# Perceived salience of issues: Analysis of Meta's opinion data

Keywords: issue salience, individual-level factors, rationality, climate change opinion, machine learning

#### **Extended Abstract**

Issue salience, which refers to the issues atop the public's mind (Bevan & Jennings, 2019), is an important concept in communication, public opinion, and policy studies. The more salient an issue is to the public, the relationship between public opinion and policy is likely to be stronger (Burstein, 2003); this notion that the public view of an issue's salience influences policy has led to scholars investigating the factors explaining it. Extant literature has discussed factors such as the problem status of an issue (John, Bertelli, Jennings, & Bevan, 2013; Wlezien, 2005) and elite mobilization (Cohen, 1995; Lovett, Bevan, & Baumgartner, 2015). Further, numerous studies consider the media the most important in shaping the public's views, which are studied mostly at an aggregate level. Still, they fundamentally occur at an individual level. Nevertheless, fewer studies have focused on individual-level factors, and those mostly focus on an individual's background characteristics. More importantly, a theoretical perspective has been lacking to explain why individuals attach importance to an issue.

Therefore, this study probes the individual-level factors to explain issue salience, taking the perspective of rationality from rational choice theory (see Fig 1 for the overall framework). We evaluate rationality in this study based on issue perception, perceived risk, and perceived benefit. If one perceives an issue as more risky or beneficial to oneself, one may also consider it important; similarly, a low perceived risk and benefit may lead to one considering it less important. The study is conducted in the context of climate change. Therefore, the issue salience in the study is individuals' perceived importance of climate change. It offers a relevant context because numerous previous studies posit that despite most of the public agreeing that climate change is happening, many do not consider it a salient issue (Bromley-Trujillo & Poe, 2020; Crawley, Coffé, & Chapman, 2022).

The study's analysis is based on Meta's 2022 climate opinion data, one of the largest global surveys (N = 108,496) about public views toward climate change. The analysis method involves standard classification and two machine learning estimators based on the random forest algorithm: Ordered Forest (OF) (Lechner & Okasa, 2019) and Interaction Forest (IF) (Hornung & Boulesteix, 2022). Three questions are probed: first, we test whether the perception of an issue's salience depends on the individual's perceived risk and benefit. (Results: in all comparisons, higher perceived risk and benefit improve the odds of issue salience falling in higher categories compared to the reference (P <0.001)). Second, to determine if the assumption of rationality is highly predictive of issue salience, OF's (see Fig 4 for OF's model performance) variable importance measure is used to determine the most important predictors. (Results: the three most important variables are perceived risk, GNI (Gross National Income), which is used as an indicator of the macroeconomic condition of a country, and perceived benefit). Third, humans tend to be complex (Earp & Trafimow, 2015), and any psychological phenomenon may be moderated by various factors (Cesario, 2014). Therefore, instead of simply examining interactions, we investigate the most important

### 9<sup>th</sup> International Conference on Computational Social Science IC<sup>2</sup>S<sup>2</sup> July 17-20, 2023 – Copenhagen, Denmark

interactions (variable pairs) concerning their interaction effects' importance to prediction. Then, we examine the nature of the bivariate influence. (Results: i) perceived risk (small) and GNI (large) (p < 0.001); ii) perceived risk (small) and issue exposure (large) (p < 0.05). For this type of quantitative interaction (see., Hornung, Wright, & Hornung, 2022), it can be said that if the level of perceived risk is small and, at the same time, the level of GNI is large, the expected value of issue salience is (considerably) different from all other cases. This means that when the perceived risk is high, the influence of GNI is weak, and strong when the perceived risk is low (see Fig 5). The same applies to issue exposure and perceived risk interaction (see Fig 6).

It is found in this study that an individual's perceived risk and benefit of an issue share a significant positive relationship to issue salience, thus giving evidence of rationality in individuals attaching importance to issues. Then again, the interaction results show that the relationship is not straightforward, showing significant interaction at the lower end of the perceived risk scale. The results show that if one has a high perceived risk and benefit of an issue, it is more likely for one to consider it important. But if one perceived the risk as low, the perceived importance of the issue is contingent on GNI and issue exposure. To explain this, we rely on the literature on the psychology of social class (situational attributions) and informational influence (uncertainty). Because rationality should manifest in both ways: high risk, high importance, and low risk, low importance, the study's findings indicate that the rational perspective does not offer a sufficiently nuanced explanation of issue salience. Besides the theoretical contributions, this study illustrates the utility of recent advances in interpretable machine learning that can contribute to theoretical development. The methodology adopted allowed a deductive-inductive approach to inference, testing the theoretical assumption of rationality and simultaneously bringing nuance to it through exploration.

