. They also inform public debates on degrowth and green growth.

Keywords: climate change; psychology; mental models; economic growth; policy acceptance

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Policy insights:

- Understanding how people think climate change, climate policies, economic growth, and health and wellbeing relate to each other is crucial to understand policy acceptance.
- Our survey mapped these 'mental models' and found that people have coherent mental models, yet there is little consensus on both individual causal relationships and overall models.
- While there is no dominant mental model, notable frequent perceptions included that economic growth and climate policies both increase wellbeing; policies decrease climate change; and policies do not affect growth.
- These findings warn against making assumptions about how citizens will evaluate policy proposals, and inform public debate on degrowth.

1. Introduction

Selecting effective climate mitigation measures while preserving economic growth and promoting wellbeing is a fiendishly complex policy problem. Selecting good policies requires careful judgment of multiple causal relationships: from policy to climate change (e.g., Fernández-i-Marín et al., 2026), from policy to growth (e.g., Stock, 2020), from growth to climate change (e.g., Clulow, 2018), and from all of these to health and wellbeing (e.g., Van Den Bergh & Botzen, 2018), among others. Such patterns of causality occur across multiple industries, policy areas, geographical levels and locations, and dimensions (e.g., collective vs. individual, present vs. future), contributing further to the complexity of the problem.

Our study investigates whether and how the complexity of the climate policy problem is reflected in the ways that ordinary citizens picture it. Psychology research on 'mental models' argues that people use simplified mental representations to reason about complex topics involving multiple causal relationships (Johnson-Laird 1983; Ambuehl et al., 2026). Our study seeks to map people's mental models of the climate policy problem. Do people perceive causal patterns between policy, climate change, economic growth, and health and wellbeing? How complex and coherent are these mental models? Are there identifiable models in the population? Is there a dominant mental model? These questions matter because voters' mental models are likely to shape their support for climate policies, and the enactment of policies often hinges on public support. Currently, we know little about people's mental models.

To our knowledge, this is the first study that sets out to map mental models of climate policy. It builds on a wealth of climate psychology literature that can be separated into three strands. The first strand investigates psychological determinants of policy support (Drews & van den Bergh, 2016a), such as knowledge and worry about climate change (Bouman et al., 2020; Martin et al., 2024); environmental attitudes (Rauwald & Moore, 2002; Peñasco & Grossman, 2025;); perceived policy fairness and effectiveness (Jagers et al., 2024; Poortinga, 2025); and policy framing (Chen et al., 2025), amongst others. The second strand focuses on potential trade-offs between climate costs and economic costs, often deploying surveys to measure public opinion about alternative growth paradigms such as green growth and degrowth (Drews & van den Bergh, 2016b; Drews et al., 2019; Gugushvili, 2021; Paulson & Büchs, 2022). The third strand identifies flaws in laypeople's mental models of how climate change (Reynolds et al., 2011; Bostrom, 2017; Chen, 2011) or the economy (Leiser & Krill, 2017; Binetti et al., 2024) work, and how these models affect policy preferences (Bostrom et al., 2012). While these literatures investigate individual factors or relationships relevant to policy acceptance, our study instead investigates people's system-level psychology of the climate policy problem itself.

This approach has the potential to diagnose sources of support for, or resistance to, climate policy. The aim is to uncover previously unseen patterns in how people understand the likely effects of policy and the associated variability across the population, based not on specific attitudes or perceived trade-offs, but on an overall mental model that contains a combination of essential relationships. In doing so, we can observe and directly compare the relative strength of different elements of people's mental models. This approach may improve understanding of policy acceptance by detailing the model(s) that citizens use to judge the likely impact of a proposed policy.

The study uses original survey data to measure mental models via a series of questions about causal relationships between different potential model elements and follow-up questions about these relationships. The survey was carried out in Ireland, where climate perceptions are broadly in line with other European countries, notwithstanding Ireland's relatively large agricultural sector (e.g., Ergun et al., 2024; European Commission, 2025).

2. Methods

We conducted an original survey to measure people's mental models. The pre-registered analysis plan and full survey questionnaire are available on the Open Science Framework.[1] The study was conducted in line with the ESRI Research Ethics Committee ethics policy.

2.1. Participants and procedure

Our study sample consisted of 1,200 participants from Ireland. They were recruited via a market research agency's existing online survey panel,[2] using recruitment quotas to achieve an approximately nationally representative sample based on age (39% under 40 years old, 35% between 40-59 years old, 27% aged 60 and over), gender (49% male), region (57% Leinster, 28% Munster, 15% Connacht and Ulster), and socio-economic grade (13% higher or intermediate professionals, 35% clerical or junior professionals or students, 20% skilled manual workers, 28% semi-skilled or unskilled manual workers, casual workers, full-time carers, or unemployed, 4% agricultural workers or unsure). This study does not focus on or analyse demographic variables, as explained in the pre-registration.[3]

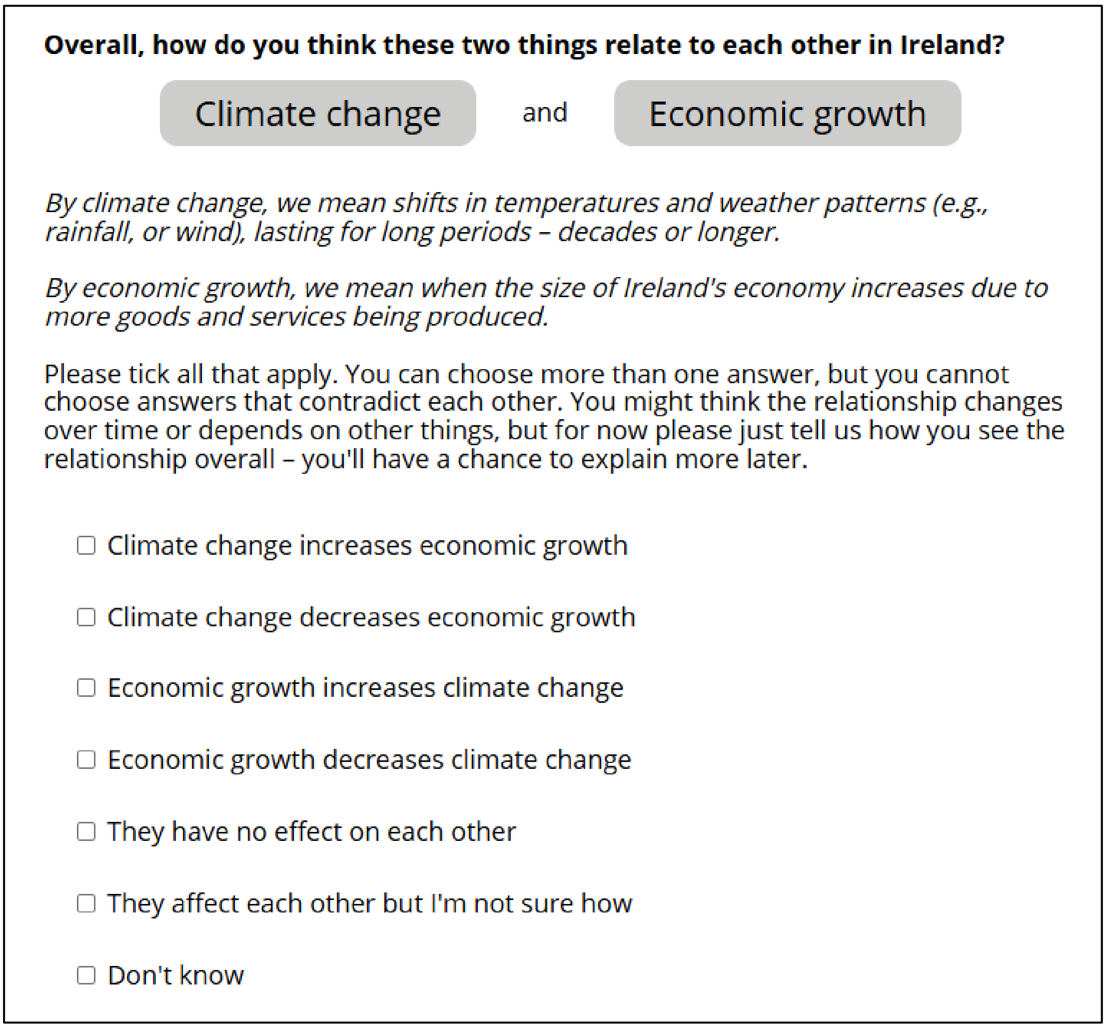
Participants completed the survey online in October and November 2025, after providing informed consent.[4] They were paid a small compensation fee (approximately €4). To avoid selection bias, they were not told that the study was about climate change before starting. Survey completion time averaged 20 minutes[5] and the attrition rate was 16%.[6]

