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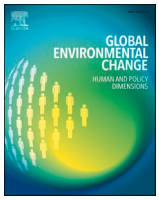

# Perceived plasticity of climate-relevant behaviors and policy support among high- and lower-income individuals

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ABSTRACT

Widespread behavior change is essential for mitigating climate change. This study explores how country and income differences are associated with the perceived likelihood of changing climate-relevant behaviors (referred to as perceived behavioral plasticity) and support for climate policies. Using an online survey ($n$ = 4,003) from Denmark, India, Nigeria, and the United States – with 50 % of participants from the top 10 % income bracket – we reveal marked heterogeneity in the perceived plasticity of climate-friendly investment behaviors (e.g., purchasing an electric vehicle) and curtailment behaviors (e.g., reducing red meat consumption). Perceived behavioral plasticity was generally higher in India and Nigeria, though these differences should be interpreted cautiously, as response tendencies might have influenced perceptions and reporting of plasticity. While high-income participants reported greater perceived plasticity of certain investment behaviors and eating less red meat, the relationship between income and perceived plasticity differed substantially across behaviors and countries. We also found that higher perceived behavioral plasticity was related to greater support for domain-matched climate policies, and this relationship was stronger among high-income participants. Taken together, the results reveal substantial income- and country-level differences in perceived behavioral plasticity and show that individuals who perceive greater potential for change also express stronger support for corresponding climate policies. These findings underscore the interdependence between individual behavior and policy support and highlight both socioeconomic and psychological levers for designing more targeted and publicly supported climate initiatives.

## 1. Introduction

Large-scale behavioral changes can substantially help limit climate change (Creutzig et al., 2022a; Creutzig et al., 2022b; De Coninck et al., 2018; Nielsen et al., 2024b). The Intergovernmental Panel on Climate Change (IPCC) distinguishes three categories of demand-reducing behavior changes (Creutzig et al., 2022b): (1) adopting improved end-use technologies (e.g., energy-efficient appliances, heat pumps, or electric vehicles), (2) shifting activities to less energy-intensive provisioning systems (e.g., shifting from cars to public transport), and (3) avoiding or reducing carbon-intensive activities (e.g., reducing or avoiding air travel, car driving, or meat consumption). Despite the potential of behavioral changes to substantially reduce greenhouse gas (GHG) emissions, they remain largely untapped (Geels, 2023; Nielsen

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et al., 2024b). Numerous factors contribute to this, including feasibility barriers common to many mitigation solutions (Geels, 2023; Nielsen et al., 2020; Stern et al., 2023). These barriers include socioeconomic constraints, the characteristics and availability of climate-friendly behavioral alternatives, and often limited political and organizational prioritization of behavior change initiatives (Dablander et al., 2025a; Westlake et al., 2024).

The feasibility of behavioral changes varies profoundly across behaviors, individuals, and contexts. A key concept for examining this variability is behavioral plasticity, referring to the degree to which individuals can change their behavior. For example, the feasibility of substituting a fossil-fuel-powered vehicle with an electric vehicle depends on financial capability, the availability and affordability of electric vehicles, access to charging station(s) at home or in one's neighborhood, mobility needs, social norms, and more—all of which can vary within and between countries (Günther et al., 2025). Behavioral plasticity is ideally evaluated using evidence from implemented policy initiatives or high-quality experimental or observational studies to understand the malleability of behaviors across and within population groups with high ecological validity (Dietz et al., 2009; Nielsen et al., 2021a; Stern, 2011). However, such evidence may be unavailable or available only in specific socio-cultural contexts or for behaviors other than the targeted one, potentially challenging the design, prioritization, and implementation of behavior change initiatives.

A more practical approach to obtaining behavior- and policy-relevant evidence is to assess perceived behavioral plasticity, which involves examining people's perceptions of the likelihood of changing their behavior while considering associated costs and barriers (Allen et al., 2015; Kukowski et al., 2023b; McFadden et al., 2022). Perceived behavioral plasticity reflects both self-efficacy and the willingness to change, extending beyond conventional intention measures by incorporating perceptions of the structural and contextual factors that may facilitate or hinder change. Notably, perceived behavioral plasticity represents a psychological evaluation of the likelihood of change rather than an observation of actual behavior. Perceived plasticity may therefore not perfectly correspond to actual behavioral plasticity, consistent with research on the intention-behavior gap (Dablander et al., 2025b; Sheeran and Webb, 2016). Yet, evidence of perceived behavioral plasticity offers valuable insights into which behavioral changes may be achievable in the short term, which face feasibility or willingness barriers, and how these factors vary across population segments and contexts. For example, low plasticity of purchasing an electric vehicle may reflect objective feasibility barriers, such as lack of finances or limited availability of charging stations, and perceived barriers, such as range anxiety (Herberz et al., 2022). Policymakers, organizations, and other change agents can use this knowledge to inform and target their behavior change initiatives, especially when evidence of actual behavioral plasticity and initiative effectiveness is limited.

Socioeconomic status, particularly income and wealth, shapes behavioral plasticity and people's capability and opportunity to adopt low-carbon behaviors and technologies (Dietz and Whitley, 2018; Duncan et al., 2024; Kukowski and Garnett, 2023; Nielsen et al., 2021b). For example, wealthier individuals have more financial resources to adopt low-carbon consumer technologies, a higher capacity for utilizing subsidies or tax credits (e.g., for energy-efficiency upgrades) (Borenstein and Davis, 2016; Sovacool et al., 2022), and a greater opportunity to outsource information-seeking and skill development related to low-carbon behaviors (e.g., finding a reliable solar-panel provider or learning to cook tasty and nutritious plant-based meals). Furthermore, wealthier neighborhoods often have more access to low-carbon behavioral alternatives, such as public transportation, active travel infrastructure, plant-based foods, and electric vehicle charging stations, which can lower adoption-related barriers (Babagoli et al., 2019; Ermagun and Tian, 2024). Finally, wealthier individuals usually have substantially higher carbon footprints than the population average (Bruckner et al., 2022; Chancel, 2022; Oswald et al., 2020; Tian et al., 2024), thereby presenting a greater potential (and responsibility) for emission reductions through curtailing consumption.

Despite the generally higher feasibility of engaging in low-carbon behavior, wealthier individuals may not recognize or be willing to seize these opportunities for change (Cass et al., 2023; Duncan et al., 2024; Moorcroft et al., 2024). For example, a recent study involving high-income participants in the United Kingdom found a prevalent reluctance against climate-relevant behavior change, partially justified by a desire to maintain their lifestyle and privileges (Cass et al., 2023; see also Mundaca and Wamsler, 2025). This finding suggests that wealthier individuals may be primarily willing to adopt low-carbon behaviors that maintain or enhance their social status (De Nardo et al., 2017; Uren et al., 2021), particularly those that require minimal behavioral adjustments (Duncan et al., 2023). Numerous studies conducted in and across Europe have found a greater willingness among wealthier individuals to adopt low-carbon technologies (De Nardo et al., 2017; Duncan et al., 2024; Moorcroft et al., 2024; Umit et al., 2019), such as energy-efficient appliances, which require limited behavioral adjustment to reduce GHG emissions. Conversely, they found a lower willingness to curtail consumption, such as reducing energy usage, often requiring substantial behavioral adjustments. However, many of these studies relied on relatively small and selective samples of high-income individuals, particularly at the upper end of the income distribution, limiting the generalizability of their conclusions. As such, current evidence on the behavioral plasticity of high-income individuals remains scarce and warrants further investigation.

Addressing climate change requires both individual and system-level changes (Creutzig et al., 2022b; Gibson et al., 2000; Nielsen et al., 2024b; Stern et al., 1992). Consequently, studies increasingly explore the connections between people's past or intended behavior and their support for climate policies (Dechezleprêtre et al., 2025; Maki et al., 2019; Sparkman et al., 2021; Wamsler et al., 2022; Werfel, 2017). Among other things, these studies have examined relationships, for example, between people's current meat consumption and their support for a policy aimed at reducing meat consumption. However, further studies are needed to fully unpack the relationship between perceived behavioral plasticity and climate policy support (Kukowski et al., 2023a; Kukowski et al., 2023b), which poses a subtly different research question; namely, do people who perceive themselves as likely to eat less meat in the near future express more or less support for a policy aiming to facilitate a transition away from meat consumption. Here, there are good reasons to expect either a negative or a positive relationship. For example, people who perceive a behavioral change as highly likely may see less need for policies that promote it, suggesting a potential crowding-out effect of policies that promote individual behavior change (Werfel, 2017). Conversely, they may support policies that incentivize or remove barriers to change to facilitate broader adoption, suggesting a potential double-dividend.

In the most extensive study to date, Kukowski et al. (2023b) found a positive relationship between perceived behavioral plasticity and support for climate policy, particularly for carbon-intensive behaviors. However, the study could not adequately assess the role of income and included primarily participants from North America and Europe. This leaves two key knowledge gaps. First, we know little about how perceived behavioral plasticity varies across socioeconomic groups and how these differences shape support for corresponding climate policies. Second, existing evidence is geographically narrow, limiting our understanding of whether these patterns generalize across countries with distinct economic, infrastructural, and policy contexts. Although the relevance of income can vary across climate policies and countries (Dechezleprêtre et al., 2025), several studies find a positive relationship between income and support for climate policies (Poortinga, 2025; Zhang et al., 2025). There is also reason to expect that income moderates the relationship between perceived behavioral plasticity and policy support. Income may shape whether perceived plasticity translates into policy support by influencing the material, psychological, and social

conditions under which behavioral change is evaluated. For example, high-income individuals typically face fewer financial and structural barriers, have greater political efficacy, and are often more embedded in climate-relevant norms and discourse, potentially making them more likely to support policies that align with behaviors they already perceive as feasible. Addressing these gaps is therefore essential for understanding how socioeconomic factors interact with perceptions of behavioral plasticity to shape climate policy preferences.

This article explores country- and income-level differences in the perceived behavioral plasticity of climate-relevant behaviors and their relationship to climate policy support. To assess the generalizability of these relationships, we use data from an online survey conducted in four countries: Denmark, India, Nigeria, and the United States. These countries were selected to capture a broad range of contextual conditions relevant to climate change mitigation, including differences in cultural norms, economic development, carbon footprint inequality, and climate policy frameworks. They also represent regions that differ substantially in the maturity of low-carbon infrastructures and in exposure to climate impacts. Furthermore, the author team had established research expertise and language proficiency in these contexts, facilitating survey implementation in English or a native language and ensuring appropriate interpretation of local conditions. This selection strategy prioritized contextual diversity and analytical feasibility within budgetary and logistical constraints, allowing us to test whether observed patterns are context-specific or hold across distinct national settings. Moreover, it helps move beyond the overwhelming focus on Western countries in behavioral research (Brick et al., 2024; Ghai, 2021; Henrich et al., 2010).

Within each country, we recruited around 1000 participants, equally divided into two population segments: individuals whose personal income was in the top 10 % and those whose personal income was below the threshold for the top 10 %. The oversampling of high-income individuals is rare in survey-based and behavioral science research (Ivanova and Wood, 2020; Otto et al., 2019; Ravallion, 2022). While our samples were not nationally representative by design, this targeted approach enabled balanced comparisons across income groups and yielded a unique opportunity to examine the behavioral and policy preferences of high-income individuals whose personal carbon footprints and political influence are typically disproportionately large (Bruckner et al., 2022; Chancel, 2022; Nielsen et al., 2021b).

