Creating clear and reliable scientific evidence for marine stakeholders with felt responsibility to act against climate change

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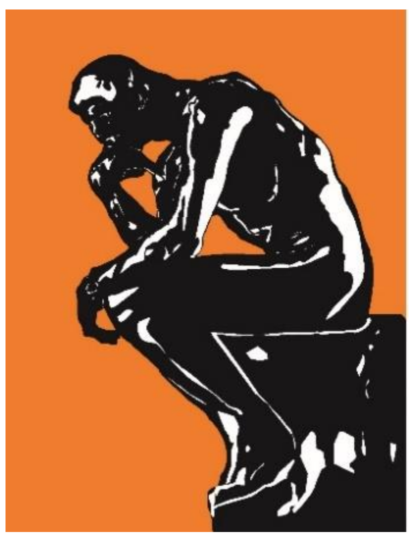

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Abstract

Climate change prevention necessitates the communication of transparent and reliable scientific evidence to improve public awareness and support. Felt responsibility is an essential factor influencing human environment-related psychology and behavior. However, the knowledge about the relationship between the felt responsibility and perceived uncertainty of scientific evidence regarding climate change has remained limited. The current study examines factors associated with the perceived uncertainty of scientific evidence (including felt responsibility to act on climate change) among stakeholders of marine and coastal ecosystems in 42 countries. Employing the Bayesian Mindsponge Framework (BMF) analytics on a dataset of 709 stakeholders generated by MaCoBioS—a research project funded by the European Commission Horizon 2020, we reveal several main insights. Stakeholders with lower educational levels, being males and not from high-income countries, are more likely to think scientific evidence regarding how to act on climate change is uncertain. Moreover, people with a higher felt responsibility to act on climate change are also more likely to perceive higher uncertainty of scientific evidence. Based on these findings, we discuss how scientific evidence should be communicated to build the eco-surplus culture and, subsequently, the felt responsibility of stakeholders while inoculating them from climate change misinformation and disinformation.

Keywords: responsibility; marine and coastal ecosystems; climate change denialism, Mindsponge Theory; information processing.

"— Perch or carp, no matter what is up to the Heaven."

In "Joint Venture"; *The Kingfisher Story Collection* (2022)

1. Introduction

Climate change constitutes a substantial issue with far-reaching consequences for the environment, society, and future generations (IPCC, 2023). Impacts include increased frequency of extreme weather events, the growing danger of rising sea levels to coastal communities, adverse effects on agriculture and the assurance of food security, changes to ecosystems leading to a decline in biodiversity, and major economic outcomes (UNCCS, 2019). Effectively tackling this pressing global challenge necessitates policy reforms and well-informed decision-making. The strategies need to involve both mitigations, which aim to lower greenhouse gas emissions using renewable energy sources (Fawzy et al., 2020), and adaptations, which concentrate on setting policies in place, including early warning systems to deal with the effects of climate change (Eriksen et al., 2021). For such strategies to be implemented effectively, public involvement is required.

However, several obstacles hinder human efforts to combat this global phenomenon. These include a lack of awareness of the problem (Clar et al., 2013), a lack of scientific understanding (Drummond & Fischhoff, 2017), and the denial of climate change (Gifford, 2011). Numerous studies have examined the role of awareness in ensuring individuals understand the significance of climate change and its implications (Lee et al., 2015; Reid, 2019). They suggest that without a greater understanding of the urgent situation, policymakers and the general public are unlikely to fully support and adopt comprehensive climate policies.

Even if people are aware of the problem but lack essential scientific knowledge, they may still find it challenging to thoroughly understand the complexities of climate change and its consequences. This knowledge gap can lead to misconceptions, uncertainty, and ineffective decision-making in tackling climate-related issues (Maibach et al., 2023). In some cases, the lack of scientific understanding even leads to climate change denial, which can undermine public support for necessary actions, delay regulation implementation, and disseminate misleading information (Bain et al., 2012). Some individuals or groups even deny the scientific consensus on climate change for political reasons. For example, former president of the United States of America, Donald J. Trump, even stated that he did not know climate change was "man-made" and even made a notorious decision to withdraw from the Paris Accords and overhaul government spending to cut programs overseen by the Environmental Protection Agency (EPA) (Friedman, 2018; Outka & Warner, 2019).

Therefore, the clarity of scientific information is crucial for climate change prevention as it helps raise public awareness and understanding of climate change. People and communities can better understand the severity and urgency of the problem when there is strong evidence of the effects of climate change (Van Kooten et al., 1997). For someone with little prior knowledge of science, the clarity and understandability of scientific facts may bridge the understanding gap. When scientific knowledge is conveyed understandably and straightforwardly, people can better understand the fundamental ideas and processes underlying climate change (Spence et al., 2012). Transparent and unambiguous scientific evidence also helps counter climate change denialism by providing insights and irrefutable data (Shi et al., 2016). Clear scientific communication helps eliminate misunderstandings and skepticism, making it harder for denialist narratives to gain traction. People are less likely to be persuaded by misleading assertions and align themselves with the scientific consensus when they can access convincing evidence (Farrell et al., 2019).

In addition, convincing communication (i.e., transparent, accessible, jargon-free statements with specified parameters and precise wording) is an effective tool for combating disinformation, revealing the realities around climate change (Dryhurst et al., 2022). When scientific discoveries are well communicated, it may create concern and a sense of obligation in people, inspiring them to look for more information, take part in sustainable actions, and advocate for rational legislation. Clear findings from research that convey a sense of urgency could motivate those who understand the implications to take urgent action. In contrast, the presence of uncertainty may cause some people to adopt a more cautious strategy and hesitate to make significant behavioral changes until they have more precise information (Whitmarsh, 2011).

Given the importance of precise and unambiguous scientific evidence, many studies have studied the complicated aspects of how people perceive and respond to information about climate change. They have shown sociodemographic factors (e.g., age, gender, education level, income, and cultural background) are elements that can potentially influence individuals' comprehension and acceptance of scientific evidence (Calculli et al., 2021; Guo et al., 2022; Sharon & Baram-Tsabari, 2020; Tranter, 2020). However, their impacts may vary depending on cultural and geographical contexts. Scientific findings generalizable to societies with different contextual factors can enhance policy implementation effectiveness and reduce costs associated with science (Vuong, 2018). Therefore, cross-national research is essential to provide a comprehensive, consistent understanding across various contexts.

Global issues like climate change require cooperation and coordinated actions from all nations (Subramanian et al., 2023). Although there is existing research on national economic conditions, such as levels of economic development and income inequality that can impact individuals' attitudes and beliefs about climate change (Levi, 2021; Peisker, 2023), further research is needed to examine how a country's economic level shapes people's perceived uncertainty regarding scientific evidence for combating climate change. Understanding how people interpret scientific information based on their nation's economic context might help international policymakers identify groups of countries with high public uncertainty about science, facilitating the planning of public communication agendas and programs.

The perception of responsibility is vital in tackling global challenges such as climate change as it can greatly influence human environment-related psychology and behavior (Babcock, 2009; Bouman et al., 2020; Kaiser et al., 1999; Moser, 2014; Taylor et al., 2014). Several studies have suggested that the perception of individual responsibility toward the environment strongly predicts pro-environmental behavior. In a study of the United States (US) public, the felt responsibility is found to be the mediation between beliefs in global warming and anthropogenic causation and climate engagement (Bateman & O'Connor, 2016). Meanwhile, in a study of 22 European countries, Bouman et al. (2020) also found the mediation role of feelings of personal responsibility to reduce climate change between worry about climate change and climate policy support. In a more recent study, Munson et al. (2021) even discovered that the feeling of personal responsibility can affect people's climate change-related political participation. Specifically, the public's felt responsibility has a significant positive relationship with future behavioral intent, such as willingness to join a campaign and support pro-climate presidential candidates. Despite these insights, a noticeable gap exists in the systematic exploration of the relationship between perceived responsibility and the perception of uncertainty within scientific evidence.

