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Four Europes: Climate change beliefs and attitudes predict behavior and policy preferences using a latent class analysis on 23 countries

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ABSTRACT

Building public will for climate action requires designing messages for different audiences. Previous studies that identified groups based on similar beliefs, behavior, and political preferences related to climate change were in single countries. The current pre-registered study ran latent class analysis on the European Social Survey (ESS 2016; $N = 44,387$) to identify groups of people according to their climate change attitudes and beliefs in 22 European countries and Israel. We found strong evidence for four groups: Engaged (18%), Pessimistic (18%), Indifferent (42%), and Doubtful (21%) and we compare the segment structure and proportions within Europe and to other countries. We identify differences between the groups in values, life satisfaction, and social trust, and then revealed that the groups uniquely predict self-reported behaviors not included in the segmentation. The findings characterize climate change beliefs for all of Europe and guide governments and pan-European bodies in designing effective communications to promote climate beliefs and actions.

1. Introduction

Past research has established with high certainty that humans are the main cause of the existence, causes, and harms of climate change (IPCC, 2013). Thoughts, behaviors, and policies will determine how much global temperatures rise in the coming century. Scientists and others can help communicate connections between individual behaviors, public policy, and climate mitigation and adaptation. One major challenge has been how to understand the public opinion on climate change and the factors that influence these individual preferences and behaviors.

Public surveys address this need by tracking environmental opinions and issue importance and are particularly useful for monitoring absolute changes over time (Goldberg et al., 2020; Kvaloy et al., 2012; Lee et al., 2015). For example, concern about environmental issues is at the highest point in decades in the U.S. (Gallup, 2021) and the U.K. (Smith, 2019). Even as concern rises worldwide about human-caused climate change, beliefs seem increasingly polarized by political ideology and other group-based factors (Kahan, 2012; Pew Research Center, 2020). Similarly, individuals change their reported beliefs about basic scientific facts such as average global temperatures to avoid unwanted policies (Campbell & Kay, 2014).

Such polling supports predicting and influencing behaviors in the common interest. For example, regression analyses show that Theory of Planned Behavior variables such as beliefs and intentions predict environmental policy preferences (Brick & Lai, 2018). Such designs isolate between-subjects factors and rarely combine predictors and therefore offer a limited picture on the causes of real-world behaviors like activism. For example, it is unclear how to synthesize findings between studies about which predictors are most important (Goldberg et al., 2020; van der Linden, 2014). Specifically, a lot of studies use regression-style designs to identify the strongest linear effects, either in correlation or regression. However, given the range of possible predictors, populations, and contexts, there's no consensus about which psychological predictors are the most universally important for climate change beliefs and action across countries. Further, while regressions show the relationships between variables, they do not increase the understanding of different audiences and their characteristics (Füchslin, 2019). Segmentation is a promising alternative that enables a perspective beyond individual effects.

1.1. Segmentation

Segmentation analyses help divide the general public into homogeneous, mutually exclusive subgroups (Hine et al., 2014). These groups

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can provide a more holistic, interpretable narrative of how climate change beliefs shift over time through changes in group composition and size (Bostrom et al., 2013; Detenber & Rosenthal, 2020; Hine et al., 2017; Maibach et al., 2011; Metag & Schäfer, 2018). The revealed groups can be compared using demographics and relationships with other predictors and behaviors.

Also, segmentation may facilitate effective messaging. Social marketers have long been separating the public into groups based on thoughts and behaviors and then targeting these groups with specific messages (Kotler et al., 2002). This is similar to targeted messaging designed after eliciting audience characteristics in other theoretical programs such as Information Motivation Behavioral Skills (IMB) theory (Ehret et al., 2020). However, targeted messages informed by segmentation do not always work (Lorenzoni & Hulme, 2009), likely in part because experimental manipulations are rarely validated (Chester & Lasko, 2019). There may also be a file drawer of unpublished, non-significant interventions like in related literatures (Spellman, 2012).

Segmentation has been criticized for weaknesses including study cost, variable selection, stigmatization of the revealed groups, whether the groups are discovered or socially constructed (Brick et al., 2021), and abstract questions like whether differences between people are best characterized by categories or dimensions (Hine et al., 2017). The groups, often called segments, classes, or clusters, are rarely theoretically derived and are instead data-driven (Mead et al., 2012). However the current study items are based on well-established theoretical dimensions (see Table 2).

Despite legitimate concerns, segmentation has unique advantages. It is becoming more common and being used by governments, media, educators, and advocates, particularly in the United States using the Six Americas project (Leiserowitz et al., 2021). It is unclear how much a climate change segmentation applies across populations and cultures. Every population may have idiosyncratic views of climate change. However, similarities across such populations might also exist, particularly among countries in a similar geographical, economic, and sociopolitical context. Europe is of particular interest because it comprises many rich countries with high greenhouse gas emissions. How much these countries mitigate in the coming years will depend in part on effective targeted messaging and psychologically informed policy. Developing a segmentation scheme that is robust across different European countries can support these goals.

1.2. Groups based on climate change beliefs and attitudes

Previous segmentation studies on climate change have been reported in a few, predominantly Western countries, including the well-known Six Americas survey in the United States (Maibach et al., 2011; Chryst et al., 2018; Leiserowitz et al., 2021); and similar studies in the UK (Rhead et al., 2018); Germany (Metag et al., 2017); Netherlands (Wonneberger et al., 2020); Australia (Morrison et al., 2013; Shaw et al., 2011); New Zealand (Milfont et al., 2015; Sibley & Kurz, 2013); India (Leiserowitz et al., 2013); Singapore (Detenber et al., 2016); and Bangladesh (Mamun et al., 2013). Our approach uses the same pan-European data as one previous k-means cluster analysis we discovered after completing our study (Sciullo et al., 2019). Their study presented four segments of individuals based on environmentally relevant beliefs, perceptions, and behaviors. The authors characterized the segments using a vast range of sociodemographic and country-level variables, including a self-constructed 'Environmental Divide Index.' The analytic approach was less focused on latent classes and more exploratory than our narrow, confirmatory test of how many groups exist in Europe based on model fit. The results presented by Sciullo et al. (2019) are also problematic for several reasons. There was no formal validation of the identified segments. Further, the k-means clustering method generally produces biased estimates and does not provide any guidance to determine the optimal number of classes (Magidson & Vermunt, 2002). Therefore, we suggest there is benefit to a narrower, more robust identification of clusters within Europe.

