A Methodology to Address Perceived Hazards from the Twin Transition Among Disadvantaged Groups

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Abstract.

This paper outlines a framework for identifying and prioritizing hazards linked to the green and digital transitions by integrating harmonized surveys with Bayesian-network modeling. Following the FITTER-EU project guidelines, we utilize translated questionnaires across six countries to assess the likelihood and severity of 26 hazards in three sectors: Energy, Housing, and Transport. Our methodology incorporates EU-SILC-inspired socio-demographic stratification to generate indices for disadvantaged groups (DGs). The analysis involves three stages: predicting hazards using Naïve Bayes and regression, conducting ANOVA for socio-demographic patterns, and employing Bayesian Networks to model dependencies and assess policy effectiveness. Our approach innovatively combines participatory data collection with explainable AI to foster anticipatory governance for an inclusive transition. Future developments aim for scalability, technical integration with the FITTER platform, and external validation for effective policy implementation.

Keywords: Twin transition; Hazards prediction; Naïve Bayes classifier; Bayesian networks; Inclusivity; AI; Policy support.

1. Introduction

The European Union's twin green and digital transition targets climate neutrality and digital leadership by 2030–2050, but rapid measures like PV installation, home retrofitting, and EV adoption can disadvantage groups such as low-income households, the elderly, people with disabilities, tenants, migrants, and rural populations through higher costs, infrastructure gaps, and unequal benefits.

The FITTER-EU project develops an anticipatory governance ecosystem for inequalities. This study operationalizes predictive modelling within its "Spring" phase, transforming perceptual hazard data into a framework for risk assessment

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and intersectional mitigation. The goal is to create and validate a predictive hazards model that quantifies perceived risk, identifies high-risk group–hazard pairs, and aids in scenario forecasting and prioritizing mitigation for inclusive policy design. Its unique approach combines EU-SILC-aligned survey data with Bayesian Networks for explainable probabilistic inference and policy simulation, shifting from descriptive mapping to predictive, profile-specific risk intelligence.

2. Methodology

2.1 Survey Design and Data Collection

Three sector-specific questionnaires were developed following a harmonised protocol informed by case studies and EU-SILC variables:

- **Energy** (PV installations): 7 hazards (e.g., higher electricity bills)
- **Housing** (retrofitting): 13 hazards (e.g., rent increases)
- **Transport** (EV acquisition): 6 hazards (e.g., higher purchase/charging costs)

Questionnaires included Part A (access determinants), Part B (sociodemographic/EU-SILC variables), and Part C (5-point Likert scales for Probability and Severity). The target sample was 456 valid responses per sector (total 1,368), calculated using Cochran's formula with parameters of p=0.20, 95% confidence, 5% margin of error, and 85% power. Stratified quota sampling through Prolific adhered to EU-SILC proportions for country, income, gender, tenancy status, and disability, with quotas per country/sector. Quality controls maintained 85–90% retention.

2.2 Research Design and Analytical Framework

This study develops a framework to analyze the link between socio-demographic traits and perceived risks from Europe's green and digital transition policies. It uses a structured survey along with probabilistic classification, regression modeling, subsample validation, and ANOVA testing to interpret hazard perceptions across various segments.

2.3 Analytical Pipeline

The methodology follows a sequential pipeline from data ingestion to policy simulation, implemented individually for transport, energy, and housing sectors. Our methodological pipeline is as follows (Figure 1):

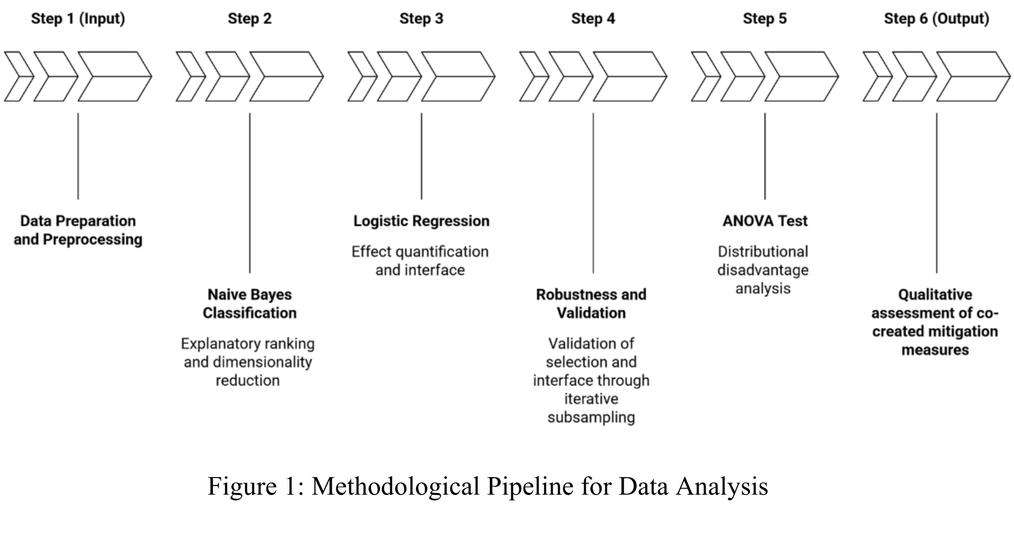

Figure 1: Methodological Pipeline for Data Analysis

Step 1.- Data Preparation and Preprocessing: Missing responses in surveys were retained as meaningful indicators of informational constraints, such as knowledge gaps or uncertainty. This approach highlights barriers to understanding or unfamiliarity with topics like transition hazards, revealing awareness deficits in disadvantaged groups instead of treating them as errors.