Moreover, earlier studies about felt responsibility mostly focused on general populations and paid limited attention to stakeholders of marine and coastal ecosystems. Marine and coastal ecosystems are indispensable for climate change reduction due to their roles in carbon sequestration and moderating extreme events, and marine and coastal ecosystems stakeholders are closely related to the conservation and usage of ecosystems (He & Silliman, 2019; Jankowska et al., 2022; Siikamäki et al., 2013). For this reason, gaining insights into the relationship between the stakeholders' felt responsibility and the perceived uncertainty of scientific evidence is needed.

Based on the above reasons, we aimed to examine the socio-economic factors that can predict the perceived uncertainty of scientific evidence. Applying the Mindsponge Theory, a theory of the mind that describes how people absorb and process information (Vuong, 2023; Vuong, Nguyen, et al., 2022a), we also attempted to reason how stakeholders' felt responsibility affects their perceived uncertainty of scientific evidence. The Bayesian Mindsponge Framework (BMF) analytics was employed to validate the theoretical reasoning to analyze MaCoBioS's dataset of 709 stakeholders in 42 countries (Nguyen et al., 2022a, 2022b). In general, this study has the following three main Research Objectives (ROs):

- **RO1:** Examine the impacts of sociodemographic factors on marine stakeholders' the perceived uncertainty of scientific evidence for acting against climate change
- **RO2:** Examine the impact of the national economic background on marine stakeholders' perceived uncertainty of scientific evidence for acting against climate change.
- **RO3:** Examine the impacts of marine stakeholders' felt responsibility on their perceived uncertainty of scientific evidence for acting against climate change.

2. Methodology

2.1. Theoretical foundation

The Mindsponge Theory was employed in the current study to provide theoretical reasoning for the third Research Objective (Vuong, 2023): Examining the role of people's responsibility on their perceived uncertainty of scientific evidence. Thus, this Subsection is dedicated to presenting the theory and its fundamental principles employed for the reasoning.

In the work examining the acculturation and the global mindset, Quan-Hoang Vuong and Nancy Napier introduced the concept of the "mindsponge mechanism" to describe the dynamic process by which the mind accepts or rejects new cultural values depending on a number of factors (Vuong & Napier, 2015). The metaphor "mindsponge" is used to explain how the mind works as "a sponge that squeezes out inappropriate values and absorbs new ones that fit or complement the context" (Vuong & Napier, 2015). The mindsponge mechanism has recently been developed into the Mindsponge Theory, an information-processing theory describing how the mind collects and processes information. The theory has been widely applied to a variety of socio-psychological studies (Asamoah et al., 2023; Jin et al., 2023; Kantabutra & Ketprapakorn, 2021; Khuc, Dang, et al., 2023; Khuc, Tran, et al., 2023; Kumar et al., 2022; Nguyen, Le, et al., 2023; Ruining et al., 2023; Ruining & Xiao, 2022; Santirocchi et al., 2023; Shu et al., 2023; Tanemura et al., 2022; Vuong et al., 2023; Vuong, Le, et al., 2022).

According to the Mindsponge Theory, the mind is a “collection-cum-processor” of information that absorb and process information and interact with the surrounding infosphere. The following characteristics make up the information-processing mechanism of the mind (Vuong, 2023):

- It is a dynamically self-balancing process that mirrors the innate patterns of systems in the biosphere.
- It involves a cost-benefit evaluation to maximize perceived benefits and minimize perceived costs for the system.
- It has objectives and priorities in accordance with the system’s requirements.
- It consumes energy and thus follows the principle of energy saving
- Its crucial function is to ensure the system's survival and growth through growth and reproduction.

Within the mind, the mindset is a set of highly-trusted information (core values or beliefs) retained in the memory, influencing subsequent thinking and driving behaviors. Core values in the mindset are used as the benchmark to evaluate the cost and benefit of the absorbed information during the filtering process, leading to the decision of rejecting or accepting the new information. Specifically, if the perceived benefits surpass the perceived costs, the information will be allowed to enter the core, and vice versa. Once entering the mindset, the information will become core values and be used as references for the mind’s future information processing (Vuong, Nguyen, et al., 2022a).

Felt responsibility is defined as a psychological construct reflecting the extent to which individuals feel compelled to take action toward a desired result (Munson et al., 2021). Speaking differently, the construct manifests an individual's belief that they should be the one doing the thing rather than assume that someone else will (Bateman & O’Connor, 2016). Felt responsibility is believed to play a critical role in translating abstract beliefs and attitudes about an issue into concrete actions (Munson et al., 2021). This view is supported by the Value-Belief-Norm Theory (Stern et al., 1999).

Through the information-processing lens of the Mindsponge Theory, we define felt responsibility as a psychological outcome of the information process within the mind. This process is greatly influenced by the mindset's core values (or beliefs). After the felt responsibility is generated, it will be stored in the mindset and influence the subsequent thinking processes (including the information absorption and filtering process) and drive behaviors (including the information-seeking process). Thus, when the person feels responsible for acting against climate change, conducting behaviors to reduce climate change might become one of their goals, giving value to information related to climate change. As a result, information related to climate change is easier to absorb and go through the mind's filter, subsequently affecting the person's behaviors toward climate change. Empirically, researchers have found that felt responsibility is positively associated with climate change engagement (e.g., climate action intentions and support for climate change adaptation and mitigation strategies) (Bateman & O'Connor, 2016).

Scientific evidence accounts for a significant proportion of information related to climate change, so the more information related to climate change is absorbed, the more scientific evidence about climate change is also absorbed. Nevertheless, uncertainty is inherent to scientific evidence, which is the concern of not only scientists and philosophers of science but also the general public, particularly in terms of the risks posed by social decisions based on ambiguous or disputed evidence (Bammer & Smithson, 2012; Pellizzoni, 2003). In a study of both Germans and Americans, Retzbach et al. (2016) found that people with more engagement with science, especially those with higher methodological scientific knowledge, are more likely to perceive scientific evidence as uncertain. Based on the information-processing reasoning and findings of former studies, we assumed that stakeholders with higher responsibility for acting on climate change might tend to perceive higher uncertainty in scientific evidence.

2.2. Materials and variable selection

The current research used a secondary dataset published and peer-reviewed in *Data in Brief*. The dataset was generated from an online, self-administered public awareness survey conducted between November 2021 and February 2022 by the MaCoBioS (Marine Coastal Ecosystems Biodiversity and Services in a Changing World). The survey resulted in 709 responses from marine and coastal ecosystems stakeholders in 42 different nations (Fonseca et al., 2023). The survey was designed to target stakeholders with an interest in marine and coastal ecosystems, climate change, and ecosystem management, which covers four main topics:

1) perceptions of climate change,
2) the value of and threats to coasts, oceans, and wildlife,
3) perceptions of climate change responses, and
4) sociodemographic data.