By and large, the above studies found 4–6 groups that were largely interpretable on a one-dimensional scale from less concern to more concern about climate change. For reviews, see (Detenber & Rosenthal, 2020; Hine et al., 2017; Metag & Schäfer, 2018). Most of the studies used latent class analysis to extract groups based on climate change beliefs and attitudes, but one study in Finland used pro-environmental behaviors as the input instead (Korkala et al., 2014).

As a high-quality example, Metag et al. (2017) entered seven clear constructs into a model (concern about climate change, environmental concern, car use, abstention from longer car/plane journeys, eco-power, political activism on energy issues, and ecological conservatism) and compared the resulting classes across descriptives such as mass media use and demographics. Comparing results between segmentation studies is challenging, as the labels for the resulting groups are brief and subjective. Even if the data had very clear, unambiguous patterns—rare in latent class analysis—single labels from everyday language can aggregate too much and even mislead (Brick et al., 2021). That said, Metag et al. (2017) identified five groups in Germany: Alarmed, Concerned Activists, Cautious, Disengaged, and Doubtful. There was no highly Dismissive segment, in contrast to results from in the United States, Australia, and India (as noted by (Hine et al., 2017). It is unknown for Europe whether a comparable Dismissive group is present and how many groups best characterize climate change attitudes.

1.3. Current study

How do groups of people across Europe think about climate change and energy, and are these groups comparable to previous results such as the Six Americas (Leiserowitz et al., 2021)? We present a latent class analysis (Nylund-Gibson & Choi, 2018) across 22 European countries and Israel, using high-quality, probability sampling data from the ESS 2016 (European Social Survey, 2021).

The current project adds value to the study of climate change in several ways. First, compared to previous segmentation studies (Maibach et al., 2011; Metag et al., 2017; Milfont et al., 2015; Morrison et al., 2013; Rhead et al., 2018; Shaw et al., 2011; Sibley & Kurz, 2013; Wonneberger et al., 2020), this segmentation covers a multi-national sample, which enables to test configural invariance of the segmentation across countries. Second, we demonstrate predictive validity of the revealed classes by showing that the class membership predicts conservation behaviors and collective actions like attending a protest. Third, by using some items that will be repeated in future ESS waves, we facilitate tracking these specific groups over time. Previous segmentations, with the exception of the Six Americas survey (Maibach et al., 2011; (Leiserowitz et al., 2021), used more ad-hoc items and one-off samples, which makes it difficult to integrate between papers and test predictions. Fourth, this study has a detailed two-stage pre-registration. By defining the model structure before seeing the pre-existing data, we minimized the number of arbitrary decisions that might threaten the credibility and interpretability of the findings (see Nosek et al., 2018). Further, we initially fit a model in a random half of the data, and then cross-validated that model in the unseen holdout sample. This approach penalizes model over-fit and therefore balances model bias and variance. To the authors' knowledge, no previous segmentation study on climate change beliefs used cross-validation nor pre-registration.

2. Method

2.1. Dataset

The European Social Survey (ESS; (Norwegian Centre for Research Data, Norway – Data Archive and distributor of ESS data for ESS ERIC, 2016) is a cross-national survey measuring public attitudes, beliefs, and behaviors across a range of social topics. We used data from Round 8 because it contained the Climate Change and Energy module. During the current project, this was the most recent publicly available pan-European data with appropriate items. The module mapped public views towards climate change and energy security, covering areas such as climate change-related beliefs, environmental concern, pro-environmental behaviors, and environmental policy support. The complete list of items is here (Poortinga et al., 2018). Round 8 contains responses from 44,387 individuals from 22 European countries and Israel (see Table 1 for descriptive statistics). Respondents were selected through multistage national probabilistic sampling, and the data was collected through face-to-face interviews between August 2016 and December 2017. Detailed information about the data collection procedure is available online (European Social Survey, 2021).

2.2. Variable selection

The analytic approach and variable selection were pre-registered, and the cleaning and analysis scripts are posted at the Open Science Framework: https://osf.io/zvrmq/?view_only=ef1c28b753c847c593a02ca373d6c9e2. In line with the pre-registration protocol, the variable domains used for the segmentation analyses were climate change beliefs, climate change concern, environmental personal norm, climate change salience, efficacy beliefs, and biospheric value orientation (see Table 2). These psychological constructs form the key components of the conceptual framework of the ESS′ climate change module, which itself builds on the Value-Belief-Norm model (VNB; Stern, 2000) as the theoretical basis (European Social Survey, 2016). The VBN model is one of the most prominent theoretical frameworks in environmental psychology (Kaiser et al., 2005). It proposes that individuals' environmentally relevant actions are determined by personal values, beliefs, and feelings of personal responsibility (i.e., personal norms). In addition to the VBN model, the ESS conceptual framework also contains related concepts such as climate change concern and efficacy beliefs, which we included in the model development. Table 2 lists each variable used to in the model development and its link to the overarching theoretical concept. The climate module also included several other variables that were less relevant for the purpose of the present study (e.g., energy security concern). We did not include such variables in the latent analyses to preserve parsimony. The outcome measures used to test the predictive validity of identified classes were energy policy support, energy saving behavior, and activist behaviors.

Table 1
Sample size by country, unweighted.

