In search of value: The intricate impacts of benefit perception, knowledge, and emotion about climate change on marine protection support

Minh-Hoang Nguyen [1,*], Minh-Phuong Thi Duong [2], Quang-Loc Nguyen [3], Viet-Phuong La [1,4], Vuong-Quan Hoang [1]

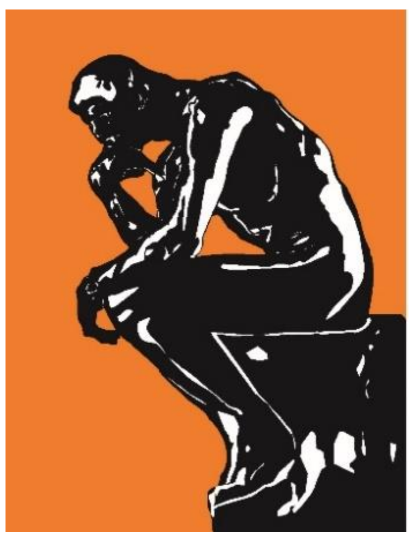
[1] Centre for Interdisciplinary Social Research, Phenikaa University, Yen Nghia Ward, Ha Dong District, Hanoi 100803, Vietnam

[2] Faculty of Social Sciences and Humanities, Ton Duc Thang University, Ho Chi Minh City, Vietnam

[3] SP Jain School of Global Management, Lidcombe, NSW 2141, Australia

[4] A.I. for Social Data Lab(AISDL), Vuong & Associates, Hanoi 100000, Vietnam

* Corresponding: Minh-Hoang Nguyen; Email: hoang.nguyenminh@phenikaa-uni.edu.vn



October 1, 2023

Preprint v.1.1

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Abstract

Marine and coastal ecosystems are crucial in maintaining human livelihood, facilitating social development, and reducing climate change impacts. Studies have examined how the benefit perception of aquatic ecosystems, knowledge, and emotion about climate change affect peoples' support for marine protection. However, their interaction effects remain understudied. The current study explores the intricate interaction effect of the benefit perception of aquatic ecosystems, knowledge, and worry about climate change on marine protection support. Bayesian Mindsponge Framework (BMF) analytics was employed on a dataset of 709 stakeholders from 42 countries generated by MaCoBioS—a research project funded by the European Commission Horizon 2020. The statistical analysis shows that the impacts of benefit perception of ocean ecosystems, knowledge, and worry about climate change on marine protection support vary due to their interactions. Specifically, when stakeholders perceive ocean ecosystems to have little utility in mitigating climate change, greater climate change knowledge and concern are associated with a higher level of marine protection support. Nevertheless, in the scenarios where stakeholders perceive the benefits of ocean ecosystems, the effect of climate change knowledge becomes conditional on the worry level. If stakeholders are concerned about climate change, those with a greater level of climate change knowledge will associate with a higher level of marine protection support. Otherwise, greater climate change knowledge will result in lower support. These findings highlight emotion's importance in directing climate change knowledge's effect on marine protection support. Linking people's "objects of care" to the consequences of climate change can help improve climate change communication effectiveness.

Keywords: climate change communication; Mindsponge Theory; emotional responses; eco-anxiety; climate anxiety

> "– In the same field, how can the two sides be so different? […]
>
> – Sir, it's because our circumstances are different. Our bunch is light and free, while those guys spend all day long worried and guarding their ripe grains. What a terrible waste of time! Beautiful sunny days are for singing, dancing, and chattering away…"
>
> In "Light and Free"; *The Kingfisher Story Collection* (Vuong, 2022)

1. Introduction

Throughout history, Earth's oceans and coasts have played a crucial role in enhancing human well-being, delivering essential services, supporting diverse activities, such as fishing, tourism, transportation, and recreational opportunities, and exerting global-scale climate control (Visbeck, 2018). Furthermore, one-tenth of the global population relies on the ocean as a readily available provider of both protein and livelihood opportunities (Taylor et al., 2019). However, the unsustainable exploitation of marine resources driven by various economic activities has raised concerns about the biodiversity and well-being of aquatic ecosystems (Sambo & Sule, 2023). Challenges like overfishing, habitat degradation, pollution, and the effects of climate change pose imminent threats to marine ecosystems (Kusumawati & Huang, 2015; Taylor et al., 2019).

For example, local-level activities such as urban expansion and infrastructure construction in coastal zones can have detrimental consequences. These actions can result in more significant runoff, flooding, and the loss of vital wetlands and marshes that serve as buffers against sea-level rise and storms, exacerbating the adverse effects of climate change on coastal areas (Aguilera & González, 2023). This also underscores the intricate nature of coastal ecosystems and the varying requirements of communities while emphasizing the objective of achieving a harmonious coexistence between humans and the coastal environment (Rangel-Buitrago, 2023).

Proactive measures and policies are essential to preserve marine and coastal regions effectively. These measures should encompass dynamic, iterative, and collaborative processes aimed at promoting both the sustainable utilization and protection of coastal zones (Bennett & Dearden, 2014; Cigliano et al., 2015b; Hiriart-Bertrand et al., 2020; McNeill et al., 2018; Rangel-Buitrago, 2023). Recently, there has been an increased focus on understanding how individuals perceive the benefits of protecting the oceans and their role in addressing climate change (Jefferson et al., 2021; Pakalniete et al., 2017). A consistent trend observed in numerous studies highlights a positive correlation between perceived benefits and support for ocean protection. This suggests that individuals are more inclined to endorse conservation efforts when they grasp the fundamental role that marine and coastal ecosystems play in mitigating climate change (Chilvers et al., 2014; Roberts et al., 2017).

In addition, extensive research in the literature has consistently highlighted the critical role of climate change knowledge in shaping individuals' support for ocean protection initiatives (Fernández Otero et al., 2019; Thornton & Scheer, 2012). Studies have pointed out a robust and positive correlation between a deep understanding of climate change and heightened backing for efforts aimed at safeguarding our oceans. This correlation implies that individuals who possess a comprehensive grasp of climate change-related concepts and their implications for marine and coastal ecosystems are more inclined to actively support measures designed to protect these vital natural resources (Brennan et al., 2019; Nguyen, Duong, et al., 2023; Ziervogel et al., 2022).

Moreover, emotions, which are an integral aspect of the human experience, exert a significant influence on responses to complex challenges like climate change (Brosch, 2021).

Considerable research has explored how various emotional states, spanning a spectrum including concern, fear, hope, anger, and apathy, affect the willingness to take protective actions (Kolandai-Matchett & Armoudian, 2020; Kollmuss & Agyeman, 2002; van Putten et al., 2018). Recent studies indicate a shift toward increasing concern, anxiety, and even dread as people become more aware of the effects of climate change, consequently leading to increased support for ocean protection (Gelcich et al., 2014; Kelly et al., 2022).

While research on public support for marine protection policies has expanded, critical gaps remain. One crucial area requiring further investigation is the intricate relationship between individuals' perceptions of the benefits of marine protection, their climate change knowledge, and their emotional responses to it. This intricate interplay can unveil nuanced variations in public support for ocean protection efforts, enriching the existing state-of-the-art regarding psychology and behaviors related to marine ecosystems and climate change and offering valuable insights into diverse perspectives within the population and guiding targeted interventions.

In particular, it is vital to delve into how people's knowledge interacts with their perceptions of the benefits derived from marine and coastal environments. As Brennan et al. (2019) elaborated, ocean literacy extends beyond traditional literacy, encompassing a spectrum of dimensions, including attitudes, actions, and the capacity for meaningful discussions on ocean-related topics. When individuals possess a solid understanding of this relationship, they are more inclined to make informed choices and advocate for actions that benefit both the ecosystem and future generations (Ziervogel et al., 2022). Informed citizens are essential contributors to environmental conservation efforts.

It is fundamental to understand the profound link between individuals' emotions and how they perceive the advantages originating from marine and coastal environments. This recognition is pivotal for shaping effective climate change communication strategies and conservation initiatives. By leveraging the emotional component of this connection and tailoring messages to connect with individuals deeply, we can inspire greater public endorsement for protecting and preserving these essential marine ecosystems (Becken & Curnock, 2022). This holistic approach serves as a bridge between the realms of science, policy, and public engagement, making a significant contribution to the cause of ocean conservation (Chapman et al., 2017).

Therefore, it is imperative to undertake comprehensive research to disentangle the complexities within the three-way interaction involving perceptions of marine and coastal benefits in climate change mitigation, levels of climate change knowledge, and emotional responses to climate change. Our primary research objective is to delve into the interplay of these three variables and their impact on individuals' endorsement of ocean protection initiatives. More precisely, we seek to ascertain whether the association between perceived marine and coastal benefits for climate change reduction and support for ocean protection is modulated by climate change knowledge and emotional responses to climate change.

Furthermore, it is crucial to acknowledge that support for marine and coastal conservation exhibits substantial variation across nations, driven by a multitude of contextual factors such as social, cultural, political, economic, and historical influences. To enhance the efficiency of policy implementation, reduce the cost of doing science, and acquire a better understanding of the contextual factors that exert varying influences on different countries (Vuong, 2018), conducting a cross-national study is essential, even if uncovering a universal pattern remains challenging.

Consequently, this comprehensive approach aims to illuminate the intricate dynamics that drive public engagement in preserving marine and coastal ecosystems in the context of climate change. By doing so, it has the potential to offer valuable insights into the various factors influencing public support for ocean protection measures in the climate change context, ultimately guiding policymakers, conservation groups, and educators in developing more effective strategies to engage and mobilize communities in environmental conservation efforts. Moreover, it contributes to a broader comprehension of human behavior and decision-making in environmental matters, a vital component in tackling the challenges posed by climate change.