## 2. Methods

We conducted an online survey in Denmark, India, Nigeria, and the United States. Participants were recruited via the market research companies Nielsen (Denmark and Nigeria) and Qualtrics (India and the United States) and received financial compensation for their participation. The survey was administered in English, except in Denmark, where it was administered in Danish. In India, to ensure sufficient English comprehension, only participants who reported feeling comfortable answering in English completed the survey. A total of 4,003 participants completed the study with the following country breakdown: Denmark ($n = 1001$), India ($n = 1001$), Nigeria ($n = 1001$), and the United States ($n = 1000$). In each country, the sampled participants were equally split into two income groups: participants whose personal income fell into the top 10 % income bracket and participants whose personal income was below the threshold for the top 10 % income bracket. We used the following income thresholds for the top 10 % (CEPOS, 2019; PK, 2023; The Times of India, 2022): Denmark (650.000 DKK), India (300,000 INR), Nigeria (35,000,000 NGN), and the United States (130,000 USD). For reference, the 2022 World Bank PPP conversion factors (indicator PA.NUS.PPP) are Denmark = 6.23, India = 20.49, Nigeria = 152.44, and the United States = 1.00 (World Bank Open Data, 2025). These thresholds were derived from national data sources when available, although some uncertainty remains for India and Nigeria due to limited reliable income data. We adopted this recruitment strategy to ensure greater representation of high-income individuals, thereby deliberately trading off the survey's representativeness. Importantly, while the country-specific top 10 % income brackets reflect local economic conditions and facilitate within-country comparisons, caution is needed when making direct cross-country comparisons due to differences in absolute income levels and purchasing power.

Although we had a priori expectations for the studied relationships, we did not preregister any hypotheses or an analysis plan and, consequently, label our study as exploratory. However, the survey design, materials, and data exclusion criteria were pre-registered via the Open Science Framework (OSF) in relation to another article using the same dataset (osf.io/8qtfy). The current research questions, reported analyses, and conclusions are distinct from that work. All data and analysis code for the present study are likewise available on OSF.

We automatically screened out participants if one or more of the following criteria were met: (1) reported being under 18 years old ($n = 50$); (2) felt uncomfortable answering the survey in English (only in India); (3) reported 'prefer not to answer' on the income question ($n = 205$); (4) failed the attention check ($n = 1,841$); (5) answered the comprehension check for the concept of personal carbon footprint wrongly twice (a concept only used in another study; Nielsen et al., 2024a) ($n = 1,274$). Although not pre-registered, we also excluded participants who were likely bots based on their Recaptcha score ($n = 10$), who completed the survey quicker than one-third of the median completion time within each country sample ($n = 180$), or who completed the survey more than once ($n = 1$). These participants were subsequently replaced with other respondents by Nielsen and Qualtrics.

In the full sample, the mean age was 42.35 (SD = 16.59), and 56.8 % identified as male, 42.8 % as female, 0.3 % as non-binary, and 0.01 % preferred not to say. An overview of descriptive statistics for each country is presented in Table 1.

### 2.1. Measures

***Perceived behavioral plasticity.*** Mirroring recent studies (Allen et al., 2015; Kukowski et al., 2023b), participants reported their perceived behavioral plasticity of five investment behaviors and five curtailment behaviors. The behaviors were selected due to their relevance for substantially reducing household carbon footprints (Ivanova et al., 2020; Oswald et al., 2020; Poore and Nemecek, 2018; Tian et al., 2024; Wynes et al., 2021). For both behavioral clusters, participants read the following instruction: "Taking into consideration the COSTS AND INCONVENIENCE for each action, how likely is it that YOU PERSONALLY will take the following actions within the next 1–2 years?" We measured the following investment behaviors rated on a 7-point scale (0 = *I cannot do this*, 1 = *very unlikely*, 5 = *very likely*, 6 = *I have already done this*): (1) purchase an electric vehicle; (2) replace older appliances with newer energy efficient models (e.g., refrigerators, air conditioner); (3) improve the insulation of your home; (4) move private investments to climate-friendly financial products (e.g., free from fossil fuels); and (5) install solar panels at home. The curtailment behaviors, rated on a 6-point scale (1 = *very unlikely*, 5 = *very likely*, 6 = *I don't [behavior]*), were (1) take fewer national or international flights, (2) eat less red meat (e.g., beef, lamb, veal), (3) eat less white meat (e.g., chicken, pork), (4) drive fewer kilometers in your car, and (5) use less energy for heating or cooling your home. For both investment and curtailment behaviors, the perceived behavioral plasticity measure was created from response options 1–5 (1 = *very unlikely*, 5 = *very likely*), thereby excluding participants who could not perform the behavior (e.g., due to structural constraints) or already performed it.

***Climate policy support.*** Participants indicated their support for 12 prospective climate policies inspired by recent cross-country research (Dechezleprêtre et al., 2025). Due to the countries' heterogeneous political systems and policy landscapes, we developed the policy wording collaboratively, drawing on existing cross-country research and refining it using the authors' contextual expertise to ensure conceptual

**Table 1**
Descriptive statistics. Statistics for continuous variables are reported with mean and standard deviation, whereas categorical variables are reported as percentages.

| | Denmark | | | India | | | Nigeria | | | United States | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD | N | Mean | SD | N | Mean | SD |
| **Socio-demographics** | | | | | | | | | | | | |
| Age | 1,001 | 52.80 | 15.42 | 1,001 | 31.11 | 9.62 | 1,001 | 35.43 | 10.51 | 1,000 | 50.07 | 17.85 |
| Income group | 1,001 | | | 1,001 | | | 1,001 | | | 1,000 | | |
| … General population | 501 | 50 % | | 501 | 50 % | | 500 | 50 % | | 500 | 50 % | |
| … Top 10 % of income | 500 | 50 % | | 500 | 50 % | | 501 | 50 % | | 500 | 50 % | |
| Income (15 categories) | 1,001 | 8.27 | 3.33 | 1,001 | 9.01 | 4.34 | 1,001 | 8.00 | 4.66 | 1,000 | 8.32 | 3.66 |
| Gender | 1,001 | | | 1,001 | | | 1,001 | | | 1,000 | | |
| … Male | 540 | 54 % | | 587 | 59 % | | 738 | 74 % | | 408 | 41 % | |
| … Female | 460 | 46 % | | 411 | 41 % | | 261 | 26 % | | 583 | 58 % | |
| … Non-binary / third gender | 1 | 0.1 % | | 2 | 0.2 % | | 1 | 0.1 % | | 9 | 0.9 % | |
| … Prefer not to say | 0 | 0 % | | 1 | 0.1 % | | 1 | 0.1 % | | 0 | 0 % | |
| Education | 1,001 | | | 1,001 | | | 1,001 | | | 1,000 | | |
| … No schooling completed | 1 | 0.1 % | | 1 | 0.1 % | | 1 | 0.1 % | | 3 | 0.3 % | |
| … Primary school | 3 | 0.3 % | | 3 | 0.3 % | | 1 | 0.1 % | | 6 | 0.6 % | |
| … Lower secondary school | 51 | 5 % | | 7 | 0.7 % | | 9 | 0.9 % | | 9 | 0.9 % | |
| … Vocational degree | 241 | 24 % | | 20 | 2 % | | 32 | 3 % | | 59 | 6 % | |
| … High school | 89 | 9 % | | 59 | 6 % | | 149 | 15 % | | 221 | 22 % | |
| … College degree | 303 | 30 % | | 487 | 49 % | | 599 | 60 % | | 428 | 43 % | |
| … Master's degree or above | 313 | 31 % | | 424 | 42 % | | 210 | 21 % | | 274 | 27 % | |
| Political orientation (left–right) | 993 | 4.17 | 1.51 | 1,001 | 4.91 | 1.55 | 1,001 | 4.95 | 1.60 | 998 | 4.25 | 1.75 |
| **Perceived behavioral plasticity** | | | | | | | | | | | | |
| Purchase an electric vehicle | 780 | 2.62 | 1.42 | 857 | 4.24 | 1.10 | 941 | 3.39 | 1.44 | 812 | 2.63 | 1.56 |
| Replace older appliances with newer energy-efficient models | 729 | 3.44 | 1.28 | 853 | 4.21 | 1.07 | 804 | 4.09 | 1.09 | 762 | 3.36 | 1.35 |
| Improve the insulation of your home | 522 | 2.83 | 1.42 | 886 | 4.05 | 1.06 | 920 | 3.83 | 1.15 | 742 | 3.19 | 1.47 |
| Move private investments to climate-friendly financial products | 743 | 2.62 | 1.30 | 932 | 4.06 | 1.08 | 947 | 3.78 | 1.21 | 851 | 2.63 | 1.42 |
| Install solar panels at home | 534 | 2.36 | 1.41 | 841 | 4.33 | 1.07 | 693 | 4.28 | 1.04 | 738 | 2.72 | 1.56 |
| Take fewer national or international flights | 860 | 2.83 | 1.42 | 923 | 3.80 | 1.20 | 965 | 3.29 | 1.35 | 812 | 3.10 | 1.50 |
| Eat less red meat | 944 | 2.88 | 1.43 | 727 | 3.78 | 1.37 | 962 | 3.41 | 1.45 | 948 | 2.71 | 1.51 |
| Eat less white meat | 972 | 2.38 | 1.26 | 827 | 3.65 | 1.34 | 977 | 2.89 | 1.47 | 976 | 2.32 | 1.37 |
| Drive fewer kilometers in your car | 870 | 2.61 | 1.37 | 935 | 3.93 | 1.21 | 957 | 3.13 | 1.45 | 948 | 3.06 | 1.51 |
| Use less energy for heating or cooling your home | 985 | 3.20 | 1.34 | 950 | 4.21 | 0.99 | 968 | 3.55 | 1.27 | 992 | 3.30 | 1.36 |
| **Climate policy support** | | | | | | | | | | | | |
| Climate policy support(composite) | 1,001 | 4.40 | 1.23 | 1,001 | 5.06 | 1.04 | 1,001 | 4.73 | 0.97 | 1,000 | 4.04 | 1.41 |
| Carbon tax | 1,001 | 4.23 | 1.78 | 1,001 | 4.60 | 1.92 | 1,001 | 4.48 | 1.84 | 1,000 | 3.60 | 2.07 |
| Expand public transport | 1,001 | 4.98 | 1.72 | 1,001 | 6.05 | 1.38 | 1,001 | 5.66 | 1.49 | 1,000 | 5.09 | 1.64 |
| Increase price of peak electricity consumption | 1,001 | 3.12 | 1.79 | 1,001 | 3.76 | 2.05 | 1,001 | 4.08 | 2.09 | 1,000 | 3.05 | 1.94 |
| Subsidize renewable energy | 1,001 | 5.50 | 1.55 | 1,001 | 5.89 | 1.53 | 1,001 | 5.18 | 1.71 | 1,000 | 4.85 | 1.92 |
| Strengthen energy efficiency requirements in buildings | 1,001 | 5.20 | 1.45 | 1,001 | 5.74 | 1.40 | 1,001 | 5.50 | 1.48 | 1,000 | 5.04 | 1.70 |
| Mandate GHG disclosure by banks and investment companies | 1,001 | 4.21 | 1.80 | 1,001 | 5.46 | 1.56 | 1,001 | 5.14 | 1.65 | 1,000 | 4.31 | 1.96 |
| Tax on red meat | 1,001 | 3.25 | 2.00 | 1,001 | 4.64 | 2.10 | 1,001 | 3.82 | 1.92 | 1,000 | 2.88 | 1.96 |
| Tax on air travel | 1,001 | 4.30 | 1.95 | 1,001 | 4.19 | 1.97 | 1,001 | 4.13 | 1.87 | 1,000 | 3.26 | 1.98 |
| Introduce mandatory carbon footprint label | 1,001 | 4.46 | 1.71 | 1,001 | 5.48 | 1.55 | 1,001 | 5.04 | 1.62 | 1,000 | 4.19 | 1.94 |
| Ban diesel and petrol cars | 1,001 | 3.27 | 1.95 | 1,001 | 3.97 | 2.03 | 1,001 | 3.82 | 2.16 | 1,000 | 2.94 | 1.96 |
| Subsidize CDR technologies | 1,001 | 5.39 | 1.49 | 1,001 | 5.44 | 1.79 | 1,001 | 5.15 | 1.66 | 1,000 | 4.80 | 1.86 |
| Subsidize low-impact foods | 1,001 | 4.85 | 1.71 | 1,001 | 5.52 | 1.66 | 1,001 | 4.80 | 1.84 | 1,000 | 4.51 | 1.93 |