Country	*N*	Age Mean (SD)	Male
Austria	2010	49.70 (17.36)	44.8%
Belgium	1766	47.02 (18.87)	50.2%
Czechia	2269	46.06 (17.09)	48.4%
Germany	2852	48.56 (18.50)	52.9%
Estonia	2019	49.65 (18.99)	45.8%
Spain	1958	49.60 (18.22)	49.8%
Finland	1925	50.13 (18.96)	49.9%
France	2070	52.38 (18.93)	46.0%
Great Britain	1959	51.38 (18.76)	44.5%
Hungary	1614	50.78 (18.75)	41.9%
Switzerland	1525	47.83 (18.78)	51.7%
Ireland	2757	50.16 (17.90)	49.0%
Israel	2557	46.94 (19.50)	48.0%
Iceland	880	48.69 (18.17)	49.7%
Italy	2626	48.81 (19.11)	48.9%
Lithuania	2122	49.92 (18.40)	40.6%
Netherlands	1681	51.22 (18.70)	44.7%
Norway	1545	46.96 (18.87)	53.7%
Poland	1694	47.17 (18.28)	47.7%
Portugal	1270	52.05 (18.30)	41.7%
Russia	2430	46.73 (18.02)	42.7%
Sweden	1551	51.56 (19.06)	49.9%
Slovenia	1307	49.06 (18.66)	45.8%
Overall	*44,387*	*49.14 (18.61)*	*47.4%*

Table 2
European social survey variables used in segmentation.

Code	Wording	Range	Theoretical concept
impenv*	Important to care for nature and environment (1: like me)	1–6	Personal values
clmchng*	Think world's climate is changing (1: definitely changing)	1–4	Climate change beliefs
clmthgt*	Thought about climate change before today (5: great deal)	1–5	Climate change beliefs
ccnthum*	Climate change caused by natural processes, human activity, or both (5: humans; 6: not happening)	1-5; 6 (not happening)	Climate change beliefs
ccgdbd	Climate change good or bad impact across world (11: extremely good)	1–11	Climate change beliefs
wrclmch*	Worried about climate change (5: worried)	1–5	Climate concern
ccrdprs	Feel personal responsibility to reduce climate change (11: great deal)	1–11	Pro-environmental personal norms
cflsenr	Confident you could use less energy than now (11: confident)	1–11	Efficacy beliefs
lkredcc	Imagine large numbers of people limit energy use: how likely to reduce climate change (11: likely)	1–11	Efficacy beliefs
lklmten	How likely large numbers of people limit energy use (11: likely)	1–11	Efficacy beliefs
gvsrdcc	How likely governments take action to reduce climate change (11: likely)	1–11	Efficacy beliefs
ownrdcc	How likely limiting own energy use to reduce climate change (11: likely)	1–11	Efficacy beliefs

Note. Variables using six or fewer Likert scale points (marked with *) were treated as categorical. *ccnthum* (whether climate change is happening) had a response option of 6, "not happening", which means that item is nominal. LCA doesn't distinguish between ordinal and nominal variables, and a small proportion of one class reported "not happening" as seen in Fig. 1b.

While behavioral variables like energy-saving behavior and activism could have been included in the segmentation analysis like in some previous studies (e.g., Goldberg et al., 2021), we kept behaviors separate for several reasons. First, compared to attitudes and beliefs, pro-environmental behaviors are not latent psychological variables (Lange & Dewitte, 2019), which makes them less suitable for the latent class analysis used for the segmentation in the present study, and also not substitutable (that is, one could not include some behaviors and use the segments to predict other behaviors, because this would assume there is a latent variable of all pro-environmental behavior). Self-reported pro-environmental behaviors appear remarkably inaccurate (Kormos & Gifford, 2014), and if different behavioral measures were included in the same segments over time, that could be misleading because different behaviors have very different causes (Lange & Dewitte, 2019). Second, whereas values, beliefs, norms, and related concepts of the Value-Belief-Norm model (Stern, 2000) are well captured in the ESS dataset, the dataset only contains a few behavioral variables and they do not capture the full breadth of pro-environmental behaviour defined by VBN (Stern, 2000). Adding the limited behavioral items to this segmentation might therefore produce bias. Third, including the behavioral variables would make it impossible to validate the identified attitude segments by predicting behavior.

Finally, to compare the classes descriptively we selected several variables previously linked to climate change views (Gifford & Nilsson, 2014). These included socio-demographic variables, political orientation, media consumption, social and institutional trust, personality traits, and post-materialistic values. The complete list of outcome variables and descriptive comparison variables is available in Table 4.

2.3. Analysis strategy

Latent class analysis (LCA) was the primary analysis technique to investigate whether Europeans could be classified into homogeneous classes based on their climate change views. LCA is a type of mixture model and is considered superior to other segmentation techniques such as k-means and hierarchical clustering because LCA enables to assess model fit, can accommodate both categorical and continuous variables, and can be used with weights (Nylund-Gibson & Choi, 2018).

Prior to analyses, we randomly split the ESS dataset into two subsets, each containing a half of the total sample. The first subset was used for exploratory analyses and the second subset was used to cross-validate the optimal solution identified in the exploratory phase. This step penalizes model over-fit and reduces false-positive findings in the confirmatory results (see Koul et al., 2018; Yarkoni & Westfall, 2017). Further, as part of the pre-registration process we limited the maximum number of classes to nine to maximize interpretability and practical applicability.

2.3.1. Exploratory phase

Using latent class analysis with 100–1000 random starts, we fit models with a varying number of classes (from 1 to 9) using pooled data from all 23 countries using Mplus version 7.31 (L. K. Muthén & Muthén, 2011). To ensure convergence, a higher number of random starts was applied to models with a higher number of latent classes. To account for the sampling bias and different population sizes across European countries, we applied sampling design weights in combination with population weights when fitting the latent models. Both types of weights were provided in the ESS dataset. We used a MLR estimator (maximum likelihood estimation with robust standard errors) as it allows for applying weights when fitting latent class models. Finally, all variables used for model construction that were on 4, 5, or 6-point Likert scales were entered into the models as categorical variables (five items). The remaining variables used for model construction, i.e., those on the 11-point Likert scale, were entered into the model as continuous variables (seven items). All continuous items were originally measured on a 0–10 scale. However, LCA does not support zero values and all items were therefore transformed to a 1–11 scale.