2.2. Measurement and analysis

[1] Analysis plan at https://osf.io/pxrqn/overview?view_only=6d9a8a9c613240bbaf75fb9895ec1ddc; survey questionnaire at https://osf.io/53e6p/overview?view_only=9676a09f37194def9d5e679a0ca84dc9.
[2] Further details on the online survey panel are available from the market research company, RED C, at: https://redcresearch.com/technique/online-research/
[3] The focus of the paper is on overall mental models in the population and not on how these models vary with individual characteristics, which will be the topic of a subsequent study. Hence we did not access detailed demographic data, as explained in the pre-registration.
[4] The participant information form and subsequent consent form shown to participants is available as part of the survey questionnaire: https://osf.io/53e6p/overview?view_only=9676a09f37194def9d5e679a0ca84dc9.
[5] As a robustness check, we replicated all analyses while excluding the top 5% and bottom 5% of participants in terms of survey completion times, and we found consistent results throughout.
[6] The true attrition rate is somewhat lower, as this figure includes participants who were rejected for being over the desired quota of participants in their demographic group, but who didn't click out of the survey and were thus either timed out or rejected manually. These cases cannot be distinguished from 'true' attritions.

To measure mental models, we asked participants about the relationships between six pairs of topics consisting of all combinations of ‘climate change’, ‘climate policy’, ‘economic growth’, and ‘health and wellbeing in society’. For each pair, they could indicate that one topic increases or decreases the other, and/or vice-versa, or that they have no effect on each other, or that they affect each other but the participant is not sure how. Figure 1 shows an example of this, using the ‘climate change’ and ‘economic growth’ pair. To familiarise participants with the question format, before showing them the six pairs, we displayed a practice question in the same format about the relationship between oversleeping and setting an alarm.

Figure 1. Survey question example


Overall, how do you think these two things relate to each other in Ireland?

Climate change and Economic growth

By climate change, we mean shifts in temperatures and weather patterns (e.g., rainfall, or wind), lasting for long periods – decades or longer.

By economic growth, we mean when the size of Ireland's economy increases due to more goods and services being produced.

Please tick all that apply. You can choose more than one answer, but you cannot choose answers that contradict each other. You might think the relationship changes over time or depends on other things, but for now please just tell us how you see the relationship overall – you'll have a chance to explain more later.

- ☐ Climate change increases economic growth
- ☐ Climate change decreases economic growth
- ☐ Economic growth increases climate change
- ☐ Economic growth decreases climate change
- ☐ They have no effect on each other
- ☐ They affect each other but I'm not sure how
- ☐ Don't know

Notes: Ticking ‘no effect’, ‘not sure, or ‘don’t know’ answers unticks other answers. It is not possible to tick opposite answers (e.g., growth increases and decreases climate change). It is possible to tick up to two answers, one per direction (growth on climate and vice versa). The order of the pairs, topics within pairs, and associated responses was randomised.

Once the participant had answered for all six pairs, we displayed a diagram of their mental model based on their own answers (see example in Figure A1 in Appendix). At this stage, participants had a chance to correct their model, if they wanted to. They then rated how closely it showed their thinking (on a 7-point scale from 1 ‘not at all’ to 7 ‘completely’). We also included two exploratory open-text questions, one asking participants to explain how one relationship works (randomly chosen out of the ones they selected), and one asking how they would improve the diagram (e.g., any additional elements they would include).

Since our mental model survey instruments are novel, we also measured several secondary variables, including participants' confidence in each of their answers (on 7-point scales from 1 'not at all' to 7 'extremely' confident), and how difficult they found the survey overall (on a 7-point scale from 1 'very easy' to 7 'very difficult'). In addition, we asked participants follow-up questions about each effect that they identified, such as its duration (long-term, short-term, or both), stability (always true, usually true but other factors affect it, very much depends on other factors), and distribution (everyone affected the same way, some groups affected differently).

Our pre-registered analysis plan includes two steps. First, we provide descriptive results on the effects that people identified, that is, the elements of their mental models, and on the prevalence of any specific effects. This also allows us to show the population's average mental model (not pre-registered). Second, we use cluster analysis to test for potential patterns in the co-occurrence of reported effects. We did not pre-register any hypotheses on mental models, as the study is descriptive and exploratory.

3. Results

3.1. Mental model elements

Almost all participants (97%) reported at least one effect of climate change, climate policies, health and wellbeing in society, or economic growth on each other.[7] On average, they reported 4.9 effects (SD=2.4). Figure 2 shows the distribution of answers for each possible effect. The most commonly reported effects were that growth improves wellbeing (55% of participants), climate change worsens wellbeing (48%), climate policies decrease climate change (46%) and improve wellbeing (45%), and growth increases climate change (37%). For all other possible effects (7 out of 12), the most frequent answer was 'no effect', though in some cases a substantial share of participants still reported an effect: for example, 46% of participants reported that climate change has no effect on climate policies, but 39% said that it increases them. The effect with the least agreement was that of how climate policies influence growth, where the most frequent answer was 'no effect', although only 32% of participants said this.

