Predictors of Residents' Sensitivity to Air Quality Index Ratings Amid Wildfire Smoke: Evidence from the United States

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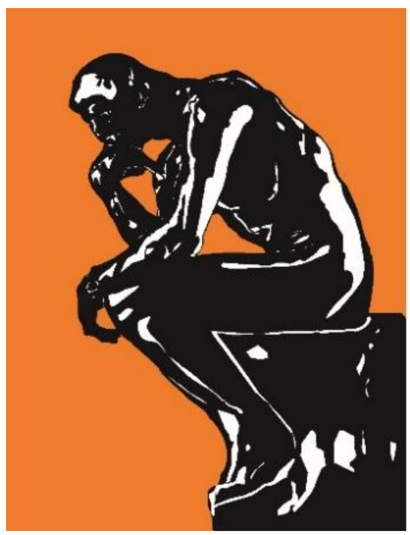

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"Smoke flies out from the cave, even faintly, but it is enough to make Kingfisher squeamish and almost blackout."

—In "A Shocking Secret"; *Wild Wise Weird* (2024)

Abstract

Wildfires have become an increasing global threat to public health and quality of life. Many countries employ air quality monitoring and reporting systems to mitigate health risks associated with air pollution, including wildfire smoke. This study investigates the factors influencing individuals' sensitivity to air quality information, specifically their likelihood of reducing or ceasing outdoor activities in response to air quality ratings, with a focus on wildfire smoke exposure in the western United States. Using the Bayesian Mindsponge Framework (BMF) analytics, the study analyzed data from 2,237 participants in the Boise Metropolitan Area of Idaho and Boise State University. The findings reveal that women, older individuals, and those with higher educational levels are more likely to reduce outdoor activities at lower unhealthy AQI levels (the lowest being 'good air quality,' while the highest being 'hazardous air quality'), while individuals with higher incomes are less responsive. Women and older adults, in particular, are even more likely to eliminate all outdoor activities. Additionally, individuals who perceive wildfire smoke as more severe than other natural disasters are more inclined to reduce or eliminate outdoor activities at lower unhealthy air quality levels. Experiences of wildfire smoke-related illness—either personally or within their households—further amplify this effect. These findings highlight the importance of localized, context-specific approaches to AQI dissemination and wildfire smoke risk communication to build resilience and safeguard public health in the face of escalating wildfire challenges driven by climate change.

Keywords: wildfire smoke; risk perception; climate change; Mindsponge Theory; eco-surplus culture

1. Introduction

Wildfires have emerged as a growing threat to public health and quality of life on a global scale, with far-reaching consequences for air quality, human well-being, and the environment. Exposure to wildfire smoke, particularly fine particulate matter (PM2.5), has been linked to a wide range of adverse health outcomes, including respiratory illnesses such as asthma and chronic obstructive pulmonary disease (COPD), cardiovascular complications, mental health, and even premature mortality (Cascio, 2018; Doubleday et al., 2020; Eisenman & Galway, 2022; Reisen et al., 2015; Xu et al., 2024). In recent decades, the frequency and intensity of wildfires have increased markedly, driven by climate change and human activities, compounding their detrimental effects on air quality and human health (Rizzo & Rizzo, 2024; Xu et al., 2024).

The western region of the United States has been particularly affected by the growing wildfire problem, with the unique geographical and meteorological conditions of this area, combined with climate change and human activities, contributing to an increased occurrence of large, high-severity wildfires (Burke et al., 2021; Garofalo et al., 2019; O'Dell et al., 2019). As a result, communities in the western U.S. are experiencing more frequent and prolonged exposure to hazardous levels of wildfire smoke, which can travel long distances and significantly degrade air quality, even in urban and semi-urban areas (Chen et al., 2021; Jaffe et al., 2020; Navarro et al., 2018). For example, the 2020 wildfire season in California, Oregon, and Washington was particularly severe, with widespread smoke events affecting millions of people and leading to unhealthy air quality levels for extended periods (DQE, 2023).

Wildfire smoke is a complex mixture of pollutants, including fine particulate matter (PM2.5), CO, O3, NO2, SO2, NMOCs, and Hg (Chen et al., 2021; Reisen et al., 2015). These pollutants pose substantial risks to respiratory and cardiovascular health, particularly among vulnerable populations such as children, older people, and individuals with pre-existing conditions (Chen et al., 2021; Heaney et al., 2022; Liu et al., 2015; Reisen et al., 2015). The health consequences of exposure to poor air quality, including wildfire smoke, are well-documented and wide-ranging, affecting various bodily systems and exacerbating pre-existing conditions. Wildfire smoke has been associated with increased respiratory morbidity, such as asthma exacerbations, COPD, and respiratory infections, as well as cardiovascular complications, including heart attacks, strokes, and arrhythmias (Aguilera et al., 2021; Brunekreef, 2010; Cascio, 2018). Studies have also linked wildfire smoke exposure to adverse birth outcomes, such as preterm birth and low birth weight (Gellman & Wibbenmeyer, 2024), and to mental health problems, including anxiety, depression, and post-traumatic stress disorder (Eisenman & Galway, 2022; Sivarethinamohan et al., 2021). The impact is further exacerbated in low-income communities, where limited access to healthcare and protective resources amplifies health risks (Thomas et al., 2022). Moreover, the economic burden of these health impacts are substantial, encompassing direct healthcare costs, lost productivity, and long-term societal impacts, including reduced quality of life and increased healthcare dependency (Izah et al., 2024; Sivarethinamohan et al., 2021). A study by Xu et al. (2024) highlighted the global mortality burden of landscape fire-sourced air pollution, estimating over 1.53 million annual deaths, with the majority attributed to PM2.5 exposure. Additionally, cardiovascular mortality associated with wildfire smoke has shown a concerning upward trend globally, driven by population growth and increasing pollutant exposure.

To help mitigate the health risks associated with air pollution, including wildfire smoke, many countries have implemented air quality monitoring and reporting systems, such as the Air Quality Index (AQI) in the United States. The AQI is designed to provide the public with timely and easily understandable information about local air quality conditions and associated health risks (Adeyemi et al., 2022; Kumari & Jain, 2018). By raising awareness about air pollution levels and encouraging individuals to take protective actions during periods of poor air quality, the AQI plays a crucial role in safeguarding public health (Santana et al., 2021; Wang et al., 2019). For instance, the AQI can help individuals make informed decisions about reducing outdoor activities, staying indoors, or using air filtration devices to minimize their exposure to harmful pollutants (Al-Kindi et al., 2020; Laumbach et al., 2015; Rajagopalan et al., 2020).

However, the effectiveness of the AQI in promoting health-protective behaviors depends on individuals' awareness, understanding, and responsiveness to the information provided (Borbet et al., 2018). Studies have shown that public awareness and sensitivity to air quality information can vary widely across different socio-demographic groups and geographical areas (Rajagopalan et al., 2020; Reames & Bravo, 2019; Wang et al., 2019). Factors such as age, education, income, and pre-existing health conditions have been found to influence individuals' perceptions of air quality risks and their likelihood of taking protective actions (Chen et al., 2021; D'Antoni et al., 2017; Heaney et al., 2022; Ramírez et al., 2019; Reisen et al., 2015). For example, a study by Wang et al. (2019) found that individuals' knowledge and perception of air pollution had a significant positive impact on their decision to respond to air quality warnings, with females being more likely to comply with the information provided. While existing studies explore general responses to disasters (Mullan et al., 2024; Musacchio et al., 2021; Völker & Sujaritpong, 2024), limited research addresses factors influencing sensitivity to the AQI, especially in the context of wildfire smoke in the U.S.

There is also a lack of studies that examine the relationship between individuals' experiences of illness perceptions of air quality severity and sensitivity towards AQI, particularly in the context of wildfire smoke exposure. Existing studies have often focused on single factors, making it difficult to gain a holistic understanding of the complex interplay between health experiences, risk perception, and behavioral responses to air quality information (Chen et al., 2021; Oltra & Sala, 2018; Reames & Bravo, 2019; Wang et al., 2019). For instance, a study by Oltra and Sala (2018) investigated the perception of risk from air pollution and reported behaviors in four European cities, highlighting the influence of various socio-demographic and contextual factors on individuals' responses to air pollution. However, the study did not specifically focus on wildfire smoke exposure or examine the interaction effects between health experiences and severity perceptions.

Furthermore, there is a need for innovative analytical approaches that can provide more nuanced insights into these relationships. Traditional statistical methods may not fully capture the complex, multidimensional nature of the factors influencing individuals' sensitivity to air quality information. The Bayesian Mindsponge Framework (BMF) is a promising analytical approach that has the potential to address this gap by integrating multiple data sources and allowing for a more comprehensive examination of the interactions between variables (M. H. Nguyen et al., 2022). The BMF combines Bayesian inference with the Mindsponge concept, which posits that an individual's mindset is shaped by the continuous interaction between their internal beliefs and external information (Vuong et al., 2022). By applying this framework to the analysis of factors influencing individuals' sensitivity to air quality information, researchers can gain a more nuanced understanding of the complex dynamics at play.

In light of these knowledge gaps and methodological limitations, the present study aims to investigate the factors associated with individuals' sensitivity to air quality information by reducing outdoor activities in response to air quality ratings, with a specific focus on wildfire smoke exposure in the western United States. Specifically, the following three research questions will be answered:

1) How are residents' socio-demographic factors associated with their sensitivity towards the air quality index to change their behaviors (e.g., reducing outdoor activities and eliminating outdoor activities)?
2) How is residents' perception of wildfire smoke's severity in comparison to other natural disasters associated with their sensitivity towards the air quality index?
3) Does residents' past negative experiences of wildfire smoke (proxied by wildfire smoke-induced illness) moderate the relationship between their severity perception and sensitivity?

By employing the BMF approach to answer these research questions, this study seeks to provide a more comprehensive understanding of the complexity underlying individuals' behavioral responses to air quality information. By identifying the key determinants of individuals' sensitivity to air quality information and their propensity to take protective actions, this research can inform the design of more effective public health messages and programs that account for the diverse needs and experiences of different socio-demographic groups.

2. Method

2.1. Theoretical foundation

While the first research question has an exploratory nature, we utilized the mindsponge theory (MT) as the theoretical foundation to attempt to answer the second and third research questions (Vuong, 2023; Vuong & Napier, 2015). MT employs an information-processing approach to elucidate various mental products, including perception and complex human behaviors. It conceptualizes the human mind as an information-collecting and processing entity, which aids in understanding human thought, perception, belief formation, behavior, and social constructs (Vuong, 2023). Recently, MT has been further incorporated with knowledge from quantum mechanics and Shannon's information theory to enhance its reasoning of human cognition and value formation processes (Hertog, 2023; Rovelli, 2018; Shannon, 1948; Vuong & Nguyen, 2024a).