equivalence and local relevance across countries. The instructions for the policy support items read: "Many countries have introduced new policies to reduce the risk of climate change. This includes policies that require or create incentives for reductions in greenhouse gas emissions across domains and actors. How much do you support or oppose adopting the following policies in [country]?" Responses were assessed on a 7-point Likert scale (1 = *strongly oppose*, 7 = *strongly support*). The policies were: (1) increase or introduce taxes on products and services that are made from or use fossil fuels (e.g., coal, oil, gas); (2) expand public transport (buses, trams, trains); (3) increase the price of electricity consumption during peak times; (4) increase subsidies for renewable energy projects (e.g., wind and solar energy); (5) strengthen requirements for energy efficiency in buildings; (6) mandate banks and investment companies to reveal their greenhouse gas emissions to consumers; (7) increase or introduce taxes on red meat (e.g., beef, lamb, veal); (8) increase or introduce taxes on air travel; (9) introduce a mandatory carbon footprint label on consumer products; (10) ban the sale of diesel and petrol-engine cars; (11) increase subsidies for technologies that remove greenhouse gases from the atmosphere; and (12) increase subsidies for food products with low greenhouse gas emissions (e.g., fruit, vegetables, legumes, cereals).

***Income.*** We measured participants' personal income by asking, "What was your total annual personal income before taxes in 2022?" rated on a 10-point scale (plus a 'prefer not to answer' option). We phrased the question to refer to total personal income from all sources. The answer options were adapted to each country, with response option 10 being the income threshold for belonging to the top 10 % of income (e.g., "*₹300,000 or more*"). Participants who reported an income belonging to the top 10 % were subsequently asked another 6-point income question to assess their personal income more accurately, permitting the identification of income differences among participants within the top 10 %: "You indicated that your total annual personal income before taxes in 2022 was more than [top 10 % income threshold]. Please select the band that most precisely describes your income." We subsequently created a combined income measure with 15 response categories. The survey also included other measures not detailed here (see the pre-registration for further details).

### 2.2. Analytical strategy

We used Bayesian inference, which addresses long-standing criticisms of classical hypothesis testing based on *p*-values (Greenland et al.,

2016; Wasserstein and Lazar, 2016). Unlike the frequentist view of probability as a long-run frequency, Bayesian inference treats probabilities as degrees of belief (Diaconis and Skyrms, 2018; Jaynes, 2003; Lindley, 2000). It combines prior distributions over parameters with observed data to produce posterior distributions, enabling a coherent update of uncertainty. Bayesian methods offer several advantages (Wagenmakers et al., 2016), including quantifying evidence for both the presence and absence of effects via Bayes factors (Kass and Raftery, 1995) and incorporating prior information in a principled way. Appropriate priors act as regularizers, inducing partial pooling or "shrinkage" toward plausible values and thereby reducing overconfidence and improving out-of-sample performance (Gelman et al., 2012). Power analyses are valuable during the planning phase of a study as they inform the, in expectation, necessary sample size to detect a particular effect size of interest. However, once the data have been collected, conducting a post-hoc power analysis is generally discouraged, as it can be misleading and is generally considered inappropriate in statistical practice (e.g., Hoenig and Heisey, 2001). Given that these data were collected for another study, we did not conduct a power analysis. However, our Bayesian analysis provides a straightforward uncertainty quantification of effect sizes, without recourse to long-run error rates and fixed decision thresholds (Wagenmakers et al., 2015).

To assess the relationship between perceived behavioral plasticity and income across countries, we used the R package *BayesFactor* (Schönbrodt and Wagenmakers, 2018) to estimate linear models for each climate-relevant behavior, with perceived behavioral plasticity as the outcome variable and income, country, and their interaction as predictor variables. Bayes factors indicate how likely the data are under different models or hypotheses. For example, $BF_{01} = 10$ means that the data are ten times more likely under the null hypothesis than the alternative hypothesis. We refer to Bayes factors in favor of a model between 1 and 3 as indicating weak, between 3 and 10 as moderate, and greater than 10 as strong evidence (cf. van Doorn et al., 2021).

We assigned a default (zero-centered) Jeffreys-Zellner-Siow priors with scale $\sqrt{1/2}$ (0.7071) to the effect of country and $\sqrt{1/2/4}$ (0.1768) to the effects of income and the interaction, given that we a priori expected smaller effects for continuous variables than for country (Rouder and Morey, 2012). These so-called "default" priors fulfill a number of desiderata (Rouder and Morey, 2012) and have been used in a wide range of applications. They refer to standardized effect sizes for continuous variables. For example, a prior scale of 0.1768 for income means that we expected 50 % of the probability mass for the effect of a one standard deviation increase in income to be within a 0.1768 standard deviation increase or decrease in perceived behavioral plasticity (with the mean being a 0 increase). For the effect of country, a scale of 0.7071 means that the difference between two countries in mean perceived behavioral plasticity is, with 50 % probability, between −0.7071 and 0.7071. We compared five models that included: (1) only an intercept, (2) only the main effect of income, (3) only the main effect of country, (4) both main effects, and (5) both main effects and their interaction. We have added extensive sensitivity analyses to assess the robustness of our conclusions concerning different choices of priors (see Supplementary Figs. S6-S7). Notably, the *BayesFactor* R package estimates Bayes factors for linear models with very high numerical precision (yielding almost zero numerical error for small Bayes factors and up to 3 % error for log Bayes factors in the hundreds, i.e., where the evidence is overwhelming even considering the numerical imprecision).

We used Bayes factors to assess the strength and evidence for or against an effect, yet it is not apparent which models to compare. For example, to evaluate the evidence of the effect of income, one might be tempted to compare the model that includes only the main effect of income against the intercept-model only or compare the model that includes both income and country against a model that only includes country. The problem of selecting a reference model becomes more acute as the number of variables increases. Instead, we used model-averaging and inclusion Bayes factors, which avoid this problem and account for the uncertainty across models (Hinne et al., 2020; van den Bergh et al., 2020). Inclusion Bayes factors are defined as the ratio of posterior odds that a particular effect is present in the data compared to its prior odds. We assumed a uniform prior over models, but our results are robust to different choices (e.g., the popular beta-binomial prior with $a = b = 1$).

Take the example of income again. First, we calculated the prior odds that income is included as an effect; that is, we divided the prior probability that income is included in a model by the prior probability that it is not included in a model while removing from the set of models those that include an interaction including income, as this would change its meaning. In this case, where we only have five models, the prior odds for income are 1. The procedure for calculating the posterior odds remains the same, except that we use posterior model probabilities. The inclusion Bayes factor is then the ratio of the posterior odds to the prior odds. When assessing the evidence for an interaction, we only use those models that include the interaction and those that do not include it but include all relevant main effects (van den Bergh et al., 2020). In our primary analysis, we report the model with the highest marginal likelihood, that is, the model that best predicted the data.

We used a similar approach for analyzing the relationship between perceived behavioral plasticity and domain-matched policy support across income and countries. Specifically, we estimated linear models with the domain-matched climate policy as the outcome variable and the domain-matched perceived behavioral plasticity, income, and country as predictors. We again assigned JZS priors with scale $\sqrt{1/2}$ to the effect of country and $\sqrt{1/2/4}$ to the effect of perceived behavioral plasticity and income, as well as any interaction. We estimated models that include only an intercept, only the main effects (individually or jointly), main effects and two-way interactions, and main effects and two-way interactions and the three-way interaction. For each model that had an interaction, we specified that the respective main effect must also be included. This yielded a total of 19 different models. We again used model-averaging to calculate inclusion Bayes factors, taking the uncertainty across all models into account. Again, we assigned a uniform prior to the models, but our results are robust with respect to a different choice of prior.

We conducted the Bayesian proportion tests (see Supplementary Material) using the *BayesFactor* R package using a default Beta (1, 1) prior and assumed an independent multinomial sampling plan (Jamil et al., 2017).

## 3. Results

### 3.1. Perceived behavioral plasticity across countries

Across the four countries, participants indicated their likelihood of performing five curtailment behaviors (e.g., taking fewer flights, eating less red meat) and five investment behaviors (e.g., purchasing an electric vehicle, replacing older appliances with newer energy-efficient ones) within the next 1–2 years. To measure perceived behavioral plasticity, we excluded participants who already performed these behaviors (e.g., vegetarians or those without a car) or could not perform them (e.g., not owning a house). This exclusion decision ensures that we focus on the subset of participants for whom behavior change is within the realm of possibility, thereby providing a more accurate measure of the potential for change.

We observed marked descriptive differences in perceived behavioral plasticity across behaviors and countries (Fig. 1 and Table 1). In Denmark, a larger proportion of participants reported it as (very) unlikely that they will drive fewer kilometers (48 %), take fewer flights (43 %), eat less white (57 %) and red meat (43 %), improve home insulation (42 %), install solar panels (57 %), purchase an electric vehicle (48 %), and move investments to climate-friendly products (46 %). Conversely, more participants found it (very) likely to use less energy for heating or cooling (45 %) and replace older appliances with energy-efficient