After fitting the models with all 12 items, the optimal 4-class solution was selected based on fit indices and interpretability of the classes. After choosing the 4-class model, we fitted several regression models to assess the model predictive validity. Using multilevel regressions, we assessed to what extent the class membership predicts pro-environmental behavior, activism behavior and environmental policy support, respectively. This was done through fitting multilevel models with random intercepts for countries in R Studio version 1.2.5042–1 (RStudioTeam, 2020).

2.3.2. Cross-validation phase

In the cross-validation phase, we re-ran the latent class analysis using the confirmatory subset of the data. We used exactly the same model specification that yielded the optimal 4-class solution in the exploratory phase. Similarly to the exploratory phase, we estimated latent models with 1–9 classes using Mplus version 7.31 with a MLR estimator. We used 5000 random starts for each model estimation to ensure that the models would converge on the global maximum. After running the models again, the 4-class model again clearly emerged as the optimal model based several fit indices (see Model comparison). Next, we assessed the model's predictive validity using the same regression model specifications as in the exploratory phase. Consistent with the exploratory phase, we assessed the extent of various behaviors and policy support predicted by class membership.

3. Results

3.1. Model comparison

We compared the fit of the models with 1–9 latent classes in both exploratory and confirmatory phase. Table 3 displays the models including their fit statistics. The four-class model had the best fit on a combination of Bayesian information criterion change (ΔBIC), entropy, and Lo-Mendel-Rubin adjusted likelihood ratio test (LMR-LRT) in both phases. Even though the BIC values continue to decrease for more complex solutions, the diminishing difference between models with more than four classes suggest a presence of an elbow point indicating a sufficient fit of the 4-class model (Nylund-Gibson & Choi, 2018). For entropy, values greater than 0.7 are considered acceptable for a latent class model (B. O. Muthén, 2004), and higher values indicate clearer

Table 3
LCA models and fit indices.

Classes	Param.	Entropy	logLik	AIC	BIC	ΔBIC	LMR	*p*
Exploratory dataset (n = 22,183)								
1	35	1.000	−463843	927756	928037	–	–	–
2	64	0.748	−450748	901625	902137	−25899	26096	.763
3	93	0.779	−444163	888512	889257	−12880	13125	.016
4	**122**	**0.773**	**−441377**	**882999**	**883976**	**−5281**	**5552**	**.013**
5	151	0.741	−439610	879524	880733	−3243	3521	.396
6	180	0.742	−438303	876968	878409	−2324	2605	.685
7	209	0.759	−437281	874981	876655	−1753	2037	.273
8	238	0.770	−436380	873237	875142	−1513	1797	.829
9	267	0.780	−435469	871474	873611	−1531	1815	.802
Confirmatory dataset (n = 22,189)								
1	35	1.000	−464950	929969	930250	–	–	–
2	64	0.733	−452218	904565	905077	−25173	25375	.016
3	93	0.776	−445534	891253	891998	−13079	13323	.020
4	**122**	**0.777**	**−442535**	**885314**	**886291**	**−5707**	**5976**	**.003**
5	151	0.732	−441008	882317	883526	−2765	3044	.474
6	180	0.725	−439809	879978	881419	−2107	2389	.762
7	209	0.745	−438762	877942	879616	−1803	2086	.793
8	238	0.756	−437949	876373	878279	−1337	1621	.692
9	267	0.745	−437106	874746	876883	−1396	1673	.796

Note. logLik = Log-likelihood, AIC = Akaike's information criterion, BIC = Bayesian information criterion, ΔBIC = BIC difference from a model with k-1 classes, LMR-LRT = Lo-Mendell-Rubin likelihood ratio test statistic, *p* = LMR-LRT *p*-value. Bold indicates the selected model.

Table 4
Descriptive and outcome variables by class, mean or median (SD or IQR).

Variable	Engaged	Pessimistic	Indifferent	Doubtful	Total
Socio-demographics					
Gender (% men)	45%	46%	47%	50%	47%
Median age (IQR)	48 (28)	47 (28)	50 (30)	51 (33)	49 (30)
Median household income (IQR)	6 (5)	6 (5)	5 (4)	4 (5)	4 (4)
Median ISCED (IQR)	4 (3)	4 (3)	4 (3)	4 (3)	5 (3)
Political orientation (0–10)					
Left-right scale	4.75 (2.32)	4.71 (2.26)	5.38 (2.12)	5.40 (2.35)	5.14 (2.25)
Media consumption in minutes per day					
Political news consumption	87 (130)	82 (128)	86 (138)	83 (133)	85 (134)
Internet consumption	205 (177)	208 (176)	186 (162)	201 (179)	197 (171)
Social and institutional trust (0–10)					
People trust	5.67 (2.35)	5.17 (2.41)	5.38 (2.24)	4.73 (2.53)	5.27 (2.37)
Parliament trust	5.11 (2.57)	4.31 (2.57)	4.81 (2.40)	3.85 (2.53)	4.59 (2.55)
Big Five proxies (1–6)					
Openness to experience[a]	4.32 (1.31)	4.08 (1.38)	3.94 (1.31)	3.72 (1.45)	3.99 (1.37)
Agreeableness[a]	5.11 (0.88)	4.98 (0.91)	4.70 (1.01)	4.56 (1.13)	4.80 (1.01)
Post-materialistic values (1–6)					
Universalism[a]	5.16 (0.95)	5.05 (1.00)	4.68 (1.05)	4.63 (1.20)	4.82 (1.08)
Environmental policy support (1–5)					
Support increase taxes on fossil fuels[a]	3.22 (1.29)	2.89 (1.28)	2.77 (1.12)	2.23 (1.17)	2.77 (1.23)
Support subsidized renewable energy[a]	4.28 (0.94)	4.19 (0.98)	3.86 (0.99)	3.58 (1.24)	3.94 (1.06)
Support ban of energy inefficient appliances[a]	3.95 (1.09)	3.79 (1.14)	3.45 (1.09)	3.11 (1.26)	3.54 (1.17)
Individual energy-saving behavior					
How likely to buy most energy efficient home appliance (0–10)	8.52 (1.83)	8.14 (2.12)	7.60 (2.12)	7.06 (2.87)	7.76 (2.29)
How often do things to reduce energy use (1–6)	4.68 (1.90)	4.58 (3.34)	4.22 (3.43)	4.53 (6.10)	4.43 (3.90)
Activist behavior (% in last 12 months)					
Contacted politician or government	21%	19%	13%	13%	15%
Worked in political party or action group	7%	5%	3%	3%	4%
Worked in another organization or association	23%	21%	15%	9%	16%
Worn or displayed campaign badge/sticker	13%	12%	7%	5%	9%
Signed petition	37%	36%	19%	13%	24%
Taken part in lawful public demonstration	13%	12%	6%	4%	8%
Boycotted certain products	31%	29%	12%	9%	18%
Posted or shared anything about politics	25%	25%	13%	1%	17%
Mean number of activities	4.84 (0.93)	4.78 (0.88)	4.42 (0.71)	4.31 (0.63)	4.54 (0.80)