Drawing on Shannon's information theory, MT views information as a spectrum of possible alternatives, with the mind functioning as a dynamic filtering system within an "infosphere," the surrounding informational landscape (Shannon, 1948; Vuong & Nguyen, 2024b). This entropy-based perspective emphasizes how core values serve as cognitive anchors, influencing the cognitive processes by contributing to the cost-benefit evaluation of new information. The mindset is a collection of such core values and beliefs. Information that aligns with these values and is perceived as beneficial is integrated, reinforcing cognitive processes in a self-affirming cycle, while conflicting information is generally rejected. MT has found extensive application across various fields, including environmental and health disciplines, to investigate how individuals process information from their surroundings to sustain the system and promote well-being (Kumar et al., 2023; Nguyen et al., 2024; Nguyen & Jones, 2022b; Santirocchi et al., 2023; Sari et al., 2024; Vuong et al., 2024).

From the perspective of MT, the decision to continue engaging in outdoor activities, reduce such activities, or completely eliminate them after seeing the air quality index is viewed as a responsive outcome of the mind's information-processing mechanisms in response to a changing environment. How an individual responds depends on their environmental sensitivity, specifically how they perceive and process new environmental information, including air quality data. Environmental sensitivity can be categorized into two main types: sensitivity and responsivity (Greven et al., 2019; Pluess, 2015). Sensitivity refers to the perception and internal processing of external influences, such as interpreting and evaluating the air quality index. Responsivity, on the other hand, refers to the behavioral outcomes of this processing, such as continuing outdoor activities, reducing them, or ceasing them.

For the mind's internal information process to be triggered, the air quality index must first be absorbed, evaluated, and internalized. Individuals unfamiliar with the air quality system are more likely to reject such information due to a lack of prior knowledge needed to evaluate the meaning of air quality ratings. In this study, we excluded participants unfamiliar with the air quality index system to ensure that all considered individuals could interpret and evaluate air quality levels and make decisions aimed at maximizing their perceived benefits.

Among those familiar with the air quality system, air quality information interacts with pre-existing mental constructs (i.e., subjective spheres of influence) to be evaluated (Nguyen et al., 2023). This evaluation process helps individuals determine the optimal responsive decision that aligns with the changing environment. Pre-existing information within the mind significantly influences this subjective cost-benefit evaluation. Specifically, information about wildfire smoke risks—such as severity, familiarity, and controllability—can directly affect survival-related considerations (Slovic, 2010; Tanemura et al., 2022). Individuals who perceive higher wildfire smoke risks are more likely to assign greater weight to the potential loss caused by the smoke, prompting decisions that reduce or eliminate outdoor activities to mitigate these risks.

For such thinking to translate into behavior, the perceived benefits of avoiding risks must outweigh the perceived benefits of tolerating them (e.g., maintaining the inertia of engaging in outdoor activities) (Jenkins et al., 2024). Although identifying a precise threshold for avoidance behaviors to be triggered is challenging, the mind's sensitivity to risk-signaling information, such as air quality ratings, serves as a useful proxy. Given similar levels of benefits for continuing outdoor activities, we expect that individuals with higher risk perception (e.g., greater perceived severity of wildfire smoke) are expected to have a lower threshold for converting their thoughts into behavior—resulting in reduced or eliminated outdoor activities.

In addition to perceived severity, experiencing or observing the consequences of wildfire smoke can further influence the subjective cost-benefit evaluation process. Internalized information about these consequences can serve as a cognitive anchor, increasing the perceived costs of wildfire smoke and assigning greater probability to decisions that mitigate these costs (Cai et al., 2023; Santirocchi et al., 2023; Vuong & Nguyen, 2024b). Consequently, individuals who have experienced or witnessed wildfire smoke-related illnesses are likely to have amplified perceptions of its severity, further lowering the threshold for responsive behaviors. As a result, we expect the effects of perceived wildfire smoke severity on reducing or eliminating outdoor activities to be amplified by personal experiences of wildfire smoke-related illness.

2.2. Model Construction

2.2.1. Dataset and variables

The current study's analysis is based on a dataset of 614 randomly selected individuals in the Boise Metropolitan Area (including Boise, Eagle, Caldwell, Kuna, Meridian, and Nampa) through an in-person survey and 1,623 Boise State University affiliates (e.g., students, faculty members, and employees) via an online survey (see Figure 1). The dataset focuses on human perception and response to wildfire smoke, including knowledge of air quality information sources, preferences for effective messaging, perceptions of wildfire smoke as a hazard, and smoke-related health experiences. The data was collected through a questionnaire with five main categories: demographic information, activity data, air quality notifications, natural hazards, and health. The survey took place from August to October 2018 and is available in CSV format, along with metadata in Extensible Markup Language (XML) and text formats. It underwent peer review before being published in *Scientific Data* (Fowler et al., 2019).

The respondents' profiles include a significant proportion of at-risk individuals, such as older people and those with pre-existing conditions, particularly in the in-person survey. The online survey, however, included a larger portion of younger participants, primarily aged 18–22. In contrast, the in-person survey focused more on older generations, with the majority of participants in their 20s to 40s. The survey also captured a sizable portion of Hispanic/Latino participants and moderate- to low-income households with incomes below $50,000 annually. Notably, 35% of in-person and 29% of online participants reported household incomes of $100,000 or more. A large proportion of in-person survey respondents held a bachelor's degree, while Boise State staff made up the majority of online survey participants (Fowler et al., 2019).

Figure 1. Senior author (Q.H.V.) and his family enjoying fresh air by the Boise River before returning to Vietnam (20th June, 2014). Source: Q.H.V

Seven variables were derived from the dataset to address the objectives of our study. These variables are *Gender*, *Education*, *Income*, *WildfireSmokeIllness*, *PerceivedSeverity*, *AirQualitySensitivity_Reduce*, and *AirQualitySensitivity_Eliminate*. Socio-demographic factors of respondents are represented by variables *Gender*, *Education*, and *Income*. *WildfireSmokeIllness* variable captures the occurrence of wildfire smoke-related illnesses experienced by the individual or their household members. *PerceivedSeverity* variable reflects the severity of wildfire smoke in comparison to other natural disaster events. *AirQualitySensitivity_Reduce* variable refers to the minimum air quality index value that prompts an individual to reduce outdoor activities, while *AirQualitySensitivity_Eliminate* variable indicates the minimum air quality index value at which outdoor activities are completely eliminated for the day. The air quality index has six levels, ranging from good (green) to hazardous (maroon). The lower the minimum air quality index is, the more sensitive the respondents are to the wildfire smoke. People reporting not familiar with the air quality index were coded as 'NA.'

Table 1 below provides a detailed description of these quantitative variables.

Table 1: Variable Description

Variable	Generating Question	Data type	Value
Gender	Which gender do you identify with?	Numerical	1= Female 0 = Male
Education	What is the highest degree or level of school you completed?	Numerical	1 = 8th grade or less 2 = Some high school, no diploma

	If currently enrolled, highest degree.		3 = High school graduate, diploma or GED 4 = Some college, no degree 5 = Associate degree 6 = Bachelor’s degree 7 = Master’s degree 8 = Ph.D, M.D., J.D. or similar
Income	What is your total household income, including income from all members of your family, in 2017 before taxes? This figure should include salaries, wages, pensions, dividends, interest, and all other income.	Numerical	1 = $25,000 or less 2 = >$25,000 to $49,999 3 = $50,000 to $74,999 4 = $75,000 to $99,999 5 = $100,000 or more
WildfireSmokeIllness	Have you, or anyone in your household, experienced wildfire smoke-related illness?	Numerical	1 = Yes 2 = No 3 = Not sure
PerceivedSeverity	As a public health threat, are wildfire smoke events more important, less important, or about as important as other natural disasters, such as hurricanes or tornadoes?	Numerical	1 = Much less severe/important 2 = Somewhat less severe/important 3 = About as severe/important 4 = Somewhat more severe/important 5 = Much more severe/important
AirQualitySensitivity_Reduce	What is the minimum air quality index rating that would cause you to reduce your outdoor	Numerical	1 = Green – Good 2 = Yellow – Moderate

	activity on a particular day?		3 = Orange – Unhealthy 4 = Red – Unhealthy
AirQualitySensitivity_Eliminate	What is the minimum air quality index rating that would cause you to eliminate your outdoor activity on a particular day?	Numerical	5 = Purple – Very Unhealthy 6 = Maroon – Hazardous 7 = I am not familiar with this rating

2.2.2. Statistical Model

Model 1 was constructed to examine the factors associated with the respondents' sensitivity toward the air quality index to reduce outdoor activities. The logical network of Model 1 is presented below (see Figure 2).

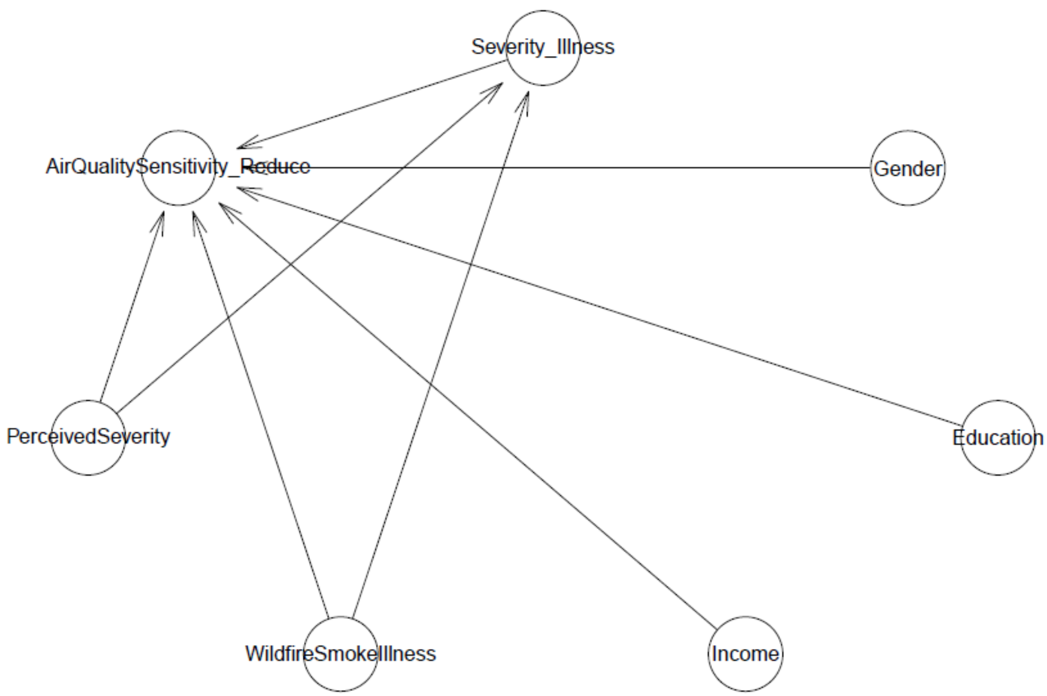

Figure 2. Model 1a's logical network

Model 1 was formulated as follows:

$$AirQualitySensitivity\_Reduce \sim \text{normal}\ (\mu, \sigma) \quad (1.1)$$

$$\mu_i = \beta_0 + \beta_1 * Gender_i + \beta_2 * Education_i + \beta_3 * Income_i + \beta_4 * LnAge_i + \beta_5 * PerceivedSeverity_i + \beta_6 * PerceivedSeverity_i * WildlifeSmokeIllness_i \quad (1.2)$$

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

The probability around μ is determined by the form of the normal distribution, where the width of the distribution is specified by the standard deviation σ. μ_i indicates the minimum air quality index rating that respondent i will reduce his/her outdoor activity on a particular day. $Gender_i$, $Education_i$, and $Income_i$ indicate the socio-demographic background of respondent i. $LnAge_i$

indicates the natural logarithm of respondent i's age. $PerceivedSeverity_i$ is the level of importance of wildfire smoke compared to other natural disasters, according to respondent i. The model has an intercept, β_0, and six coefficients, β_1-β_6, with the Mean denoted M, and the standard deviation denoted S.