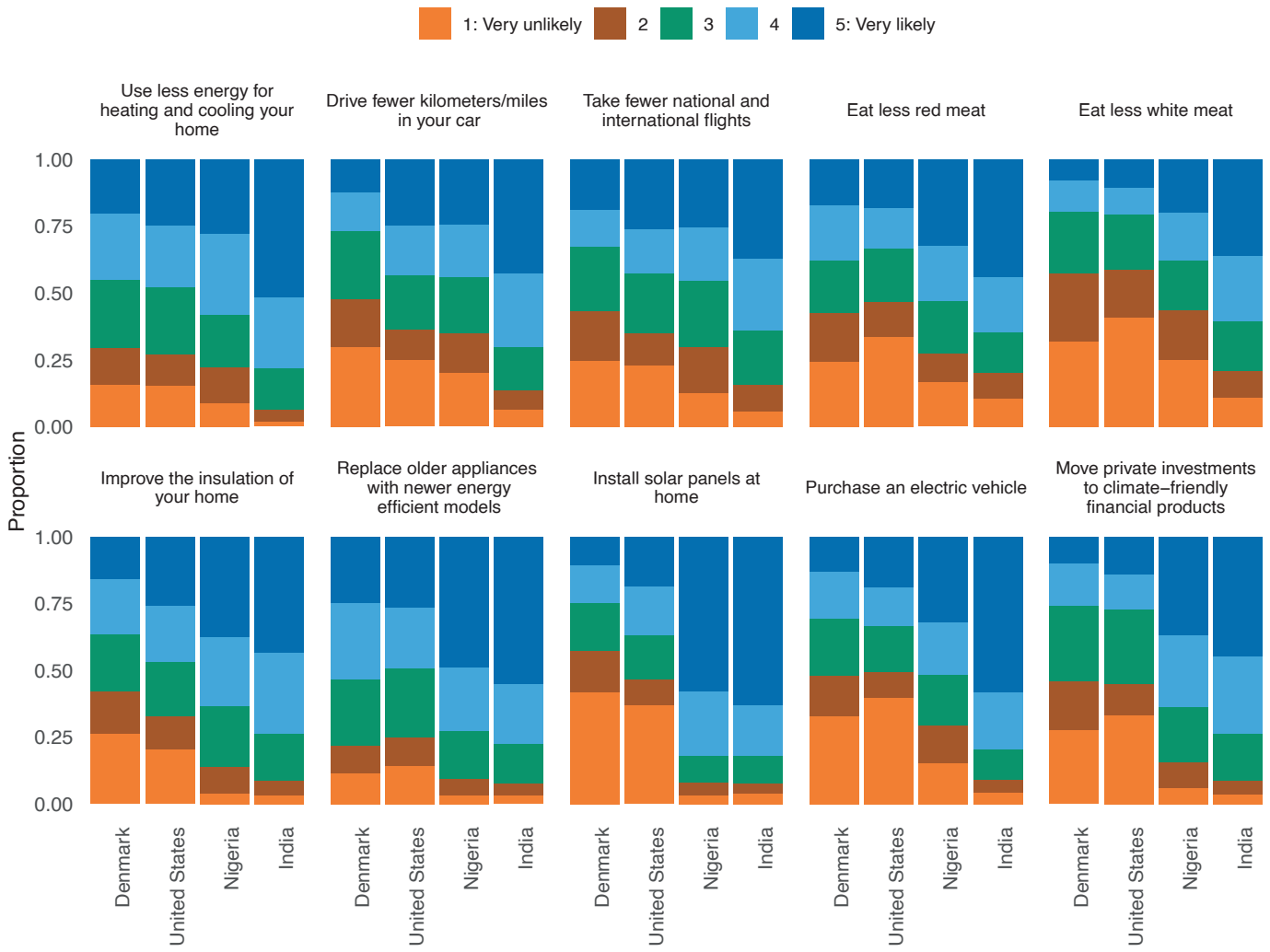


**Fig. 1.** Perceived behavioral plasticity across behaviors and countries. Proportions of perceived behavioral plasticity across curtailment (top) and investment (bottom) behaviors and countries.

models (53 %). The United States showed a similar pattern, except a larger proportion found it (very) likely to drive fewer kilometers (43 %), take fewer flights (43 %), and improve home insulation (47 %), in addition to using less energy for heating or cooling (48 %) and replacing older appliances (49 %). These descriptive findings starkly contrast those from Nigeria and India. The majority of participants in these countries reported high perceived plasticity, indicating that they were (very) likely to perform all behaviors (average of 57 % for Nigeria and 72 % for India), except for eating less white meat in Nigeria (38 %). The proportional differences in perceived plasticity between countries are mirrored in the mean perceived behavioral plasticity (Fig. 1). In Denmark and the United States, the mean perceived plasticity across all behaviors (i.e., the mean of the means) was relatively low ($M = 2.80$ and 2.90, respectively), while the average standard deviations were relatively high ($SD = 1.36$ and 1.46, respectively). In contrast, the mean perceived behavioral plasticity was considerably higher in Nigeria and India ($M = 3.60$ and 4.00, respectively), while the average standard deviations were lower ($SD = 1.30$ and 1.15, respectively; Fig. S2).

There were notable country differences in the proportion of participants who reported already or never performing a behavior (Fig. S3 and S4), with 30 % of participants in Nigeria reporting that they had already installed solar panels and almost 30 % of participants in India reporting that they never eat red meat. In contrast, participants from Denmark and the United States indicated much more often that they could not perform a particular behavior (Fig. S3). For example, about 30 % of participants in Denmark reported that they could not improve home insulation, while almost 40 % reported that they could not install solar panels. The proportion of participants indicating this was slightly lower in the United States, with about 10 % and 20 %, respectively. The proportion of already performing a behavior was positively associated with the mean perceived behavioral plasticity in Denmark, the United States, and Nigeria, but negatively associated in India.

### 3.2. *Perceived behavioral plasticity across income groups*

We next used Bayesian regression models to examine whether perceived behavioral plasticity varied across income groups and whether this relationship differed across countries and behaviors (Fig. 2). We measured income in 15 categories, with the top six categories corresponding to the top 10 % income group in the respective countries. We show the predictions of the best-performing Bayesian regression model in Fig. 2, and report model-averaged Bayes factors for all relevant relationships. Across all countries, we found moderate evidence against a relationship between income and perceived behavioral plasticity for using less energy for heating and cooling and installing solar panels (Bayes factors ($BFs_{01}$ 4.2 and 6.5). However, across all countries, we found strong evidence that higher incomes were associated with higher perceived behavioral plasticity for eating less red meat, purchasing an electric vehicle, and moving private investment to climate-friendly financial products (log $BFs_{10}$ 25.3, 40.5, 6). For taking

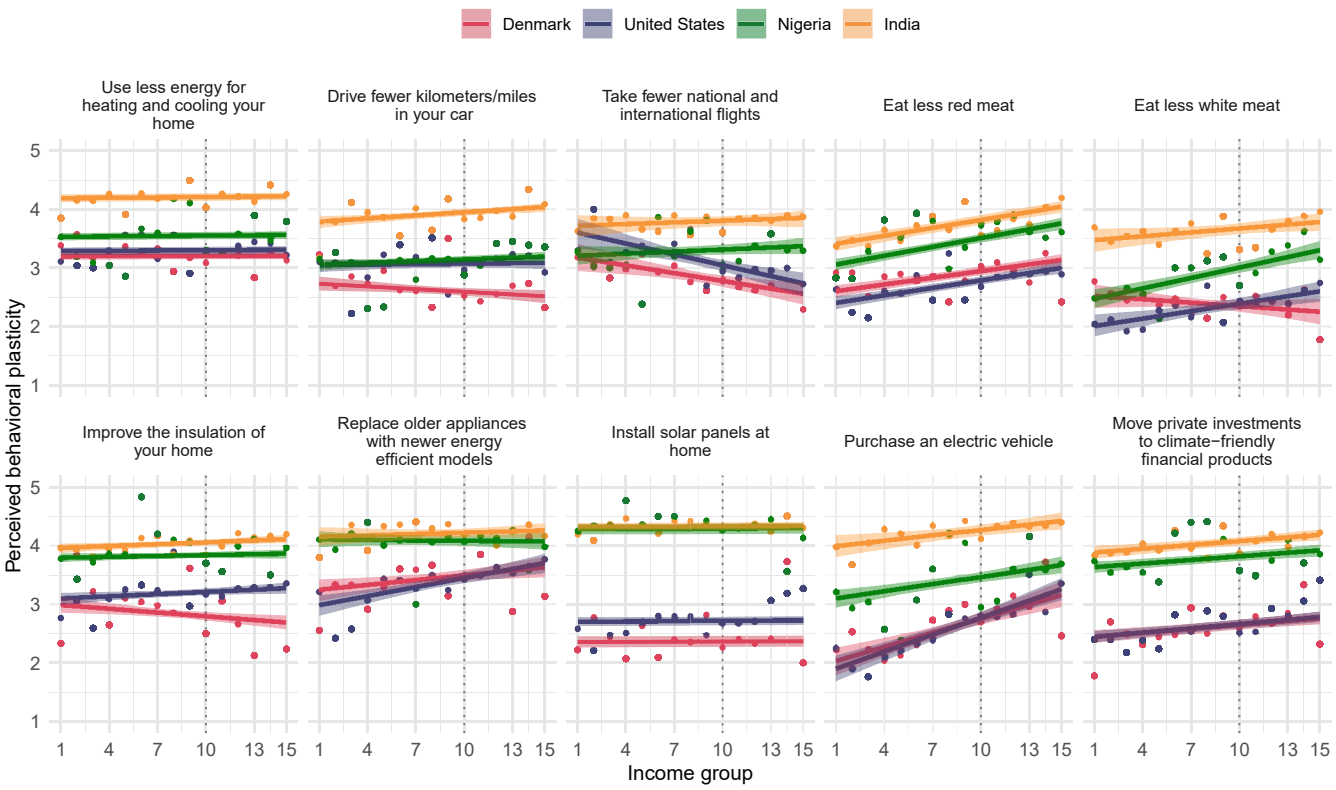


**Fig. 2.** Relationship of income and perceived behavioral plasticity across behaviors and countries. Model-averaged posterior mean and 95% credible intervals of the relationship between mean perceived behavioral plasticity and income groups across actions and countries. Points indicate empirical means within income groups. The dotted vertical line indicates the threshold of belonging to the top 10% of income.

fewer national and international flights and eating less white meat, we found strong evidence that the relationship between income and perceived behavioral plasticity differed across countries ($BFs_{10}$ 5653 and 865). In particular, participants with higher incomes from Denmark and the United States reported being less likely to take fewer flights. In Denmark, they also reported being less likely to eat less white meat. We found weaker evidence for differences across countries for driving fewer kilometers ($BF_{10}$ 3.6), improving home insulation ($BF_{10}$ 4.6), and replacing older appliances with newer energy-efficient models ($BF_{10}$ 17.2). Model-averaged posterior estimates for the effect of income on perceived behavioral plasticity across behaviors and countries are presented in Fig. S5. Differences in mean perceived behavioral plasticity between participants in the top 10 % income and the general population mirror the results here (Fig. S6). The Bayes factors are robust to different prior specifications (Fig. S7 and S8).

There were also notable differences in the proportion of participants who reported already performing the behaviors across income groups (Fig. S9). As expected, there was strong evidence across countries (log $BFs_{10}$ from 7.40 to 52.3) that low-income participants were more likely to never fly and not own a car, except for India ($BFs_{10}$ 0.29 and 0.18). Across all countries, we found evidence against an income difference in reporting not heating or cooling the home and not eating red meat ($BFs_{01}$ ranging from 2.76 to 1036.70). There were no income differences regarding not eating white meat, except in Nigeria ($BF_{01}$ 31.13), where lower-income participants reported not eating white meat more frequently.

The pattern was often reversed for the investment behaviors. There was strong evidence that high-income participants more often reported already having improved home insulation in Denmark (log $BF_{10}$ 22.60) and the United States (log $BF_{10}$ 6.47). In contrast, there was strong evidence for no income differences in India ($BF_{01}$ 26.50) and Nigeria ($BF_{01}$ 112.97). For replacing older appliances with newer ones, we found strong evidence for income differences in Denmark ($BF_{10}$ 26.45). We found interesting income differences in Nigeria, where fewer participants in the middle-income category reported having replaced older appliances and installed solar panels. The evidence for income differences regarding installing solar panels was weak for Denmark and the United States, with strong evidence against income differences in India ($BF_{01}$ 87.98). There was strong evidence that participants with higher incomes reported already having purchased an electric vehicle in Denmark (log $BF_{10}$ 25.19) and that there were no income differences in Nigeria ($BF_{01}$ 92.43), with equivocal evidence for the United States and India. Lastly, there was evidence against income differences related to already having moved private investments to climate-friendly financial products across all countries ($BFs_{01}$ ranging from 4.56 to 389.97).