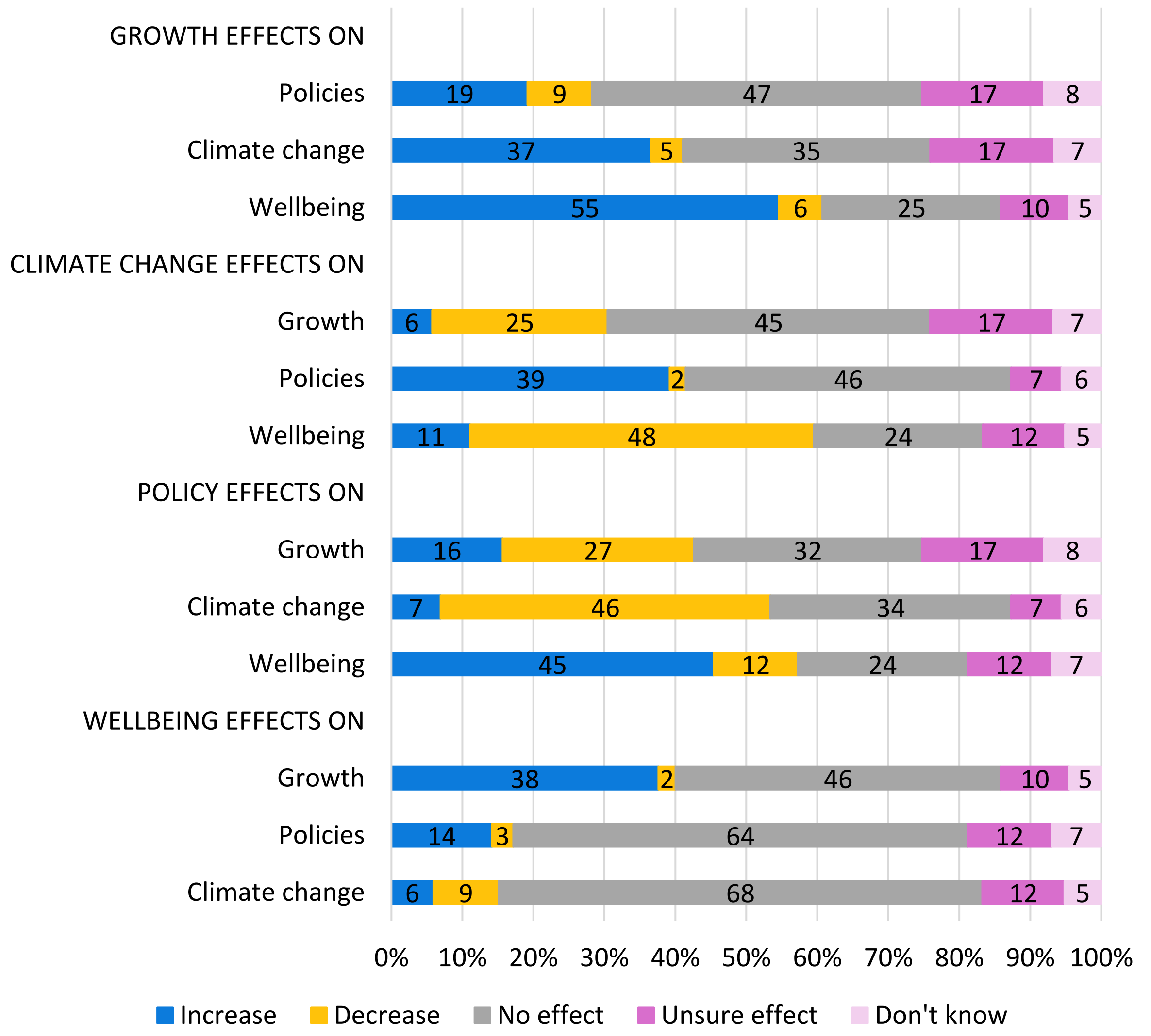
Despite the complexity of the topic, few participants reported being unsure (between 7% and 17% depending on the pair) or answered 'don't know' (between 5% and 8%).[8] This is reflected in the high levels of confidence that participants reported in their answers, with average ratings between 5.1 and 5.7 across effects (SDs range from 1.2 to 1.4), and an average confidence rating per person of 5.4 (SD=1.0). The average reported difficulty of the survey was at the midpoint at 4.0 (SD=1.7), and participants' average rating of how closely

[7] As a robustness check, we replicated all analyses while excluding the 26 participants who reported 'no effect' or 'don't know' for all pairs or for all but the first pair they saw (in case this reflected low attention), and we found consistent results throughout.
[8] It is possible that 'no effects' were overreported, and 'unsure effects' and 'don't knows' underreported, due to participants ticking no effect when they were unsure of the effect (due to not wanting to appear ignorant).

their mental model diagram represented their thinking was high at 5.4 (SD=1.1).[9] Taken together, these findings suggest that participants are relatively sure of their mental models, and that our survey worked well as a measurement tool for these models.

Finally, participants' answers to follow-up questions about effect characteristics showed little variation. Participants mainly reported that effects apply both in the short-term and the long-term (between 51% and 72% of participants depending on the effect), are usually true but depend on other factors (between 52% and 62%), and apply differently to some groups in society (between 62% and 71%). This shows that the variation we found between participants is not due to them answering questions based on different underlying logic (e.g., focusing on particular timelines or influencing factors, or not being aware of heterogeneous effects). It also suggests that participants have awareness of long-term effects, distributive effects, and potential moderating roles of other factors on effects.

Figure 2. Distribution of mental model elements



[9] As a robustness check, we replicated all analyses excluding the 96 participants who reported any difficulty (e.g., said the topic was complicated) or reason not to use their data, and found consistent results throughout.

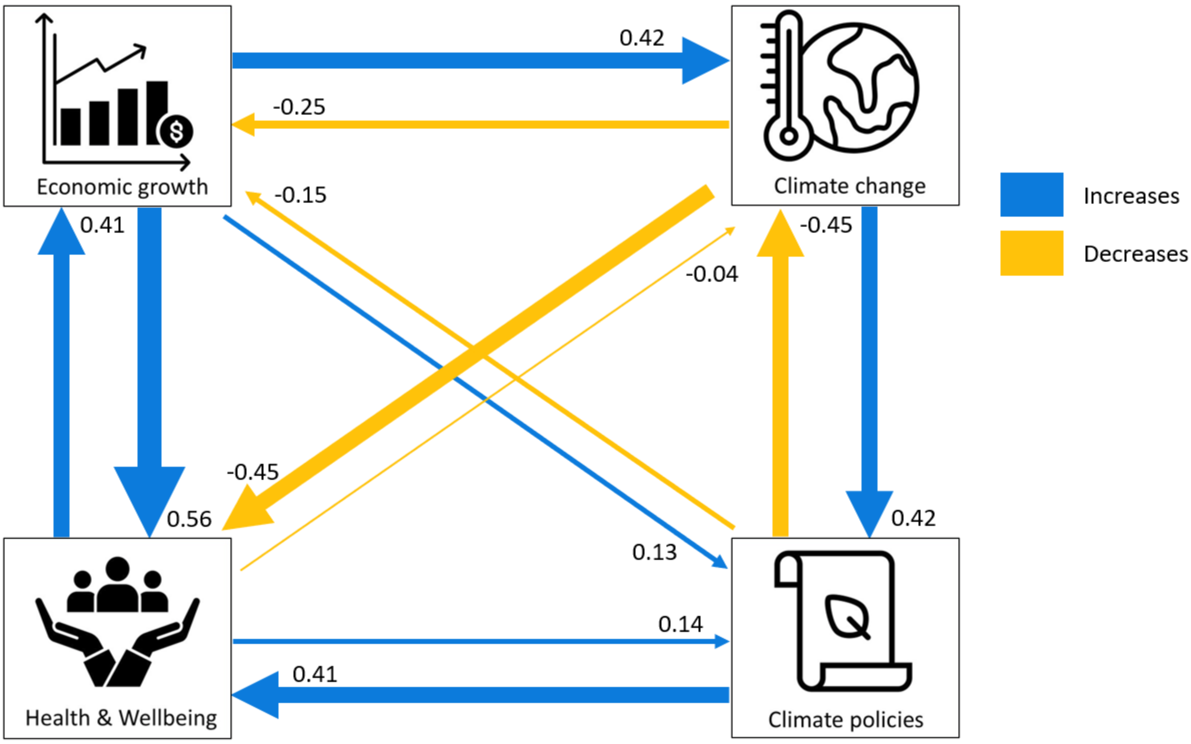
Notes: Responses are duplicated in both directions for each pair of topics if there is an unsure or no relationship between them (but not if there is an effect in one direction only).