Model 2 was constructed to examine the factors associated with the respondent's sensitivity toward the air quality index to eliminate outdoor activities. The logical network of Model 2 is presented below (see Figure 3).

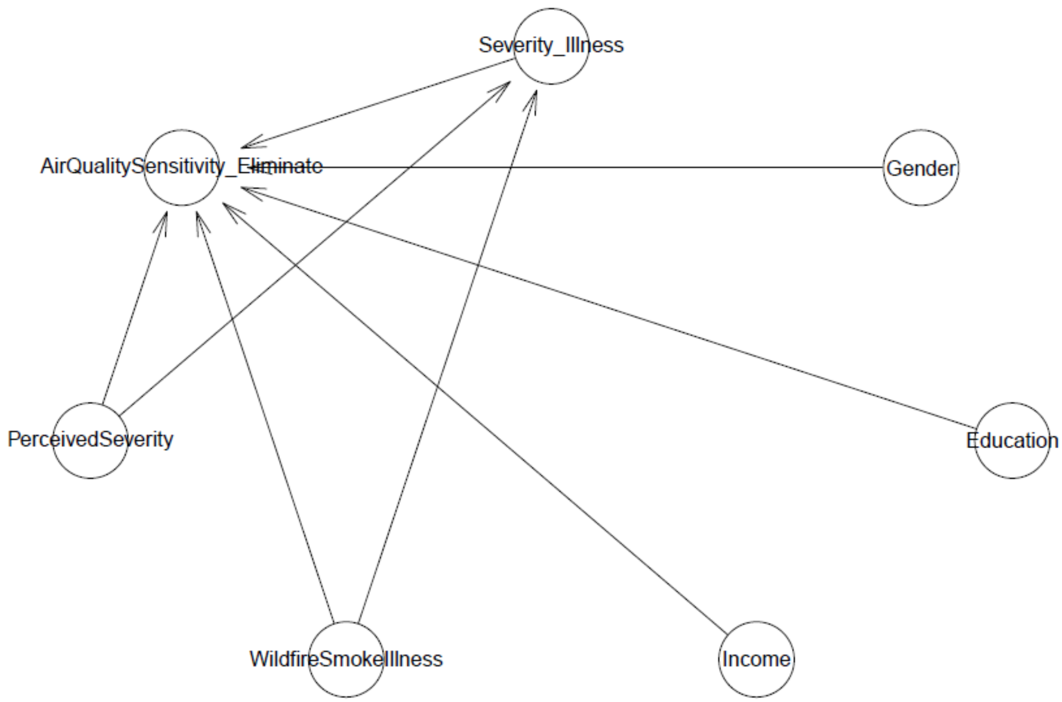

Figure 3. Model 2's logical network

Model 2 was formulated as follows:

$$AirQualitySensitivity\_Eliminate \sim \text{normal}\ (\mu, \sigma) \quad (2.1)$$

$$\mu_i = \beta_0 + \beta_1 * Gender_i + \beta_2 * Education_i + \beta_3 * Income_i + \beta_4 * LnAge_i + \beta_5 * PerceivedSeverity_i + \beta_6 * PerceivedSeverity_i * WildfireSmokeIllness_i \quad (2.2)$$

$$\beta \sim normal(M, S) \quad (2.3)$$

In Model 2, μ_i indicates the minimum air quality index rating that can make respondent i eliminate his/her outdoor activity on a particular day. The rest of the variables are identical to those in Model 1.

2.2. Analysis and Validation

Bayesian Mindsponge Framework (BMF) analytics was employed for several reasons (M.-H. Nguyen et al., 2022; Vuong et al., 2022). First, the analytical method integrates the logical reasoning capabilities of MT with the inferentialadvantages of Bayesian analysis, exhibiting a high degree of compatibility (M.-H. Nguyen et al., 2022). Second, Bayesian inference is a statistical approach that treats all the properties (including the known and unknown ones) probabilistically (Csilléry et al., 2010; Gill, 2014), enabling reliable prediction of parsimonious models. Nevertheless, utilizing the Markov chain Monte Carlo (MCMC) technique still allows Bayesian analysis to deal effectively with various intricate models, such as multilevel and nonlinear regression frameworks like the current study (Dunson, 2001). Third, Bayesian inference utilizes credible intervals for result interpretation instead of relying solely on the dichotomous decision based on *p*-values (Halsey et al., 2015; Wagenmakers et al., 2018).

In Bayesian analysis, selecting the appropriate prior is required during the model construction process. Due to the exploratory nature of this study, uninformative priors or a flat prior distribution were used to provide as little prior information as possible for model estimation (Diaconis & Ylvisaker, 1985). We also performed the prior-tweaking technique to check the model's robustness against varying priors. Specifically, informative priors reflecting our disbelief in the associations are employed to rerun the estimations. If the estimations' results using informative priors are similar to those using uninformative priors, the results are deemed robust.

In addition, we also employed the Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) diagnostics to check the models' goodness-of-fit with the data at hand (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 calculated through the data minus data point i. The *k*-Pareto values are used in the PSIS method for computing the LOO cross-validation in the R **loo** package. Observations with *k*-Pareto values greater than 0.7 are often considered influential and problematic for accurately estimating LOO cross-validation. When a model's *k* values are less than 0.5, it is typically regarded as being fit.

If the model fits well with the data, we will proceed with the convergence diagnosesand result interpretation. In the current study, we validated the convergence of Markov chains using statistical values and visual illustrations. Statistically, the effective sample size (*n_eff*) and the Gelman–Rubin shrink factor (*Rhat*) can be used to assess the convergence. The *n_eff* value represents the number of iterative samples that are not auto-correlated during stochastic simulation, while the *Rhat* value is referred to as the potential scale reduction factor (Brooks & Gelman, 1998). If *n_eff* is larger than 1000, it is generally considered that the Markov chains are well-convergent, and the effective samples are sufficient for reliable inference (McElreath, 2018). As for the *Rhat* value, if the value exceeds 1.1, the model does not converge. The model is considered convergent if *Rhat* = 1. Visually, the Markov chains' convergence was validated using trace plots.

The Bayesian analysis was performed on the R platform using the **bayesvl** open-access package, which provides good visualization capabilities (La & Vuong, 2019). Considering the issues of data transparency and the cost of reproduction, all data and code snippets of this study were deposited onto a preprint server (Vuong, 2018): https://zenodo.org/records/14722648.

3. Results

3.1. Model 1: Predictors of sensitivity to reduce outdoor activities

Initially, we evaluate whether Model 1 is a good fit with the data. As can be seen in Figure 4, all estimated *k*-values are below the 0.5 threshold, indicating a good fit signal of the model.

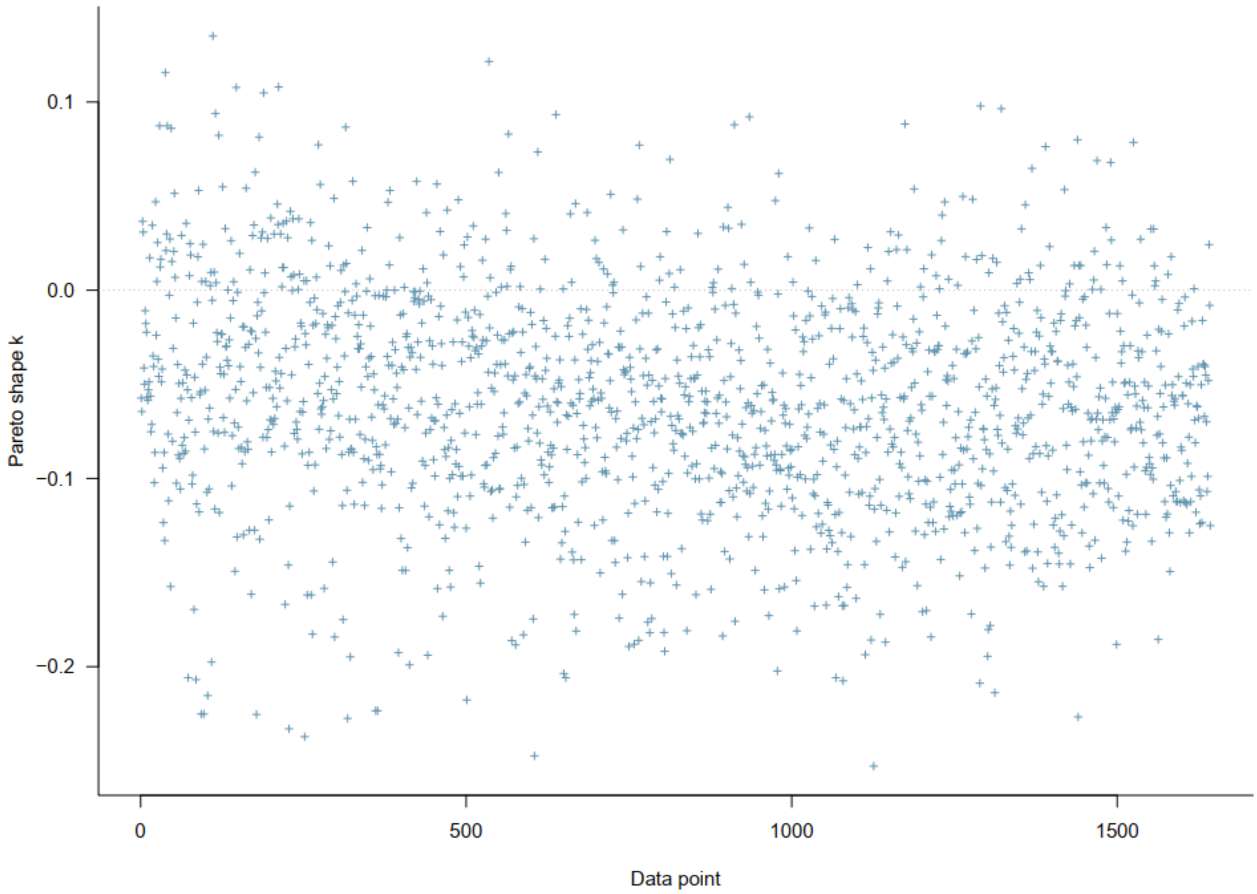

Figure 4. Model 1's PSIS-LOO diagnosis

The posterior distribution statistics of Model 1 are shown in Table 2. All *n_eff* values are greater than 1000, indicating there are sufficient iterative samples for inference. Meanwhile, *Rhat* values equal to 1, also suggesting the well-convergence of Markov chains. The trace plots shown in Figure 5 further confirm the convergence as all four Markov chains fluctuate around a central equilibrium.