### 3.3. *Perceived behavioral plasticity and climate policy support*

Finally, we examined whether the perceived plasticity of a behavior was associated with support for a domain-matched policy (see Fig. S10 for descriptive results on climate policy support) and whether this relationship differed across income and countries (Fig. 3). We found strong evidence that higher perceived behavioral plasticity was associated with higher policy support across the three domain-matched policies: taking fewer national and international flights and increase taxes on air travel (log $BF_{10}$ 203); eating less red meat and increasing taxes on red meat (log $BF_{10}$ 345); and moving private investment to climate-friendly financial products and mandating banks and investment companies to disclose their greenhouse gas emissions to consumers (log $BF_{10}$ 233). We also found strong evidence that this relationship varied across countries ($BFs_{10}$ 631, 129, 7160; Fig. 3).

Further, we found moderate to strong evidence that the higher the income, the stronger the relationship between perceived behavioral plasticity and matched policy support across all behaviors and countries ($BFs_{10}$ 11.3, 4.4, 6456), and strong evidence that this interaction does not differ across countries ($BFs_{01}$ 233, 67.8, 208.7). We conducted

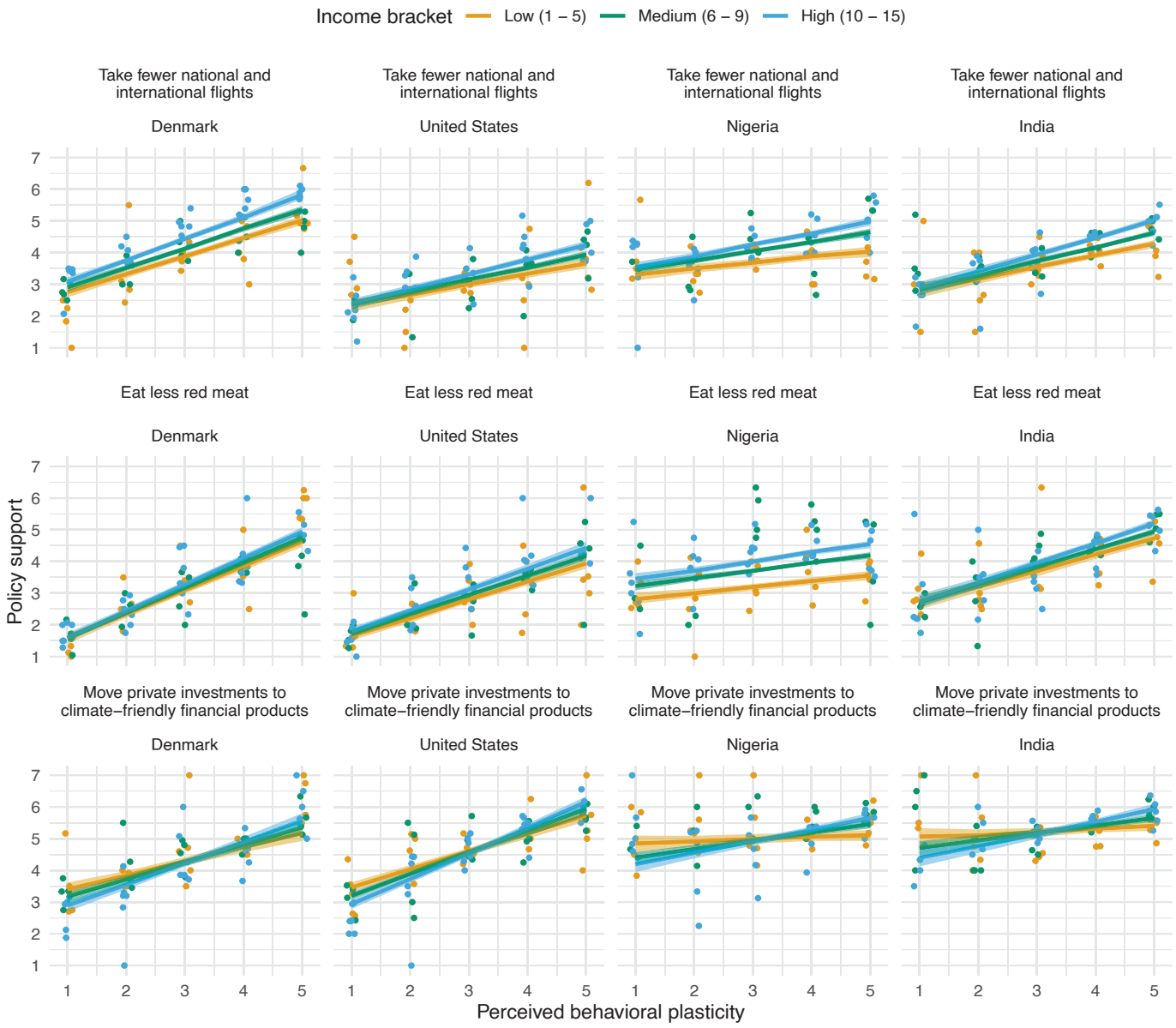


**Fig. 3.** Relationship between perceived behavioral plasticity and domain-matched policy support across income and countries. Model-averaged posterior mean and 95% credible intervals of domain-matched mean policy support across perceived plasticity of behaviors, income groups, and countries. Points indicate empirical means within income groups and levels of perceived behavioral plasticity. Taking fewer flights was matched with support for increasing taxes on air travel, eating less red meat with increasing taxes on red meat, and moving private investment to more climate-friendly financial products by requiring banks and investment companies to disclose their greenhouse gas emissions to consumers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

several sensitivity analyses and found that all Bayes factors are robust to different prior specifications (Fig. S11). Model-averaged posterior estimates for the effect of behavioral plasticity, income, and their interaction on policy support across behaviors and countries are presented in Fig. S12.

We observed a similar pattern when examining the relationship between perceived behavioral plasticity and climate policy support for more loosely domain-matched policies, such as driving fewer kilometers and supporting the expansion of public transport (Fig. S13 and S14). Additionally, we found a consistent pattern when averaging perceived behavioral plasticity across all behaviors and policy support across all policies (Fig. S15). We also conducted pairwise correlations between all behaviors and climate policies across countries (Fig. S16-S19). The results indicate that climate policy support correlated more strongly with perceived plasticity for domain-relevant behaviors compared to those that are not, underscoring the robustness of the finding that perceived behavioral plasticity was strongly associated with domain-matched climate policy support.

## 4. Discussion

This study explored income differences in perceived behavioral plasticity and its link to climate policy support across four diverse countries. Our results reveal substantial heterogeneity in the perceived plasticity of investment and curtailment behaviors across countries, with higher plasticity observed descriptively in the Indian and Nigerian samples. Additionally, we identified varying relationships between income and perceptions of behavioral plasticity across different behaviors and countries. Finally, extending previous research (Kukowski et al., 2023b), we found that participants with higher perceived behavioral

plasticity reported greater support for domain-matched climate policies, and this relationship was stronger among high-income participants.

Our study's oversampling of high-income individuals permitted a unique examination of potential differences in perceived behavioral plasticity along the income distribution. While some heterogeneity was expected given the diversity of countries, socioeconomic contexts, and the behaviors studied, we generally expected a positive relationship between income and perceived behavioral plasticity. This expectation was grounded in observations that wealthier individuals typically face fewer adoption barriers and have larger carbon footprints, offering more potential for curtailment with potentially limited impact on wellbeing or basic needs. However, we found no consistent overall relationship between income and perceived behavioral plasticity. Instead, the results revealed substantial heterogeneity across behaviors and countries. Income was positively associated with perceived behavioral plasticity for certain behaviors, such as eating less red meat and purchasing an electric vehicle, across all countries; however, there was no evidence of a relationship with the perceived plasticity of using less energy for heating and cooling or installing solar panels at home. For other behaviors, such as taking fewer flights and replacing older appliances with newer energy-efficient models, the relationship between income and perceived behavioral plasticity differed across countries. For example, while participants with higher incomes in Denmark and the United States were less likely to take fewer flights in the near future, no strong relationship was observed in Nigeria and India. This finding is particularly interesting, as air travel is considerably more common among the wealthy in Denmark and the United States, typically accounting for a dominant share of their carbon footprints (Gössling, 2019; Gössling and Humpe, 2020; Ivanova and Wood, 2020; Otto et al., 2019). Their presumed more frequent air travel should offer them greater overall potential for reduction while still achieving the underlying goals (e.g., visiting family or friends or enjoying a family vacation). Yet, this finding may suggest that either higher-income participants are unwilling to reduce air travel, potentially due to a perceived wellbeing loss from foregoing trips or using other means of transport, or that their current air travel is behaviorally locked in (e.g., due to work-related responsibilities or prevailing social norms) (Cass, 2022; Gössling et al., 2019; Schmidt et al., 2023).

The heterogeneous results for income highlight its complex relationship with perceptions of behavioral plasticity. For example, unlike previous behavior-focused research conducted in Western contexts (Umit et al., 2019), high-income participants did not consistently report higher perceived plasticity for investment behaviors compared to curtailment behaviors. The inconsistent relationship between income and perceived behavioral plasticity likely reflects various factors that differ across countries. One reason may be that although wealthier individuals often have a higher feasibility of adopting low-carbon behavior, they may not be willing to seize these opportunities for change (e.g., due to perceived wellbeing or status implications). This would suggest a perceptual or motivational barrier to change. Another reason could be the presence of structural barriers (e.g., unavailability of public transport or low-carbon financial investment products) and skewed incentives (e.g., subsidized air travel, fossil-fuel-based household equipment, or meat products) (Creutzig et al., 2022b; Günther et al., 2025; Seto et al., 2016), which may make specific climate-friendly behavioral changes challenging, even for the wealthy in Denmark and the United States. Such barriers and skewed incentives are shaped not only by existing infrastructure and markets but also by the ambition, design, and achieved implementation of national climate policies and commitments (e.g., nationally determined contributions, NDCs), which may influence the perceived feasibility and salience of specific low-carbon behaviors. Moreover, because the top 10 % income thresholds were defined for each country, absolute purchasing power varied substantially across the samples. As a result, a high-income participant in Nigeria or India may still face financial, infrastructural, or market constraints (e.g., limited availability of electric vehicles or plant-based meat alternatives) that do not necessarily affect high-income participants in Denmark or the United States. However, the generally high perceived plasticity observed in India and Nigeria suggests that other factors, such as a wider knowledge gap in climate action, response bias, or aspirations for investment behaviors (Marquardt et al., 2023), may also be at play. Further research is required to replicate and disentangle these complex findings.

Our primary analyses focused on participants who could realistically perform the behaviors, thereby representing the pool of realizable behavior changes best. However, this pool is dynamic and can change substantially over time. Ideally, an increasing number of people would adopt low-carbon behaviors, but people can, in principle, also adopt or revert to carbon-intensive behaviors, such as eating red meat, traveling by air, or purchasing a fossil-fuel-powered vehicle. Given the cross-sectional nature of our study, we cannot capture such dynamic changes. Consequently, systematically collecting and curating data on climate-relevant behavior is crucial and will enable effective monitoring of changes in behavior and perceived behavioral plasticity across population segments and over time (Jenny and Betsch, 2022; Nielsen et al., 2024b). Moreover, it will enable assessing the extent to which perceived behavioral plasticity translates into actual behavior change. Currently, such evidence is scarce. While a perfect correspondence is unlikely, as widely revealed by studies of the intention-behavior relationship (Dablander et al., 2025b; Sheeran and Webb, 2016), even a moderate alignment would not diminish the scientific or practical value of perceived behavioral plasticity as an indicator of where and how behavioral change is most likely to occur. People may under- or overestimate their likelihood of change, and as our results show, such self-assessments can still meaningfully shape policy preferences. Accordingly, perceived behavioral plasticity may reflect motivational, capability, or opportunity constraints that are directly relevant to climate policy design, even if behavior change does not ultimately materialize.