Utilizing the Mindsponge Theory, which explains how people perceive and process information, this research aims to address the gaps above and provides novel insights into marine protection policies. The study seeks to comprehend the factors influencing stakeholder support for policies centered on marine and coastal preservation across 42 countries. Therefore, the present study has four primary objectives:

1. Examine the connection between perceived marine and coastal benefits for mitigating climate change and individuals' support for ocean protection.
2. Examine the moderating effect of climate change knowledge on this association.
3. Explore the moderating effect of emotions related to climate change on the same association.
4. Examine the potential existence of a three-way interaction among perceived marine and coastal benefits for climate change mitigation, climate change knowledge, and emotions related to climate change.

2. Methodology

2.1. Theoretical foundation

The current study employed the Mindsponge Theory as the theoretical foundation for constructing models to fulfill the research objectives above (Vuong, 2023). Mindsponge Theory is a novel theory of how the human mind possesses and processes information, which was developed upon the mindsponge mechanism and the most recent evidence in the field of life science and neuroscience (Vuong, 2023; Vuong & Napier, 2015). The theory has been widely applied to a variety of socio-psychological studies, including environmental psychology (Asamoah et al., 2023; Jin et al., 2023; Kantabutra & Ketprapakorn, 2021; Khuc, Dang, et al., 2023; Khuc et al., 2022; Khuc, Tran, et al., 2023; Kumar et al., 2022; Li et al., 2022; Nguyen, Le, et al., 2023; Nguyen & Vuong, 2021; Ruining & Xiao, 2022; Santirocchi et al., 2023; Shu et al., 2023; Tanemura et al., 2022; Vuong, Le, et al., 2023; Vuong, Le, Khuc, et al., 2022; Vuong, Le, La, & Nguyen, 2022; Vuong, Le, La, Nguyen, et al., 2022; Zeng et al., 2022).

The metaphorical term "mindsponge" characterizes the mind as a sponge that absorbs pertinent information that fits or enhances the context while expelling irrelevant information. According to the theory, the mind can be seen as an information collection-cum-processor that gathers and processes information according to the demands (priorities) of oneself and the surrounding environment. The system's primary goal is to prolong its existence through survival, growth, or reproduction. The mind uses a subjective cost-benefit appraisal that aims to maximize the perceived benefits and minimize the perceived costs of the system to accomplish its goal and maintain its priority. In other words, the mind is not just a passive receiver of information but also an active information processor that can filter information from the environment and then respond to changes in the environment (Asamoah et al., 2023; Nguyen, Duong, et al., 2023; Vuong, 2023).

The mindset has a significant impact on the mind's output generation, input acquisition, and filtering processes. According to the theory, a person's mindset is a collection of highly trusted values (beliefs or facts). The terms "information," "idea," and "value" can be used interchangeably because information is regarded as the most fundamental entity from the perspective of information processing (Davies & Gregersen, 2014). The terms "idea" and "value" can be distinguished as the mind's individualized interpretations of the information that constitutes them (Vuong, Nguyen, et al., 2022). Fundamentally, a mindset exists because of the mind's (or the brain's) capacity to store information or memory (Vuong, Nguyen, et al., 2023). As the mind constantly interacts with the surrounding environment, it is not an isolated system. Trusted values are information that has been absorbed from the environment, evaluated, and integrated into the mindset, so the mindset's content evolves over time better to match the mind's mental representations of reality (Nguyen, Le, et al., 2023).

From the information-processing perspective, stakeholders' support for ocean protection is an outcome of their information process. For the idea of supporting ocean protection to appear in the mindset and influence subsequent thinking and behaviors, it must be perceived as beneficial (Vuong, Nguyen, et al., 2022). The ramifications of climate change, such as natural disasters and extreme climate and weather events, can inflict significant damage to human's "objects of care" (which encompass valued objects, people, and places in one's life, as well as core identities), especially those directly engaged with the marine and coastal environment (He & Silliman, 2019; Siikamäki et al., 2013; Wang et al., 2018). Thus, people acknowledging the risks of climate change will be more likely to attribute information that can alleviate the climate change more value and absorb it into the mindset: the idea of supporting ocean protection. A previous study found a positive association between the perceived benefits of ocean ecosystems in climate change reduction and support for marine preservation policies, showing support for this assumption (Nguyen, Duong, et al., 2023). However, whether stakeholders' information-filtering process favors and prioritizes information related to ocean protection also depends on the amount of climate change knowledge they have within their minds. Thus, we assume that how well the stakeholders are informed of climate change will moderate the relationship between perceived ocean ecosystems' benefits and support for marine protection.

Emotion is also a crucial factor influencing how a person processes information, as it was found to inform cognition and affect motivation, perceptions of risk, and decision-making processes (Damasio, 1999; Haltinner et al., 2021; Roeser, 2012). Among types of emotions, fear is a common one. Although scientists have not reached a consensus on the definition of fear, they suggest that the antecedents (i.e., signals giving rise to fear) and consequents (i.e., objectively observable behaviors) should be fundamental components of a complete definition of fear (Mobbs et al., 2019). From the information-processing perspective of Mindsponge Theory, antecedents may be classified into two categories: external antecedents, which refer to perceived risks from the surrounding environment, and internal antecedents, which relate to expected risks based on past knowledge and memory (Adolphs, 2013; Vlaeyen et al., 2016).

Worry can be deemed a variation of fear, which is "a less intense emotion better suited to the issue of climate change. Worry tends to motivate, not short-circuit, more intense cognitive and analytical processing of risk information" (Smith & Leiserowitz, 2014). Pihkala (2020a) hints that despite their distinctions, worry, fear, and anxiety are often referred to as "negative" because they feel unpleasant. Dynamically, worry, as an outcome of the prior information process, can be used as an input for subsequent information processes. Thus, we assume that the stakeholders' worry about climate change will moderate the relationship between perceived ocean ecosystems' benefits and support for marine protection.

Additionally, certain experiences, acquired knowledge, and specific forms of exposure might contribute to the development of eco-anxiety in individuals; for instance, naturalists and climate scientists experience eco-anxiety due to their knowledge and emotional connections to the natural environment (Clayton, 2018; Pihkala, 2020b). Thus, it is also expected that knowledge of climate change will influence the relationship between the benefit perception of ocean systems and marine protection support as well as the moderation effect of worry, forming a three-way interaction effect between the benefit perception of ocean ecosystems, climate change knowledge, and climate change worry.

2.2. Material and variable description

The current study employs a secondary dataset about public perceptions of the interlinked effects of humans, climate change, and the value and management of marine and coastal ecosystems (Fonseca et al., 2023). The online platform Qualtrics (https://www.qualtrics.com) was used for the online survey from 16 November 2021 until 16 February 2022. The self-administered questionnaire was available in four languages: English, French, Spanish, and Italian. The survey was part of a funded project by the European Commission H2020 on "Marine Coastal Ecosystems Biodiversity and Services in a Changing World" (MaCoBioS).

The survey collection was designed to gather information about individuals interested in marine and coastal ecosystems, climate change, and ecosystem management. It specifically targeted stakeholders who were involved in (i) the production of fishing and/or seafood, (ii) tourism and creation, and (iii) conservation, management, and/or scientific services. Before disseminating the survey, the questionnaire was piloted on a sample of 20 respondents.

The questionnaire contained 20 questions, divided into four main sections: perceptions of climate change, the value of and dangers to coasts, oceans, and animals, perceptions of climate change responses, and sociodemographic data. At the beginning of the survey, the respondents were provided informed consent, and all respondents' information was anonymized in the final dataset. There were 717 responses from 42 countries that had been received by the time the survey collection was completed. Then, screening for inconsistent responses (i.e., inconsistent responses between the existence of climate change and impact of climate change) and for target stakeholder representation (i.e., reported not interacting/interested in the coast/ocean) resulted in the final sample size of 709 responses. For more details of the dataset, the data article was peer-reviewed and uploaded at: https://www.sciencedirect.com/science/article/pii/S2352340923000422

Table 1 describes the variables used for constructing the models that examine the assumptions formulated in Subsection 2.1. There are four variables: one outcome variable and three predictor variables. To measure the degree of marine protection support, we generated the outcome variable *SupportforOcean* from variable *Q12_6* in the original dataset. The variable reflects how much the stakeholders agreed, "I would support actions to protect the oceans, even if it meant eating less seafood and paying more for it." The stakeholders were given a 5-point Likert scale to answer, ranging from '1' being 'strongly disagree' to '5' being 'strongly agree.'

Variable *Benefits_ClimatechangeReduction*, generated from variable *Q8_6* in the original dataset, was used to demonstrate the stakeholders' perceived benefits of marine and coastal ecosystems in climate change reduction. It was measured by a 5-point Likert scale, ranging from '1' being 'strongly disagree' to '5' being 'strongly agree.' *KnowledgeTowardClimateChange* variable was used to represent the stakeholders' climate change knowledge, while *EmotionTowardClimateChange* was used to represent the stakeholders' worry about climate change. *KnowledgeTowardClimateChange* was measured using a 5-point Likert scale, ranging from '1' being 'not at all informed' to '5' being 'very well informed.' *KnowledgeTowardClimateChange* was measured using a 4-point Likert scale, ranging from '1' being 'not at all concerned to '4' being 'very concerned.' It should be noted that concern can be used interchangeably with worry (Fischer et al., 2012; Wang et al., 2018).