For classification modeling, hazard perception variables were converted to binary outcomes for high perceived risk: For each hazard "h", the dependent variable Y(h) = 1 (denoted as C in subsequent steps) if hazard is scored >= 4 on a Likert scale by the respondent, else 0 if the hazard is less than 4 on the Likert scale. This isolates respondents with maximal concern and identifies characteristics linked to extreme perceived risk exposure. This classification is a modelling choice and not a statistical necessity.

Step 2.- Exploratory Pattern Identification: Naive Bayes Classification; The first analytical stage employed a Multinomial Naive Bayes classifier to explore associations between explanatory indicators and high hazard perception. The classifier estimates the conditional likelihood of high hazard perception given a respondent's indicator profile (Eq.1):

$$P(C|X_1, X_2, \ldots, X_n) \propto P(C) \prod_{i=1}^{n} P(X_i|C) \qquad \text{(Eq.1)}$$

Being:

- C = High-level perception (all hazards scored at 6)
- X_i = Explanatory variable (some socio-demographic variables of the survey, Direct variables, and other indirect variables)
- n = the total number of encoded explanatory features derived from the socio-demographic and behavioural indicators included in the model

For interpretability, log-transformations of conditional probabilities were examined (Eq.2):

$$\log\, P(X_i \mid C = 1) \qquad \text{(Eq.2)}$$

Indicators were ranked based on their contribution to the likelihood of high hazard perception, serving as a feature screening mechanism rather than an inferential model. Predictors were ranked according to their conditional log-likelihood contributions within the high-hazard class. To control dimensionality, the top 15 predictors were retained per hazard outcome. Stability of predictor selection was assessed across 100 subsampled iterations, and only predictors demonstrating consistent recurrence were retained for regression modeling.

Step 3.- Effect Quantification: Logistic Regression — To quantify the magnitude and direction of associations identified during screening, binary logistic regression models were estimated for each hazard outcome. The general specification is (Eq.3):

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \sum_{i \in S} \beta_i X_i \qquad \text{(Eq.3)}$$

Where:

p is the probability of reporting high hazard perception, *S* denotes the subset of screened predictors, X_i are explanatory indicators. Through this equation, we obtain Odds Ratio and p-value. Odds ratios were used to determine how large is the effect. They measure magnitude of influence. While p-values were used to determine the statistical reliability. Regression coefficients were exponentiated to obtain odds ratios (Eq.4):

$$OR_i = e^{\beta_i} \qquad \text{(Eq.4)}$$

Odds ratios above one indicate a higher likelihood of high hazard perception related to the indicator, while those below one indicate a lower likelihood. The framework separates exploratory screening from inferential modeling to maintain clarity between identifying marginal associations and estimating conditional effects. Predictors were considered robust if they demonstrated statistical significance at the 5% level, exhibited meaningful odds ratios, and appeared consistently across subsample iterations.

Step 4.- Robustness and Validation: To evaluate structural robustness and reduce the risk that results are driven by particular respondent configurations, an iterative subsample validation procedure was implemented.

Let N denote the total number of respondents. A subsample size was defined as (Eq.5):

$$n = 0.30 \times N \qquad \text{(Eq.5)}$$

In each of the 100 iterations, a random sample of size n was drawn without replacement, leading to varying respondent compositions. During each iteration, the Naive Bayes classifier was re-estimated, a feature screening rule was applied, and logistic regression was performed using the selected predictors. Predictor rankings, coefficient signs, and statistical significance were recorded.

Stability was assessed by examining the recurrence and consistency of predictors across iterations. Conceptually, predictor stability can be expressed as (Eq.6):

$$\text{Stability}_i = \frac{\text{Number of iterations where predictor } i \text{ remains significant}}{100}$$

(Eq.6)

Predictors demonstrating high recurrence and consistent coefficient direction were interpreted as structurally robust associations rather than sample-specific artifacts.

Step 5.- ANOVA test with Socio-demographic groups Comparison To analyze perceived hazard exposure inequalities, we conduct a distributional analysis using group comparisons. For the hazard with the highest predicted risk, we compare survey scores on a 1-5 Likert scale across socio-demographic categories. We use one-way ANOVA to assess significant differences in mean perceived risk, identifying those with disproportionately higher perceptions of risk.