3.2. Average mental model

In light of the amount of variation in responses to each pair of elements (Figure 2), we compiled participants' answers into an overall, average mental model as an exploratory (not pre-registered) summary of our descriptive findings. To do so, we converted answers into numeric variables (1 for increases, -1 for decreases, 0 for no effects, excluding 'don't knows' and 'unsure effects'). The average ratings therefore show whether the average effect is an increase or a decrease (based on its sign), and its strength (based on its distance from zero). Note that low strength can result either from a high proportion of 'no effect' answers, or from a high level of disagreement (similar proportions of 'increase' and 'decrease' answers).

Figure 3 shows the average mental model in our (nationally representative) sample, based on the average numeric ratings for each effect. This model is not representative of any one participant as it does not account for the co-occurrence of beliefs, but rather it shows a 'best summary' of our descriptive findings. It is notable that, on average, the public perceives bi-directional relationships that are both self-reinforcing (e.g. growth increases wellbeing, wellbeing increases growth) and self-limiting (e.g. climate change increases climate policy, climate policy decreases climate change). The relationship between economic growth and climate change is notably perceived as self-limiting.

Figure 3. Average mental model



Notes: The numbers in the figure show the average numeric rating for each effect (1 for increase, -1 for decrease, 0 for no effect). Arrow widths reflect distance from 0.

3.3. Patterns in mental models

To investigate patterns in the co-occurrence of different effects in participants' mental models, we first used Cramer's V to test the strength of associations between answer pairs across all 12 potential effects.[10] However, this analysis found only weak associations, ranging in strength from 0.13 to 0.32 (see Table A1 in Appendix for full results).[11] This suggests that there is no single dominant pattern of association in the population.

We then used a cluster analysis to test whether there might be several association patterns. We carried out a hierarchical cluster analysis (as this does not require pre-specifying the number of clusters) and applied the average linkage method (which allows for categorical variables, is robust to outliers, and is not overly prone to equal-sized or compact clusters)[12], based on Gower's distance (a simple, widely used measure for categorical variables). The aim was to identify clusters of participants who are clearly grouped together in the dendrogram (a diagram showing the clustering steps and results), who share similar combinations of causal beliefs (i.e., the modal effects in each cluster are reported by a majority of the cluster), and who are grouped together consistently regardless of participant order (this last criterion is because when the clustering algorithm faces a tie between two options, it breaks it by choosing the closest one by row order).

We first ran the cluster analysis on all 12 potential effects, as pre-registered. We did not find evidence of meaningful clustering in the sample: the dendrogram showing the clustering process (see Figure A2 in Appendix) was 'chained' throughout (i.e., the agglomeration of the sample into clusters was based on the gradual addition of observations to groups, rather than existing groups being combined, Bakker, 2026) with no clear or recognisable clustering.

Since this essentially amounts to a null result, we undertook multiple additional analyses to ensure that we were not missing meaningful groupings within people's mental models of climate policy. One possibility is that our initial failure to observe clusters might reflect the high number of variables (all 12 effects) in the cluster analysis with weak underlying associations between effects and low baseline agreement between participants about individual effects. Hence, as a second, exploratory step (not pre-registered), we tested whether clusters emerged when reducing the number of variables to those likely to be the most meaningful in people's mental models. We based the choice of variables on the literature on perceived trade-offs between economic and climate considerations and the debate on growth and wellbeing as policy goals (e.g., Drews & van den Bergh, 2016b; Gugushvili, 2021; Fioramonti et al., 2022). This led us to include four effects: the effect of economic growth on climate change, the effect of climate policies on growth, the effect of climate change on wellbeing, and the effect of growth on wellbeing.

[10] The decision to use Cramer's V instead of correlation tests is because participants' answers were categorical and there was no way to account for 'unsure effects' and 'don't know' answers if using numeric variables.
[11] An exception to this was the strong associations between effects within pairs (e.g., effect of policy on growth and effect of growth on policy), but this is artificial as if participants answered 'no relationship', 'unsure relationship', or 'don't know' for the pair, the answer was the same for both effects in the pair by construction.
[12] As a robustness check, we also ran the cluster analysis using the nearest-neighbour and furthest-neighbour linkage methods, and the output of these analyses led to the same conclusions as the average linkage method.

This second cluster analysis with four effects yielded a dendrogram that showed significant chaining and no clear-cut clustering. To further investigate any potential clustering, we 'cut' the dendrogram into eight clusters (dendrogram in Figure A3 in Appendix, red lines indicate cuts) and examined modal effects by cluster. This number of clusters was chosen based on a visual inspection of the dendrogram and on the need to preserve a relatively large number of clusters (given the low agreement among participants) while avoiding creating very small new clusters. However, we found low agreement even within clusters: in the largest two clusters, modal beliefs for two effects were shared by fewer than 50% of cluster members, such that defining characteristics of clusters were based on a minority of their members.

In addition, the clusters resulting from the analysis were not robust to participant order. As a robustness check to address the tie-breaking issue (see above), we repeated the cluster analysis (with four effects) on 25 randomly re-ordered versions of the dataset, cutting the dendrograms into eight clusters again for consistency. This analysis was not pre-registered, but testing that results are consistent regardless of row order is recommended as best practice (e.g., Van Der Kloot et al., 2005). We found that the size and modal beliefs of the largest two clusters varied significantly across iterations (see Table A2 in Appendix), again suggesting no robust clusters.

Finally, to confirm that our null result was not due to a problem with the method of analysis, as an exploratory sensitivity check we altered the dataset to simulate clusters with stochastic noise. To do this, we defined two mental models. Model A was a plausibly "green" mental model, in which climate change harms wellbeing, growth increases climate change, growth does not affect wellbeing, and policy does not affect growth. Model B was a sceptical mental model, in which climate change does not affect wellbeing, growth does not affect climate change, growth increases wellbeing, and policy decreases growth. We then divided participants into 3 groups: 500 participants in group A, 500 in group B, and 200 in group C. For each of the four effects, we assigned participants from group A (B) a 50% probability of that effect matching the one in mental model A (B) (if it did not already). We did not modify group C's answers. We then ran the cluster analysis again. We observed two clear clusters in the dendrograms (see Figure A4 in Appendix) and found that the modal beliefs in these two clusters perfectly matched the defining beliefs of the two mental models, with consistent results across 25 re-orderings of the data (see Table A3 in Appendix).

In summary, our cluster analysis located no stable clusters in people's mental models of climate policy, either with 12 variables or 4. When we artificially introduced noisy clusters into the data, the same method of analysis robustly recognised them. We conclude that there is no evidence of clustering within the data.

4. Discussion

People have coherent mental models of how the main elements of the climate policy problem relate to each other. Participants' answers revealed that they perceive causal relationships between economic growth, climate change, climate policy, and health and wellbeing. This main finding is reinforced both by the high level of confidence that participants reported in their answers, and by the high accuracy ratings that they gave to the mental model diagrams we showed them based on their own answers.

The study also found substantial variability across participants' mental models. There was significant disagreement on most causal relationships, with only one directional effect having a modal answer that was shared by more than half of the participants. This variability occurred not just at the level of the individual relationships between elements, but also at the level of the overall mental model: association tests and a cluster analysis did not identify recognisable patterns of effects. Consequently, while we find that people have coherent mental models of the climate policy problem, we find no evidence that these mental models are similar across the population; there is neither a dominant mental model nor a set of distinct divergent patterns.

There are nevertheless notable results when examining individual effects. On average, the strongest individual effect in the survey was the perception that economic growth increases wellbeing. Other clear individual effects were the perception that climate policies increase wellbeing and that climate policies decrease climate change, both of which are positive for pro-climate policy. Similarly, on average, participants did not perceive a clear negative influence of climate policies on growth. This is perhaps surprising given the focus given to this issue in policy debates.