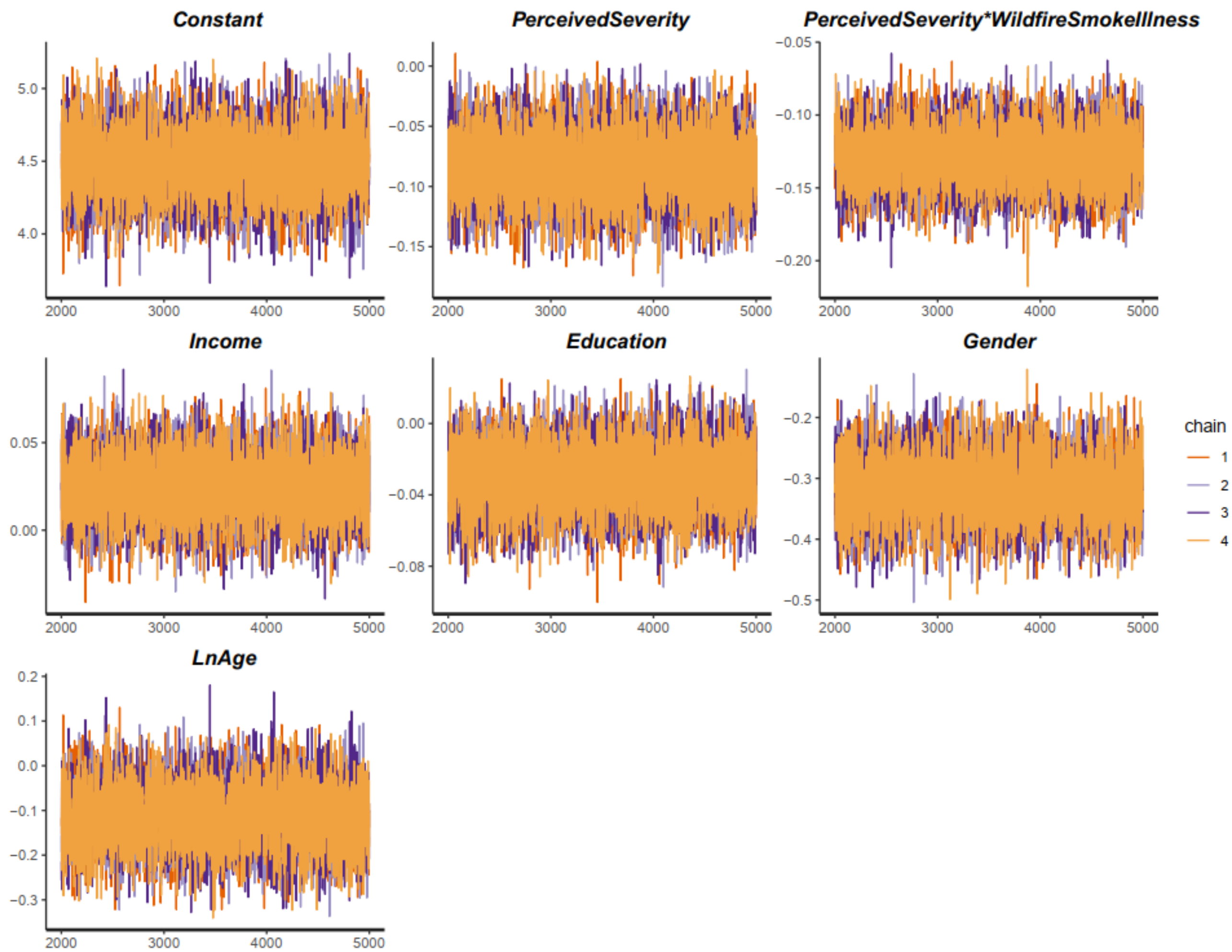

Figure 5. Model 1's trace plots

Table 2. Estimated results of Model 1

Parameters	Uninformative priors				Informative priors			
	Mean	SD	*n_eff*	*Rhat*	Mean	SD	*n_eff*	*Rhat*
Constant	4.49	0.22	7784	1	4.48	0.22	7458	1
PerceivedSeverity	-0.08	0.03	11474	1	-0.08	0.03	12512	1
PerceivedSeverity WildfireSmokeIllness*	-0.13	0.02	11235	1	-0.13	0.02	12365	1
Income	0.02	0.02	13965	1	0.02	0.02	14148	1
Education	-0.03	0.02	10543	1	-0.03	0.02	10962	1
Gender	-0.32	0.05	12654	1	-0.31	0.05	13514	1
LnAge	-0.11	0.07	7264	1	-0.11	0.07	7197	1

Since the diagnostic test confirms the goodness of fit for Model 1, the simulated results can be reliably interpreted. The analysis using uninformative priors reveals that *Education*, *Gender*, and *LnAge* have negative associations with *AirQualitySensitivity_Reduce* ($M_{Education}$ = -0.03 and $S_{Education}$ = 0.02; M_{Gender} = -0.32 and S_{Gender} = 0.05; M_{LnAge} = -0.11 and S_{LnAge} = 0.07), whereas *Income* has an opposite association (M_{Income} = 0.02 and S_{Income} = 0.02). Residents' severity perception is also found to be negatively associated with *AirQualitySensitivity_Reduce* ($M_{PerceivedSeverity}$ = -0.08 and $S_{PerceivedSeverity}$ = 0.03). If the respondents or their family members experience wildfire smoke-induced illness, the negative association is further amplified ($M_{PerceivedSeverity*WildfireSmokeIllness}$ = -0.13 and $S_{PerceivedSeverity*WildfireSmokeIllness}$ = 0.02). The estimation using informative priors also shows identical results, suggesting that the estimated results are robust against varying priors.

The posterior distributions of Model 1's six coefficients are shown in Figure 6, with the thick black line in the middle representing Highest Posterior Density Intervals (HPDI) at 95%. As can be seen, the 95% HPDIs of $PerceivedSeverity$, $PerceivedSeverity * WildfireSmokeIllness$, and $Gender$ are located entirely on the negative sides, suggesting highly reliable negative associations. Although a proportion of $Education$'s and $LnAge$'s 95% HPDIs are still distributed on the positive side, it is negligible. Thus, their negative associations are also considered highly reliable. Meanwhile, a proportion of $Income$'s 95% HPDI is located on the negative side, and its mean value is equal to its standard deviation, so the positive association of $Income$ can only be considered moderately reliable.

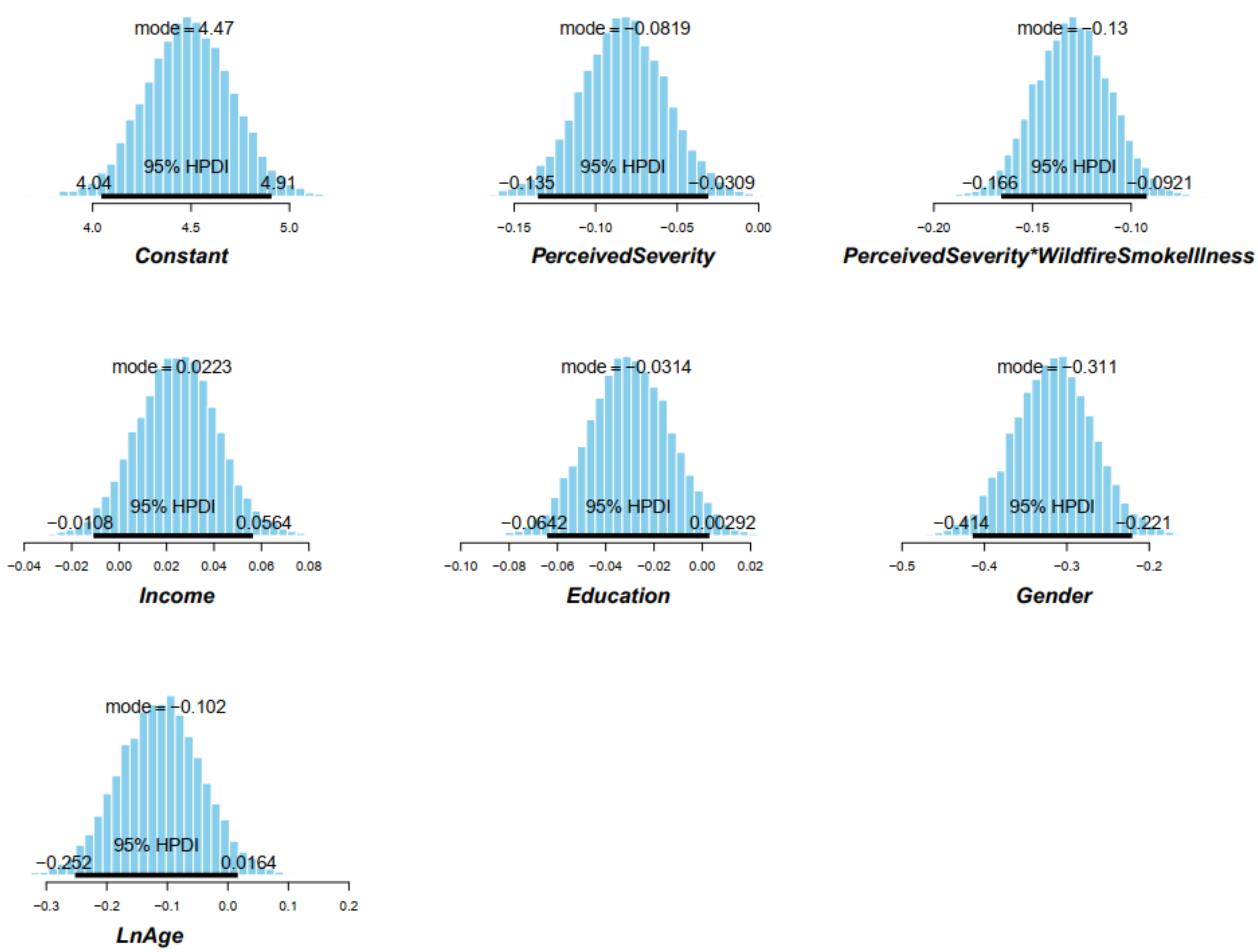

Figure 6. Posterior distributions of Model 1's coefficients with 95% HPDI

3.2. Model 2: Predictors of sensitivity to eliminate all outdoor activities

The PSIS-LOO test's result of Model 2 is visualized in Figure 7. All *k*-values are below the threshold of 0.5, suggesting that Model 2 has an acceptable fit with the dataset. The statistics of *n_eff* and *Rhat* shown in Table 3 imply the good convergence of Model 2's Markov chains. The convergence is also validated by the trace plots shown in Figure 8. As a result, Model 2's estimated results are eligible for interpretation.