Note.
[a] Reversed. Values in parentheses indicate standard deviations unless stated otherwise. IQR = interquartile range. ISCED = International Standard Classification of Education. The 95% confidence intervals are very narrow given the large sample size, and they are provided in Supplement Table S4.

separation of classes. For the LMR-LRT, a significant p-value of the test indicates a better fit compared to a model with k-1 classes (Nylund et al., 2007). A statistically significant value suggests that more complex models did not meaningfully improve the likelihood ratio.

The four-class model was the most complex model that yielded $p < .05$ in both the exploratory and confirmatory subsets. The four-class model also had the highest entropy in the confirmatory subset and offered the best interpretability. Further, the four-class model also offered the most straightforward interpretation. Compared to three- and five-class solutions, the four segments showed the clearest attitudinal and sociodemographic patterns (see Fig. 2b and Table 4). Therefore, the four-class model was identified as the optimal solution in both phases and was used in further analyses.

3.2. Cross-cultural comparability and measurement invariance

We attempted to test configural invariance of the identified model across countries in line with the pre-registration. To do so, we followed the approach outlined in Jackson and Kuha (2014) and constructed separate LCA models for every country in the dataset. We then assessed to what extent the country-level models matched individuals to the same class as the global model. Matched classifications ranged from 50% (Poland) to 87% (Switzerland). These accuracy levels are generally below the reasonable levels for establishing configural invariance proposed by (Jackson & Kuha, 2014). Therefore, configural invariance was not established. Each country had unique homogeneous classes above and beyond the classes identified through the pooled model. This means that a single four-class solution is less appropriate for comparing between countries. However, the global model still provides a Europe-wide picture of climate-change related attitudes and behaviors in separate groups. We focus the subsequent analyses on the pan-Europe model, as exploring each country would have required a separate approach and interpretation.

3.3. Characteristics of the four classes

All analyses reported below are based on the confirmatory subset. Based on the pattern of responses for all items in the global model, we labeled the four classes Engaged, Pessimistic, Indifferent, and Doubtful

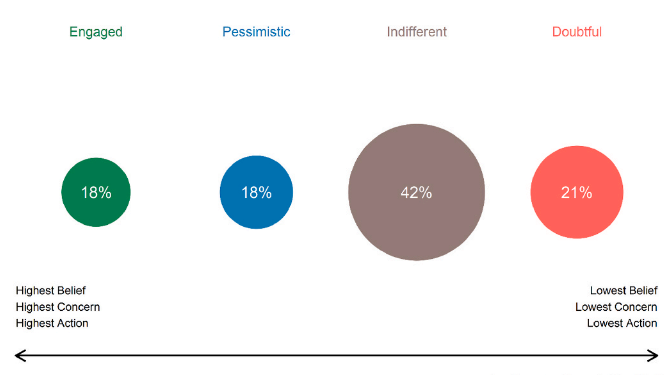

Fig. 1. Class proportions in Europe.

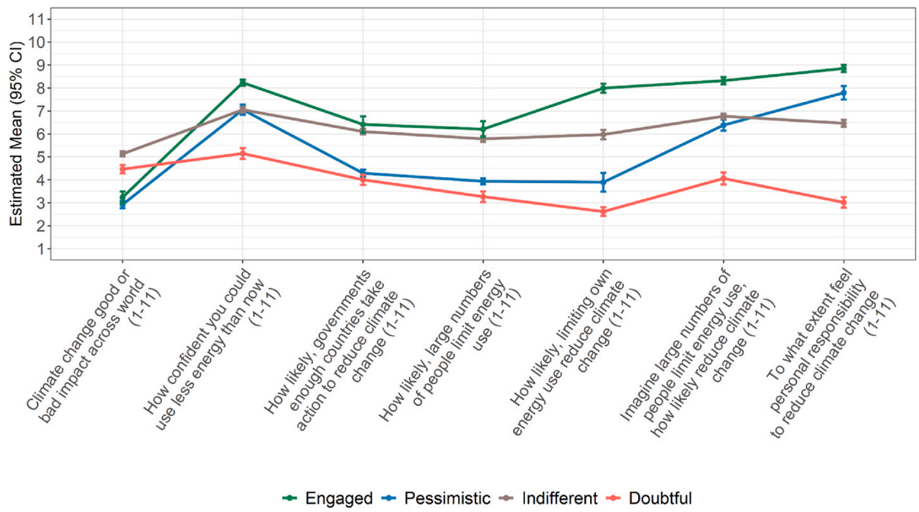

Fig. 2. *Item Responses by Class*

Note. Variables using six or fewer Likert scale points were treated as categorical. Whether climate change is happening was a nominal item and had a conceptually separate response option of 6, "not happening". LCA doesn't distinguish between ordinal and nominal variables, and a small proportion of the Doubtful reported "not happening" as seen above. The item 'important to care for nature and environment' had ordinal response options from 1 to 6.