MaCoBioS adopted purposive snowballing sampling to collect the data because it allowed the survey collection team to access hard-to-reach populations effectively (Szolnoki et al., 2013). In particular, they publicized the survey through the social media accounts of MaCoBioS (i.e., Twitter and Instagram). They contacted 105 stakeholder groups to ask them to share the survey with their members. Those stakeholder groups represent conservation, tourism/recreation, and fishing/seafood interests in the countries and territories MaCoBioS team works, such as the United Kingdoms (UK), Norway, Ireland, France, Italy, Spain, Bonaire, Martinique, and Barbados. The survey was disseminated in four different languages: English, French, Spanish, and Italian. Although the survey coverage is high, with the participation of stakeholders in 42 countries, it cannot be assumed to be representative due to the unequal distribution of the respondents. In this study, high-income and upper-middle-income nations provided more than 95% of the samples.

The IRB approval for the original research was acquired on November 2, 2021 (Ref. No.: 491857) from the College of Life and Environmental Sciences at the University of Exeter's Research Ethics Committee. During the survey collection, respondents were shown an introductory information screen and asked to give their informed consent before completing the survey.

Table 1. Variable description.

Variable	Description	Type of Variable	Value
Age	The stakeholder's age	Numerical	1: <18 years old 2: 18–30 years old 3: 31–40 years old 4: 41–50 years old 5: 51–60 years old 6: >60 years old
Gender	The stakeholder's gender	Categorical	0: Female 1: Male
Education	The stakeholder's educational level	Numerical	1: Did not attend school

			2: High/secondary school, or equivalent 3: Bachelor's degree (e.g., BA, BSc) 4: Master's degree (e.g., MA, MSc, MRes, MEd) 5: Doctorate (e.g., PhD)
CountryIncomeLevel	The stakeholder's country income level (based on the United States classification)	Categorical	1: Low income 2: Low to middle income 3: Upper middle income 4: High income
IndividualsResponsibility	The level of responsibility that individuals have for acting on climate change	Numerical	1: None 2: Some 3: A lot
UnclearScientificEvidence	To what degree do participants agree that scientific evidence is not clear regarding what to do to stop climate change	Numerical	1 Strongly Disagree 2 Disagree 3 Neither agree nor disagree 4 Agree 5 Strongly agree

As shown in Table 1, the variable *Age* is used to reflect participants' age, with 1 being participants under 18, 2 being the participants between 18-30, 3 being participants between 31-40, 4 being the participants 41-50, 5 being the participants over 50. The *Gender* variable refers to the self-identified gender of the respondents. The variable *Education* denotes the participants' education attainment; it also uses a 5-point Likert Scale, where 1 means "Did not attend school," 2 means "high/secondary school or equivalent," 3 means "Bachelor's degree," 4 means "Master's degree," and 5 means "Doctorate degree." *CountryIncomeLevel* was generated based on the United Nations' classifications of countries by income level (United Nations, 2014). The variable is categorized into four groups: Low-income country, Low-middle-income country, Upper-middle-income country, and high-income country.

IndividualsResponsibility is a variable that asks for the level of responsibility individuals have for acting on climate change. It is a 3-point Likert Scale with 1 being "none," 2 being "some," and 3 being "a lot." The variable *UnclearScientificEvidence* examines to what degree participants agree with the statement that scientific evidence regarding what to do to stop climate change is unclear. It uses a 5-point Likert Scale, ranging from 1 being "strongly disagree" to 5 being "strongly agree."

2.3. Statistical models

To fulfill three research objectives, Model 1 was constructed with *UnclearScientificEvidence* being the outcome variable and other variables as predictor variables (i.e., *Age*, *Gender*, *Education*, *CountryIncomeLevel*, and *IndividualsResponsibility*).

$$UnclearScientificEvidence \sim normal(\mu, \sigma) \tag{1.1}$$

$$\mu_i = \alpha_{CountryIncomeLevel[i]} + \beta_1 * Age_i + \beta_2 * Gender_i + \beta_3 * Education_i + \beta_4 * IndividualsResponsibility_i \tag{1.2}$$

$$\alpha \sim normal(M_\alpha, S_\alpha) \tag{1.3}$$

$$\beta \sim normal(M_\beta, S_\beta) \tag{1.4}$$

The probability around the mean μ is determined by the shape of the normal distribution, where the width of the distribution is specified by the standard deviation σ. μ_i indicates the stakeholder i's degree of perceived unclear scientific evidence; $CountryIncomeLevel[i]$ indicates the country's income level of stakeholder i; Age_i indicates the age of stakeholder i; $Gender_i$ indicates the gender of stakeholder i; $Education_i$ indicates the education level of stakeholder i; $IndividualsResponsibility_i$ indicates the degree of responsibility that stakeholder i thought individuals should have for acting on climate change. Model 1 has ten parameters: the coefficients (β_1–β_4), the intercepts of stakeholders' country income levels ($\alpha_{CountryIncomeLevel[Low\ income]}$, $\alpha_{CountryIncomeLevel[Lower-middle\ income]}$, $\alpha_{CountryIncomeLevel[Upper-middle\ income]}$, $\alpha_{CountryIncomeLevel[High\ income]}$, and α), and the standard deviation of the "noise", σ. The parameters of the intercepts of the stakeholders' country income levels are distributed as a normal distribution around the mean, denoted M_α, and with the standard deviation, denoted S_α; the coefficients are distributed as a normal distribution around the mean, denoted M_β, and with the standard deviation, denoted S_β. The logical network of Model 1 is shown in Figure 1.