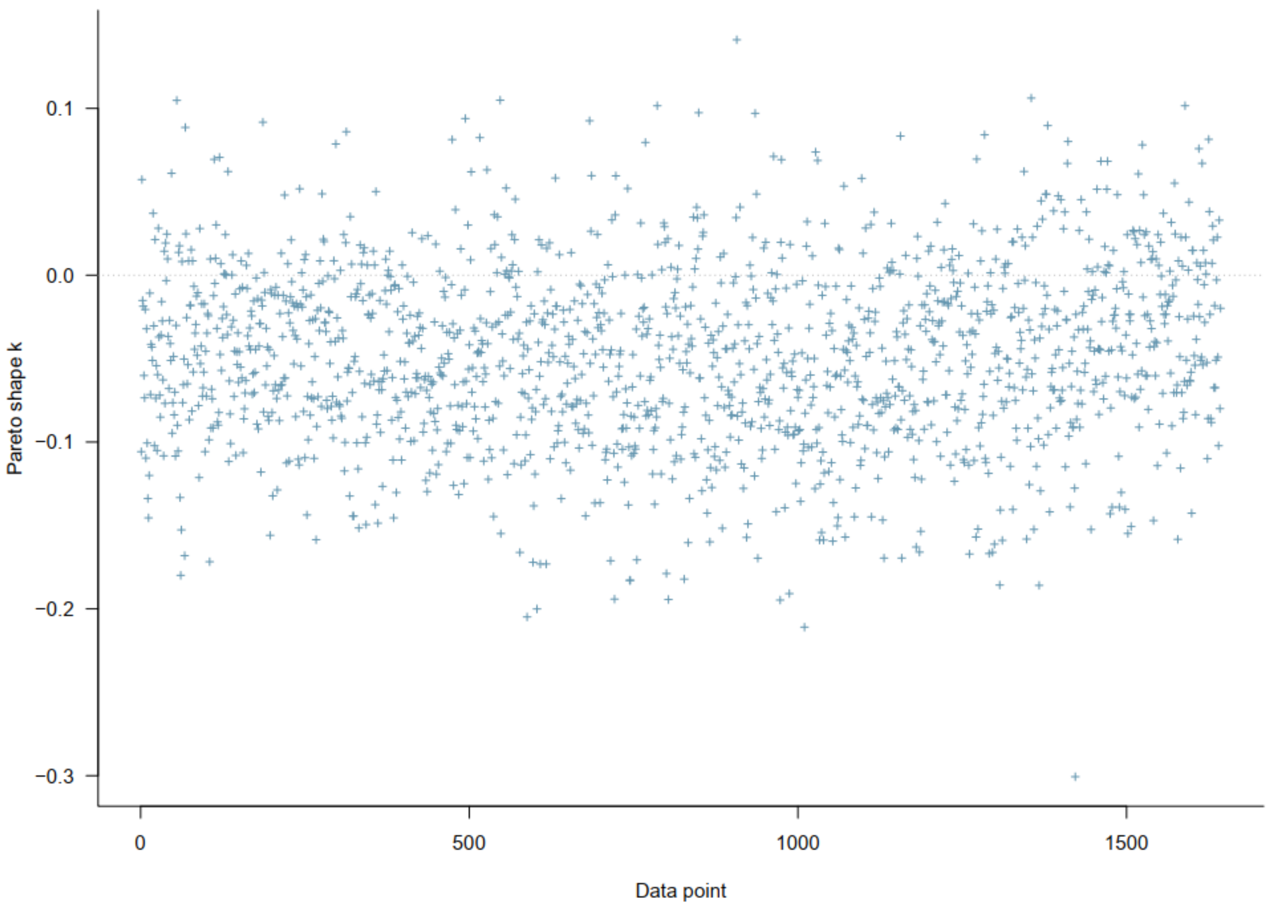

Figure 7. Model 2's PSIS-LOO diagnosis

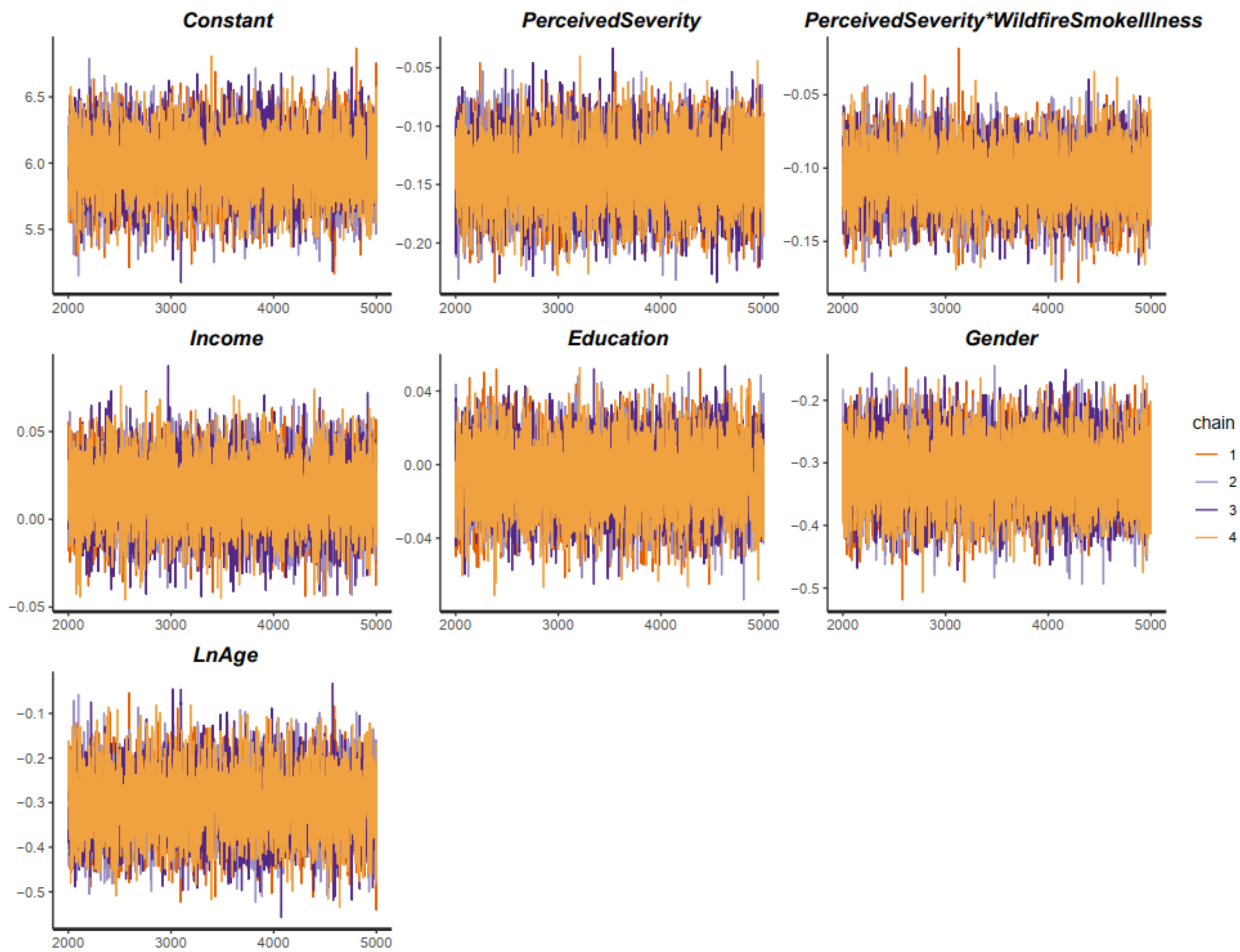

Figure 8. Model 2's trace plots

Table 3. Estimated results of Model 2

Parameters	Uninformative priors				Informative priors			
	Mean	SD	*n_eff*	*Rhat*	Mean	SD	*n_eff*	*Rhat*
Constant	5.98	0.23	7112	1	5.97	0.22	7125	1
PerceivedSeverity	-0.14	0.03	12064	1	-0.14	0.03	13685	1
PerceivedSeverity WildfireSmokeIllness*	-0.11	0.02	13025	1	-0.11	0.02	12366	1
Income	0.01	0.02	14956	1	0.01	0.02	13594	1
Education	-0.01	0.02	9965	1	-0.01	0.02	9532	1
Gender	-0.32	0.05	13255	1	-0.31	0.05	13241	1
LnAge	-0.30	0.07	6271	1	-0.30	0.07	6694	1

Analyzing Model 2, we find whereas $PerceivedSeverity$, $PerceivedSeverity * WildfireSmokeIllness$, $Gender$, and $LnAge$ have negative associations with $AirQualitySensitivity\_Eliminate$, $Income$, and $Education$ have ambiguous associations. The estimation using informative priors also implies similar results, suggesting that they are robust. 95% HPDIs of $PerceivedSeverity$, $PerceivedSeverity * WildfireSmokeIllness$, $Gender$, and $LnAge$ in Figure 9 all lie on the negative side of the *x*-axis, highlighting the high reliability of the associations.