From a policy perspective, perceived behavioral plasticity may also help identify and stimulate positive spillover effects across behaviors. When individuals perceive certain low-carbon behaviors as feasible and begin to adopt them, this perception may strengthen their confidence and motivation to engage in related behaviors or to support broader policy initiatives (Maki et al., 2019; Sparkman et al., 2021). Future research should examine whether, and under what conditions, perceived behavioral plasticity fosters such behavioral and policy spillovers, thereby amplifying the impact of targeted initiatives.

We found strong evidence that higher perceived behavioral plasticity is associated with higher climate policy support, replicating the findings of Kukowski et al. (2023b). We extend this work by showing that this association is stronger among high-income than lower-income individuals. Several mechanisms may explain this moderation (see Mundaca et al., 2022; Steg and Vlek, 2009; van Valkengoed et al., 2022 for comprehensive overviews). First, high-income individuals often have greater political efficacy and a stronger sense of influence over public decision-making, which may increase the likelihood that perceived plasticity translates into policy support. Second, supporting a policy may also reinforce or validate their own capacity or status: if a behavior seems feasible for them, they may be more likely to view policy as an appropriate way to encourage others to follow suit. Third, high-income individuals might anticipate future regulation of high-impact behaviors; if they already perceive a behavior as feasible, supporting a related policy may represent a form of strategic alignment by adopting or supporting what is coming anyway (though this might vary across political orientations). Fourth, lower-income individuals may be more likely to perceive a behavior as feasible yet still hesitate to support policies that could impose costs or seem misaligned with their broader social context (Grelle and Hofmann, 2024; Tobler et al., 2012). Fifth, higher-income individuals may be more exposed to climate discourse and expectations around low-carbon norms, particularly for investment behaviors, leading them to internalize greater alignment between their own behavior and policy preferences. Relatedly, they may be more attuned to

the availability of low-carbon alternatives (e.g., electric vehicles, climate-friendly investments), making perceived feasibility a more credible signal that policy change is timely and achievable. Future research should explore how cognitive, emotional, and structural factors shape climate policy attitudes across income groups, using experimental and longitudinal designs to disentangle causality better.

Our results have notable implications for climate policy. First, evidence of perceived behavioral plasticity can help tailor and target behavior change initiatives to specific population segments (for an overview and evidence of behavior change interventions, see Balmford et al., 2021; Bergquist et al., 2023; Composto and Weber, 2022; Khanna et al., 2021). For example, realizing behavior change among people with low perceived plasticity may require more resources and well-designed structural policies (e.g., taxation, infrastructure development, or restricting carbon-intensive behaviors). In contrast, fewer resources and initiatives may be necessary to realize behavioral changes among individuals reporting high perceived plasticity. Second, the distinction between perceived and objective barriers is important. Even if perceived behavioral plasticity does not perfectly predict behavior, it reflects how individuals appraise the motivational, structural, or opportunity-related constraints they face around climate-friendly behavior changes. Such perceptions themselves can influence policy attitudes and behavior change readiness, almost independently of whether they are aligned with 'objective' feasibility (e.g., actual availability of electric charging stations or plant-based meat alternatives in supermarkets). Third, since higher-income individuals tend to have disproportionate political and economic influence (Dietz and Whitley, 2018; Green and Healy, 2022; Nielsen et al., 2021b), their perceptions of behavioral plasticity and their willingness to support corresponding policies carry outsized weight, even in democratic countries. Lastly, our finding that income moderates the relationship between perceived behavioral plasticity and climate policy support suggests that policy design and messaging may need to be differentiated across socioeconomic groups. Among high-income individuals, who are more likely to translate perceived plasticity into policy support, communication efforts could emphasize how implementing feasible behavioral changes contributes to broader climate action. For lower-income individuals, support might depend less on perceived plasticity and more on whether policies are perceived as personally costly, fair, and tackling experienced constraints.

Our study has several limitations. Firstly, our sampling strategy deliberately prioritized a greater representation of high-income individuals, who typically have larger personal carbon footprints (Chancel, 2022; Oswald et al., 2020) and greater political, organizational, and social influence, over representativeness. This decision resulted in samples skewed from the general population, with a larger share of participants potentially being atypical or outliers in each country. Secondly, perceived plasticity was unexpectedly high for many behaviors in India and some in Nigeria; these descriptive results should therefore be interpreted with some caution. While these perceptions may reflect actual plasticity, we speculate that other factors, such as aspiration, future-oriented actions, psychological distance, self-deception, or social desirability bias, may have played a role (Gifford, 2011; Mundaca and Wamsler, 2025; Vesely and Klöckner, 2020; Vilar et al., 2020). This is particularly relevant for certain investment behaviors, such as shifting private investment to climate-friendly financial products, purchasing an electric vehicle, or installing solar panels, where availability and affordability may pose challenges. Although sampling bias in survey research across the Global South remains a persistent challenge, the diverse representation of high-income individuals from India and Nigeria is a key feature of our study. However, this representation requires careful contextualization for generalizability (Boas et al., 2020; Brown et al., 2024), and our results provide only an initial understanding of these complex behavioral dynamics and motivations. We encourage future research to complement our work with mixed-methods research and semi-structured interviews. Thirdly, despite following conventional measurement practices, the climate policy support measures did not fully capture each country's unique climate policy landscape, which is a common limitation of cross-cultural research. Fourthly, the examined behavior changes were framed as either absolute (e.g., purchasing an electric vehicle) or relative (e.g., reducing red meat consumption) to avoid underestimating the opportunity space for change—if we had asked about becoming vegan, for instance, we might have underestimated the likelihood of substantially reducing rather than eliminating meat consumption. Nonetheless, we acknowledge that perceptions of behavioral plasticity are sensitive to such framings. Fifthly, we acknowledge the limitations of sampling only Indians fluent in English, as English fluency is not widespread across the general Indian population, especially in rural areas. However, our Indian sample comprised individuals from relatively high socioeconomic backgrounds, among whom English proficiency is typically high due to educational and occupational exposure. Finally, although the perceived behavioral plasticity measure is efficient and can usefully identify promising behaviors for policy intervention, follow-up analyses are needed to determine whether low perceived plasticity reflects a lack of motivation or external factors that hinder behavioral change. Moreover, the interpretation of the measure might vary across countries due to differences in behavioral baselines, culture, and language, underscoring the need for future studies to assess the measurement invariance and contextual influences on measurement interpretation.

In this study, we primarily focused on income-related differences in the perceived plasticity of consumer behaviors and their links to climate policy support. However, people can also effectively promote or counteract climate change mitigation in other areas of their lives (Hampton and Whitmarsh, 2023; Nielsen et al., 2024b). The opportunity space and impact potential are especially large for those with high socioeconomic status (Nielsen et al., 2021b). Understanding whether wealthier individuals are aware of and willing to leverage this potential is a promising avenue for future research (Duncan et al., 2024). Our findings highlight that individual behavior change does not occur in isolation but is closely tied to systemic factors. Moreover, they demonstrate that people's behavior is directly related to their support for policies that facilitate broader societal transitions. Recognizing this interdependence is essential for designing policies that effectively integrate behavior change initiatives with structural climate solutions (Creutzig et al., 2022b; Nielsen et al., 2024b).

## 5. Conclusion

This study explored how perceived behavioral plasticity and its link to climate policy support vary across countries and income groups, using survey data from 4003 individuals in Denmark, India, Nigeria, and the United States, with high representation of high-income individuals. We found substantial heterogeneity in perceived behavioral plasticity across countries and behaviors, with particularly high perceived plasticity observed in India and Nigeria. While high-income participants reported greater perceived plasticity for some behaviors, such as purchasing electric vehicles and eating less red meat, the relationship between income and perceived behavioral plasticity was inconsistent overall. This underscores the complex interplay between socioeconomic status, behavioral feasibility, and contextual factors. Notably, perceived plasticity was strongly and positively associated with support for domain-matched climate policies, especially among high-income individuals. This suggests that increasing motivation and opportunity for individual change does not come at the expense of policy support. Instead, individual- and system-level approaches to mitigation may reinforce each other. The stronger association among high-income individuals is particularly important, as they not only have the largest carbon footprints but also disproportionate political and economic influence. By contrast, the weaker association among lower-income groups may reflect concerns about affordability and fairness, underscoring the importance of protecting vulnerable households in climate policy design.

Together, these findings suggest that perceived behavioral plasticity may provide policymakers with a useful indicator for identifying behavior changes that are both psychologically and politically feasible. However, limitations such as the potential for self-report biases, contextual variability in measurement interpretation, and a non-representative sample of high-income individuals warrant caution. Future research should explore how perceived and actual behavioral plasticity align across contexts and time, and how national climate frameworks shape both. Longitudinal and mixed-method approaches may be especially valuable for disentangling causal pathways and understanding how socioeconomic and structural factors constrain or enable behavior change.

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## Ethics statement

The survey was approved by the IRB at the University of Basel (020-22-1). We obtained informed consent from all participants before completing the survey.

## CRediT authorship contribution statement

**Kristian S. Nielsen:** . **Fabian Dablander:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Ramit Debnath:** Writing – review & editing, Methodology, Conceptualization. **Charles A. Emogor:** Writing – review & editing, Methodology, Conceptualization. **Sakshi Ghai:** Writing – review & editing, Conceptualization. **Wencke Gwozdz:** Writing – review & editing, Funding acquisition, Conceptualization. **Ulf J.J. Hahnel:** Writing – review & editing, Funding acquisition, Conceptualization. **Wilhelm Hofmann:** Writing – review & editing, Conceptualization. **Jan M. Bauer:** Writing – review & editing, Methodology, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2025.103107.

## Data availability

The data, code, and study materials are available via the Open Science Framework: osf.io/j8txq.

## References

Allen, S., Dietz, T., Mccright, A.M., 2015. Measuring household energy efficiency behaviors with attention to behavioral plasticity in the United States. Energy Res. Soc. Sci. 10, 133–140. https://doi.org/10.1016/j.erss.2015.07.014.

Babagoli, M.A., Kaufman, T.K., Noyes, P., Sheffield, P.E., 2019. Exploring the health and spatial equity implications of the New York City Bike share system. J. Transp. Health 13, 200–209. https://doi.org/10.1016/j.jth.2019.04.003.

Balmford, A., Bradbury, R.B., Bauer, J.M., Broad, S., Burgess, G., Burgman, M., Nielsen, K.S., 2021. Making more effective use of human behavioural science in conservation interventions. Biol. Conserv. 261, 109256.

Bergquist, M., Thiel, M., Goldberg, M.H., van der Linden, S., 2023. Field interventions for climate change mitigation behaviors: a second-order meta-analysis. Proc. Natl. Acad. Sci. 120 (13), e2214851120. https://doi.org/10.1073/pnas.2214851120.

Boas, T.C., Christenson, D.P., Glick, D.M., 2020. Recruiting large online samples in the United States and India: Facebook, Mechanical Turk, and Qualtrics. Polit. Sci. Res. Methods 8 (2), 232–250. https://doi.org/10.1017/psrm.2018.28.

Borenstein, S., Davis, L.W., 2016. The distributional effects of US clean energy tax credits. Tax Policy Econ. 30 (1), 191–234. https://doi.org/10.1086/685597.