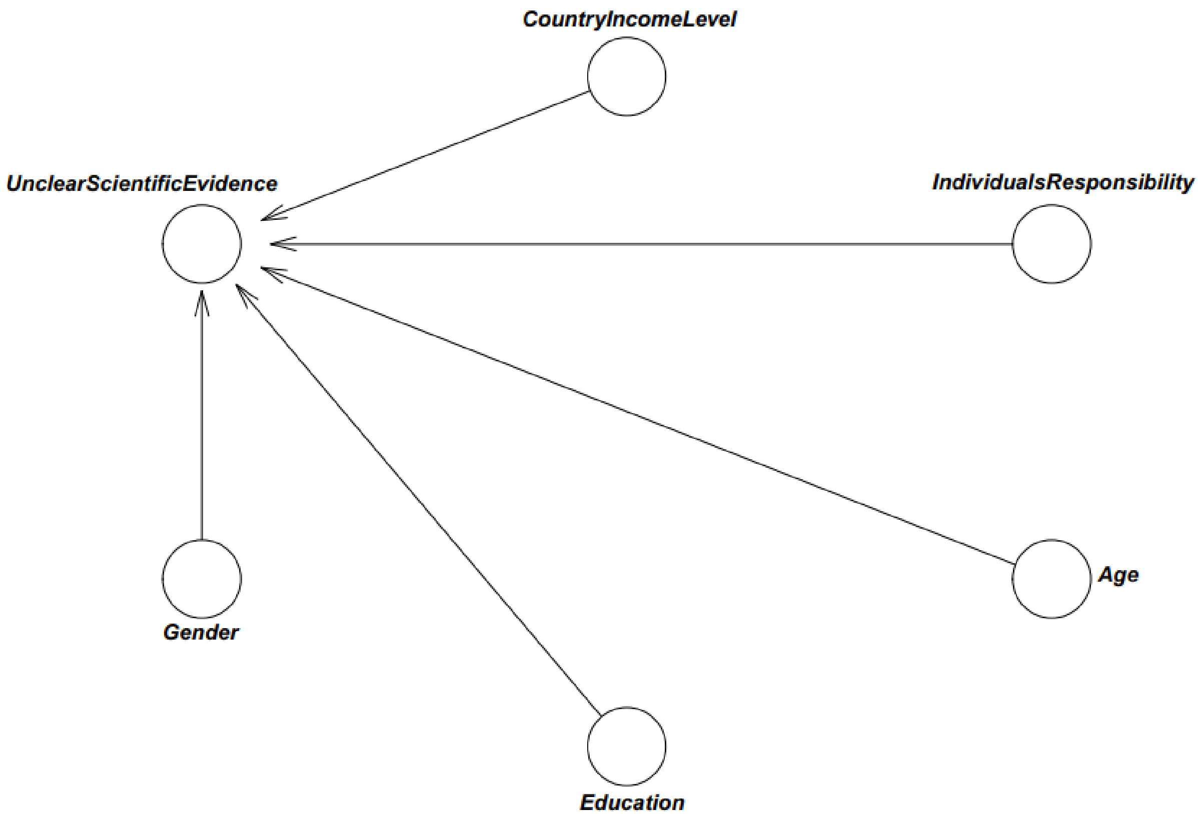

Figure 1: Model 1's logical network

2.4. Analysis and validation

The current study used Bayesian analysis to analyze the data following the protocol of the Bayesian Mindsponge Framework (BMF) analytics (Nguyen et al., 2022a, 2022b). There are several reasons for selecting BMF as the analytic tool. First, BMF combines the strengths of the reasoning power of Mindsponge theory and the inference advantages of Bayesian analysis (Vuong, Nguyen, et al., 2022a). Secondly, Bayesian inference considers all properties probabilistically, including unknown parameters, which is particularly helpful for parsimonious model construction and estimation (Cougle, 2012; Gill, 2014; Simon, 2001). Thirdly, the Bayesian approach would help avoid the dependence on the fickle *p*-value's dichotomous decision of rejecting and accepting a hypothesis (Halsey et al., 2015). Compared to the frequentist approach, Bayesian inference enables users to interpret results using the parameters' credible intervals and the value with the highest probability of occurrence, which is more theoretically advantageous (Wagenmakers et al., 2018).

Fourthly, Bayesian inference aided by the Markov Chain Monte Carlo (MCMC) technique generates more precise estimations with the data at hand than the conventional frequentist approach when the sample sizes are small and allows fitting complex models, like hierarchical regression structures (Csilléry et al., 2010; Dunson, 2001). We employed the hierarchical regression structures (or multilevel modeling) with $CountryIncomeLevel$ being the varying intercepts in this study for several reasons. Multilevel modeling improves the estimate of a dataset with imbalanced samples (McElreath, 2018); in particular, few respondents are from low-income nations (5 observations, accounting for about 1% of all observations) and lower-middle-income countries (14 observations, accounting for approximately 2%). Multilevel modeling also explicitly generates estimates of group variation, making it ideal for survey data, which are frequently non-random and limited (Spiegelhalter, 2019).

Before interpreting the Bayesian analysis results, two types of validation were performed: The Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) diagnostics and the convergence diagnostics. The PSIS-LOO diagnostic was used to test the constructed models' goodness-of-fit with the data (Vehtari & Gabry, 2019; Vehtari et al., 2017). The computed LOO can be calculated as follows:

$$LOO = -2LPPD_{loo} = -2\sum_{i=1}^{n} \log \int p(y_i|\theta) p_{post(-i)}(\theta) d\theta$$

Where $p_{post(-i)}(\theta)$ is a posterior distribution based on the data minus data point i. In the **loo** package, the PSIS method was employed to compute leave-one-out cross-validation k-Pareto values. If k values are less than 0.5, it is generally considered that the model fits well with the data. However, if k values exceed 0.7, there is a risk of model misspecification.

Then, the convergence diagnostic was performed. Statistically, the Gelman-Rubin shrink factor (*Rhat*) and effective sample size (*n_eff*) are used to diagnose chain convergence. If *n_eff* values exceed 1000 and *Rhat* values equal 1, then the model is considered well-convergent (McElreath, 2018). The formula to calculate the *Rhat* values (Lynch, 2007) is as follows:

$$\hat{R} = \sqrt{\frac{\widehat{\mathrm{V}}}{W}}$$

where $\hat{R}$ is the *Rhat* value, $\widehat{\mathrm{V}}$ is the estimated posterior variance, and W is the within-sequence variance.

Besides that, autocorrelation plots, Gelman-Rubin-Brooks plots, and trace plots were also used to assess Markov chain convergence visually.

All analysis steps were performed using the **bayesvl** package in R software because of its advantages, including open access, good visualization capabilities, and transparent operations (La & Vuong, 2019; Vuong, Nguyen, et al., 2022b). Due to the study's exploratory nature, we used uninformative priors, which help avoid subjectivity bias in the fitting process. We set 5000 iterations with 2000 iterations for warmup and four chains to fit the model.

3. Results

Before interpreting the results, we conducted the PSIS-LOO diagnostics to check Model 1's goodness of fit with the data at hand. The PSIS diagnostic plot shown in Figure 2 illustrates all *k* values are smaller than 0.5, suggesting that Model 1 has a high goodness-of-fit with the current data (see Figure 2).