What explains the variability in people's mental models of climate policy? Of course, no dominant pattern or coherent set of patterns would emerge if participants had struggled to understand or answer questions; noise in responses would generate variability and mask coherent clustering. However, this seems an unlikely explanation for what we observe. As just described, responses are far from random and the average mental model they generate has a coherent structure that makes sense, even if it perhaps contains surprises. A more likely explanation is that mental models of climate policy do not, at least yet, have a consistent relationship with psychological factors known to be associated with political attitudes generally: group identity, political affiliation, pro-environmental attitudes, socio-demographic group, pro-social preferences, and so on. For instance, within the green movement there is a debate about whether climate policy is good for economic growth or whether climate policy should explicitly set out to constrain growth. More generally, the climate debate is beset with uncertainties, not only concerning the extremity and timescale of climate impacts, but also in relation to the economic and social costs and benefits of climate policies. The absence of clustering in our data may reflect relatively weak and inconsistent views within different sections of society regarding the key relationships underlying climate policy.

The study has implications for both designing and communicating climate policy. Our results warn against making assumptions about how citizens will evaluate proposed climate policies and conceive their likely impacts, and suggest opportunities to highlight factual information relevant to people's mental models in policy debates. In the absence of clusters of beliefs associated with different sections of society, there may be greater opportunity for evidence to inform citizen's mental models than is perhaps the case in most other policy areas. The findings can also inform the policy debate on degrowth: while participants had the modal belief that climate change harms wellbeing, more than half said that economic growth improves wellbeing, and this was the strongest effect we recorded, whereas there was no consensus on the effect of growth on climate change. On the other hand, the modal belief that policy does not affect growth suggests that many do not perceive a trade-off between growth and climate policy.

Naturally, this study has some limitations. It was carried out only in Ireland. While we have no reason to believe that people's mental models of climate policy in Ireland would differ strongly from those in other countries, it would be valuable to test this. In addition, we used closed-ended questions to generate mental models and may have missed elements that should be included. That said, we based our questions on existing literature and did not uncover specific missed topics in an open-text question designed to locate missing issues. Finally, we prompted participants in order to measure their mental models, but we have no evidence regarding whether people engage these models when reacting to policy proposals, let alone voting. We hope to examine this further in a follow-up study.

In conclusion, this study investigated mental models of climate policy using survey data. We found that people do have coherent mental models of how economic growth, climate change, climate policy, and health and wellbeing in society relate to each other. However, both individual causal relationships and overall mental models were highly variable across the population, with little consensus and few emerging patterns beyond the most widely held beliefs. These findings help to inform policy debates and climate communications.

Declaration of interest statement
The authors declare that they have no conflicts of interest.

References

Ambuehl, S., Bhui, R., & Thysen, H. C. (2026). Mental Models of Causal Structure in Economics and Psychology. *arXiv preprint arXiv:2603.29070*.

Bakker, J. D. (2026). *Hierarchical Cluster Analysis. Applied Multivariate Statistics in R*. https://uw.pressbooks.pub/appliedmultivariatestatistics/

Binetti, A., Nuzzi, F., & Stantcheva, S. (2024). People's understanding of inflation. *Journal of Monetary Economics, 148*, 103652.

Bostrom, A., O'Connor, R. E., Böhm, G., Hanss, D., Bodi, O., Ekström, F., ... & Sælensminde, I. (2012). Causal thinking and support for climate change policies: International survey findings. *Global Environmental Change, 22*(1), 210-222.

Bostrom, A. (2017). Mental models and risk perceptions related to climate change. In *Oxford research encyclopedia of climate science*.

Bouman, T., Verschoor, M., Albers, C. J., Böhm, G., Fisher, S. D., Poortinga, W., ... & Steg, L. (2020). When worry about climate change leads to climate action: How values, worry and personal responsibility relate to various climate actions. *Global environmental change, 62*, 102061.

Chen, X. (2011). Why do people misunderstand climate change? Heuristics, mental models and ontological assumptions. *Climatic Change, 108*(1), 31-46.

Chen, C. Y., Benoit, V., Whitmarsh, L., & Loibl, C. (2025). From climate crisis to energy crisis: foster public support for renewable energy transition through framing. *Environmental Politics*, 1-25.

Clulow, Z. (2018). When does economic development promote mitigation and why?. *Climate Policy, 18*(2), 221-234.

Drews, S., & Van den Bergh, J. C. (2016a). What explains public support for climate policies? A review of empirical and experimental studies. *Climate policy, 16*(7), 855-876.

Drews, S., & Van Den Bergh, J. C. (2016b). Public views on economic growth, the environment and prosperity: Results of a questionnaire survey. *Global Environmental Change, 39*, 1-14.

Drews, S., Savin, I., & Van Den Bergh, J. C. (2019). Opinion clusters in academic and public debates on growth-vs-environment. *Ecological economics, 157*, 141-155.

Ergun, S. J., Karadeniz, Z. D., & Rivas, M. F. (2024). Climate change risk perception in Europe: country-level factors and gender differences. *Humanities and Social Sciences Communications, 11*(1), 1-13.

European Commission. (2025). *Special Barometer 565: Climate Change*. Eurobarometer report February-March 2025. https://europa.eu/eurobarometer/api/deliverable/download/file?deliverableId=98729

Fernández-i-Marín, X., Hinterleitner, M., Knill, C., & Steinebach, Y. (2026). Effective climate policies for 'all seasons': novel evidence from 40 countries. *Climate Policy*, 1-14.

Fioramonti, L., Coscieme, L., Costanza, R., Kubiszewski, I., Trebeck, K., Wallis, S., ... & De Vogli, R. (2022). Wellbeing economy: an effective paradigm to mainstream post-growth policies?. *Ecological Economics, 192*, 107261.

Gugushvili, D. (2021). Public attitudes toward economic growth versus environmental sustainability dilemma: Evidence from Europe. *International Journal of Comparative Sociology, 62*(3), 224-240.

Jagers, S. C., Harring, N., & Matti, S. (2024). Impact of ideology on individuals' attitudes to a climate-motivated tax on food. *Climate Policy, 24*(10), 1381-1394.

Johnson-Laird, P. N. (1983). *Mental models: Towards a cognitive science of language, inference, and consciousness* (No. 6). Harvard University Press.

Leiser, D., & Krill, Z. (2017). How laypeople understand the economy. *Economic psychology*, 139-154.

Martin, L., Timmons, S., and Lunn, P. (2024). Encouraging cooperation in climate collective action problems, EPA Behavioural Insights Series No. 3, Wexford: EPA. https://www.esri.ie/publications/encouraging-cooperation-in-climate-collective-action-problems

Paulson, L., & Büchs, M. (2022). Public acceptance of post-growth: Factors and implications for post-growth strategy. *Futures, 143*, 103020.

Peñasco, C., & Grossman, E. (2025). The paradox of environmental consciousness: dissecting the gap between climate change awareness, environmental concern and policy support. *Climate Policy*, 1-18.

Poortinga, W. (2025). The role of policy appraisals and second-order beliefs in public support for climate policies in the UK. *Climate Policy*, 1-15.

Rauwald, K. S., & Moore, C. F. (2002). Environmental attitudes as predictors of policy support across three countries. *Environment and behavior, 34*(6), 709-739.

Reynolds, T. W., Bostrom, A., Read, D., & Morgan, M. G. (2010). Now what do people know about global climate change? Survey studies of educated laypeople. *Risk Analysis: An International Journal, 30*(10), 1520-1538.

Stock, J. H. (2020). Climate change, climate policy, and economic growth. *NBER Macroeconomics Annual, 34*(1), 399-419.