Table 1: Variable description

Variable	Description	Coded in dataset	Type of variable	Coded value
SupportforOcean	The degree that the stakeholder would support actions to protect the oceans, even if it meant eating less seafood and paying more for it	*Q12_6*	Numerical	1: Strongly disagree; 2: Disagree; 3: Neither agree nor disagree; 4: Agree; 5: Strongly agree
Benefits_ClimatechangeReduction	Perceived marine and coastal ecosystems benefits in climate change reduction	*Q8_6*	Numerical	1: Strongly disagree; 2: Disagree; 3: Neither agree nor disagree; 4: Agree; 5: Strongly agree
KnowledgeTowardClimateChange	The respondent's level of	*Q3*	Numerical	1: Not at all informed;

	climate change knowledge			2: Not well informed; 3: Somewhat informed; 4: Well informed; 5: Very well informed
EmotionTowardClimateChange	The respondent's level of climate change worry	*Q4*	Numerical	1: Not at all concerned; 2: Not very concerned; 3: Somewhat concerned; 4: Very concerned

2.3. Model construction

To validate the assumptions presented in Subsection 2.1, we constructed four models, from simple to complex. Specifically, to check whether knowledge of climate change moderates the relationship between the benefit perception of ocean ecosystems and marine protection support, Model 1 is constructed.

$$SupportforOcean \sim normal(\mu, \sigma) \quad (1.1)$$

$$\mu_i = \beta_0 + \beta_1 * Benefits\_ClimatechangeReduction_i + \beta_2 * KnowledgeTowardClimateChange_i + \beta_3 * KnowledgeTowardClimateChange_i * Benefits\_ClimatechangeReduction_i \quad (1.2)$$

$$\beta \sim normal(M, S) \quad (1.3)$$

The probability around μ is determined by the form of the normal distribution, whose width is specified by the standard deviation σ. μ_i indicates stakeholder i' degree of marine protection support; $KnowledgeTowardClimateChange_i$ indicates the level of stakeholder i's knowledge about climate change; $Benefits\_ClimatechangeReduction_i$ indicates the level of stakeholder i's perceived benefits of marine and coastal ecosystems in climate change reduction; β_3 indicates the coefficient of the non-additive effect of $Benefits\_ClimatechangeReduction_i$ and $KnowledgeTowardClimateChange_i$ on $SupportforOcean$. If the coefficients β_3's distribution is significant, the association between the benefit perception of ocean ecosystems and marine protection support is considered moderated by climate change knowledge. Model 1 has five parameters: the coefficients, β_1 – β_3, the intercept, β_0, and the standard deviation of the "noise", σ. The coefficients are distributed as a normal distribution around the mean denoted M and with the standard deviation denoted S.

Similar to Model 1, Model 2 was constructed to check whether worry about climate change moderates the relationship between the benefit perception of ocean ecosystems and marine protection support:

$$SupportforOcean \sim normal(\mu, \sigma) \tag{2.1}$$

$$\mu_i = \beta_0 + \beta_1 * Benefits\_ClimatechangeReduction_i + \beta_2 * EmotionTowardClimateChange_i + \beta_3 * EmotionTowardClimateChange_i * Benefits\_ClimatechangeReduction_i \tag{2.2}$$

$$\beta \sim normal(M, S) \tag{2.3}$$

β_3 indicates the coefficient of the non-additive effect of $Benefits\_ClimatechangeReduction_i$ and $EmotionTowardClimateChange_i$ on $SupportforOcean$. If the coefficients β_3's distribution is significant, the association between the benefit perception of ocean ecosystems and marine protection support is considered moderated by worry emotion toward climate change.

To check the robustness of the predictions (whether the effects remain unchanged when the model becomes more complex), we combined Model 1 and Model 2 to construct Model 3:

$$SupportforOcean \sim normal(\mu, \sigma) \tag{3.1}$$

$$\mu_i = \beta_0 + \beta_1 * Benefits\_ClimatechangeReduction_i + \beta_2 * KnowledgeTowardClimateChange_i + \beta_3 * KnowledgeTowardClimateChange_i * Benefits\_ClimatechangeReduction_i + \beta_4 * EmotionTowardClimateChange_i + \beta_5 * EmotionTowardClimateChange_i * Benefits\_ClimatechangeReduction_i \tag{3.2}$$

$$\beta \sim normal(M, S) \tag{3.3}$$

Model 3 has seven parameters: the coefficients, β_1 – β_5, the intercept, β_0, and the standard deviation of the "noise", σ.

Finally, Model 4 was constructed to examine a three-way interaction effect between the benefit perception of ocean ecosystems, climate change knowledge, and climate change worry on marine protection support.

$$SupportforOcean \sim normal(\mu, \sigma) \tag{4.1}$$

$$\mu_i = \beta_0 + \beta_1 * Benefits\_ClimatechangeReduction_i + \beta_2 * KnowledgeTowardClimateChange_i + \beta_3 * KnowledgeTowardClimateChange_i * Benefits\_ClimatechangeReduction_i + \beta_4 * EmotionTowardClimateChange_i + \beta_5 * EmotionTowardClimateChange_i * Benefits\_ClimatechangeReduction_i + \beta_6 * EmotionTowardClimateChange_i * Benefits\_ClimatechangeReduction_i * KnowledgeTowardClimateChange_i \tag{4.2}$$

$$\beta \sim normal(M, S) \tag{4.3}$$

Model 4 has eight parameters: the coefficients, $\beta_1 - \beta_6$, the intercept, β_0, and the standard deviation of the "noise", σ. β_6 indicates the coefficient of the non-additive effect of $Benefits\_ClimatechangeReduction_i$, $KnowledgeTowardClimateChange_i$ and $EmotionTowardClimateChange_i$ on $SupportforOcean$. If the coefficient β_6's distribution is significant, it will confirm the intricate interaction effects between the benefit perception of ocean ecosystems, climate change knowledge, and climate change worry on marine protection support. The logical network of Model 4 is shown in Figure 1.

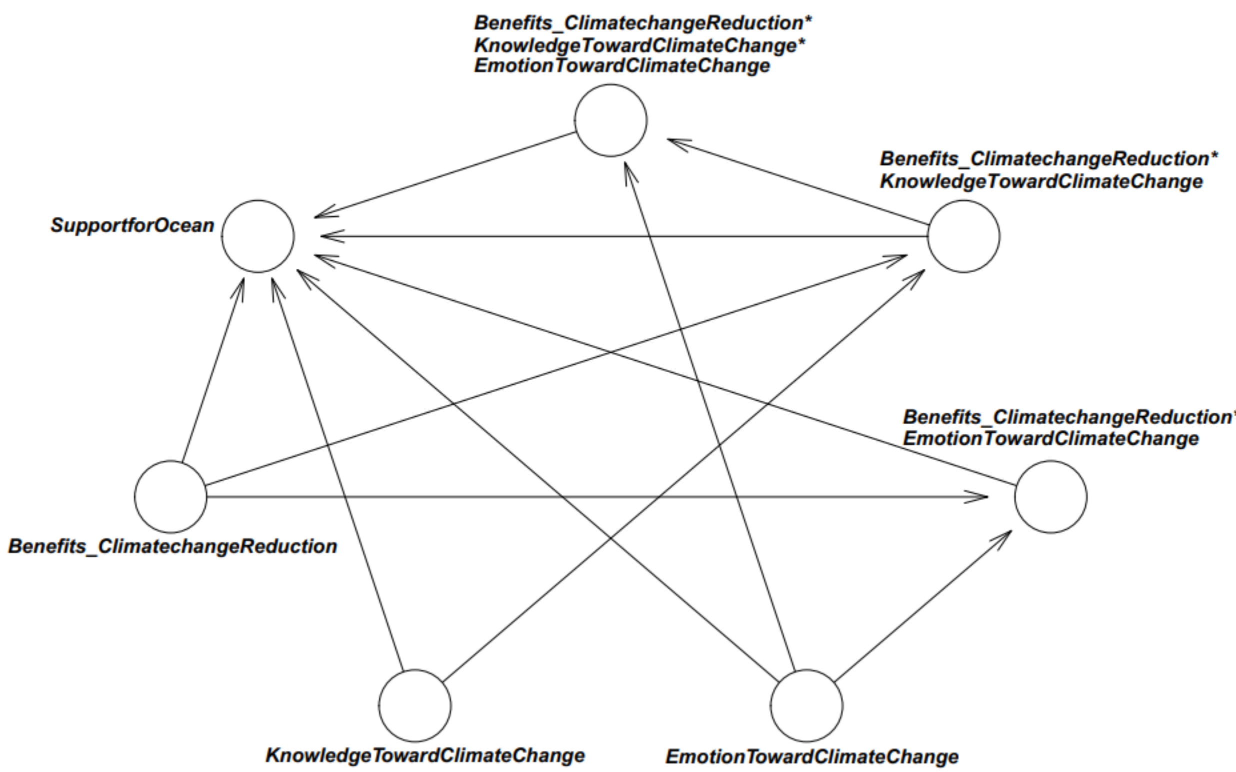

Figure 1: Model 4's logical network

2.4. Analysis and validation

Bayesian Mindsponge Framework (BMF) analytics was utilized as the methodology of this study. It comprises two fundamental components: 1) theoretical reasoning using the Mindsponge Theory, and 2) statistical analysis using the Bayesian analysis. This analytical framework has several advantages (Nguyen et al., 2022; Vuong, Nguyen, et al., 2022). First, it combines the logical reasoning power of Mindsponge Theory's information-processing perspective with the inferential benefits associated with Bayesian analysis. Since these two techniques demonstrate a significant level of compatibility, they can help researchers to take advantage of parsimonious models (Csilléry et al., 2010; Gill, 2014; Nguyen et al., 2022; Simon, 2001). Second, Bayesian inference aided by the Hamiltonian Monte Carlo algorithm still enables fitting various types of models with high levels of complexity, like multilevel and nonlinear models (Dunson, 2001). Therefore, it allows us to examine the model's two-way and three-way interaction effects. Third, Bayesian inference has some theoretical advantages when compared to the frequentist approach. One noteworthy benefit is the capacity to employ credible intervals to interpret results rather than depending on the dichotomous evaluation based on *p*-values (Halsey et al., 2015; Wagenmakers et al., 2018).