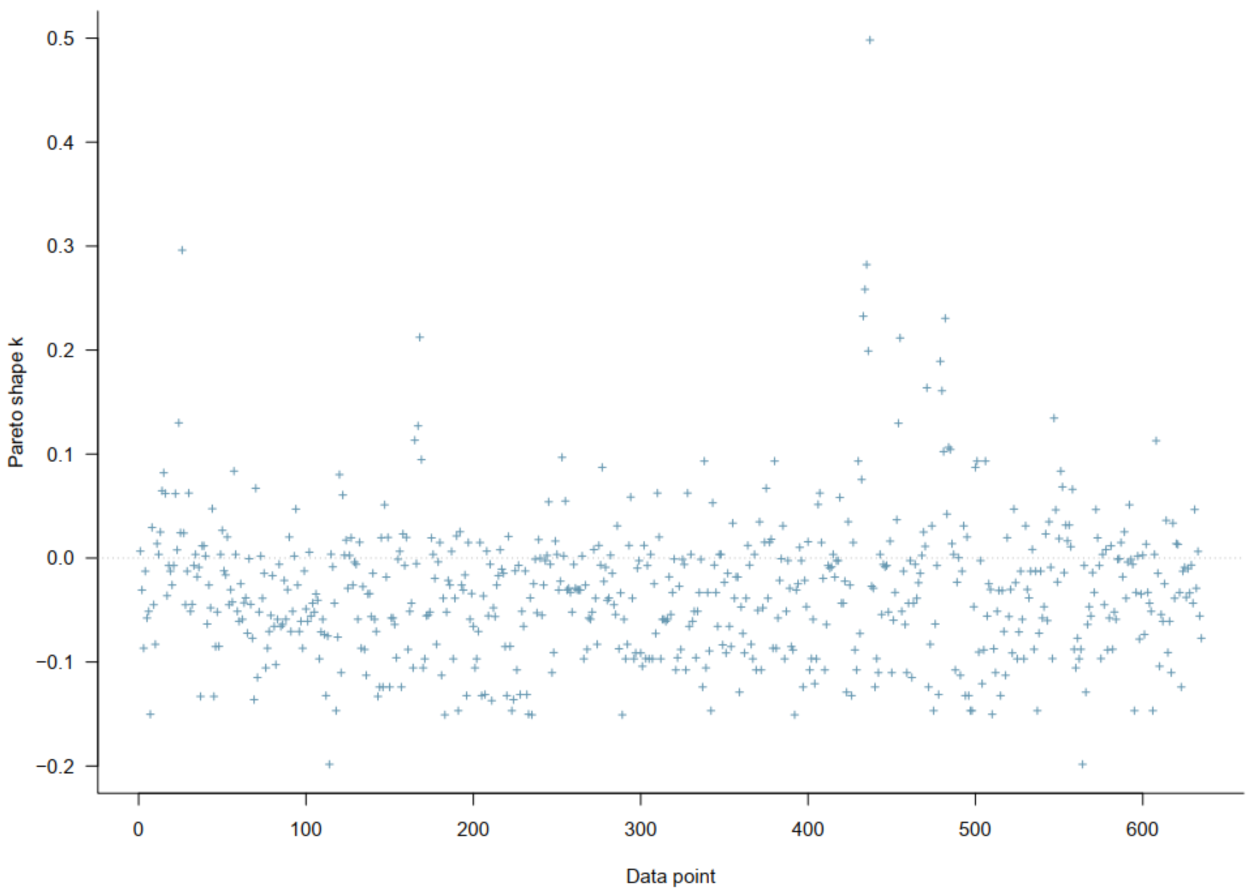

Figure 2: Model 1's PSIS diagnostic plot

Then, the convergence diagnostics were performed. The *n_eff* and *Rhat* values displayed in Table 2 indicate the good convergence of the model's Markov chains; all the *n_eff* values are larger than 1000, and all the *Rhat* values are equal to 1.

Table 2: Model 1's simulated posteriors

Parameters	**Mean (M)**	**Standard deviation (S)**	***n_eff***	***Rhat***
Age	-0.02	0.03	9375	1
Gender	0.13	0.08	9736	1
Education	-0.18	0.04	9218	1
IndividualsResponsibility	0.22	0.07	9821	
CountryIncomeLevel[Low income]	2.95	0.47	12638	1
CountryIncomeLevel[Lower-middle income]	3.03	0.39	10568	1
CountryIncomeLevel[Upper-middle income]	2.86	0.34	9695	1
CountryIncomeLevel[High income]	2.02	0.29	8184	1
Constant	2.71	0.68	1537	1

Figure 3 shows the trace plots of Model 1. The colored lines in the middle of trace plots are Markov chains. The chains' fluctuation around a central equilibrium after the warmup period (2,000th iterations) implies their good-mixing and stationary characteristics. These two characteristics indicate a good convergence signal of the Markov chains.

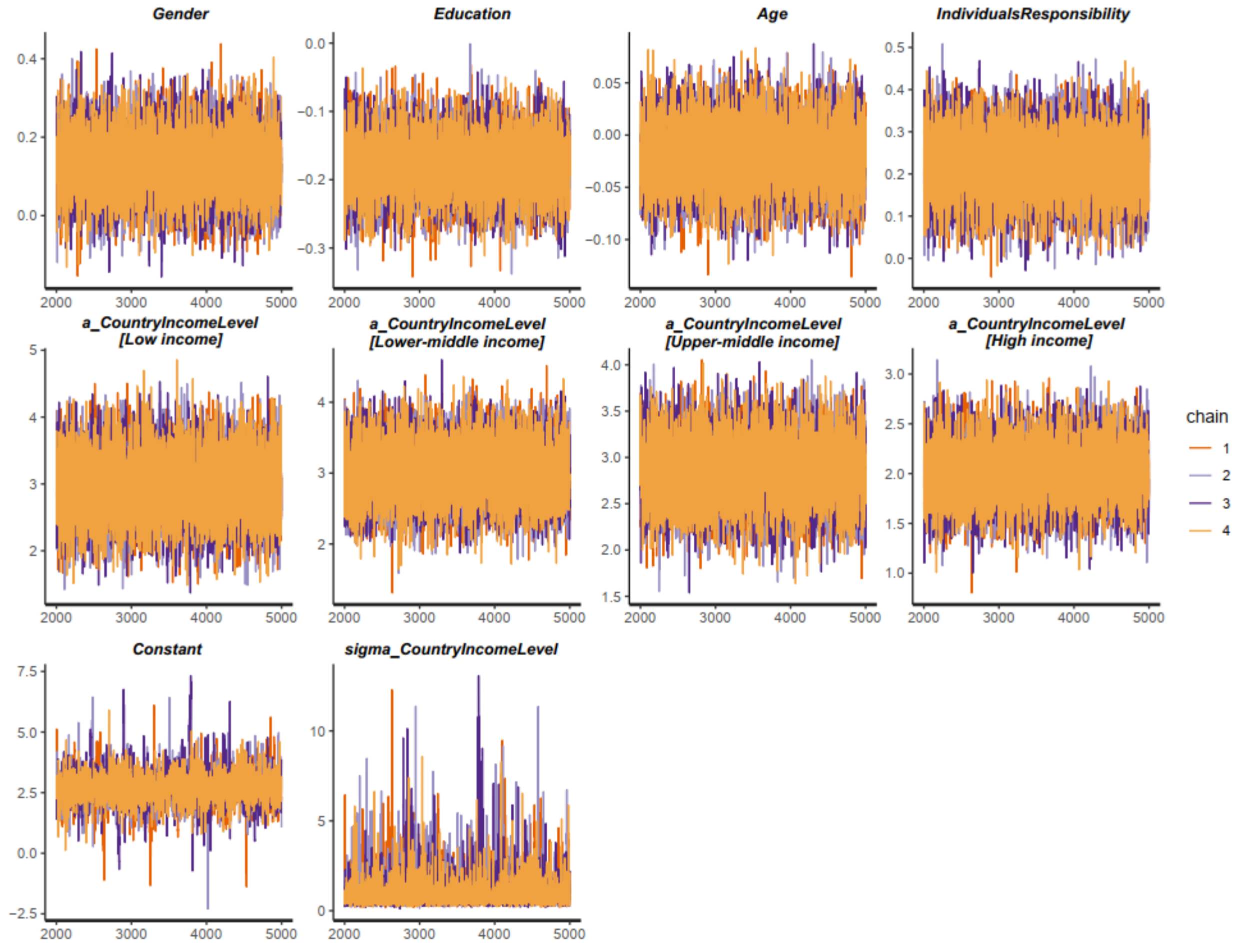

Figure 3: Model 1's trace plots

Besides the trace plots, we also visualized the Gelman-Rubin-Brooks and autocorrelation plots to diagnose the Markov chains' convergence (or the Markov chain central limit theorem). In Figure 4, all Gelman-Rubin-Brooks plots' shrink factors decline rapidly to 1 within the warmup period (before the 3,000th iteration). Meanwhile, in Figure 5, the autocorrelation levels of all coefficients' iterations also diminish to 0 quickly after a certain number of lags. Both Figures suggest the good convergence of Markov chains, so the simulated results are qualified for interpretation.