Van Den Bergh, J. C., & Botzen, W. W. (2018). Global impact of a climate treaty if the Human Development Index replaces GDP as a welfare proxy. *Climate Policy, 18*(1), 76-85.

Van Der Kloot, W. A., Spaans, A. M., & Heiser, W. J. (2005). Instability of hierarchical cluster analysis due to input order of the data: the PermuCLUSTER solution. *Psychological methods, 10*(4), 468.

Appendix: Supplementary tables and figures

Table A1. Cramer's V

	CC to CP	EG to WB	CP to CC	WB to CC	CC to EG	EG to CC	CP to EG	WB to EG	CC to WB	EG to CP	CP to WB	WB to CP
CC to CP	1	0.17	0.74	0.13	0.19	0.18	0.19	0.17	0.15	0.22	0.19	0.2
EG to WB		1	0.16	0.17	0.22	0.22	0.19	0.75	0.18	0.21	0.23	0.22
CP to CC			1	0.15	0.19	0.23	0.2	0.17	0.16	0.2	0.24	0.18
WB to CC				1	0.17	0.2	0.16	0.19	0.72	0.17	0.23	0.29
CC to EG					1	0.73	0.24	0.22	0.23	0.23	0.19	0.18
EG to CC						1	0.22	0.22	0.19	0.24	0.19	0.2
CP to EG							1	0.2	0.17	0.75	0.22	0.19
WB to EG								1	0.18	0.19	0.22	0.28
CC to WB									1	0.18	0.32	0.23
EG to CP										1	0.19	0.2
CP to WB											1	0.72
WB to CP												1

Notes: CC stands for climate change, CP for climate policies, EG for economic growth, and WB for wellbeing. For example, the top right cell shows the association between the effect of wellbeing on policies and the effect of climate change on policies, using Cramer's V. Note the strong associations observed between effects within pairs (e.g., effect of policy on growth and effect of growth on policy) are by construction, as when participants answer 'no relationship', 'unsure relationship', or 'don't know' for a pair, their answer is automatically the same for both effects in the pair, artificially inflating the association between them.

Table A2. Modal beliefs of largest two clusters

			Modal beliefs in largest cluster					Modal beliefs in second largest cluster				
Iteration	Seed	Clusters	Size	Effect of growth on climate change	Effect of policies on growth	Effect of climate change on wellbeing	Effect of growth on wellbeing	Size	Effect of growth on climate change	Effect of policies on growth	Effect of climate change on wellbeing	Effect of growth on wellbeing
1	63783	8	711	Increases (39%)	No effect (33%)	Decreases (54%)	Increases (91%)	291	No effect (43%)	No effect (37%)	Decreases (44%)	No effect (91%)
2	81631	8	372	Increases (90%)	No effect (36%)	Decreases (70%)	Increases (67%)	281	No effect (94%)	Decreases (40%)	Decreases (39%)	Increases (92%)
3	31852	8	766	No effect (47%)	No effect (43%)	Decreases (55%)	Increases (64%)	189	Increases (50%)	Unsure (80%)	Decreases (58%)	Increases (74%)
4	36063	8	433	No effect (61%)	Decreases (33%)	Decreases (43%)	Increases (90%)	354	Increases (98%)	Tie (decrease/no)	Decreases (61%)	Increases (68%)
5	87534	8	445	Increases (62%)	No effect (32%)	Decreases (96%)	Increases (51%)	323	No effect (56%)	Decreases (49%)	No effect (38%)	Increases (93%)
6	11604	8	662	Increases (47%)	Decreases (32%)	Decreases (87%)	Increases (59%)	235	No effect (63%)	No effect (43%)	No effect (97%)	Increases (42%)
7	87292	8	604	Increases (38%)	Decreases (46%)	Decreases (71%)	Increases (63%)	265	Increases (48%)	No effect (98%)	Decreases (48%)	Increases (63%)
8	43616	8	469	Increases (88%)	Decreases (35%)	Decreases (66%)	Increases (54%)	397	No effect (87%)	No effect (34%)	Decreases (40%)	Increases (74%)
9	40185	8	786	No effect (41%)	No effect (37%)	Decreases (53%)	Increases (80%)	127	Increases (39%)	Decreases (61%)	Decreases (52%)	No effect (98%)
10	51419	8	476	Increases (69%)	Decreases (34%)	Decreases (75%)	Increases (75%)	254	No effect (96%)	No effect (44%)	No effect (61%)	Increases (58%)
11	97451	8	432	Increases (89%)	Decreases (36%)	Decreases (66%)	Increases (59%)	433	No effect (83%)	No effect (36%)	No effect (42%)	Increases (59%)
12	13639	8	539	Increases (44%)	No effect (26%)	Decreases (90%)	Increases (67%)	232	No effect (62%)	No effect (41%)	No effect (47%)	Increases (97%)
13	85375	8	732	No effect (53%)	No effect (38%)	Decreases (51%)	Increases (77%)	172	Increases (61%)	No effect (34%)	Decreases (46%)	No effect (94%)
14	45364	8	421	Increases (74%)	Decreases (31%)	Decreases (83%)	Increases (44%)	500	No effect (68%)	No effect (39%)	No effect (48%)	Increases (70%)
15	33392	8	664	Increases (57%)	No effect (35%)	Decreases (70%)	Increases (69%)	306	No effect (96%)	Decreases (45%)	No effect (46%)	Increases (60%)
16	77563	8	439	Increases (62%)	Decreases (41%)	Decreases (87%)	Increases (73%)	284	No effect (46%)	No effect (81%)	Decreases (30%)	No effect (45%)
17	66496	8	393	Increases (82%)	Decreases (36%)	Decreases (78%)	Increases (54%)	325	No effect (83%)	Decreases (37%)	Decreases (34%)	Increases (90%)
18	22773	8	492	Increases (71%)	Decreases (32%)	Decreases (80%)	Increases (63%)	442	No effect (86%)	No effect (44%)	Decreases (39%)	Increases (64%)
19	48307	8	443	Increases (86%)	No effect (35%)	Decreases (66%)	Increases (61%)	396	No effect (97%)	No effect (39%)	Decreases (43%)	Increases (61%)
20	32826	8	381	Increases (90%)	Decreases (31%)	Decreases (80%)	Increases (45%)	308	No effect (75%)	Decreases (57%)	Decreases (43%)	Increases (64%)
21	16179	8	720	Increases (42%)	Decreases (32%)	Decreases (59%)	Increases (84%)	175	No effect (37%)	No effect (46%)	Decreases (69%)	No effect (93%)
22	89631	8	798	Increases (41%)	Decreases (35%)	Decreases (63%)	Increases (70%)	117	No effect (45%)	No effect (70%)	No effect (76%)	No effect (71%)
23	19141	8	594	Increases (41%)	Decreases (33%)	Decreases (63%)	Increases (92%)	231	Increases (37%)	Decreases (33%)	Decreases (58%)	No effect (58%)
24	71114	8	520	Increases (65%)	No effect (29%)	Decreases (79%)	Increases (62%)	431	No effect (88%)	No effect (39%)	No effect (36%)	Increases (63%)
25	65565	8	503	Increases (48%)	Decreases (41%)	Decreases (71%)	Increases (69%)	435	No effect (49%)	No effect (80%)	No effect (40%)	Increases (67%)

Table notes: We swapped the largest and second largest clusters in iterations 11 and 14 as cluster sizes were similar and the beliefs matched those of the other cluster in other iterations better.