Brick, C., Nielsen, K.S., Berger, S., Henn, L., Wolske, K.S., Lange, F., Hanss, D., Bauer, J. M., Aldoh, A., Sachisthal, M.S.M., Johnsen, S.Å.K., Cologna, V., 2024. Current research practices on pro-environmental behavior: a survey of environmental psychologists. J. Environ. Psychol. 97, 102375. https://doi.org/10.1016/j.jenvp.2024.102375.

Brown, S., Saxena, D., Wall, P.J., 2024. Data collection in the global south: practical, methodological, and philosophical considerations. Inf. Technol. Dev. 30 (3), 379–399. https://doi.org/10.1080/02681102.2023.2185581.

Bruckner, B., Hubacek, K., Shan, Y., Zhong, H., Feng, K., 2022. Impacts of poverty alleviation on national and global carbon emissions. Nat. Sustainability 5, 311–320. https://doi.org/10.1038/s41893-021-00842-z.

Cass, N., 2022. Hyper-aeromobility: the drivers and dynamics of frequent flying. Consumpt. Soc. 1–23. https://doi.org/10.1332/LCWC4408.

Cass, N., Büchs, M., Lucas, K., 2023. How are high-carbon lifestyles justified? Exploring the discursive strategies of excess energy consumers in the United Kingdom. Energy Res. Soc. Sci. 97, 102951. https://doi.org/10.1016/j.erss.2023.102951.

CEPOS. (2019). Income, distribution, and incentives in Denmark 2019. https://cepos.dk/publications/income-distribution-and-incentives-in-denmark-2019/.

Chancel, L., 2022. Global carbon inequality over 1990–2019. Nat. Sustainability 5, 931–938. https://doi.org/10.1038/s41893-022-00955-z.

Composto, J.W., Weber, E.U., 2022. Effectiveness of behavioural interventions to reduce household energy demand: a scoping review. Environ. Res. Lett. 17 (6), 063005. https://doi.org/10.1088/1748-9326/ac71b8.

Creutzig, F., Niamir, L., Cullen, J., Díaz-josé, J., Lamb, W., Perkins, P., 2022a. Demand-side solutions to climate change mitigation consistent with high levels of wellbeing. Nat. Clim. Chang. 12, 36–46. https://doi.org/10.1038/s41558-021-01219-y.

Creutzig, F., Roy, J., Devine-Wright, P., Díaz-José, J., Geels, F., Grubler, A., Maïzi, N., Masanet, E., Mulugetta, Y., & Onyige-Ebeniro, C. (2022). Demand, services and social aspects of mitigation. In IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (s. 752–943). Cambridge University Press.

Dablander, F., Hickey, C., Sandberg, M., Zell-Ziegler, C., Grin, J., 2025a. Embracing sufficiency to accelerate the energy transition. Energy Res. Soc. Sci. 120, 103907. https://doi.org/10.1016/j.erss.2024.103907.

Dablander, F., Lange, F., Brick, C., Aron, A.R., 2025b. Expressing intentions is not climate action. Proc. Natl. Acad. Sci. 122 (28), e2512457122. https://doi.org/10.1073/pnas.2512457122.

De Coninck, H., Revi, A., Babiker, M., Bertoldi, P., Buckeridge, M., Cartwright, A., Dong, W., Ford, J., Fuss, S., & Hourcade, J. (2018). Strengthening and implementing the global response. I Global warming of 1.5C: Summary for policy makers (s. 313–443). IPCC-The Intergovernmental Panel on Climate Change.

De Nardo, M., Brooks, J.S., Klinsky, S., Wilson, C., 2017. Social signals and sustainability: Ambiguity about motivations can affect status perceptions of efficiency and curtailment behaviors. Environ. Syst. Decis. 37 (2), 184–197. https://doi.org/10.1007/s10669-017-9624-y.

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Sanchez Chico, A., Stantcheva, S., 2025. Fighting climate change: International attitudes toward climate policies. Am. Econ. Rev. 115 (4), 1258–1300.

Diaconis, P., Skyrms, B., 2018. Ten Great Ideas About Chance. Princeton University Press.

Dietz, T., Gardner, G.T., Gilligan, J., Stern, P.C., Vandenbergh, M.P., 2009. Household actions can provide a behavioral wedge to rapidly reduce U.S. carbon emissions. Proc. Natl. Acad. Sci. 106 (44), 18452–18456.

Dietz, T., Whitley, C.T., 2018. Inequality, decisions, and altruism. Sociol. Dev. 4, 282–303.

Duncan, S., Hjelmskog, A., & Papies, E. K. (2023). A low-carbon future? Individuals with high socioeconomic status in the UK show little willingness to change high-carbon lifestyles for climate change mitigation. Doi: 10.31234/osf.io/mh8dq.

Duncan, S., Hjelmskog, A., Papies, E.K., 2024. No agency and responsibility for the privileged? Perceptions of climate action among high socioeconomic status citizens in the United Kingdom. Energy Res. Soc. Sci. 115, 103604. https://doi.org/10.1016/j.erss.2024.103604.

Ermagun, A., Tian, J., 2024. Charging into inequality: a national study of social, economic, and environment correlates of electric vehicle charging stations. Energy Res. Soc. Sci. 115, 103622. https://doi.org/10.1016/j.erss.2024.103622.

Geels, F.W., 2023. Demand-side emission reduction through behavior change or technology adoption? Empirical evidence from UK heating, mobility, and electricity use. One Earth 6 (4), 337–340. https://doi.org/10.1016/j.oneear.2023.03.012.

Gelman, A., Hill, J., Yajima, M., 2012. Why we (usually) don't have to worry about multiple comparisons. J. Res. Educ. Effect. 5 (2), 189–211.

Ghai, S., 2021. It's time to reimagine sample diversity and retire the WEIRD dichotomy. Nat. Hum. Behav. 5, 971–972. https://doi.org/10.1038/s41562-021-01175-9.

Gibson, C.C., Ostrom, E., Ahn, T.K., 2000. The concept of scale and the human dimensions of global change: a survey. Ecol. Econ. 32 (2), 217–239. https://doi.org/10.1016/s0921-8009(99)00092-0.