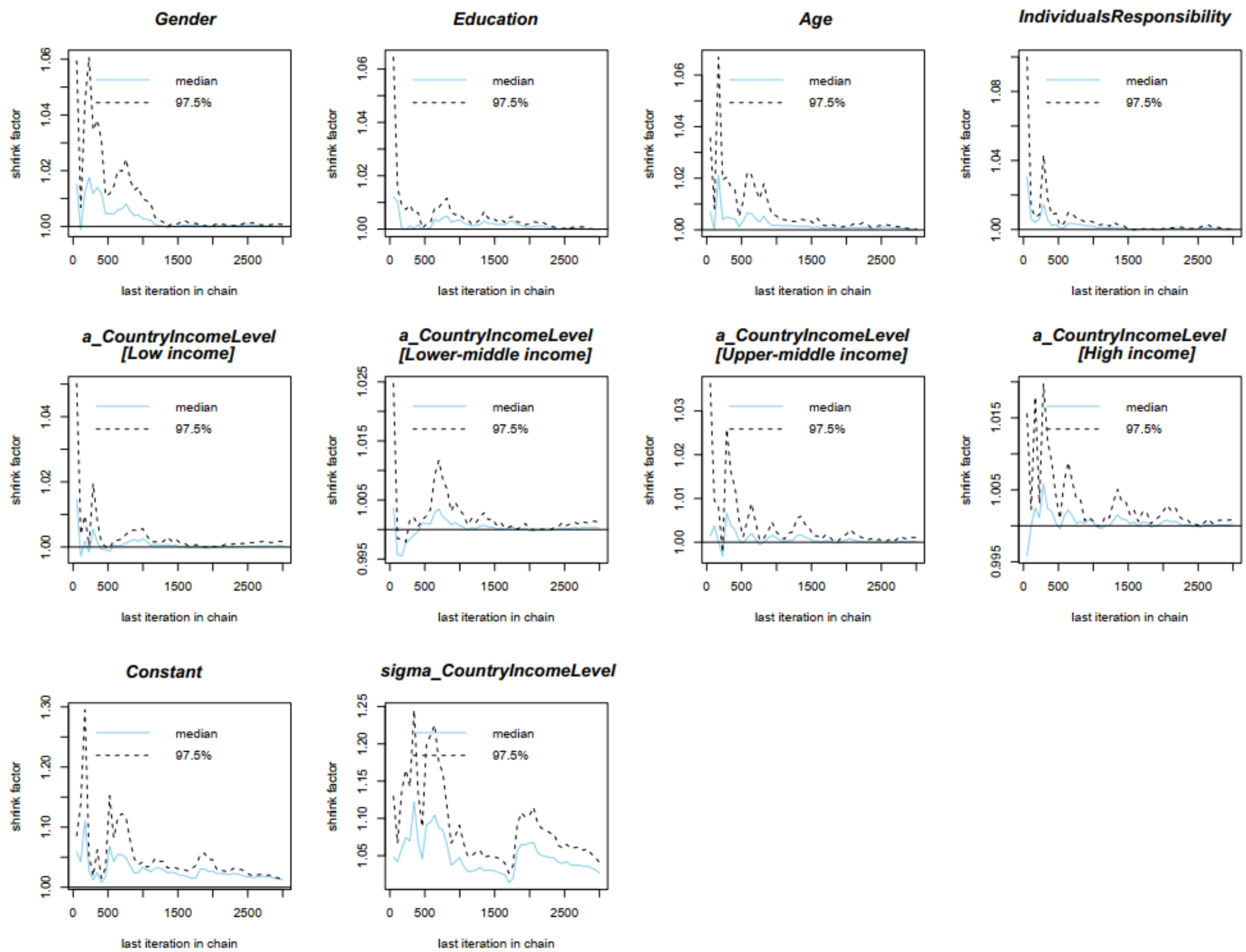

Figure 4: Model 1's Gelman-Rubin-Brooks plots

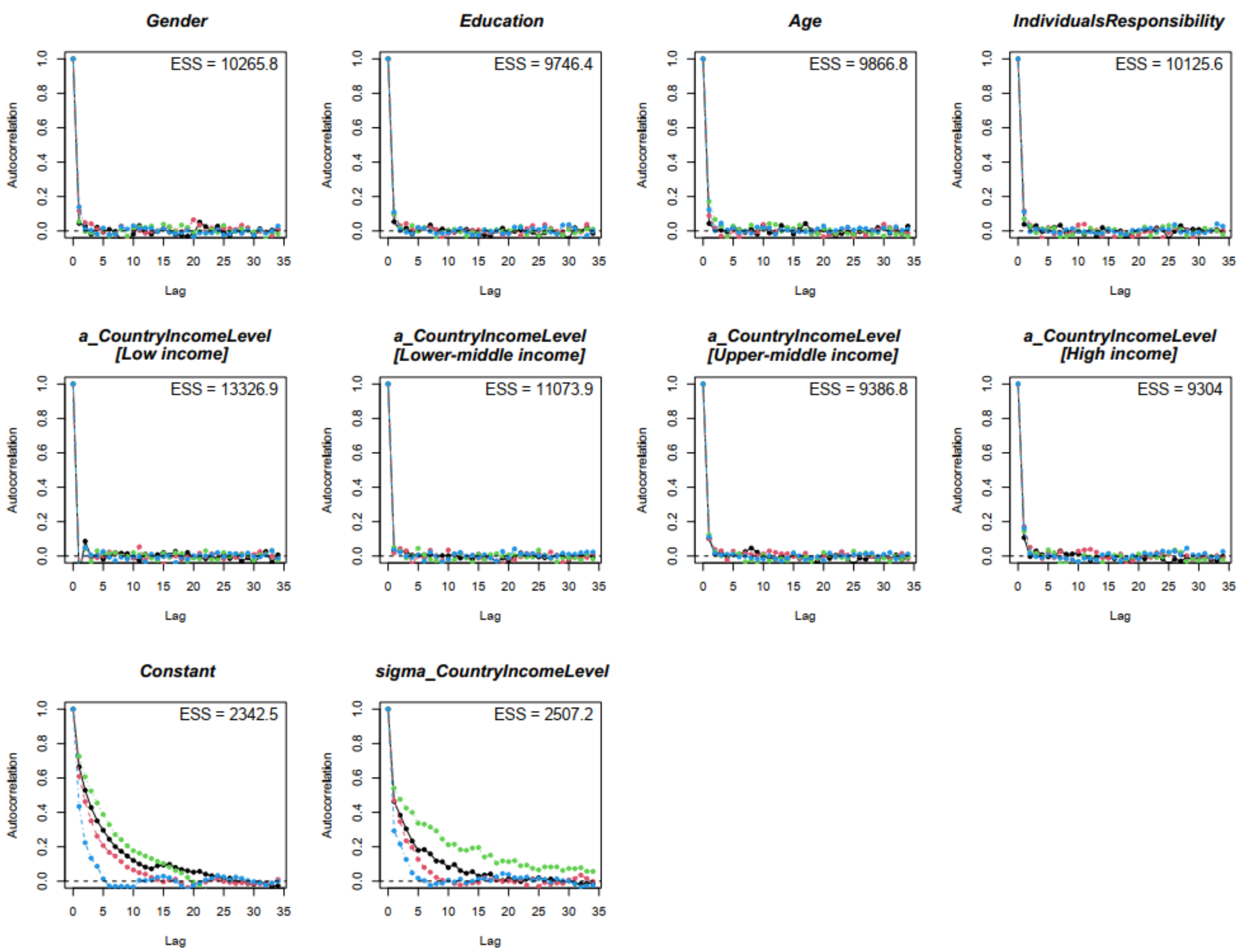

Figure 5: Model 1's autocorrelation plots

The posterior distributions of the coefficients of Model 1 are shown in Table 2. According to the estimated results, *Age* and *Education* have negative associations with *UnclearScientificEvidence* (M_{Age} = -0.02 and S_{Age} = 0.03; $M_{Education}$ = -0.18 and $S_{Education}$= 0.04), while *Gender* has a positive association (M_{Gender} = 0.13 and S_{Gender}= 0.08). To elaborate, stakeholders with lower ages, educational levels, and being males tended to think the scientific evidence was uncertain regarding what to do to stop climate change. We also found that stakeholders who thought that individuals should have more responsibility to act on climate change were more likely to think the scientific evidence was not clear regarding what to do to stop climate change ($M_{IndividualsResponsibility}$ = 0.22 and $S_{IndividualsResponsibility}$ = 0.07). All the coefficients' posterior distributions are illustrated in Figure 6. As can be seen, the Highest Posterior Density Intervals (HPDI) at 89% of *Gender* and *IndividualsResponsibility* are located entirely on the positive side of the *x*-axis, while that of *Education* is located entirely on the negative side. These illustrations suggest that the effects of *Gender*, *Education*, and *IndividualsResponsibility* are reliable. However, a proportion of *Age*'s HPDI is located on the positive side, so its negative effect on *UnclearScientificEvidence* is weakly reliable.