Table A3. Modal beliefs of largest two clusters, simulated data set

			Cluster A's modal beliefs					Cluster B's modal beliefs				
Iteration	Seed	Clusters	Size	Effect of growth on climate change	Effect of policies on growth	Effect of climate change on wellbeing	Effect of growth on wellbeing	Size	Effect of growth on climate change	Effect of policies on growth	Effect of climate change on wellbeing	Effect of growth on wellbeing
1	63783	5	555	Increases (87%)	No effect (54%)	Decreases (70%)	No effect (52%)	528	No effect (92%)	Decreases (54%)	No effect (57%)	Increases (67%)
2	81631	5	585	Increases (79%)	No effect (57%)	Decreases (73%)	No effect (54%)	518	No effect (83%)	Decreases (60%)	No effect (56%)	Increases (71%)
3	31852	5	558	Increases (68%)	No effect (63%)	Decreases (74%)	No effect (70%)	604	No effect (62%)	Decreases (52%)	No effect (55%)	Increases (90%)
4	36063	5	443	Increases (65%)	No effect (66%)	Decreases (72%)	No effect (92%)	689	No effect (55%)	Decreases (47%)	No effect (45%)	Increases (88%)
5	87534	6	507	Increases (65%)	No effect (75%)	Decreases (79%)	No effect (65%)	627	No effect (60%)	Decreases (60%)	No effect (57%)	Increases (80%)
6	11604	5	544	Increases (90%)	No effect (55%)	Decreases (69%)	No effect (45%)	579	No effect (84%)	Decreases (50%)	No effect (52%)	Increases (70%)
7	87292	5	561	Increases (83%)	No effect (55%)	Decreases (72%)	No effect (50%)	582	No effect (85%)	Decreases (53%)	No effect (58%)	Increases (72%)
8	43616	5	610	Increases (71%)	No effect (65%)	Decreases (75%)	No effect (55%)	547	No effect (72%)	Decreases (67%)	No effect (57%)	Increases (81%)
9	40185	5	569	Increases (77%)	No effect (64%)	Decreases (71%)	No effect (63%)	609	No effect (67%)	Decreases (58%)	No effect (58%)	Increases (84%)
10	51419	5	561	Increases (71%)	No effect (66%)	Decreases (69%)	No effect (68%)	622	No effect (64%)	Decreases (60%)	No effect (50%)	Increases (86%)
11	97451	5	656	Increases (59%)	No effect (52%)	Decreases (90%)	No effect (47%)	484	No effect (68%)	Decreases (54%)	No effect (77%)	Increases (67%)
12	13639	6	674	Increases (58%)	No effect (53%)	Decreases (81%)	No effect (47%)	438	No effect (65%)	Decreases (57%)	No effect (87%)	Increases (73%)
13	85375	5	687	Increases (55%)	No effect (54%)	Decreases (84%)	No effect (49%)	426	No effect (64%)	Decreases (62%)	No effect (83%)	Increases (73%)
14	45364	5	672	Increases (64%)	No effect (62%)	Decreases (75%)	No effect (53%)	494	No effect (70%)	Decreases (72%)	No effect (69%)	Increases (76%)
15	33392	6	641	Increases (57%)	No effect (53%)	Decreases (86%)	No effect (54%)	476	No effect (58%)	Decreases (59%)	No effect (75%)	Increases (79%)
16	77563	5	511	Increases (70%)	No effect (71%)	Decreases (78%)	No effect (66%)	620	No effect (66%)	Decreases (61%)	No effect (60%)	Increases (81%)
17	66496	6	588	Increases (80%)	No effect (56%)	Decreases (68%)	No effect (50%)	539	No effect (84%)	Decreases (58%)	No effect (57%)	Increases (70%)
18	22773	5	541	Increases (77%)	No effect (57%)	Decreases (76%)	No effect (64%)	533	No effect (57%)	Decreases (58%)	No effect (62%)	Increases (85%)
19	48307	6	446	Increases (60%)	No effect (63%)	Decreases (67%)	No effect (91%)	656	No effect (53%)	Decreases (50%)	No effect (48%)	Increases (91%)
20	32826	5	607	Increases (83%)	No effect (55%)	Decreases (72%)	No effect (57%)	516	No effect (82%)	Decreases (52%)	No effect (60%)	Increases (77%)
21	16179	5	519	Increases (80%)	No effect (65%)	Decreases (81%)	No effect (60%)	603	No effect (71%)	Decreases (59%)	No effect (59%)	Increases (69%)
22	89631	5	450	Increases (59%)	No effect (57%)	Decreases (68%)	No effect (91%)	677	No effect (53%)	Decreases (51%)	No effect (44%)	Increases (93%)
23	19141	5	498	Increases (64%)	No effect (67%)	Decreases (82%)	No effect (73%)	643	No effect (62%)	Decreases (58%)	No effect (55%)	Increases (82%)
24	71114	5	531	Increases (67%)	No effect (64%)	Decreases (79%)	No effect (71%)	602	No effect (61%)	Decreases (59%)	No effect (57%)	Increases (86%)
25	65565	5	505	Increases (80%)	No effect (65%)	Decreases (81%)	No effect (53%)	638	No effect (74%)	Decreases (55%)	No effect (58%)	Increases (71%)

Table notes: Each of the 25 iterations of the analysis used a different random row order. We set the default number of clusters at 5 (to account for any small clusters more different from the two large clusters than they are from each other), then increased to 6 when needed.

Figure A1. Example of participant mental model diagram

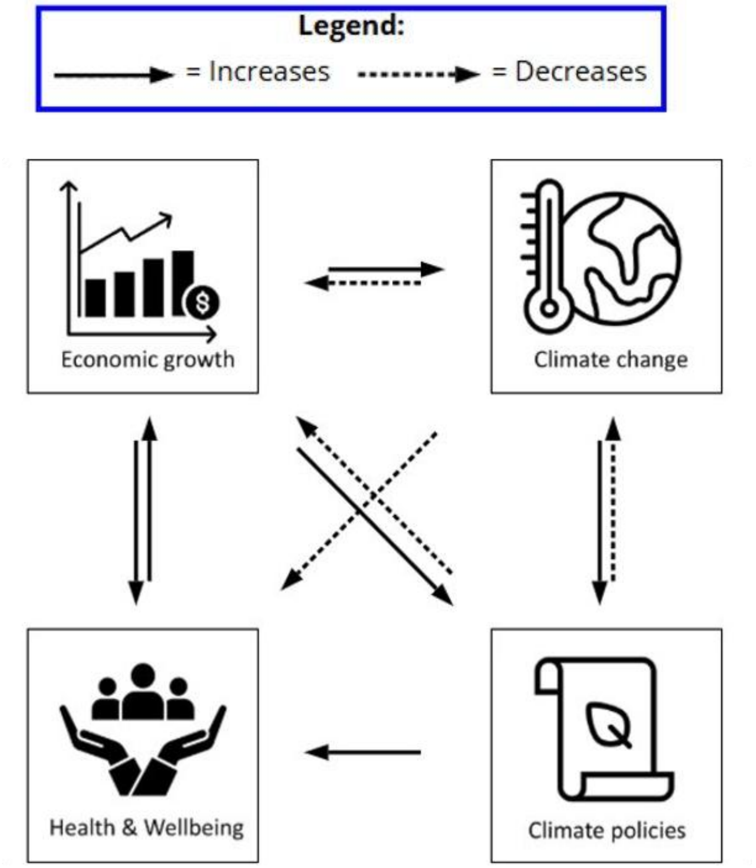


Figure A2. Cluster analysis dendrogram (12 effects)