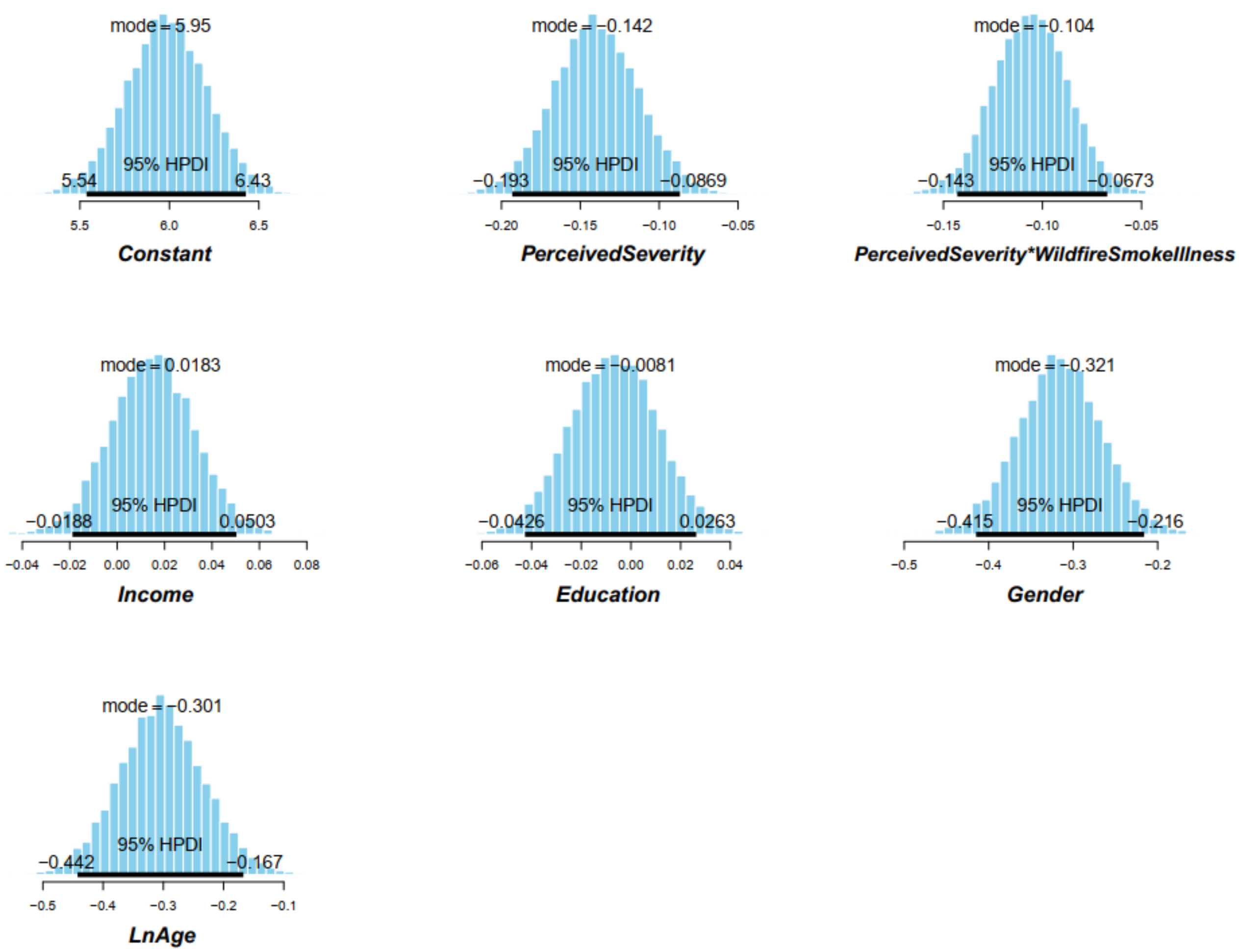

Figure 9. Posterior distributions of Model 2's coefficients with 95% HPDI

4. Discussion

Employing the BMF analytics, the study indicates that socio-demographic factors play important roles in influencing the residents' sensitivity toward the air quality index. Specifically, females, older people, and people with higher educational levels are found to be more responsive to the air quality rating by reducing outdoor activities, while people with higher incomes are less responsive. Females and older people are even more likely to eliminate all outdoor activities at a lower unhealthy air quality rating (the lowest being 'good air quality,' while the highest being 'hazardous air quality'). Besides, people with a higher severity perception of wildfire smoke are also found to be more likely to reduce and eliminate outdoor activities at a lower unhealthy air quality rating, while their experience of wildfire smoke-related illness—either personally or within households—amplifies the effect.

Our findings align with the broader body of research on environmental risk perception, highlighting the interplay of socio-demographic and cognitive factors in shaping sensitivity to the environment (Burke et al., 2022; Fan, 2024). The study by Fan (2024) on air pollution and outdoor activities illustrates that individuals with higher education levels are more likely to understand the implications of air quality data, leading to informed decisions about their outdoor activities. Environmental awareness and access to information about air quality are additional factors influencing sensitivity to the AQI. Wang and Cao (2024) found a significantly positive correlation between air pollution and public awareness of environmental problems in China. As air pollution becomes more severe, people tend to become more aware of environmental issues, which in turn makes them more sensitive to air quality information.

The observed heightened sensitivity among females and older people aligns with prior research on gender-based and age-based differences in risk perception related to air pollution and environmental risks (Bertiz & Kiras, 2022; Nolte & Hanoch, 2024; Rajper et al., 2018). Gender- and age-specific differences in AQI sensitivity may stem from documented disparities in health risk perception and protective behaviors, with females and older people generally prioritizing health and safety. This is reinforced by findings from studies on health anxiety and environmental exposure, which show that women exhibit higher levels of concern and proactive health behaviors in response to perceived threats (Xiong et al., 2018). Thaker et al. (2023) also noted that females exhibited higher health risk perceptions related to climate change compared to males. Meanwhile, multiple studies have found that older people are associated with less self-reported risk-taking in a health context, as risk-taking is perceived to be less likely to lead to gains and less enjoyable (Bonem et al., 2015; Nolte & Hanoch, 2024).

Additionally, the finding that higher-income people have a lower sensitivity toward the air quality index seems to contradict the findings of Burke et al. (2022). According to Burke et al. (2022), during major wildfire smoke events, individuals residing in higher-income areas tend to actively seek information about air quality and engage in protective behaviors, such as spending more time at home (Burke et al., 2022). Conversely, residents of lower-income neighborhoods demonstrate similar patterns in searching for air quality data but do not exhibit the same level of health-protective actions, spending less time indoors (Burke et al., 2022). This contradiction between our study and that of (Burke et al., 2022) may be explained by differences in risk-aversion solutions and the location of residence. High-income people have more resources or options to address pollution issues, like relocating temporarily to areas unaffected by wildfire smoke and stockpiles of protective equipment. Moreover, if they are dissatisfied with the environmental quality of their residence, they are more likely to consider moving to a location with better environmental conditions that can be less affected by wildfire smoke (Wang & Cao, 2024). Further studies are needed to confirm whether these explanations are plausible and find the reasons behind the study's contradiction with (Burke et al., 2022).

Meanwhile, the finding that respondents' experience with wildfire smoke-related illnesses—either personally or within households—and heightened perceptions of the severity of wildfire smoke are positively associated with AQI sensitivity aligns with the findings from Burke et al. (2022)'s study. They indicated that wildfire smoke behavioral measures are influenced by prior experiences with smoke. The role of past experiences in shaping sensitivity also aligns with theories of experience-based learning, suggesting that individuals who have personally endured adverse effects of air pollution are more likely to adopt precautionary measures. Johnson's study indicated that individuals who were aware of the AQI were more inclined to access it if they had pre-existing health conditions or perceived themselves as belonging to the target audience for the AQI information (Johnson, 2012). Experiential factors, such as previous wildfire smoke-related illnesses, reinforce risk salience, thereby intensifying sensitivity. Experiences with wildfire smoke-related illnesses and higher perceived severity of wildfire smoke influence sensitivity, likely due to increased risk perceptions. Rappold et al. (2019) found that personal experience with wildfire smoke was associated with greater perceived risk and health-protective behaviors.

The findings have important theoretical and practical implications. They confirm the reasoning capability of Mindsponge Theory, roles of experience-based learning, educational attainment, gender- and age-specific patterns, and risk perception in shaping responses to warning systems. For policymakers and public health officials, the results suggest developing tailored interventions and communication strategies targeting at-risk populations, such as females, those with less education, and lower-income communities, to enhance AQI awareness and adherence to health recommendations (D'Evelyn et al., 2022; Fish et al., 2017). Public health campaigns should emphasize the risks of wildfire smoke and the protective value of AQI adherence, especially in vulnerable communities (Holm et al., 2021; Rappold et al., 2017). Rappold et al. (2017) developed a community health vulnerability index to identify populations most at risk from wildfire smoke, which could guide targeted interventions. Additionally, policymakers should prioritize efforts to reduce wildfire smoke emissions and provide resources for home air filtration and clean air shelters, particularly in disadvantaged communities (Jaffe et al., 2020).

As climate change drives an increase in the frequency and intensity of wildfires, it is crucial to emphasize the importance of mitigating climate change to reduce the consequences of wildfire smoke when communicating with the public. Effectively conveying the benefits of climate change mitigation—particularly to those experiencing health issues caused by wildfire smoke—can enhance risk perceptions of climate change-aggravated wildfires. This, in turn, can help foster an eco-surplus culture that prioritizes environmental sustainability as the foundation of socio-cultural and economic well-being (Nguyen & Jones, 2022a; Vuong, 2021). Cultivating such values will further strengthen global efforts to mitigate the adverse impacts of climate change (Vuong & Nguyen, 2024a).

Key strengths of this study include its innovative application of the Bayesian Mindsponge Framework and advanced statistical modeling using bayesvl, as well as its focus on the highly relevant issue of wildfire smoke in the U.S. Transparent data and methodology also enhance research reproducibility. However, some limitations should be noted, including the regional specificity to the Boise Metropolitan Area, which may limit generalizability, reliance on self-reported data introducing potential recall bias, and lack of assessment of long-term behavioral changes.

References

Adeyemi, A., Molnar, P., Boman, J., & Wichmann, J. (2022). Particulate Matter (PM2.5) Characterization, Air Quality Level and Origin of Air Masses in an Urban Background in

Pretoria. *Archives of Environmental Contamination and Toxicology*, *83*(1), 77-94. https://doi.org/10.1007/s00244-022-00937-4

Aguilera, R., Corringham, T., Gershunov, A., & Benmarhnia, T. (2021). Wildfire smoke impacts respiratory health more than fine particles from other sources: observational evidence from Southern California. *Nature Communications*, *12*(1), 1493. https://doi.org/10.1038/s41467-021-21708-0

Al-Kindi, S. G., Brook, R. D., Biswal, S., & Rajagopalan, S. (2020). Environmental determinants of cardiovascular disease: lessons learned from air pollution. *Nature Reviews Cardiology*, *17*(10), 656-672. https://doi.org/10.1038/s41569-020-0371-2

Bertiz, H., & Kiras, B. (2022). Analysis of Environmental Risk Perceptions and Scores of Preservice Science Teachers in Terms of Some Variables. *International Education Studies*, *15*(6), 1. https://doi.org/10.5539/ies.v15n6p1

Bonem, E. M., Ellsworth, P. C., & Gonzalez, R. (2015). Age differences in risk: Perceptions, intentions and domains. *Journal of Behavioral Decision Making*, *28*(4), 317-330. https://doi.org/10.1002/bdm.1848

Borbet, T. C., Gladson, L. A., & Cromar, K. R. (2018). Assessing air quality index awareness and use in Mexico City. *BMC Public Health*, *18*(1), 538. https://doi.org/10.1186/s12889-018-5418-5

Brooks, S. P., & Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of computational and graphical statistics*, *7*(4), 434-455.