The Bayesian analysis in the study comprises four main steps. First of all, we employed the Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) diagnostics to check the models' goodness of fit (Vehtari & Gabry, 2019; Vehtari et al., 2017). LOO is computed as follows:

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

$p_{post(-i)}(\theta)$ is the posterior distribution based on the data minus data point i. The *k*-Pareto values are used in the PSIS method for computing leave-one-out cross-validation, which helps identify observations with a high degree of influence on the PSIS estimate. If *k*-Pareto values are greater than 0.7, the model is often considered unsuitable with the dataset. On the contrary, a model is deemed fit when the *k* values are below 0.5.

Then, we compared the weights of the models by computing the WAIC weights, Pseudo-BMA weights without Bayesian bootstrap, Pseudo-BMA+ weights with Bayesian bootstrap, and Bayesian stacking weights to identify the most predictive model (with the highest weight) (Vehtari & Gabry, 2019; Yao et al., 2018). The most predictive model will be chosen for the subsequent result diagnostics and interpretation. The third step was model convergence diagnostics. Statistically, the effective sample size (*n_eff*) and the Gelman–Rubin shrink factor (*Rhat*) values can be used to evaluate the model convergence. The *n_eff* value is the number of iterative samples that are not autocorrelated during stochastic simulation; thus, if *n_eff* is larger than 1000, Markov chains can be deemed convergent, and the effective samples are sufficient for reliable inference (McElreath, 2018). Meanwhile the *Rhat* value is referred to as the Gelman–Rubin shrink factor or potential scale reduction factor (Brooks & Gelman, 1998). The model is considered convergent if *Rhat* = 1 and not convergent when

Rhat is greater than 1.1. Besides *n_eff* and *Rhat* values, we further checked the convergence using visual diagnostics, such as trace plots, Gelman–Rubin–Brooks plots, and autocorrelation plots.

The Bayesian analysis was performed on R using the **bayesvl** open-access package due to its good visualization capabilities and functionality (La & Vuong, 2019). Before fitting the model, it is necessary to identify the prior distributions. As the study is exploratory, we decided to employ uninformative priors to avoid subjective biases. Uninformative priors or a flat prior distribution provide only minimal prior information for model estimations. In the **bayesvl** package, the uninformative prior is set as a default with a mean value of 0 and a standard deviation of 10. To improve transparency and lower the cost of reproduction, we deposited all the data and code of this study in an Open Science Framework (OSF) server (Vuong, 2018): https://osf.io/fhtgc/

3. Results

First of all, we checked the goodness of fit between the constructed models and the dataset using the PSIS-LOO test. The Pareto *k* estimates are below the threshold of 0.5, indicating that all constructed models fit well with the dataset (see Figure 2 for Model 4's PSIS-LOO test and Figures A1-A3 for other models' PSIS-LOO test). Then, we conducted the weight comparison between four models to select the most predictive model for later interpretation. As presented in Table 2, Model 4 consistently outweighs other models in all categories. Thus, Model 4 is the most predictive model to explain the data and will be chosen for result interpretation from this point. Table A1 in the Appendix shows the estimated posterior distributions of Models 1-3.

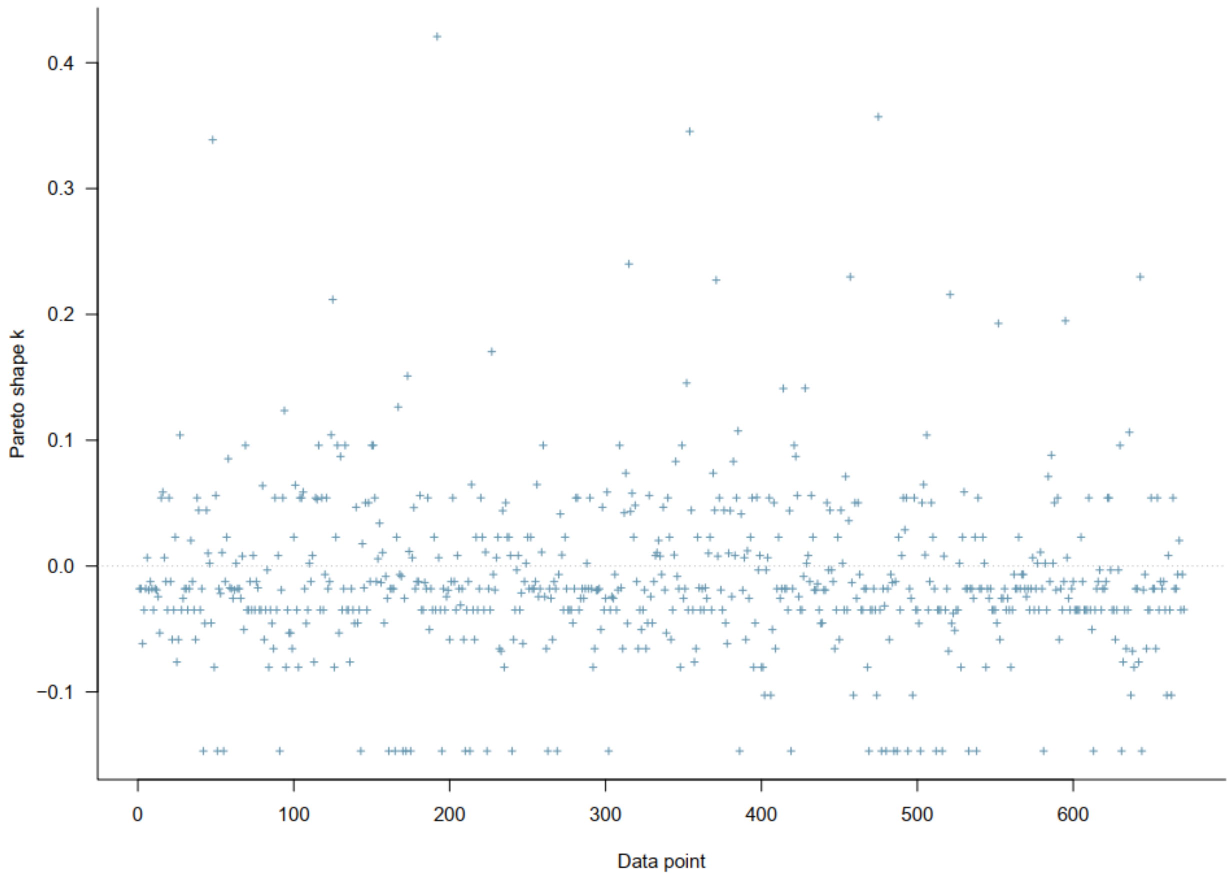

Figure 2: Model 4's PSIS-LOO test

Table 2: Model weight comparison

Model	Waic_wts	Pseudo-BMA without Bayesian bootstrap	Pseudo-BMA with Bayesian bootstrap	Bayesian Stacking
Model 1	0.000	0.000	0.043	0.180
Model 2	0.184	0.183	0.266	0.366
Model 3	0.211	0.207	0.207	0.000
Model 4	0.605	0.611	0.484	0.454

After the simulation using the Hamiltonian Monte Carlo algorithm with four chains, 5000 iterations, and 2000 warm-up iterations, the two standard diagnostic tests validate the good convergence of Model 4's Markov chains. Specifically, the *n_eff* values are all greater than 1000, and all *Rhat* values are equal to one (see Table 3). The trace plots of Model 4 illustrate the healthy mixing of all coefficients' Markov chains around an equilibrium, validating the good convergence (see Figure 3). Figures 4 and 5 also further confirm the convergence, when the shrink factors in Gelman-Rubin-Brooks plots drop rapidly to 1, and the autocorrelation levels in the autocorrelation plots decline swiftly to 0.