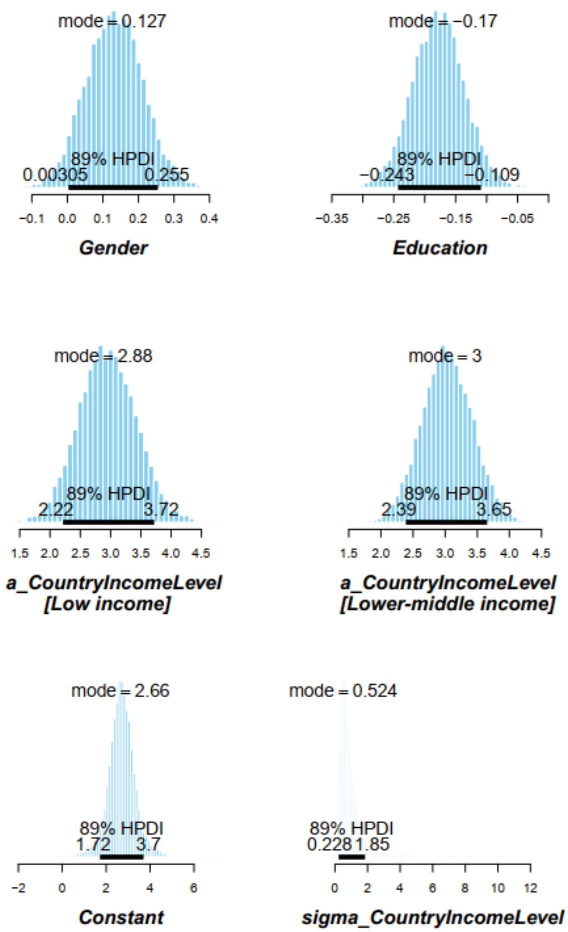

Figure 6: Model 1's posterior distributions

Each intercept corresponds to the *UnclearScientificEvidence* of stakeholders with different countries' income levels. As shown in Figure 7, the posterior distributions of Model 1's intervals are distinct between stakeholders from countries with different income levels. Stakeholders from low-income and lower-middle-income countries tended to have similar levels of *UnclearScientificEvidence* ($M_{CountryIncomeLevel[Low\ income]} = 2.95$ and $S_{CountryIncomeLevel[Low\ income]} = 0.47$; $M_{CountryIncomeLevel[Lower-middle\ income]} = 3.03$ and $S_{CountryIncomeLevel[Lower-middle\ income]} = 0.39$). People from upper-middle-income countries had slightly lower levels of *UnclearScientificEvidence* ($M_{CountryIncomeLevel[Upper-middle\ income]} = 2.86$ and $S_{CountryIncomeLevel[Upper-middle\ income]} = 0.34$), while those from high-income countries had significantly lower levels ($M_{CountryIncomeLevel[High\ income]} = 2.02$ and $S_{CountryIncomeLevel[High\ income]} = 0.29$).

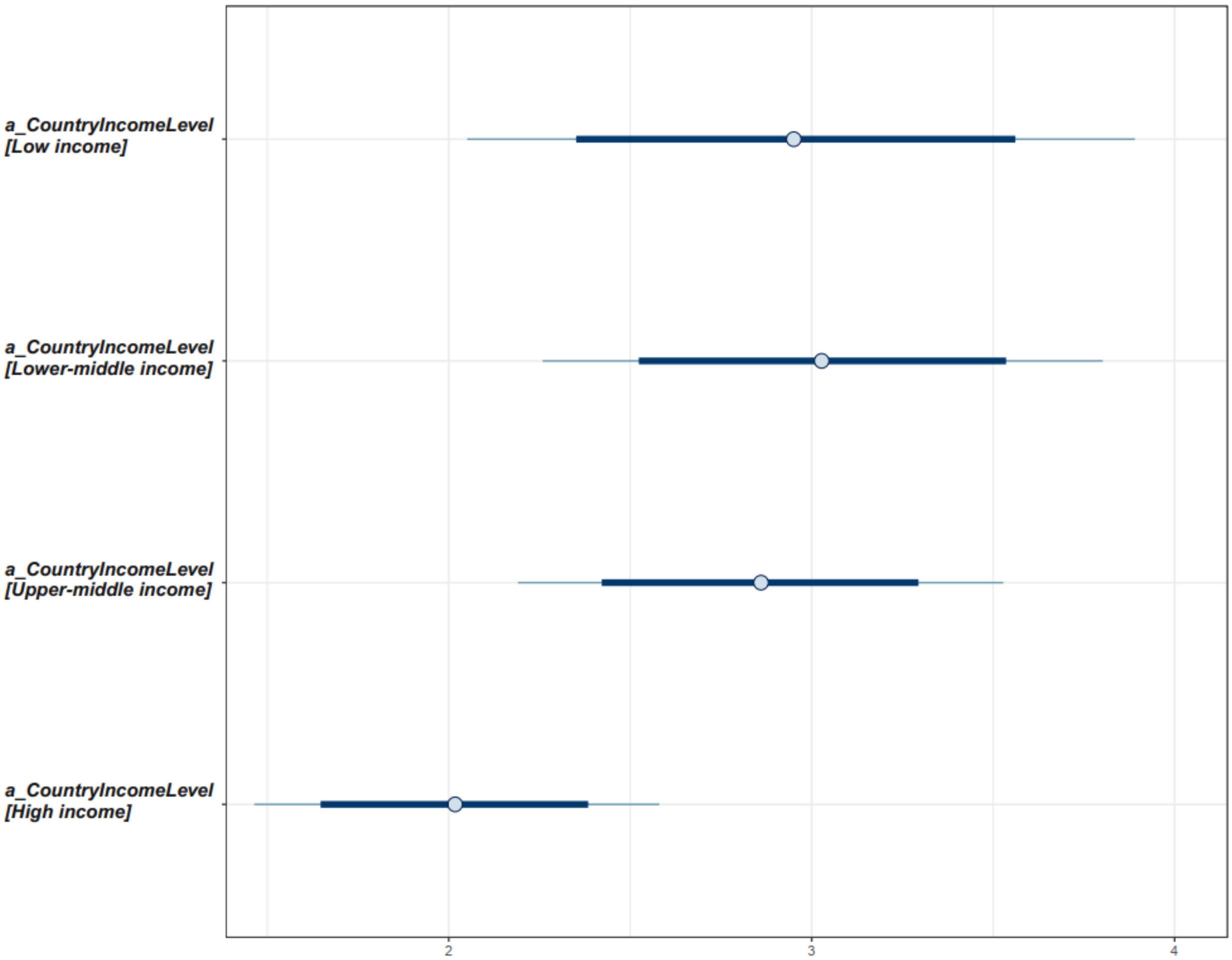

Figure 7: Posterior distributions of Model 1's intercepts

4. Discussion

The current study employed the Bayesian Mindsponge Framework analytics on the dataset of 709 marine and coastal ecosystems stakeholders to examine factors predicting their perceived uncertainty of scientific evidence. We found that sociodemographic factors, such as gender, education, and the country's economic level, were important predictors of perceived uncertainty of scientific evidence.