#### References

Bevan, S., & Jennings, W. (2019). The public agenda: A comparative perspective. (pp. 219-242) Oxford University Press.

Bromley-Trujillo, R., & Poe, J. (2020). The importance of salience: Public opinion and state policy action on climate change. Journal of Public Policy, 40(2), 280-304.

Cesario, J. (2014). Priming, replication, and the hardest science. Perspectives on Psychological Science, 9(1), 40-48.

Cohen, J. E. (1995). Presidential rhetoric and the public agenda. American Journal of Political Science, 39(1), 87-107.

Crawley, S., Coffé, H., & Chapman, R. (2022). Climate belief and issue salience: Comparing two dimensions of public opinion on climate change in the EU. Social Indicators Research, 162(1), 307-325.

Earp, B. D., & Trafimow, D. (2015). Replication, falsification, and the crisis of confidence in social psychology. Frontiers in Psychology, 6, 621.

Hornung, R., & Boulesteix, A. (2022). Interaction forests: Identifying and exploiting interpretable quantitative and qualitative interaction effects. Computational Statistics & Data Analysis, 171, 107460.

Lechner, M., & Okasa, G. (2019). Random forest estimation of the ordered choice model. arXiv Preprint arXiv:1907.02436

Lovett, J., Bevan, S., & Baumgartner, F. R. (2015). Popular presidents can affect congressional attention for a little while. Policy Studies Journal, 43(1), 22-43.

Wlezien, C. (2005). On the salience of political issues: The problem with 'most important problem.' Electoral Studies, 24(4), 555-579.