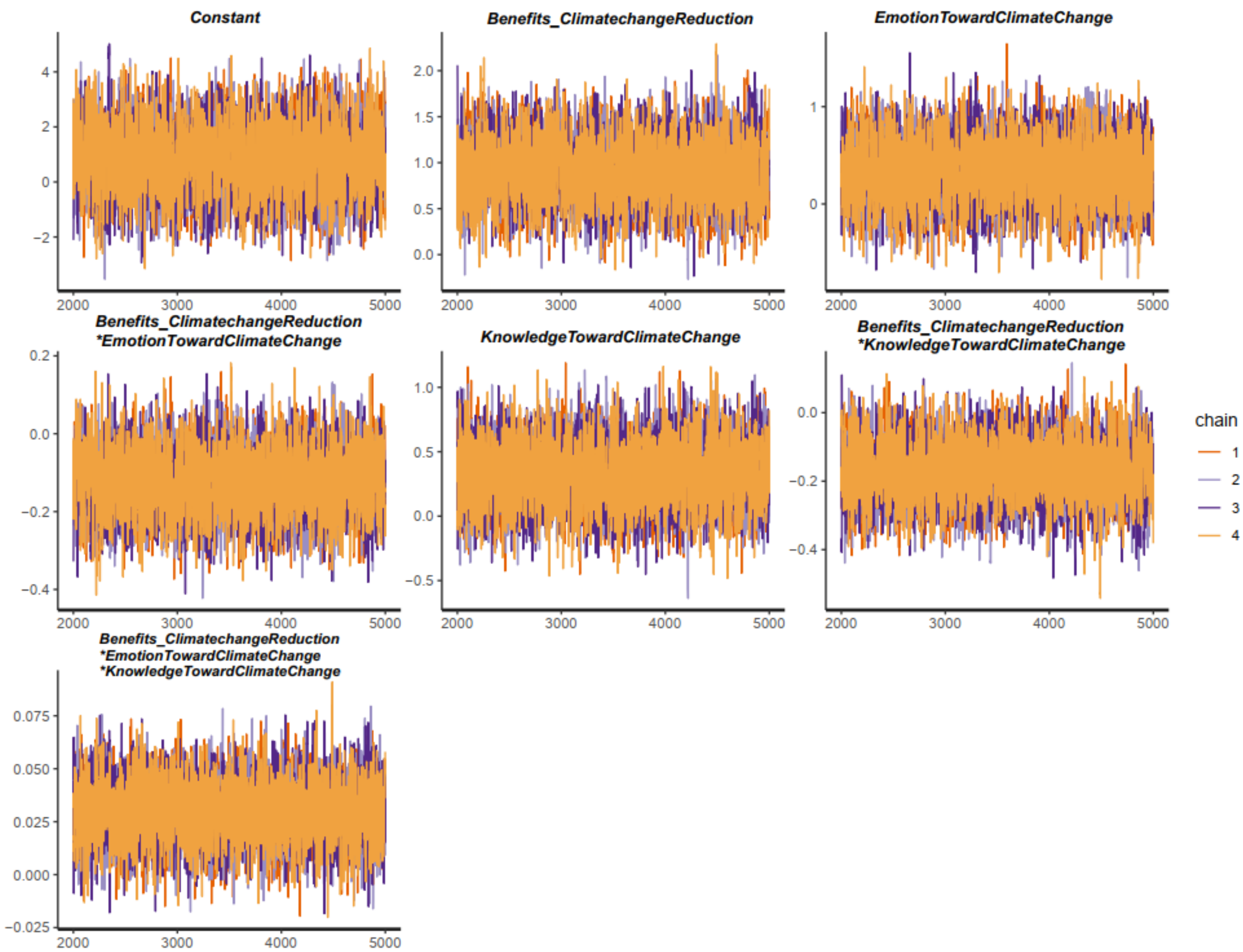

Figure 3: Model 4's trace plots

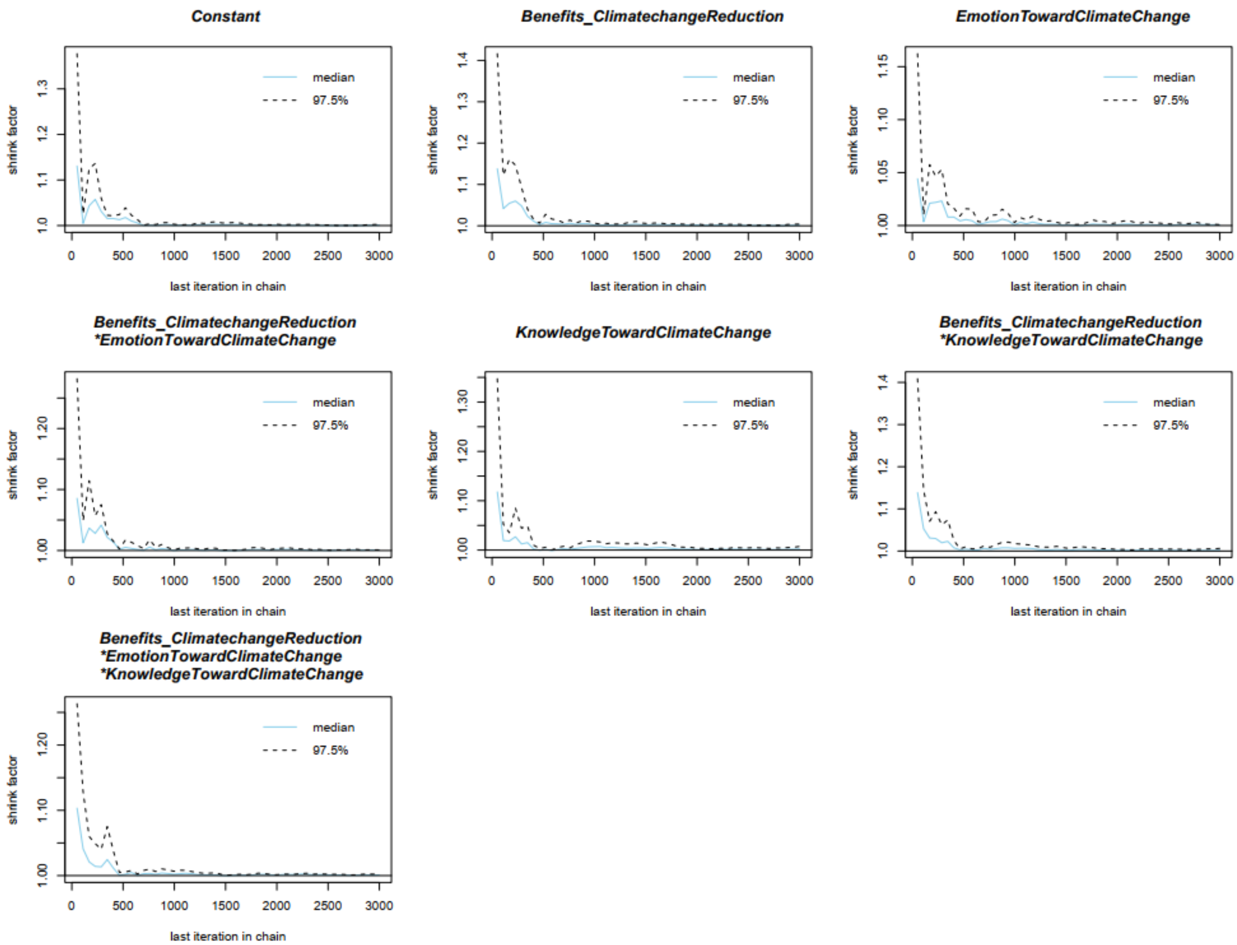

Figure 4: Model 4's Gelman-Rubin-Brooks plots

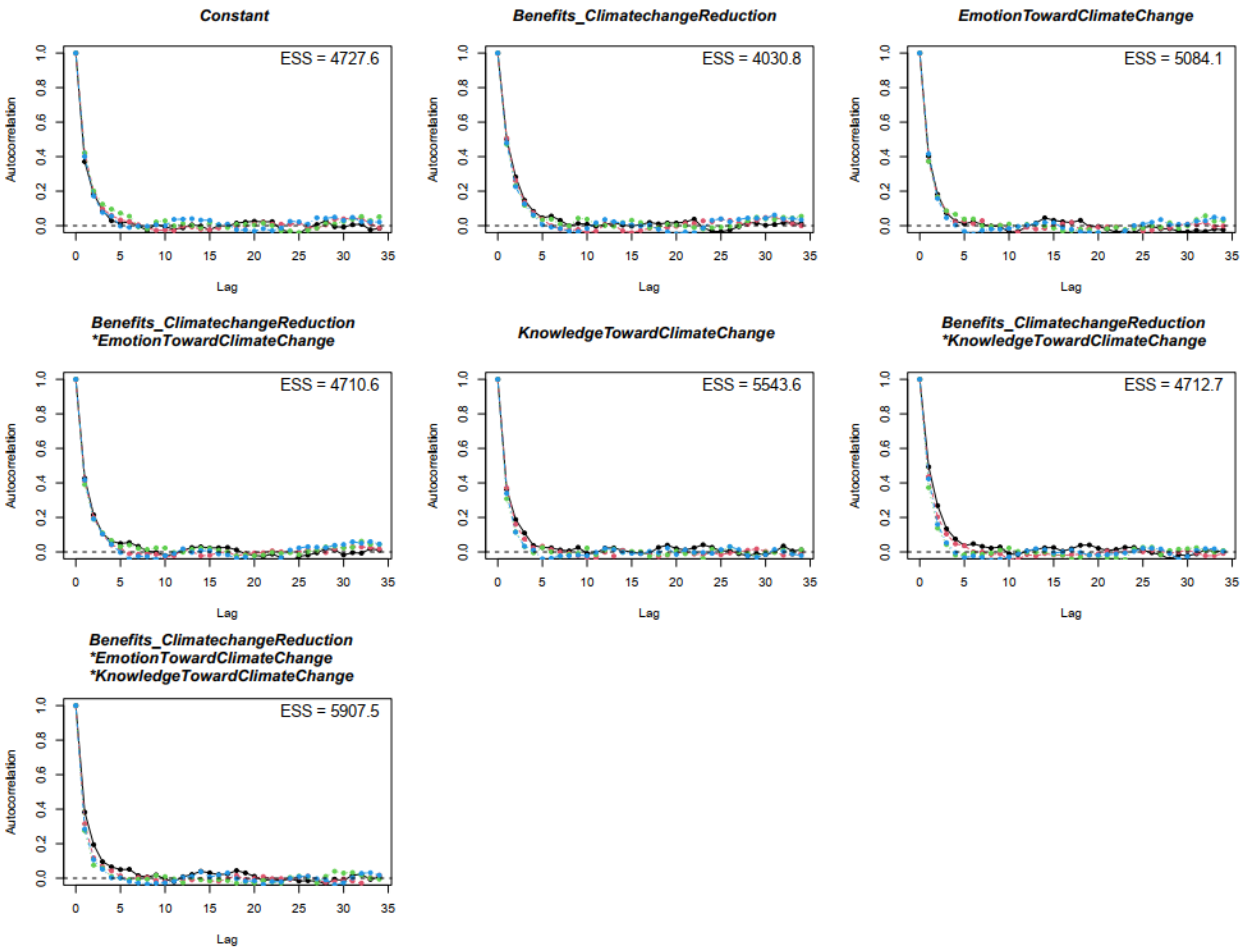

Figure 5: Model 4's autocorrelation plots

Table 3 presents the estimated posterior distributions of the constructed model. Since the constructed model is complicated with a three-way interaction involving perceptions of marine and coastal benefits in climate change mitigation, levels of climate change knowledge, and emotional responses to climate change, it is necessary to visualize the findings before interpreting them. However, the findings' reliability and robustness must be evaluated before the result interpretation.