(see Fig. 1). The class proportions differed by country. Switzerland, Portugal, Spain, and Iceland had the largest proportion of Engaged citizens, whereas Russia, the Czech Republic, and Estonia had the most Doubtful respondents (see Fig. S1 in the Supplement for the class distributions per country).

The four classes differed considerably in their climate change views (see Fig. 2a and b). The Engaged were the most concerned about climate change. Together with the Pessimistic, they showed the highest agreement that the climate is changing and it is caused by human processes. The Engaged also held the strongest biospheric values, reported the highest personal responsibility to reduce climate change, and were the most confident that people and institutions could and would take effective action to address the global issue. The Pessimistic also believed that anthropogenic climate change was happening to the same extent but were less personally involved than the Engaged. The most pronounced difference between the two classes was that the Pessimistic were much less confident that the actions of institutions, others, and themselves alone could and would effectively address the changing climate. Compared to the previous two groups, the Indifferent segment was more doubtful about whether climate change was happening and had lower personal involvement with climate change. However, compared to the Pessimistic, the Indifferent were more optimistic that society could take effective action. Finally, Doubtful respondents had the lowest belief in anthropogenic climate change, issue involvement, and perceived efficacy.

We also observed differences between the classes in sociodemographic variables, personal values, and environmentally relevant behaviors (see Table 4). Individuals in classes more engaged with climate change were more likely to be female, young, rich, and politically left. Additionally, the more engaged classes were higher in openness to experience, agreeableness, post-materialistic values, activist and pro-environmental behavior, and support pro-environmental policies. Doubtful respondents reported the lowest social and institutional trust. No clear differences were observed in educational attainment and the media consumption behavior among the four classes. In general, these demographic findings are in line with past studies examining associations between individual characteristics and pro-environmental engagement (Gifford & Nilsson, 2014).

3.4. The four classes predict behavior and policy support

We constructed multilevel regression models to test whether the class membership predicts activist behavior, two types of pro-environmental behavior, and support of three environmental policies. Separate models were estimated for each of the six dependent variables using the R package *lme4* (Bates et al., 2015). In the first step (Model 1), only demographic variables were entered as predictors (i.e., age, income, and political orientation as continuous; gender and education as dummy). In the second step (Model 2), class membership was added to the model as an additional dummy predictor. Finally, country intercepts were set to random. No multicollinearity issues were found in the regression models (see Supplement Table S4).

Table 5 shows the regression results. Segment membership predicted all outcome variables above and beyond the demographic predictors. A single exception was pro-environmental activist behavior, which education predicted better than segment membership. Further, a clear pattern emerged across the classes: The more a respondent was classified towards the Engaged segment on the Engaged-Doubtful continuum, the more likely they were to engage in activist and pro-environmental behavior as well as support pro-environmental policies. One exception was slightly higher activist behavior reported in the Doubtful compared to the Indifferent. The overall pattern suggested a strong predictive validity of the four classes.

4. Discussion

The project aim was to segment people based on their climate change attitudes and beliefs in 22 European countries and Israel. This can inform targeted messaging, enable changes to be tracked over time, and allow comparison with other regions such as the United States. Using high-quality probabilistic sampling data from the European Social Survey in 22 countries and Israel (N = 44,387), this latent class analysis revealed strong evidence of four groups that we labeled the Engaged (18%), Pessimistic (18%), Indifferent (42%), and Doubtful (21%). This project was distinguished from the methods of previous literature because of its detailed pre-registration and confirmatory testing in an unexamined holdout sample, as well as open materials, code, and data.

The classes that were more engaged with climate change had individuals that were more likely to be female, young, rich, and politically left-wing. The Engaged were the most concerned about climate change