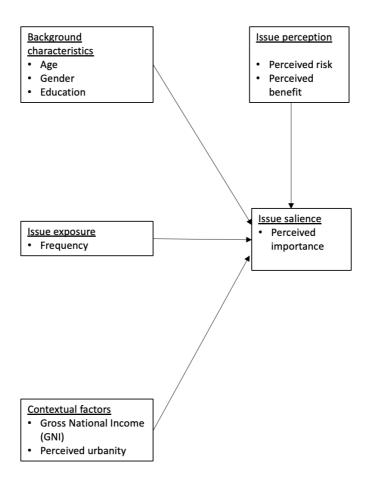


Figure 1. Factors explaining issue salience

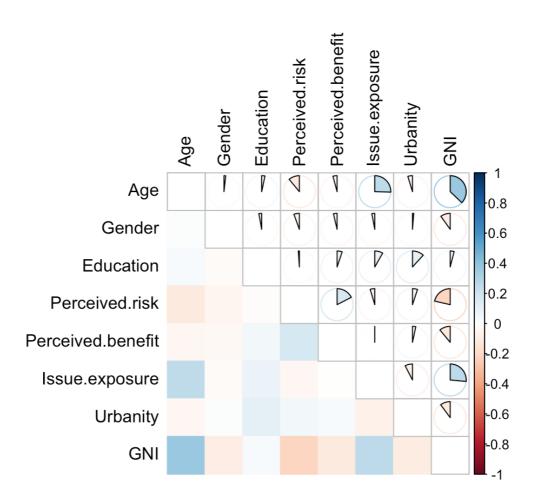


Fig 2. Spearman correlation between explanatory variables

## $9^{th}$ International Conference on Computational Social Science $IC^2S^2$ July 17-20, 2023- Copenhagen, Denmark

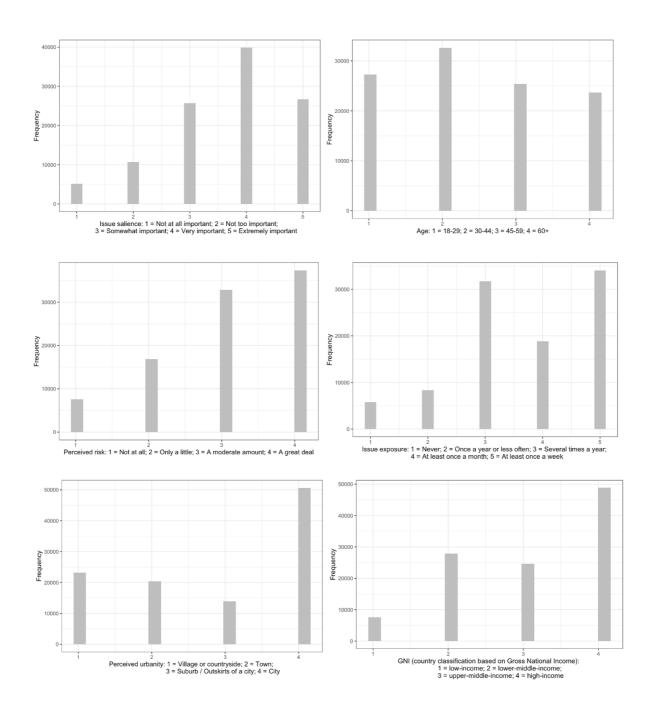


Figure 3a. Descriptive statistics

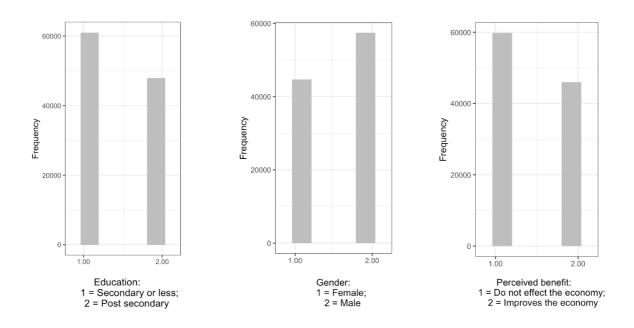


Figure 3b. Descriptive statistics

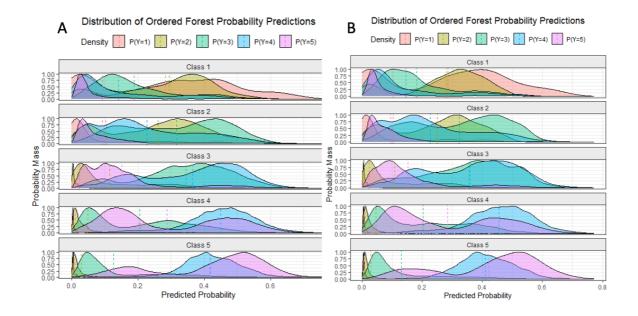


Figure 4. Predicted probability distributions of ordered forest model:

A) training set (Mean Squared Error (MSE) = 0.596; Ranked Probability Score (RPS) = 0.095)

B) test set (MSE = 0.589; RPS = 0.095)

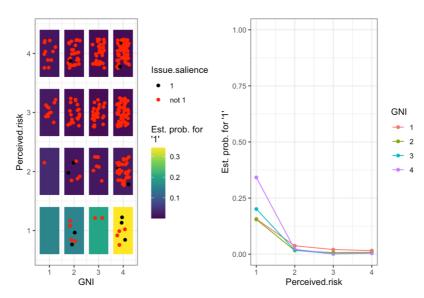


Figure 5. Interaction forest plot: GNI and perceived risk bivariate influence

Note: The estimated probabilities are predicted for the base class (1 = "not at all important.")

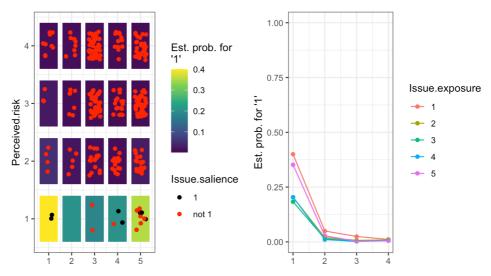


Figure 6. Interaction forest plot: Issue exposure and perceived risk bivariate influence

Note: The estimated probabilities are predicted for the base class (1 = "not at all important.")