Table 3: Estimated posterior distributions of Model 4

Variables	Mean	Standard Deviation	n_eff	Rhat
Constant	0.76	1.19	4165	1
Benefits_ClimatechangeReduction	0.94	0.34	3502	1

EmotionTowardClimateChange	0.34	0.32	4677	1
Benefits_ClimatechangeReduction EmotionTowardClimateChange*	-0.12	0.08	4057	1
KnowledgeTowardClimateChange	0.34	0.25	5398	1
Benefits_ClimatechangeReduction KnowledgeTowardClimateChange*	-0.17	0.09	4322	1
Benefits_ClimatechangeReduction EmotionTowardClimateChange* KnowledgeTowardClimateChange*	0.03	0.01	5056	1

Figure 6 demonstrates the posterior distributions of Model 4 on histograms. The thick blue lines in the histogram's middle indicate the probability mass within the 89% Highest Posterior Density Intervals. (HPDI). As seen in Figure 6, the 89% HPDI of all coefficients are entirely distributed on either the positive or negative side of the axis, except for *EmotionTowwardClimateChange* and *KnowledgeTowwardClimateChange*. Although a fraction of the HPDI of these two coefficients is located on the negative side, it is negligible. This suggests that the estimated results of these coefficients are highly reliable.

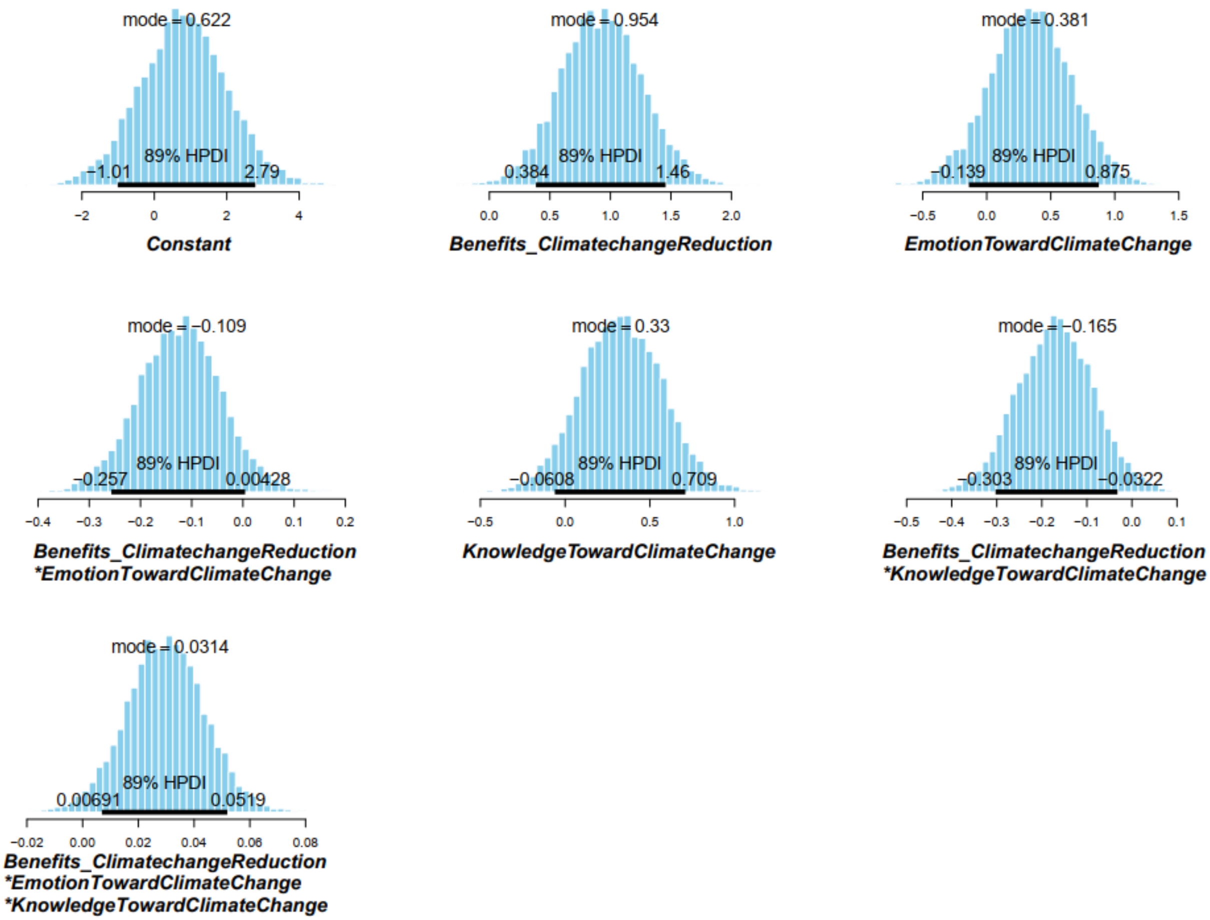

Figure 6: Model 4's posterior distributions

Employing Equation 4.2 and the estimated mean values of parameters in Table 3, we calculated degrees of marine protection support. For clarity, the estimated degrees of marine protection support in each scenario of perceived benefits of marine and coastal ecosystems in reducing climate change is plotted in Figures 7A-7E. As shown in Figures 7A-7E, when stakeholders' perceived benefits of marine and coastal ecosystems in reducing climate change increased, their support for marine protection also increased. In the scenarios where stakeholders did not perceive the benefits of marine and coastal ecosystems (i.e., strongly disagree, disagree, and neutral), stakeholders' knowledge and emotions towards climate change are positively associated with marine protection support (see Figures 7A-7C). At the same level of climate change knowledge, stakeholders more concerned about climate change have a higher level of marine protection support than those less concerned (see Figures 7-A and 7-B).

However, in the scenarios where stakeholders perceived the benefits of marine and coastal ecosystems (i.e., agree and strongly agree), climate change knowledge is positively associated with marine protection support only among stakeholders with high levels of climate change concern. For those with the low level of climate change concern (i.e., not at all concerned and not very concerned), climate change knowledge negatively affects their marine protection support (see Figures 7-D and 7-E).

The results confirm our assumption above that there exist very complex interaction effects among the perceived benefits of ocean ecosystems, knowledge of climate change, and emotion toward climate change of the stakeholders on marine protection support.

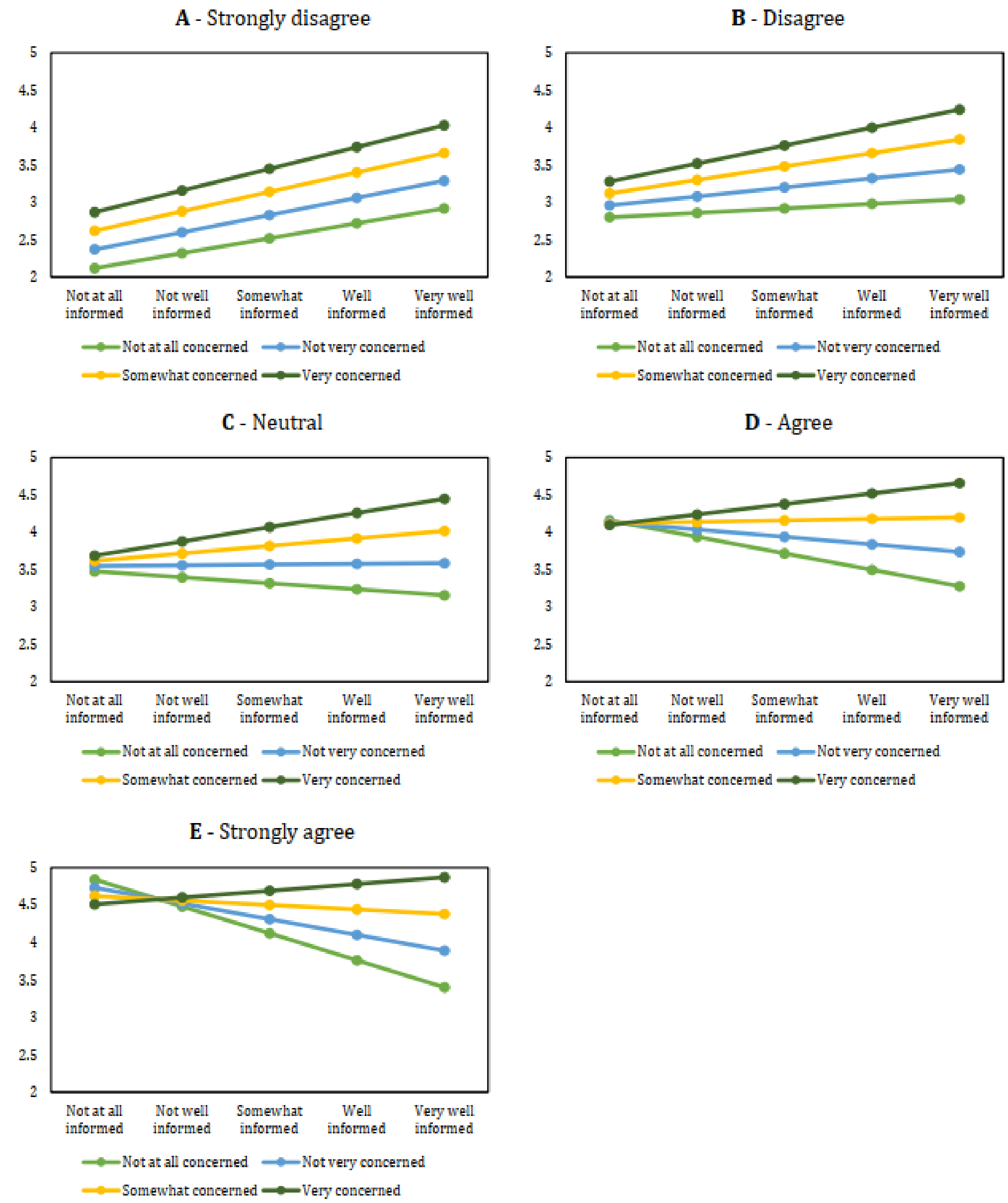

Figure 7: Estimated marine protection degree in different scenarios of perceived benefits of ocean ecosystems in climate change reduction.