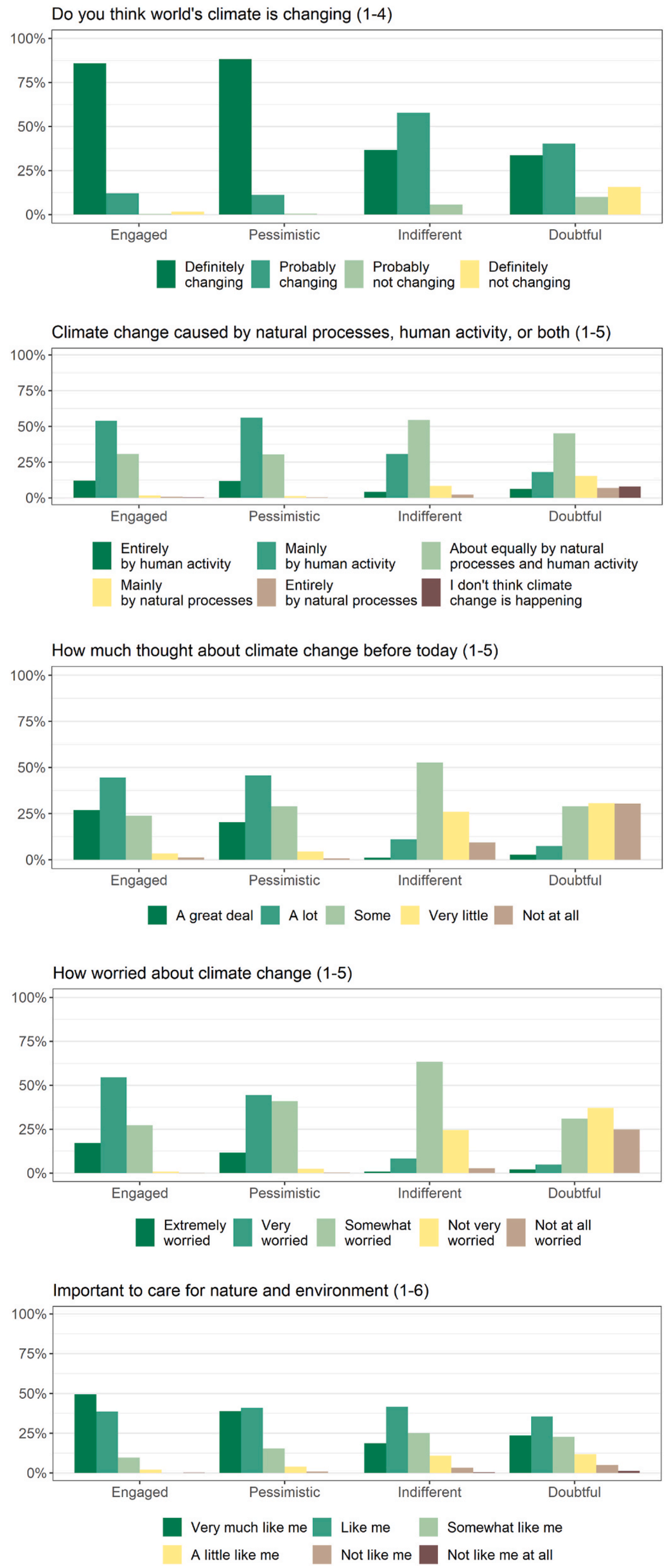

Fig. 2. (*continued*).

and the most confident that people and institutions could and would take effective action. The Pessimistic had the same belief in human-caused climate change but were less personally involved. The Pessimistic were also much less convinced that climate change could be mitigated—even less than the Indifferent, who reported less confidence that climate change was even happening. Finally, Doubtful respondents were the lowest in all the following: belief in climate change, issue involvement, perceived efficacy for mitigation, and social and institutional trust. These differences are likely due to meaningful variation in risk perceptions and decision making (Roser-Renouf et al., 2014), as discussed in (Chryst et al., 2018).

In contrast to the U.S., our findings suggest there is no separate

Table 5
Regression coefficients for all multilevel models.

Variables	Activist behavior (composite score)		Support increase taxes on fossil fuels		Support subsidized renewable energy		Support ban of energy inefficient appliances		How likely to buy most energy efficient home appliance		How often do things to reduce energy use	
Model	1	2	1	2	1	2	1	2	1	2	1	2
Age	-0.05^{c}	-0.04^{c}	-0.05^{c}	-0.04^{c}	-0.04^{c}	-0.03^{c}	0.04^{c}	0.05^{c}	0.14^{c}	0.15^{c}	0.14^{c}	0.15^{c}
Household income	0.03^{c}	0.03^{c}	0.06^{c}	0.04^{c}	0.03^{c}	0.02	0.06^{c}	0.04^{c}	0.07^{c}	0.06^{c}	-0.04^{c}	-0.05^{c}
Gender – Female	-0.05^{b}	-0.05^{c}	0.05^{b}	0.03	0.06^{c}	0.04^{b}	0.10^{c}	0.08^{c}	0.08^{c}	0.07^{c}	0.09^{c}	0.07^{c}
Edu – ISCED 2	0.20^{c}	0.18^{c}	0.05	0.02	0.15^{c}	0.12^{c}	0.11^{b}	0.08	0.13^{c}	0.10^{b}	0.19^{c}	0.16^{c}
Edu – ISCED 3	0.25^{c}	0.22^{c}	0.02	−0.02	0.16^{c}	0.12^{c}	0.16^{c}	0.12^{c}	0.29^{c}	0.26.	0.23^{c}	0.19^{c}
Edu – ISCED 4	0.43^{c}	0.39^{c}	0.13^{c}	0.09^{a}	0.26^{c}	0.21^{c}	0.13^{c}	0.08^{a}	0.27^{c}	0.22^{c}	0.28^{c}	0.22^{c}
Edu – ISCED 5	0.50^{c}	0.45^{c}	0.09^{b}	0.04	0.25^{c}	0.19^{c}	0.20^{c}	0.14^{c}	0.37^{c}	0.31^{c}	0.33^{c}	0.26^{c}
Edu – ISCED 6	0.62^{c}	0.56^{c}	0.29^{c}	0.21^{c}	0.33^{c}	0.24^{c}	0.22^{c}	0.13^{c}	0.33^{c}	0.25^{c}	0.38^{c}	0.29^{c}
Edu – ISCED 7	0.80^{c}	0.72^{c}	0.38^{c}	0.29^{c}	0.33^{c}	0.23^{c}	0.22^{c}	0.11^{b}	0.37^{c}	0.27	0.38^{c}	0.27^{c}
Left-right ideology	-0.11^{c}	-0.09^{c}	-0.09^{c}	-0.08^{c}	-0.08^{c}	-0.06^{c}	-0.07^{c}	-0.04^{c}	-0.02^{b}	0	-0.05^{c}	-0.02^{b}
Class – Pessimistic		-0.06^{a}		-0.27^{c}		-0.08^{c}		-0.14^{c}		-0.16^{c}		-0.20^{c}
Class – Indifferent		-0.35^{c}		-0.33^{c}		-0.36^{c}		-0.40^{c}		-0.36^{c}		-0.49^{c}
Class – Doubtful		-0.33^{c}		-0.72^{c}		-0.60^{c}		-0.67^{c}		-0.61^{c}		-0.61^{c}
$ICC_{country}$	0.15	0.13	0.06	0.06	0.06	0.05	0.03	0.03	0.06	0.05	0.04	0.03
AIC	43225	42789	49821	49047	45410	44474	49135	48400	69740	69119	50038	49283
BIC	43325	42912	49920	49170	45510	44887	49235	48523	69840	69242	50138	49406
$\chi 2$	43199	42757	49795	49015	45384	44732	49109	38368	69714	69087	50012	49251
$\Delta \chi 2$		441.85		779.43		651.56		740.65		627.2		761.87
p		<.001		<.001		<.001		<.001		<.001		<.001
Pseudo R^2	0.22	0.22	0.10	0.14	0.08	0.11	0.05	0.09	0.09	0.12	0.07	0.11
Δ Pseudo R^2		0.01		0.04		0.03		0.04		0.03		0.04