Gifford, R., 2011. The dragons of inaction: psychological barriers that limit climate change mitigation and adaptation. Am. Psychol. 66, 290–302. https://doi.org/10.1037/a0023566.
Green, F., Healy, N., 2022. How inequality fuels climate change: the climate case for a Green New Deal. One Earth 5, 635–649. https://doi.org/10.1016/j.oneear.2022.05.005.
Grelle, S., Hofmann, W., 2024. When and why do people accept public policy interventions? an integrative public policy acceptance framework. Perspect. Psychol. Sci. 19, 258–279. https://doi.org/10.1177/17456916231180580.
Greenland, S., Senn, S.J., Rothman, K.J., Carlin, J.B., Poole, C., Goodman, S.N., Altman, D.G., 2016. Statistical tests, P values, confidence intervals, and power: a guide to misinterpretations. Eur. J. Epidemiol. 31 (4), 337–350.
Günther, A., Engel, L., Hornsey, M.J., Nielsen, K.S., Roy, J., Steg, L., Tam, K.-P., Van Valkengoed, A.M., Wolske, K.S., Wong-Parodi, G., Hahnel, U.J.J., 2025. Psychological and contextual determinants of clean energy technology adoption. Nat. Rev. Clean Technol. https://doi.org/10.1038/s44359-025-00075-9.
Gössling, S., 2019. Celebrities, air travel, and social norms. Ann. Tour. Res. 79, 102775. https://doi.org/10.1016/j.annals.2019.102775.
Gössling, S., Hanna, P., Higham, J., Cohen, S., Hopkins, D., 2019. Can we fly less? evaluating the 'necessity' of air travel. J. Air Transp. Manag. 81, 101722. https://doi.org/10.1016/j.jairtraman.2019.101722.
Gössling, S., Humpe, A., 2020. The global scale, distribution and growth of aviation: Implications for climate change. Glob. Environ. Chang. 65, 102194. https://doi.org/10.1016/j.gloenvcha.2020.102194.
Hampton, S., Whitmarsh, L., 2023. Choices for climate action: a review of the multiple roles individuals play. One Earth 6 (9), 1157–1172. https://doi.org/10.1016/j.oneear.2023.08.006.
Henrich, J., Heine, S.J., Norenzayan, A., 2010. The weirdest people in the world? Behav. Brain Sci. 33 (2–3), 61–83. https://doi.org/10.1017/S0140525X0999152X.
Herberz, M., Hahnel, U.J.J., Brosch, T., 2022. Counteracting electric vehicle range concern with a scalable behavioural intervention. Nat. Energy 76, 503–510. https://doi.org/10.1038/s41560-022-01028-3.
Hinne, M., Gronau, Q.F., Van Den Bergh, D., Wagenmakers, E.-J., 2020. A conceptual introduction to bayesian model averaging. Adv. Methods Pract. Psychol. Sci. 3 (2), 200–215. https://doi.org/10.1177/2515245919898657.
Hoenig, J.M., Heisey, D.M., 2001. The abuse of power: the pervasive fallacy of power calculations for data analysis. Am. Statist. 55 (1), 19–24.
Ivanova, D., Barrett, J., Wiedenhofer, D., Macura, B., Callaghan, M., Creutzig, F., 2020. Quantifying the potential for climate change mitigation of consumption options. Environ. Res. Lett. 15 (9), 093001. https://doi.org/10.1088/1748-9326/ab8589.
Ivanova, D., Wood, R., 2020. The unequal distribution of household carbon footprints in Europe and its link to sustainability. Global Sustain. 3 (e18), 1–12.
Jamil, T., Ly, A., Morey, R.D., Love, J., Marsman, M., Wagenmakers, E.-J., 2017. Default "Gunel and Dickey" Bayes factors for contingency tables. Behav. Res. Methods 49 (2), 638–652. https://doi.org/10.3758/s13428-016-0739-8.
Jaynes, E.T., 2003. Probability Theory: The Logic of Science. Cambridge University Press.
Jenny, M.A., Betsch, C., 2022. Large-scale behavioural data are key to climate policy. Nat. Hum. Behav. 6 (11), 1444–1447. https://doi.org/10.1038/s41562-022-01479-4.
Kass, R.E., Raftery, A.E., 1995. Bayes Factors. J. Am. Stat. Assoc. 90 (430), 773–795. https://doi.org/10.1080/01621459.1995.10476572.
Khanna, T.M., Baiocchi, G., Callaghan, M., Creutzig, F., Guias, H., Haddaway, N.R., Hirth, L., Javaid, A., Koch, N., Laukemper, S., 2021. A multi-country meta-analysis on the role of behavioural change in reducing energy consumption and $CO_2$ emissions in residential buildings. Nat. Energy 6 (9), 925–932.
Kukowski, C.A., Bernecker, K., Nielsen, K.S., Hofmann, W., Brandstätter, V., 2023a. Regulate me! Self-control dissatisfaction in meat reduction success relates to stronger support for behavior-regulating policy. J. Environ. Psychol. 85, 101922. https://doi.org/10.1016/j.jenvp.2022.101922.
Kukowski, C.A., Garnett, E.E., 2023. Tackling inequality is essential for behaviour change for net zero. Nat. Clim. Chang. 14, 2–4. https://doi.org/10.1038/s41558-023-01900-4.
Kukowski, C.A., Hofmann, W., Roozenbeek, J., van der Linden, S., Vandenbergh, M.P., Nielsen, K.S., 2023b. The perceived feasibility of behavior change is positively associated with support for domain-matched climate policies. One Earth 6 (11), 1554–1563. https://doi.org/10.1016/j.oneear.2023.10.017.
Lindley, D.V., 2000. The philosophy of statistics. J. R. Stat. Soc. Ser. Stat. 49, 293–337. https://doi.org/10.1111/1467-9884.00238.
Maki, A., Carrico, A.R., Raimi, K.T., Truelove, H.B., Araujo, B., Yeung, K.L., 2019. Meta-analysis of pro-environmental behaviour spillover. Nat. Sustainability 2 (4), 307–315. https://doi.org/10.1038/s41893-019-0263-9.
Marquardt, J., Fünfgeld, A., Elsässer, J.P., 2023. Institutionalizing climate change mitigation in the Global South: current trends and future research. Earth Syst. Governance 15, 100163. https://doi.org/10.1016/j.esg.2022.100163.
McFadden, B.R., Ferraro, P.J., Messer, K.D., 2022. Private costs of carbon emissions abatement by limiting beef consumption and vehicle use in the United States. PLoS One 17, e0261372. https://doi.org/10.1371/journal.pone.0261372.
Moorcroft, H., Hampton, S., & Whitmarsh, L. (2024). Climate change and wealth: Understanding and improving the carbon capability of the wealthiest people in the UK (SSRN Scholarly Paper No. 4723179). Doi: 10.2139/ssrn.4723179.
Mundaca, L., Wamsler, C., 2025. Engaging high-income earners in climate action: policy insights from survey experiments. Ecol. Econ. 227, 108387. https://doi.org/10.1016/j.ecolecon.2024.108387.
Mundaca, L., Zhu, X., Hackenfort, M., 2022. Behavioural insights for sustainable energy use. Energ. Policy 171, 113292. https://doi.org/10.1016/j.enpol.2022.113292.
Nielsen, K.S., Bauer, J.M., Debnath, R., Emogor, C.A., Geiger, S.M., Ghai, S., Gwozdz, W., Hahnel, U.J.J., 2024a. Underestimation of personal carbon footprint inequality in four diverse countries. Nat. Clim. Chang. 1–8. https://doi.org/10.1038/s41558-024-02130-y.
Nielsen, K.S., Clayton, S., Stern, P.C., Dietz, T., Capstick, S., Whitmarsh, L., 2021a. How psychology can help limit climate change. Am. Psychol. 76, 130–144. https://doi.org/10.1037/amp0000624.
Nielsen, K.S., Cologna, V., Bauer, J.M., Berger, S., Brick, C., Dietz, T., Hahnel, U.J.J., Henn, L., Lange, F., Stern, P.C., Wolske, K.S., 2024b. Realizing the full potential of behavioural science for climate change mitigation. Nat. Clim. Chang. 14, 322–330.
Nielsen, K.S., Nicholas, K.A., Creutzig, F., Dietz, T., Stern, P.C., 2021b. The role of high-socioeconomic-status people in locking in or rapidly reducing energy-driven greenhouse gas emissions. Nat. Energy 6 (11), 1011–1016. https://doi.org/10.1038/s41560-021-00900-y.
Nielsen, K.S., Stern, P.C., Dietz, T., Gilligan, J.M., van Vuuren, D.P., Figueroa, M.J., Folke, C., Gwozdz, W., Ivanova, D., Reisch, L.A., Vandenbergh, M.P., Wolske, K.S., Wood, R., 2020. Improving climate change mitigation analysis: a framework for examining feasibility. One Earth 3 (3), 325–336. https://doi.org/10.1016/j.oneear.2020.08.007.
Oswald, Y., Owen, A., Steinberger, J.K., 2020. Large inequality in international and intranational energy footprints between income groups and across consumption categories. Nat. Energy 5 (3), 231–239. https://doi.org/10.1038/s41560-020-0579-8.
Otto, I.M., Kim, K.M., Dubrovsky, N., Lucht, W., 2019. Shift the focus from the super-poor to the super-rich. Nat. Clim. Chang. 9 (2), 82–84. https://doi.org/10.1038/s41558-019-0402-3.
PK. (2023, september 29). Average, median, Top 1% individual income percentiles. DQYDJ. https://dqydj.com/average-median-top-individual-income-percentiles/.
Poore, J., Nemecek, T., 2018. Reducing food's environmental impacts through producers and consumers. Science 360 (6392), 987–992. https://doi.org/10.1126/science.aaq0216.
Poortinga, W., 2025. The role of policy appraisals and second-order beliefs in public support for climate policies in the UK. Clim. Policy 1–15. https://doi.org/10.1080/14693062.2025.2539977.
Ravallion, M., 2022. Missing top income recipients. J. Econ. Inequal. 20 (1), 205–222.
Rouder, J.N., Morey, R.D., 2012. Default Bayes factors for model selection in regression. Multivar. Behav. Res. 47 (6), 877–903. https://doi.org/10.1080/00273171.2012.734737.
Schmidt, F., Sidders, A., Czepkiewicz, M., Árnadóttir, Á., Heinonen, J., 2023. 'I am not a typical flyer': Narratives about the justified or excessive character of international flights in a highly mobile society. J. Sustain. Tour. 1–24. https://doi.org/10.1080/09669582.2023.2214344.
Schönbrodt, F.D., Wagenmakers, E.-J., 2018. Bayes factor design analysis: planning for compelling evidence. Psychon. Bull. Rev. 25 (1), 128–142.
Seto, K.C., Davis, S.J., Mitchell, R.B., Stokes, E.C., Unruh, G., Ürge-Vorsatz, D., 2016. Carbon lock-in: types, causes, and policy implications. Annu. Rev. Env. Resour. 41, 425–452. https://doi.org/10.1146/annurev-environ-110615-085934.
Sheeran, P., Webb, T.L., 2016. The Intention-Behavior Gap. Soc. Pers. Psychol. Compass 10 (9), 503–518. https://doi.org/10.1111/spc3.12265.
Sovacool, B.K., Newell, P., Carley, S., Fanzo, J., 2022. Equity, technological innovation and sustainable behaviour in a low-carbon future. Nat. Hum. Behav. 6, 326–337. https://doi.org/10.1038/s41562-021-01257-8.
Sparkman, G., Attari, S. Z., & Weber, E. U. (2021). Moderating spillover: Focusing on personal sustainable behahvior rarely hinders and can boost climate policy support. Energy Res. Soc. Sci., 78 (July 2020), 102150–102150. Doi: 10.1016/j.erss.2021.102150.
Steg, L., Vlek, C., 2009. Encouraging pro-environmental behaviour: an integrative review and research agenda. J. Environ. Psychol. 29, 309–317. https://doi.org/10.1016/j.jenvp.2008.10.004.
Stern, P.C., 2011. Contributions of psychology to limiting climate change. Am. Psychol. 66 (4), 303–314. https://doi.org/10.1037/a0023235.
Stern, P.C., Dietz, T., Nielsen, K.S., Peng, W., Vandenbergh, M.P., 2023. Feasible climate mitigation. Nat. Clim. Chang. 13 (1), 6–8.
Stern, P.C., Young, O.R., Druckman, D.E., 1992. Global environmental change: Understanding the human dimensions. National Academy Press.
The Times of India. (2022, maj 20). People earning Rs 25,000 per month fall in top 10% of wage earners in India: Report. The Times of India. https://timesofindia.indiatimes.com/business/india-business/people-earning-rs-25000-per-month-fall-in-top-10-of-wage-earners-in-india-report/articleshow/91694940.cms.
Tian, P., Zhong, H., Chen, X., Feng, K., Sun, L., Zhang, N., Shao, X., Liu, Y., Hubacek, K., 2024. Keeping the global consumption within the planetary boundaries. Nature 1–6. https://doi.org/10.1038/s41586-024-08154-w.
Tobler, C., Visschers, V.H.M., Siegrist, M., 2012. Addressing climate change: determinants of consumers' willingness to act and to support policy measures. J. Environ. Psychol. 32, 197–207. https://doi.org/10.1016/j.jenvp.2012.02.001.
Umit, R., Poortinga, W., Jokinen, P., Pohjolainen, P., 2019. The role of income in energy efficiency and curtailment behaviours: findings from 22 European countries. Energy Res. Soc. Sci. 53, 206–214. https://doi.org/10.1016/j.erss.2019.02.025.
Uren, H.V., Roberts, L.D., Dzidic, P.L., Leviston, Z., 2021. High-status pro-environmental behaviors: costly, effortful, and visible. Environ. Behav. 53 (5), 455–484. https://doi.org/10.1177/0013916519882773.
van den Bergh, D., Van Doorn, J., Marsman, M., Draws, T., Van Kesteren, E.-J., Derks, K., Dablander, F., Gronau, Q.F., Kucharskỳ, Š., Gupta, A.R.K.N., 2020. A tutorial on conducting and interpreting a Bayesian ANOVA in JASP. L'année Psychologique 120 (1), 73–96.

Van Doorn, J., Van Den Bergh, D., Böhm, U., Dablander, F., Derks, K., Draws, T., Wagenmakers, E.J., 2021. The JASP guidelines for conducting and reporting a Bayesian analysis. Psychon. Bull. Rev. 28 (3), 813–826.

van Valkengoed, A.M., Abrahamse, W., Steg, L., 2022. To select effective interventions for pro-environmental behaviour change, we need to consider determinants of behaviour. Nat. Hum. Behav. 6, 1482–1492. https://doi.org/10.1038/s41562-022-01473-w.

Vesely, S., Klöckner, C.A., 2020. Social desirability in environmental psychology research: three meta-analyses. Front. Psychol. 11.

Vilar, R., Milfont, T.L., Sibley, C.G., 2020. The role of social desirability responding in the longitudinal relations between intention and behaviour. J. Environ. Psychol., 101457–101457

Wagenmakers, E.-J., Morey, R.D., Lee, M.D., 2016. Bayesian benefits for the pragmatic researcher. Curr. Dir. Psychol. Sci. 25 (3), 169–176. https://doi.org/10.1177/0963721416643289.

Wagenmakers, E.-J., Verhagen, J., Ly, A., Bakker, M., Lee, M.D., Matzke, D., Morey, R.D., 2015. A power fallacy. Behav. Res. Methods 47 (4), 913–917.

Wamsler, C., Mundaca, L., Osberg, G., 2022. Rethinking political agency: the role of individuals' engagement, perceptions and trust in transitioning to a low-carbon transport system. J. Clean. Prod. 360, 132197. https://doi.org/10.1016/j.jclepro.2022.132197.

Wasserstein, R.L., Lazar, N.A., 2016. The ASA's statement on p-values: Context, process, and purpose. Am. Statist. 70 (2), 129–133.

Werfel, S.H., 2017. Household behaviour crowds out support for climate change policy when sufficient progress is perceived. Nat. Clim. Chang. 7 (7), 512–515.

Westlake, S., Demski, C., Pidgeon, N., 2024. "We can't be too saintly": why members of parliament in the United Kingdom are reluctant to lead by example with low-carbon behaviour. Energy Res. Soc. Sci. 117, 103717. https://doi.org/10.1016/j.erss.2024.103717.

World Bank Open Data. (2025). . https://data.worldbank.org.

Wynes, S., Motta, M., Donner, S.D., 2021. Understanding the climate responsibility associated with elections. One Earth 4 (3), 363–371. https://doi.org/10.1016/j.oneear.2021.02.008.

Zhang, S., Ferreira, S., Karali, B., 2025. Understanding public acceptability of climate policies in Europe. Clim. Pol. 25 (5), 725–740.