4. Discussion

The current study employed the Bayesian Mindsponge Framework (BMF) analytics to examine the intricate interaction effects of benefit perception of ocean ecosystems, climate change knowledge, and worry emotion toward climate change on stakeholders' marine protection support. The findings confirm the effects of benefit perception of the ocean ecosystem, climate change knowledge, and worry emotion toward climate change on marine protection support. Still, these effects vary depending on different scenarios.

Specifically, when stakeholders perceive no benefits of marine and coastal ecosystems in alleviating climate change, higher climate change knowledge and worry emotion toward climate change can help improve their support for marine protection (see Figures 7-A and 7-B). However, when stakeholders perceive the benefits of marine and coastal ecosystems in climate change reduction, the effect of climate change knowledge on marine protection support becomes conditional on the stakeholders' emotions. If the stakeholders are concerned about climate change, climate change knowledge will help improve marine protection support. Otherwise, it will help reduce the support (see Figures 7-D and 7-E).

From the Mindsponge Theory perspective, the above findings can be explained by the difference in information vitality in the information process. A person's emotional responses to climate change do not result from the climate change itself but from perceiving "objects of care" as threatened by climate change (Wang et al., 2018). Thus, the greater worry emotion toward climate change might reflect the greater importance of the "objects of care" towards the person. As "objects of care" can be considered valued objects in the mindset (e.g., people, places, goals, or events), the subsequent information processes will be optimized to prolong the existence of such values. The optimization process takes use of the information stored within the mind and information absorbed from the environment (Nguyen, Le, et al., 2023; Vuong, 2023). Climate change knowledge is information stored in the mind but not necessarily in the mindset, so it might be used as the resource for the information process that aims to prolong the existence of the "objects of care."

When stakeholders are not at all concerned about climate change, they might perceive no "objects of care" threatened by climate change, or they do not believe in climate change (i.e., climate change denialists) (McCright & Dunlap, 2011; Vardy et al., 2017). In either case, they have different mindsets compared to stakeholders concerned about climate change. Such mindsets might subsequently influence their information processes to prioritize their other interests, such as livelihoods, but not information relevant to climate change reduction. For those people, climate change knowledge might be optimized to reject information about climate change reduction efforts. This reasoning might explain why, among stakeholders perceiving the benefits of marine and coastal ecosystems in climate change reduction, people with no concern about climate change have significantly lower support for marine protection when their knowledge increases. From the perspective of these people, protecting marine seems to be not valuable as they perceive no "objects of care" threatened by climate change or do not believe in climate change. Hence, they might utilize their climate change knowledge to avoid supporting marine protection, which can even incur costs to them. For stakeholders with no concern and knowledge but still perceiving the benefits of marine and coastal ecosystems in reducing climate change, they might have limited alternatives other than supporting marine protection, as it seems to be the most beneficial option.

Despite the intricate interactions among benefit perception of the ocean ecosystem, climate change knowledge, and worry emotion toward climate change, it is conclusive that all of these factors can positively affect marine protection support. Our findings suggest that marine stakeholders' support for marine protection can be improved through greater perceived benefits of ocean ecosystems in alleviating climate change, higher awareness and knowledge, and more emotional connections to climate change. Improving stakeholders' accessesibility to information related to climate change and the essential roles of the marine and coast in climate change reduction is a potential method to help build a beneficial perception of aquatic ecosystems and enhance climate change knowledge (Nguyen, Duong, et al., 2023; Nguyen & Jones, 2022b). It can be done through educational campaigns, public outreach programs, pro-environmental entertaining platforms, and environmental literature (Cigliano et al., 2015a; Diedrich et al., 2017; Fisher et al., 2021; Fjællingsdal & Klöckner, 2019; Kusumawati & Huang, 2015; Schneider-Mayerson, 2018; Vuong, 2020a).

However, raising climate change awareness and knowledge is not sufficient. Information dissemination endeavors should also focus on linking people's "objects of care" to the consequences of climate change. Doing so will increase stakeholders' risk perceptions (Roeser, 2012; Smith & Leiserowitz, 2014; Wang et al., 2018; Zeelenberg et al., 2008), which can affect their subsequent information processes to absorb and integrate information regarding the importance of environmental conservation into their mindset. Eventually, it will help develop an eco-surplus mindset among marine stakeholders. Such a mindset can influence stakeholders' thinking, decision-making, and behaviors to create more positive values "to reduce negative anthropogenic impacts on the environment and conserve and restore nature" (Nguyen & Jones, 2022a; Vuong, 2021).

Entailing emotional factors in information dissemination can sometimes trigger radical responses from the public. Recent environmental protests blocking highways, disrupting public events, and vandalizing artworks across Europe are typical examples (Binde, 2023; Healy, 2023; Limb, 2023; NTV, 2023; Speare-Cole, 2022). Although these radical environmental activities can help raise public awareness, they might also cause public distrust and opposition toward environmental protection efforts. Road blockage could even contribute to additional vehicle emissions and quickly escalate into violence. Fighting against climate change requires collaboration and solidarity among all sectors and groups of people, so all people's "objects of care" should be treated thoughtfully when communicating environmental messages.

This study has several limitations, so we disclose them below to ensure transparency (Vuong, 2020b). First, our study exclusively concentrated on the stakeholders associated with marine and coastal ecosystems. Consequently, it is important to acknowledge that the findings may not be applicable to broader populations. Second, it is worth noting that a significant proportion of the participants in the study were from high-income nations, so the conclusions drawn from this research may not accurately capture stakeholders' psychology in countries with low, lower-middle, and upper-middle income levels. Since our study is one of the first studies to examine the intricate interaction between benefit perception, climate change knowledge, and emotion toward climate change, many points remain unclear and require further studies to fill in the gap. Specifically, future study should be conducted to validate whether one's mindset or set of beliefs can influence how they use the knowledge and examine the different kinds of knowledge's and emotions' effects on one's psychology and behaviors.