Brunekreef, B. (2010). Air Pollution and Human Health: From Local to Global Issues. *Procedia - Social and Behavioral Sciences*, *2*(5), 6661-6669. https://doi.org/https://doi.org/10.1016/j.sbspro.2010.05.010

Burke, M., Driscoll, A., Heft-Neal, S., Xue, J., Burney, J., & Wara, M. (2021). The changing risk and burden of wildfire in the United States. *Proceedings of the National Academy of Sciences*, *118*(2), e2011048118. https://doi.org/doi:10.1073/pnas.2011048118

Burke, M., Heft-Neal, S., Li, J., Driscoll, A., Baylis, P., Stigler, M., . . . Gould, C. F. (2022). Exposures and behavioural responses to wildfire smoke. *Nature Human Behaviour*, *6*(10), 1351-1361. https://doi.org/10.1038/s41562-022-01396-6

Cai, J., Wu, R., Zhang, J., & Sun, X. (2023). The effect of subliminal priming on team trust: The mediating role of perceived trustworthiness. *Frontiers in Psychology*, *14*, 1099267. https://doi.org/10.3389/fpsyg.2023.1099267

Cascio, W. E. (2018). Wildland fire smoke and human health. *Science of The Total Environment*, *624*, 586-595. https://doi.org/10.1016/j.scitotenv.2017.12.086

Chen, H., Samet, J. M., Bromberg, P. A., & Tong, H. (2021). Cardiovascular health impacts of wildfire smoke exposure. *Particle and Fibre Toxicology*, *18*(1), 2. https://doi.org/10.1186/s12989-020-00394-8

Csilléry, K., Blum, M. G., Gaggiotti, O. E., & François, O. (2010). Approximate Bayesian computation (ABC) in practice. *Trends in Ecology and Evolution*, *25*(7), 410-418. https://doi.org/10.1016/j.tree.2010.04.001

D'Antoni, D., Smith, L., Auyeung, V., & Weinman, J. (2017). Psychosocial and demographic predictors of adherence and non-adherence to health advice accompanying air quality warning systems: a systematic review. *Environmental Health*, *16*(1), 100. https://doi.org/10.1186/s12940-017-0307-4

D'Evelyn, S. M., Jung, J., Alvarado, E., Baumgartner, J., Caligiuri, P., Hagmann, R. K., . . . Spector, J. T. (2022). Wildfire, Smoke Exposure, Human Health, and Environmental Justice Need to be Integrated into Forest Restoration and Management. *Current Environmental Health Reports*, *9*(3), 366-385. https://doi.org/10.1007/s40572-022-00355-7

Diaconis, P., & Ylvisaker, D. (1985). Quantifying prior opinion. In J. M. Bernardo, M. H. DeGroot, D. V. Lindley, & A. F. M. Smith (Eds.), *Bayesian statistics* (Vol. 2, pp. 133-156). North Holland Press.

Doubleday, A., Schulte, J., Sheppard, L., Kadlec, M., Dhammapala, R., Fox, J., & Busch Isaksen, T. (2020). Mortality associated with wildfire smoke exposure in Washington state, 2006–2017: a case-crossover study. *Environmental Health*, *19*(1), 4. https://doi.org/10.1186/s12940-020-0559-2

DQE, O. D. o. E. Q. A. Q. M. (2023). *Wildfire Smoke Trends and the Air Quality Index*. https://www.oregon.gov/deq/wildfires/Documents/WildfireSmokeTrendsReport.pdf

Dunson, D. B. (2001). Commentary: practical advantages of Bayesian analysis of epidemiologic data. *American journal of Epidemiology*, *153*(12), 1222-1226. https://doi.org/10.1093/aje/153.12.1222

Eisenman, D. P., & Galway, L. P. (2022). The mental health and well-being effects of wildfire smoke: a scoping review. *BMC Public Health*, *22*(1), 2274. https://doi.org/10.1186/s12889-022-14662-z

Fan, Y. (2024). Social cost of lifestyle adaptation: Air pollution and outdoor physical exercise. *Journal of Environmental Economics and Management*, *127*, 103042. https://doi.org/https://doi.org/10.1016/j.jeem.2024.103042

Fish, J. A., Peters, M. D. J., Ramsey, I., Sharplin, G., Corsini, N., & Eckert, M. (2017). Effectiveness of public health messaging and communication channels during smoke events: A rapid systematic review. *Journal of Environmental Management*, *193*, 247-256. https://doi.org/https://doi.org/10.1016/j.jenvman.2017.02.012

Fowler, M., Modaresi Rad, A., Utych, S., Adams, A., Alamian, S., Pierce, J., . . . Montrose, L. (2019). A dataset on human perception of and response to wildfire smoke. *Scientific Data*, *6*(1), 229. https://doi.org/10.1038/s41597-019-0251-y

Garofalo, L. A., Pothier, M. A., Levin, E. J. T., Campos, T., Kreidenweis, S. M., & Farmer, D. K. (2019). Emission and Evolution of Submicron Organic Aerosol in Smoke from Wildfires in the Western United States. *ACS Earth and Space Chemistry*, *3*(7), 1237-1247. https://doi.org/10.1021/acsearthspacechem.9b00125

Gellman, J., & Wibbenmeyer, M. (2024). Wildfire Smoke in the United States. *Review of Environmental Economics and Policy*, *0*(0), 000-000. https://doi.org/10.1086/732404

Gill, J. (2014). *Bayesian methods: A social and behavioral sciences approach* (Vol. 20). CRC press.

Greven, C. U., Lionetti, F., Booth, C., Aron, E. N., Fox, E., Schendan, H. E., . . . Bijttebier, P. (2019). Sensory processing sensitivity in the context of environmental sensitivity: A critical review and development of research agenda. *Neuroscience and Biobehavioral Reviews*, *98*, 287-305. https://doi.org/10.1016/j.neubiorev.2019.01.009

Halsey, L. G., Curran-Everett, D., Vowler, S. L., & Drummond, G. B. (2015). The fickle P value generates irreproducible results. *Nature methods*, *12*, 179-185. https://doi.org/10.1038/nmeth.3288

Heaney, A., Stowell, J. D., Liu, J. C., Basu, R., Marlier, M., & Kinney, P. (2022). Impacts of Fine Particulate Matter From Wildfire Smoke on Respiratory and Cardiovascular Health in California. *GeoHealth*, *6*(6), e2021GH000578. https://doi.org/https://doi.org/10.1029/2021GH000578

Hertog, T. (2023). *On the origin of time: Stephen Hawking's final theory*. Random House. https://www.google.com/books/edition/On_the_Origin_of_Time/lIBTEAAAQBAJ

Holm, S. M., Miller, M. D., & Balmes, J. R. (2021). Health effects of wildfire smoke in children and public health tools: a narrative review. *Journal of Exposure Science & Environmental Epidemiology*, *31*(1), 1-20. https://doi.org/10.1038/s41370-020-00267-4

Izah, S. C., Ogwu, M. C., Etim, N. G., Shahsavani, A., & Namvar, Z. (2024). Short-Term Health Effects of Air Pollution. In S. C. Izah, M. C. Ogwu, & A. Shahsavani (Eds.), *Air Pollutants in the Context of One Health : Fundamentals, Sources, and Impacts* (pp. 249-278). Springer Nature Switzerland. https://doi.org/10.1007/698_2024_1132

Jaffe, D. A., O'Neill, S. M., Larkin, N. K., Holder, A. L., Peterson, D. L., Halofsky, J. E., & Rappold, A. G. (2020). Wildfire and prescribed burning impacts on air quality in the United States.

Journal of the Air & Waste Management Association, *70*(6), 583-615. https://doi.org/10.1080/10962247.2020.1749731
Jenkins, S. C., Lachlan, R. F., & Osman, M. (2024). An integrative framework for mapping the psychological landscape of risk perception. *Scientific Reports*, *14*(1), 10989. https://doi.org/10.1038/s41598-024-59189-y
Johnson, B. B. (2012). Experience with urban air pollution in Paterson, New Jersey and implications for air pollution communication. *Risk Anal*, *32*(1), 39-53. https://doi.org/10.1111/j.1539-6924.2011.01669.x
Kumar, M., Kumar, A., Verma, S., Bhattacharya, P., Ghimire, D., Kim, S.-h., & Hosen, A. S. (2023). Healthcare Internet of Things (H-IoT): Current trends, future prospects, applications, challenges, and security issues. *Electronics*, *12*(9), 2050.
Kumari, S., & Jain, M. K. (2018). A Critical Review on Air Quality Index. In V. P. Singh, S. Yadav, & R. N. Yadava, *Environmental Pollution* Singapore.
La, V.-P., & Vuong, Q.-H. (2019). bayesvl: Visually learning the graphical structure of Bayesian networks and performing MCMC with'Stan'. *The Comprehensive R Archive Network (CRAN)*. https://cran.r-project.org/web/packages/bayesvl/index.html
Laumbach, R., Meng, Q., & Kipen, H. (2015). What can individuals do to reduce personal health risks from air pollution? *J Thorac Dis*, *7*(1), 96-107. https://doi.org/10.3978/j.issn.2072-1439.2014.12.21
Liu, J. C., Pereira, G., Uhl, S. A., Bravo, M. A., & Bell, M. L. (2015). A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke. *Environmental Research*, *136*, 120-132. https://doi.org/10.1016/j.envres.2014.10.015
McElreath, R. (2018). *Statistical rethinking: A Bayesian course with examples in R and Stan*. Chapman and Hall/CRC.
Mullan, K., Avery, T., Boise, P., Leary, C. S., Rice, W. L., & Semmens, E. O. (2024). Impacts of wildfire-season air quality on park and playground visitation in the Northwest United States. *Ecological Economics*, *224*, 108285. https://doi.org/https://doi.org/10.1016/j.ecolecon.2024.108285
Musacchio, A., Andrade, L., O'Neill, E., Re, V., O'Dwyer, J., & Hynds, P. D. (2021). Planning for the health impacts of climate change: Flooding, private groundwater contamination and waterborne infection – A cross-sectional study of risk perception, experience and behaviours in the Republic of Ireland. *Environmental Research*, *194*, 110707. https://doi.org/https://doi.org/10.1016/j.envres.2021.110707
Navarro, K. M., Schweizer, D., Balmes, J. R., & Cisneros, R. (2018). A Review of Community Smoke Exposure from Wildfire Compared to Prescribed Fire in the United States. *Atmosphere*, *9*(5), 185. https://www.mdpi.com/2073-4433/9/5/185
Nguyen, M.-H., Duong, M.-P. T., Nguyen, Q.-L., La, V.-P., & Hoang, V.-Q. (2024). In search of value: the intricate impacts of benefit perception, knowledge, and emotion about climate change on marine protection support. *Journal of Environmental Studies and Sciences*, 1-19. https://doi.org/10.1007/s13412-024-00902-8
Nguyen, M.-H., & Jones, T. E. (2022a). Building eco-surplus culture among urban residents as a novel strategy to improve finance for conservation in protected areas. *Humanities and Social Sciences Communications*, *9*(1), 426. https://doi.org/10.1057/s41599-022-01441-9
Nguyen, M.-H., & Jones, T. E. (2022b). Predictors of support for biodiversity loss countermeasure and bushmeat consumption among Vietnamese urban residents. *Conservation Science and Practice*, *4*(12), e12822. https://doi.org/10.1111/csp2.12822
Nguyen, M.-H., La, V.-P., Le, T.-T., & Vuong, Q.-H. (2022). Introduction to Bayesian Mindsponge Framework analytics: An innovative method for social and psychological research. *MethodsX*, *9*, 101808. https://doi.org/10.1016/j.mex.2022.101808