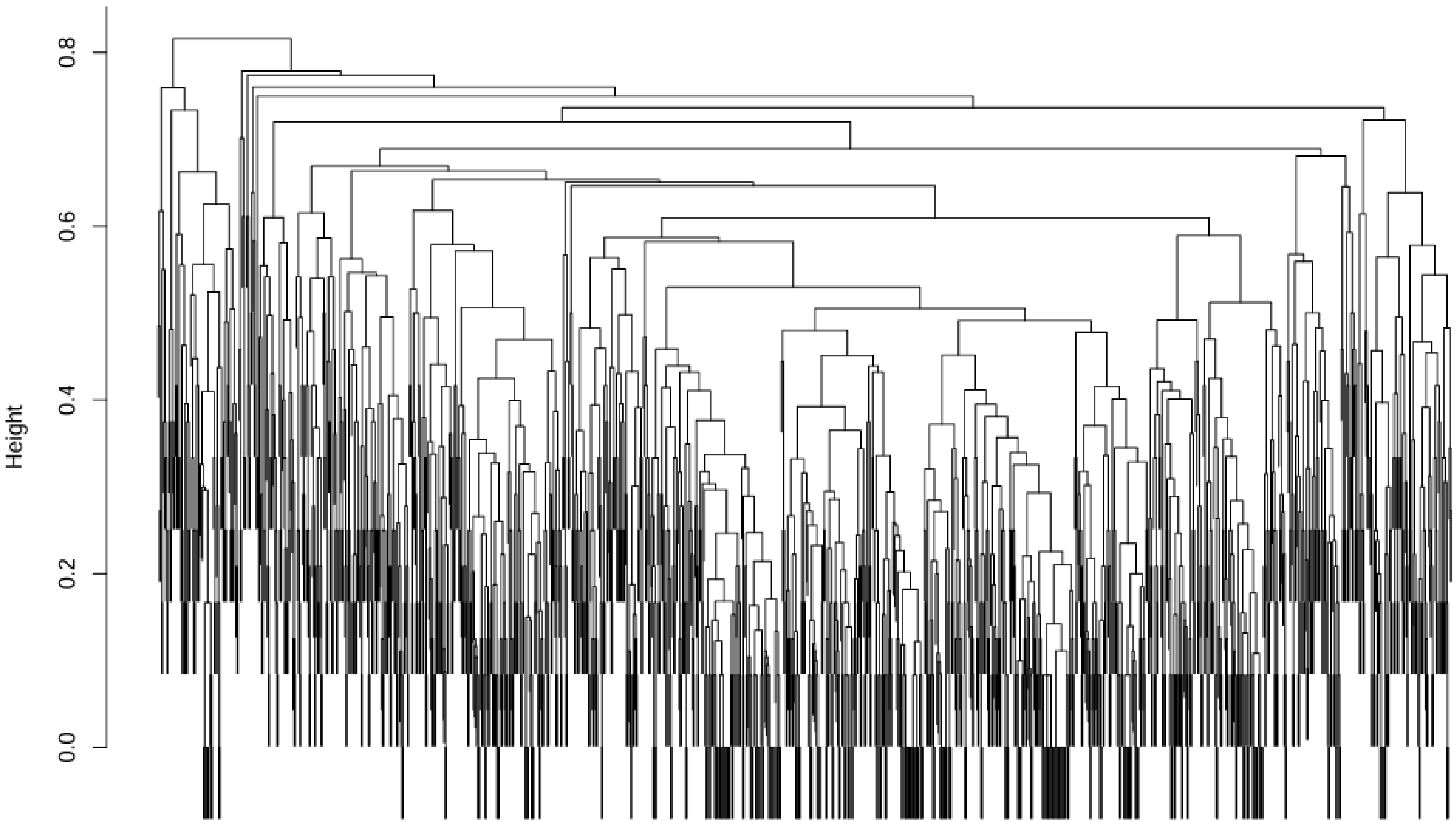


Figure A3. Cluster analysis dendrogram (4 effects)

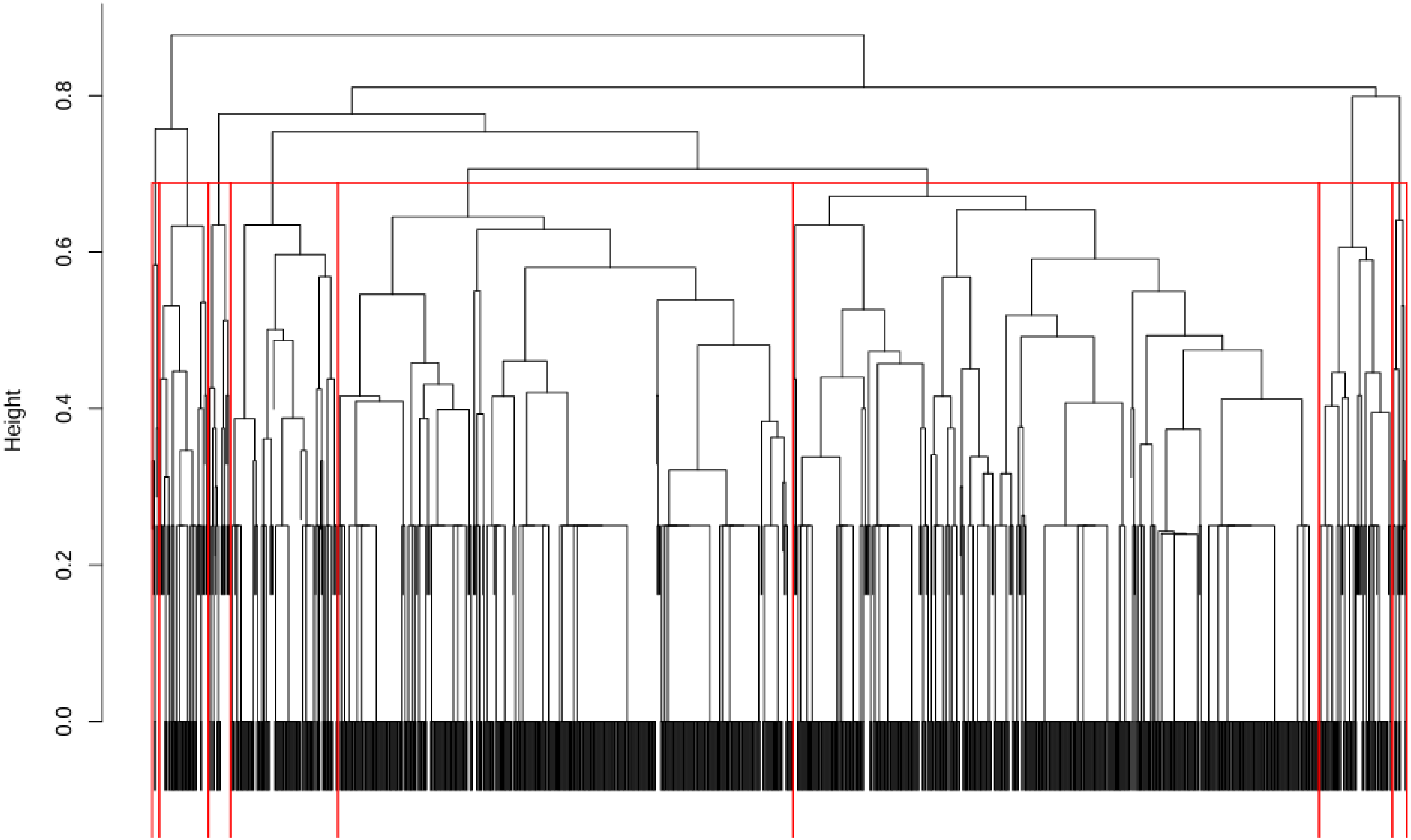


Figure A4. Cluster analysis dendrogram (4 effects, simulated dataset)