Appendix

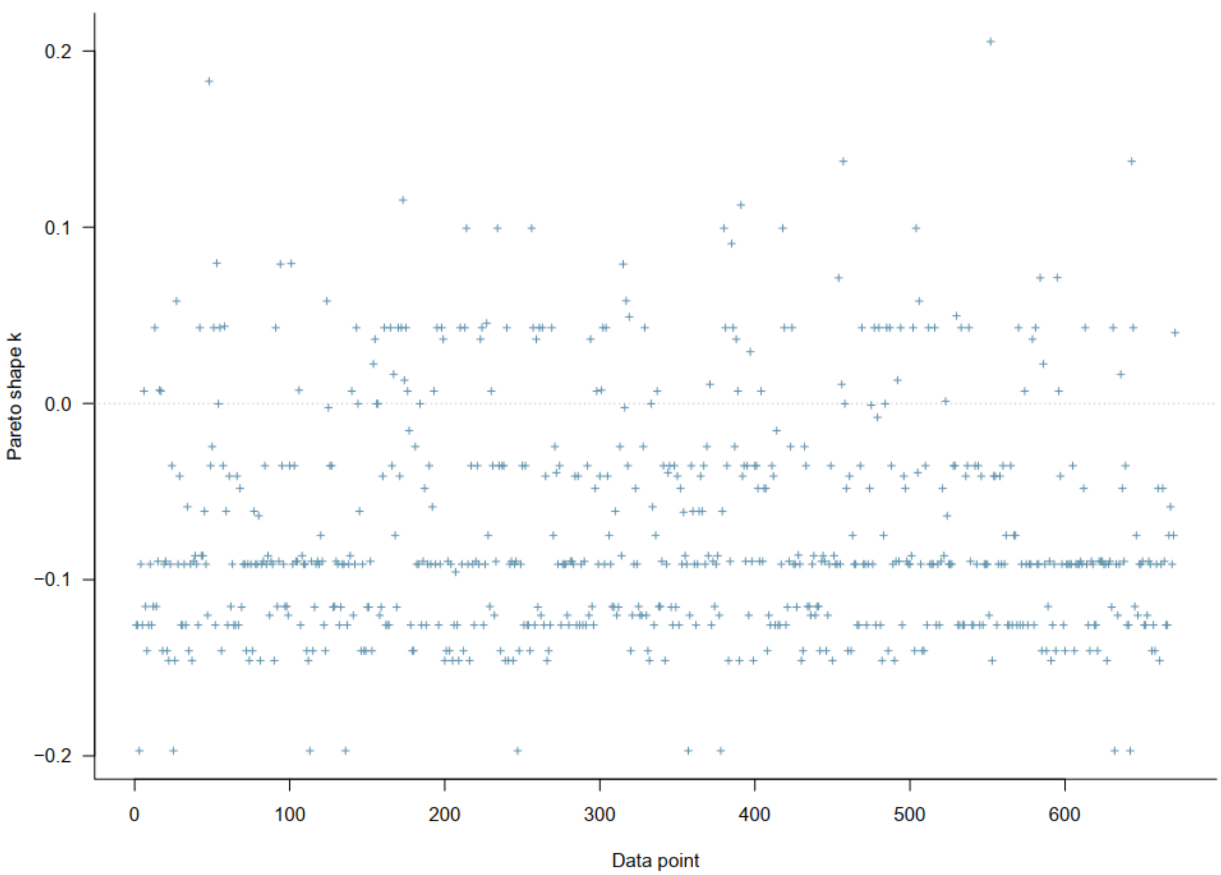

Figure A1: Model 1's PSIS-LOO test

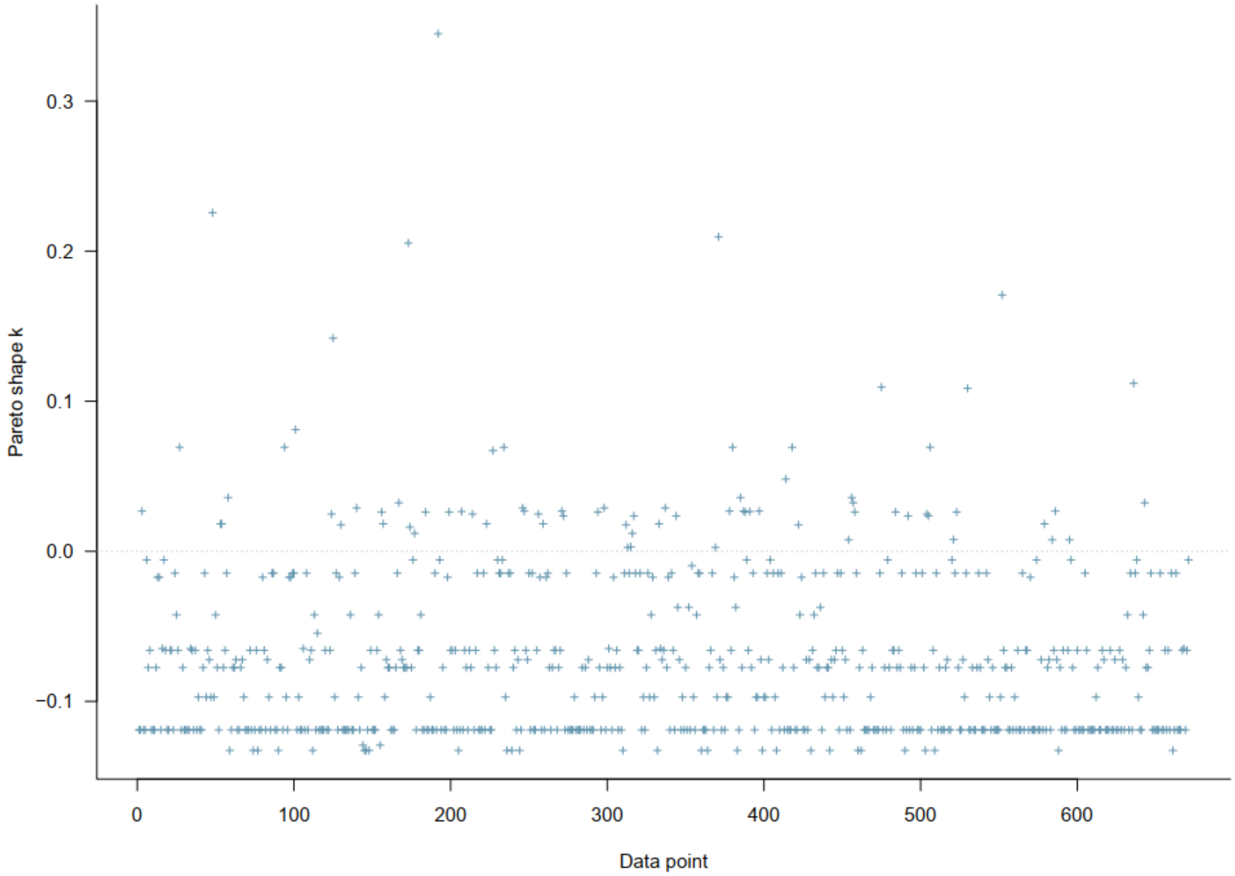

Figure A2: Model 2's PSIS-LOO test

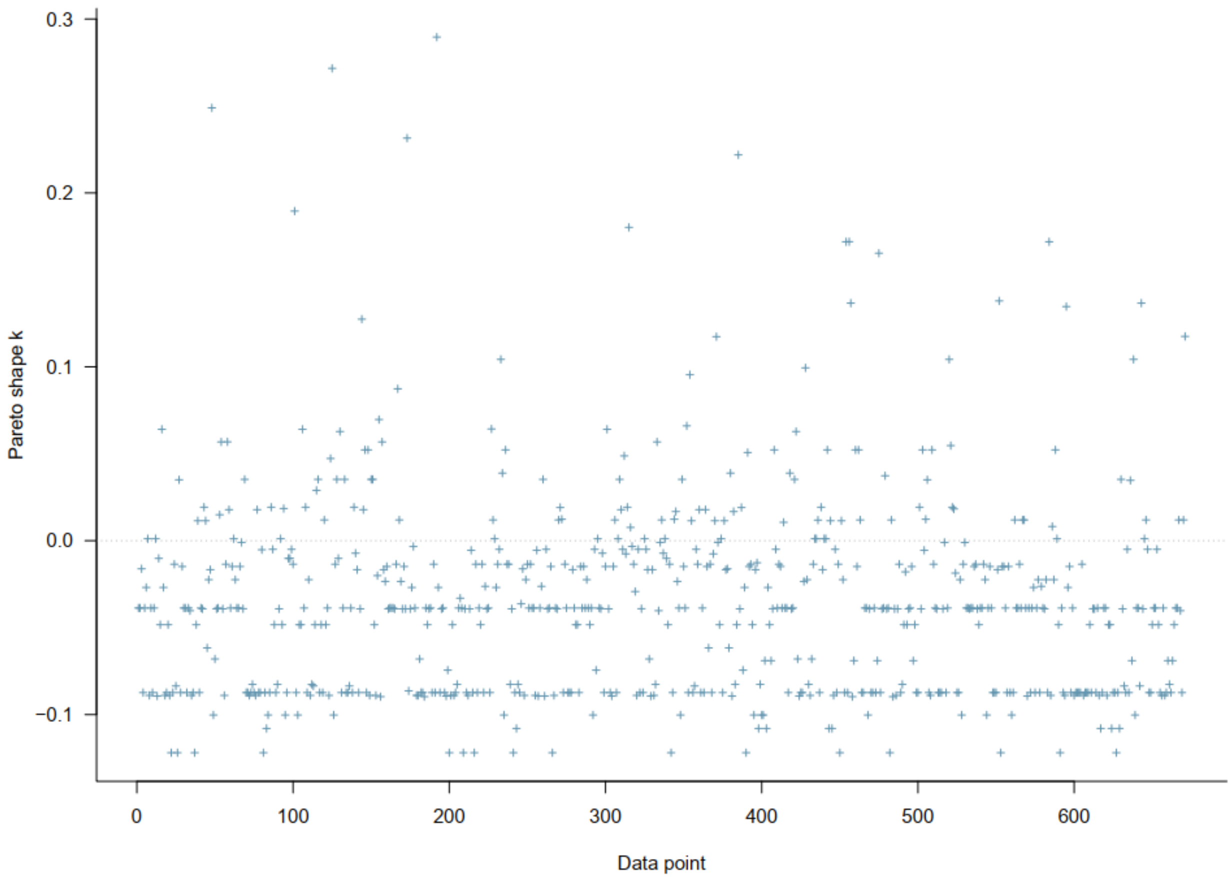

Figure A3: Model 3's PSIS-LOO test

Table A1: Estimated posterior distributions of Models 1-3

Model 1				
Variables	**Mean**	**Standard Deviation**	**n_eff**	**Rhat**
Constant	1.93	0.86	2492	1
Benefits_ClimatechangeReduction	0.48	0.19	2525	1
KnowledgeTowardClimateChange	0.28	0.23	2415	1
*Benefits_ClimatechangeReduction *KnowledgeTowardClimateChange*	-0.04	0.05	2429	1
Model 2				
Variables	**Mean**	**Standard Deviation**	**n_eff**	**Rhat**
Constant	1.47	1.08	4727	1
Benefits_ClimatechangeReduction	0.43	0.26	4734	1
EmotionTowardClimateChange	0.49	0.30	4748	1
*Benefits_ClimatechangeReduction *EmotionTowardClimateChange*	-0.05	0.07	4727	1
Model 3				

Variables	Mean	Standard Deviation	n_eff	Rhat
Constant	0.80	1.19	4292	1
Benefits_ClimatechangeReduction	0.54	0.28	4260	1
EmotionTowardClimateChange	0.49	0.31	4679	1
*Benefits_ClimatechangeReduction *EmotionTowardClimateChange*	-0.05	0.07	4634	1
KnowledgeTowardClimateChange	0.19	0.23	4737	1
*Benefits_ClimatechangeReduction *KnowledgeTowardClimateChange*	-0.03	0.05	4721	1

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