Nguyen, M.-H., Le, T.-T., & Vuong, Q.-H. (2023). Ecomindsponge: A novel perspective on human psychology and behavior in the ecosystem. *Urban Science*, *7*(1), 31. https://doi.org/10.3390/urbansci7010031

Nguyen, M. H., La, V. P., Le, T. T., & Vuong, Q. H. (2022). Introduction to Bayesian Mindsponge Framework analytics: An innovative method for social and psychological research. *MethodsX*, *9*, 101808. https://doi.org/10.1016/j.mex.2022.101808

Nolte, J., & Hanoch, Y. (2024). Adult age differences in risk perception and risk taking. *Current Opinion in Psychology*, *55*, 101746. https://doi.org/10.1016/j.copsyc.2023.101746

O'Dell, K., Ford, B., Fischer, E. V., & Pierce, J. R. (2019). Contribution of Wildland-Fire Smoke to US PM2.5 and Its Influence on Recent Trends. *Environmental Science & Technology*, *53*(4), 1797-1804. https://doi.org/10.1021/acs.est.8b05430

Oltra, C., & Sala, R. (2018). Perception of risk from air pollution and reported behaviors: a cross-sectional survey study in four cities. *Journal of Risk Research*, *21*(7), 869-884. https://doi.org/10.1080/13669877.2016.1264446

Pluess, M. (2015). Individual differences in environmental sensitivity. *Child Development Perspectives*, *9*(3), 138-143. https://doi.org/10.1111/cdep.12120

Rajagopalan, S., Brauer, M., Bhatnagar, A., Bhatt, D. L., Brook, J. R., Huang, W., . . . Council, S. (2020). Personal-Level Protective Actions Against Particulate Matter Air Pollution Exposure: A Scientific Statement From the American Heart Association. *Circulation*, *142*(23), e411-e431. https://doi.org/doi:10.1161/CIR.0000000000000931

Rajper, S. A., Ullah, S., & Li, Z. (2018). Exposure to air pollution and self-reported effects on Chinese students: A case study of 13 megacities. *PLOS ONE*, *13*(3), e0194364. https://doi.org/10.1371/journal.pone.0194364

Ramírez, A. S., Ramondt, S., Van Bogart, K., & Perez-Zuniga, R. (2019). Public Awareness of Air Pollution and Health Threats: Challenges and Opportunities for Communication Strategies To Improve Environmental Health Literacy. *Journal of Health Communication*, *24*(1), 75-83. https://doi.org/10.1080/10810730.2019.1574320

Rappold, A. G., Hano, M. C., Prince, S., Wei, L., Huang, S. M., Baghdikian, C., . . . Hubbell, B. (2019). Smoke Sense Initiative Leverages Citizen Science to Address the Growing Wildfire-Related Public Health Problem. *GeoHealth*, *3*(12), 443-457. https://doi.org/10.1029/2019GH000199

Rappold, A. G., Reyes, J., Pouliot, G., Cascio, W. E., & Diaz-Sanchez, D. (2017). Community Vulnerability to Health Impacts of Wildland Fire Smoke Exposure. *Environ Sci Technol*, *51*(12), 6674-6682. https://doi.org/10.1021/acs.est.6b06200

Reames, T. G., & Bravo, M. A. (2019). People, place and pollution: Investigating relationships between air quality perceptions, health concerns, exposure, and individual- and area-level characteristics. *Environment International*, *122*, 244-255. https://doi.org/https://doi.org/10.1016/j.envint.2018.11.013

Reisen, F., Duran, S. M., Flannigan, M., Elliott, C., & Rideout, K. (2015). Wildfire smoke and public health risk. *International Journal of Wildland Fire*, *24*(8), 1029-1044. https://doi.org/https://doi.org/10.1071/WF15034

Rizzo, L. V., & Rizzo, M. C. F. V. (2024). Wildfire smoke and health impacts: a narrative review. *Jornal de Pediatria*. https://doi.org/https://doi.org/10.1016/j.jped.2024.11.006

Rovelli, C. (2018). *Reality is not what it seems: The journey to quantum gravity*. Penguin.

Santana, F. N., Gonzalez, D. J. X., & Wong-Parodi, G. (2021). Psychological factors and social processes influencing wildfire smoke protective behavior: Insights from a case study in Northern California. *Climate Risk Management*, *34*, 100351. https://doi.org/https://doi.org/10.1016/j.crm.2021.100351

Santirocchi, A., Spataro, P., Alessi, F., Rossi-Arnaud, C., & Cestari, V. (2023). Trust in science and belief in misinformation mediate the effects of political orientation on vaccine hesitancy and intention to be vaccinated. *Acta Psychologica*, *237*, 103945. https://doi.org/10.1016/j.actpsy.2023.103945

Sari, N. P. W. P., Artsanthia, J., Marcello, S. A., Suvaree, S., & Prachyakoon, N. (2024). Examining the digital skills of nursing students: the power of information for problem-solving. *International Journal of Public Health Science*, *13*(3), 1111-1120. https://doi.org/10.11591/ijphs.v13i3.23873

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*(3), 379-423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Sivarethinamohan, R., Sujatha, S., Priya, S., Sankaran, Gafoor, A., & Rahman, Z. (2021). Impact of air pollution in health and socio-economic aspects: Review on future approach. *Materials Today: Proceedings*, *37*, 2725-2729. https://doi.org/https://doi.org/10.1016/j.matpr.2020.08.540

Slovic, P. (2010). *The feeling of risk: New perspectives on risk perception*. Routledge.

Tanemura, N., Kakizaki, M., Kusumi, T., Onodera, R., & Chiba, T. (2022). Levels of trust in risk-only negative health messages issued by public agencies: a quantitative research-based mindsponge framework. *Humanities and Social Sciences Communications*, *9*(1), 1-7. https://doi.org/10.1057/s41599-022-01415-x

Thaker, J., Richardson, L. M., & Holmes, D. C. (2023). Australians' perceptions about health risks associated with climate change: Exploring the role of media in a comprehensive climate change risk perception model. *Journal of Environmental Psychology*, *89*, 102064. https://doi.org/https://doi.org/10.1016/j.jenvp.2023.102064

Thomas, A. S., Escobedo, F. J., Sloggy, M. R., & Sánchez, J. J. (2022). A burning issue: Reviewing the socio-demographic and environmental justice aspects of the wildfire literature. *PLOS ONE*, *17*(7), e0271019. https://doi.org/10.1371/journal.pone.0271019

Vehtari, A., & Gabry, J. (2019). *Bayesian Stacking and Pseudo-BMA weights using the loo package*. In (Version loo 2.2.0) https://mc-stan.org/loo/articles/loo2-weights.html

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and computing*, *27*(5), 1413-1432. https://doi.org/10.1007/s11222-016-9696-4

Völker, M., & Sujaritpong, S. (2024). Risk perception of air pollution and behavioral responses: a mapping review of research studies during 2000–2021. *Air Quality, Atmosphere & Health*. https://doi.org/10.1007/s11869-024-01531-4

Vuong, Q.-H. (2018). The (ir)rational consideration of the cost of science in transition economies. *Nature Human Behaviour*, *2*, 5. https://doi.org/10.1038/s41562-017-0281-4

Vuong, Q.-H. (2021). The semiconducting principle of monetary and environmental values exchange. *Economics and Business Letters*, *10*(3), 284-290. https://doi.org/10.17811/ebl.10.3.2021.284-290

Vuong, Q.-H. (2023). *Mindsponge theory*. Walter de Gruyter GmbH. https://www.amazon.com/dp/B0C3WHZ2B3/

Vuong, Q.-H. (2024). *Wild Wise Weird*. AISDL. https://www.amazon.com/dp/B0BG2NNHY6

Vuong, Q.-H., Duong, M.-P. T., Sari, N. P. W. P., La, V.-P., & Nguyen, M.-H. (2024). From beauty to belief: The aesthetic and diversity values of plants and pets in shaping biodiversity loss belief among Vietnamese urban residents. *Humanities and Social Sciences Communications*, *11*, 1510. https://doi.org/10.1057/s41599-024-04036-8

Vuong, Q.-H., & Nguyen, M.-H. (2024a). *Better economics for the Earth: A lesson from quantum and information theories*. AISDL. https://www.amazon.com/dp/B0D98L5K44/

Vuong, Q.-H., & Nguyen, M.-H. (2024b). Further on informational quanta, interactions, and entropy under the granular view of value formation. https://doi.org/10.2139/ssrn.4922461

Vuong, Q.-H., Nguyen, M.-H., & La, V.-P. (2022). *The mindsponge and BMF analytics for innovative thinking in social sciences and humanities*. Walter de Gruyter GmbH. https://www.amazon.com/dp/B0C4ZK3M74/

Vuong, Q. H., & Napier, N. K. (2015). Acculturation and global mindsponge: an emerging market perspective. *International Journal of Intercultural Relations*, *49*, 354-367. https://doi.org/10.1016/j.ijintrel.2015.06.003
Wagenmakers, E.-J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., . . . Epskamp, S. (2018). Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications. *Psychonomic bulletin review*, *25*(1), 35-57. https://doi.org/10.3758/s13423-017-1343-3
Wang, C., & Cao, J. (2024). Air pollution, health status and public awareness of environmental problems in China. *Sci Rep*, *14*(1), 19861. https://doi.org/10.1038/s41598-024-69992-2
Wang, F., Zhao, H., Zhang, X., Niu, C., & Ma, J. (2019). Understanding individual-level protective responses to air pollution warning: A case study of Beijing, China. *Human and Ecological Risk Assessment: An International Journal*, *25*(6), 1473-1487. https://doi.org/10.1080/10807039.2018.1468995
Xiong, L., Li, J., Xia, T., Hu, X., Wang, Y., Sun, M., & Tang, M. (2018). Risk Reduction Behaviors Regarding PM2.5 Exposure among Outdoor Exercisers in the Nanjing Metropolitan Area, China. *International Journal of Environmental Research and Public Health*, *15*(8), 1728. https://doi.org/10.3390/ijerph15081728
Xu, R., Ye, T., Huang, W., Yue, X., Morawska, L., Abramson, M. J., . . . Li, S. (2024). Global, regional, and national mortality burden attributable to air pollution from landscape fires: a health impact assessment study. *The Lancet*, *404*(10470), 2447-2459. https://doi.org/10.1016/S0140-6736(24)02251-7