Specifically, the findings indicate that stakeholders with lower educational levels, being males and from lower-income countries, were more likely to think scientific evidence regarding how to act on climate change was uncertain. While the effects of gender and educational level on perceived uncertainty of scientific evidence are highly reliable, that of age is only weakly reliable. Our findings are aligned with the study of Whitmarsh (2011) on the UK public, which showed that the public, who were males and had lower educational levels were more skeptical about climate change. The risk perception, in conjunction with a particular worldview, might explain the high skepticism of males toward scientific evidence. In particular, it is evident that the environmental-risk-skeptical tendency of males is linked to anti-egalitarian and individualistic worldviews (Kahan et al., 2007). As males are more skeptical of environmental risks, they might be more skeptical of scientific evidence regarding climate change. However, further studies are still needed to validate this assumption. Also, a gender-specific approach to policy development and public communication should be considered to address gender discrepancies in perceived uncertainty of scientific evidence and ensure gender inclusivity in climate actions.

Our study uncovered that individuals in high-income countries demonstrated the lowest perceived uncertainty toward scientific evidence regarding how to act on climate change. It is possibly due to factors such as enhanced education, easy access to information, widespread public awareness, and robust policy initiatives (Knight, 2016; Lo & Chow, 2015). The Mindsponge Theory suggests that people's perceptions are significantly influenced by the interplay between exposure to perception-shaping information and the selective information absorption process (Vuong, 2023). Stakeholders from high-income countries in this study are mostly from Belgium, Canada, Finland, France, Germany, and United Kingdoms, which have more transparent climate change prevention agendas and more science communication initiatives than lower-income countries (e.g., Brazil, Cameroon, Ecuador, Niger, Senegal, South Africa, etc.) (European Commission, 2022). Therefore, people from high-income countries might have access to more information on how to act on climate change (including scientific evidence), and their selective absorption process is also influenced by the climate change prevention agendas set by the governments.

Regardless of country, stakeholders with a higher felt responsibility to act on climate change are more likely to perceive uncertainty of scientific evidence about how to act on climate change. This finding confirms our assumption that felt responsibility improves stakeholders' climate change engagement, subsequently increasing their knowledge of climate change, including scientific knowledge. As scientific evidence is uncertain in nature (Goldacre, 2005; Howson & Urbach, 2006; Popper, 1954; Retzbach et al., 2016), the more scientific knowledge a person obtains, the more uncertain about science they might become. It should be noted that the awareness of uncertainty inherent to scientific knowledge is not necessarily associated with anti-scientific attitudes (Jensen, 2008; Retzbach et al., 2016).

Nevertheless, why is a higher educational level associated with less perceived uncertainty of scientific evidence? There are several explanations.

First, this might be because knowledge obtained from the education system is structured knowledge which is usually systematically designed and curated based on the most widely accepted scientific facts. Meanwhile, the knowledge obtained by stakeholders with high felt responsibility is not only from formal education but also through self-learning and social interactions. Such self-learning and social interaction processes are greatly influenced by the social and political values attached to the information available. In the Internet age, the explosive growth of online media has made self-learning and social interactions easier and faster, but the disseminated contents mostly lack editorial oversight and fact-checking. Sometimes, people with felt responsibility might also debate with climate change denialists. These situations create the chance for misinformation and disinformation about climate change to spread and increase the chaos of the infosphere in the public domain (Lewandowsky, 2021; Treen et al., 2020). Thus, stakeholders with felt responsibility, who are likely to engage with climate change information during the self-learning and social interaction processes, might have higher perceived uncertainty of scientific evidence due to the exposure to contrarian information available in the public domain.

Another explanation for the contradicting effects of educational level and felt responsibility can be explained by the role of educational attainment in shaping people's cognitions of climate change. Based on the European Social Survey covering over 30 nations, Welsh (2022) discovered that better education "tends to amplify biases in the relevant cognitions that result from identity-protective information selection and processing" rather than improve climate knowledge (Welsch, 2022). Respondents in this study were stakeholders (i.e., people from conservation, recreation, and fishing/seafood sectors) who have direct or indirect connections with the marine and coastal ecosystems and were aware of climate change consequences (Fonseca et al., 2023; Nguyen, Duong, et al., 2023). The educational level might, therefore, amplify the stakeholders' cognitions and reduce the uncertain information related to climate change through the information-filtering process.

It is widely evident that felt responsibility for acting on climate change can lead to pro-environmental attitudes and behaviors (Babcock, 2009; Bouman et al., 2020; Kaiser et al., 1999; Moser, 2014; Taylor et al., 2014). From the information-processing perspective of the Mindsponge Theory, felt responsibility is a psychological outcome of the mental information process, which can be generated by building the eco-surplus mindset (a set of pro-environmental core values or beliefs) (Nguyen & Jones, 2022a; Vuong, 2021). The infosphere that nurtures an eco-surplus culture can be created through public communication, educational activities, and pro-environmental entertaining platforms (Nguyen & Jones, 2022a, 2022b). Based on our findings and information-processing reasoning, we suggest that the strategies for public communication, educational activities, and pro-environmental entertaining platforms must be conducted with highly robust and reliable scientific evidence to inoculate the public against misinformation and disinformation. If there is any uncertainty in scientific evidence, it needs to be openly discussed to increase the trustworthiness of the evidence (Jensen, 2008; Retzbach et al., 2016). Research to clarify the uncertainty in scientific evidence also needs to be quickly conducted to refrain climate change denialists from taking advantage of such scientific uncertainty and spreading misinformation and disinformation (Lewandowsky, 2021).

The current study is not without limitations, so we present them here for transparency (Vuong, 2020). First, we only focused on the stakeholders of marine and coastal ecosystems, so the results might not be generalized to other populations. Second, most of the respondents in the research were from high-income countries, so the research findings might not reflect the relationship between felt responsibility and perceived uncertainty of scientific evidence in countries with low, lower-middle, and upper-middle income. Thus, precautious reuse of the findings is suggested. Third, our study is only a preliminary attempt to study the connection between felt responsibility and perceived uncertainty of scientific evidence.

Further research with a more in-depth design should be conducted to explore this connection across diverse groups of populations and settings. For example, the mediation effect of climate change engagement between felt responsibility and perceived uncertainty needs to be tested to validate our reasoning; whether perceived uncertainty of scientific evidence about climate change affects perceptions, beliefs, and behaviors about climate change needs to be examined. Insights from those studies will help establish tailored interventions for informed decisions and proactive climate action among the public.

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