Note. The superscript letters indicate statistical significance: ^{a} $p < .05$, ^{b} $p < .01$, ^{c} $p < .001$.Age, Household income and Left-right ideology were standardized using the refit standardization method (Neter et al., 1989). *P*-values were obtained using Satterthwaite (1941) approximation. Edu = Education. ISCED = International Standard Classification of Education. Reference categories: Gender = male, Education = ISCED 1, Class = Engaged); $ICC_{country}$ = adjusted intraclass correlation for the random effects of country, AIC = Akaike's information criterion, BIC = Bayesian information criterion, $\chi 2$ = Chi-square statistic, p = p-value for Likelihood-ratio test, Pseudo R^2 = Nakagawa's conditional r-squared (includes variance of both fixed and random effects).

Dismissive group in Europe, consistent with findings from Germany alone (Metag et al., 2017). There is heterogeneity within each segment, but there are not enough or not homogeneous enough hoaxers to represent such a group in Europe. Even in the European Doubtful segment, the overwhelming majority (74%) responded that climate change is "probably" or "definitely" happening.

4.1. Limitations

First, the latent class analysis approach is data-driven, so segmentation projects mostly do not test theoretical predictions about the composition or number of classes nor their demographic correlates. Many latent class analyses do not even converge on a stable solution, so it is already of interest to identify a robust confirmatory result for all of Europe (also see Sciullo et al., 2019).

Another question concerns the temporal stability of the segments identified in the present study. Given the rising global concern about climate change in the past years (Pew Research Center, 2021), the proportions of the four classes probably changed since the 8th wave of the ESS was conducted. To date, however, there is no newer, publicly available dataset with most European countries including a comprehensive measure of climate change beliefs, associated behaviors, and political preferences. Therefore, it is not known how these classes may have shifted and determining this in future data would be useful.

A further unanswered question is whether shifts in public opinion changed the number of segments. The Six Americas survey (Leiserowitz et al., 2021) identified six audiences in 2008 and since then evaluated the proportion of the audiences on regular basis. However, to the authors' knowledge, there has been no published research that tested whether the variance in climate change opinions in the U.S. is still best characterized by six segments (Alarmed, Concerned, Cautious, Doubtful, Disengaged, and Dismissive). In Europe, there is an overall lack of multi-year data that captures climate change beliefs, associated behaviors, and political preferences using consistent measures, which makes the assessment of the main climate change audiences more difficult. Hopefully, future rounds of major international surveys will include more measures related to the pressing issue of climate change.

Further, an inherent limitation of latent class analysis is that the model selection involves assessing the model interpretability, and this step is always subjective. It is helpful when the identified factors are understandable and useful for practitioners. The four-class model best fulfils these criteria and showed the best statistical fit.

Another key limitation is that single-word labels do not fully characterize latent classes. Please see Fig. 1 for the item-level detail. A third challenge is the variability in class solutions across countries. The invariance results suggested that the class composition and number differed enough between individual countries that this four-class solution should not be compared between countries based on the current findings. In contrast, we found strong evidence that this four-class solution represents Europe as a whole (with Israel). Supporting this approach is recent evidence from network analysis finding that linear relationships between ESS items were robust and similar across European countries, and that the network structure was similar across countries using cluster analysis (Verschoor et al., 2020).

Finally, the non-invariance across countries might lead to doubts about the value of the pan-European segmentation. Country-level models will usually provide the best insight for national-level practitioners and communicators. The key value of pan-European segmentation is identifying the best solution for comparing audience segment size across countries and tracking how proportions change within Europe over time. Additionally, the pan-European segmentation might also serve as a quick starting point for EU-level regulators and program designers who have limited resources for country-specific segmentation projects.

4.2. Future directions

We encourage several future steps using the Four Europes. First, longitudinal designs could answer several pressing questions such as group stability over time, both within individuals and within whole populations. For example, across ten years in the Six Americas project, the Dismissive group shrank and the Alarmed group grew (Leiserowitz et al., 2021). Second, we encourage segmentation studies in lower-income countries, which are underrepresented in the current literature despite their importance in global emissions (e.g., China); see (Leiserowitz et al., 2013) for results in India. Third, we recommend experimental trials of framed messages across different classes, for example using pro-environmental intentions or behavior as outcomes (Hodges et al., 2020; Sapiains et al., 2016). Such studies would constitute a strong test of claims, like ours, that segmentation studies usefully inform targeted messaging in pro-environmental context as they have for health behaviors (Brick et al., 2016; Gallagher & Updegraff, 2012).

Contributor roles taxonomy

OK: Conceptualization, Pre-registration, Formal analysis, Pre-registration peer review/verification, Data analysis peer review/verification, Methodology, Project administration, Writing-original draft, Writing-review and editing. JV: Conceptualization, Pre-registration, Formal analysis, Pre-registration peer review/verification, Data analysis peer review/verification, Methodology, Visualization, Writing-original draft, Writing-review and editing. CB: Conceptualization, Pre-registration peer review/verification, Methodology, Project administration, Supervision, Writing-original draft, Writing-review and editing.

Note. See https://www.casrai.org/credit.html for the details and definitions of each role.

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Declaration of competing interest

The authors declared no potential conflicts of interests with respect to the authorship and/or publication of this article.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvp.2022.101815.

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