One-way ANOVA tests the null hypothesis H_0 (no differences between group means, $\mu_1 = \mu_2 = \ldots = n_j$) against the alternative hypothesis H_1 (at least one group mean differs). It employs the F-statistic, which follows a Fisher (F) distribution with degrees of freedom (df_{factor}, $df_{residual}$), calculated as:

$$df\_\text{factor} = (j - 1) \qquad \text{(Eq. 7)}$$

where "j” is the number of groups, and

$df_{residual}$ is the total number of data points ($N = \Sigma N_j$) minus 1 minus $df_{\_factor}$:

$$df_{residual} = (N - 1) - df_{factor} \qquad \text{(Eq. 8)}$$

where N is the total number of observations ($N = \Sigma N_j$, with N_j being the sample size per group “j”).

"$F_{statistic}$" can be calculated as:

$$F = \frac{MS_{factor}}{MS_{residual}} = \frac{\Sigma_j N_j(\mu_j - \bar{\mu})^2 / df_{factor}}{\Sigma_{ij}(x_{ij} - \mu_j)^2 / df_{residual}}$$

(Eq.9)

where MS_{factor} is the mean square between groups (variance explained by group differences) and $MS_{residual}$ is the mean square within groups (residual variance).

The significance level α (typically 0.05 for 95% confidence) determines the critical F-value from the F-distribution tables or software. If the calculated F exceeds the critical value (or $p < \alpha$), H_0 is rejected, indicating significant differences in perceived hazard exposure across groups. For example, with 2 groups ($df_{factor} = 1$) and $df_{residual} = 38$, the critical F-value at $\alpha = 0.05$ is approximately 4. If $F > 4$, the group means differ significantly with 95% confidence.

Step 6.- Qualitative assessment of co-created mitigation measures — For a qualitative assessment of the co-created mitigation measures we use a conversational probing mechanism enabled by Large Language models that connect to the world wide web for learning from the vast source of knowledge and online references, and are further fine-tuned on the research outputs of FITTER-EU project for shortlisting the references and knowledge sources that align with the project goals. This step is presented in another paper in this 65th ERSA conference (Aditya et al. 2026) [12].

3. Results

The above quantitative analysis pipeline (Step 1 to 5) enables a user to understand the key factors and reasons for the perception of the hazards by various socio-demographic groups. It enables the user to go deeper into looking at the root causes for the perceived hazards and initiate a self-reflective exercise of finding the possible mitigation measures to change these perceptions. This self-reflective exercise preceded by quantitative analysis has led to the creation of Dr. Transition-an AI agent that learns from the quantitative analysis and proposes mitigation measures using a reference from the World Wide Web that are within the scope of FITTER-EU research outputs (See Figure 2). Dr. Transition is a Natural Language

Processing (NLP) based AI agent that interact with the user and helps them to make sense of quantitative analysis for qualitative and pedagogical purposes-creating policies or mitigation measures that embed eco-social justice impact.

$$Dr. Transition\ (FITTER - EU\ digital\ platform) = Quantitative\ analysis\ (Steps\ 1 - 5) + Qualitative\ assessment\ of\ co - created\ mitigation\ measures\ (Step\ 6)$$

Figure 2. Methodological steps operationalized as digital platform

The figure below (Figure 3) shows how the dialog between the platform user and Dr. transition looks like:

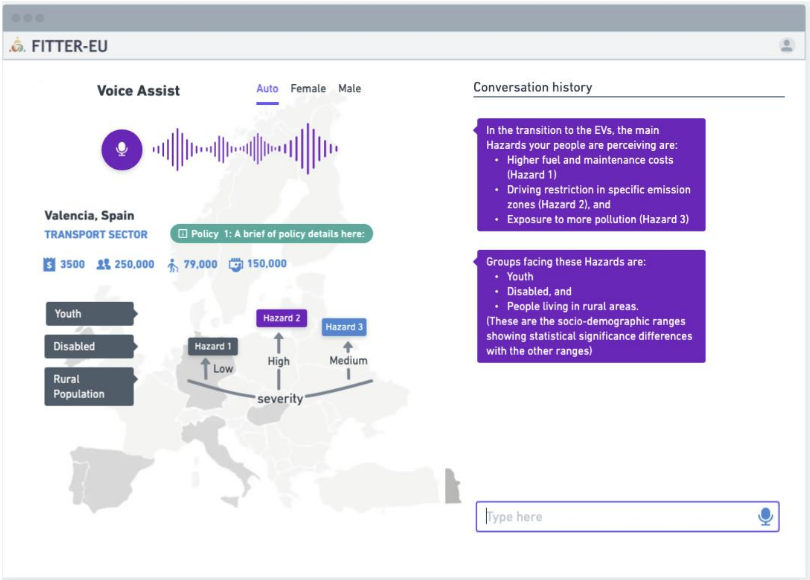

Figure 3. An example of the dialog between the platform user and Dr. Transition

We expect the platform to help policymakers, policy researchers to learn about embedding eco-social justice impact in policy design. Thereby making way for equitable policy in the future.

The FITTER-EU project is currently collecting data (target n=1,368 responses across sectors, within 6 countries (DE, ES, HU, IE, IT, PT) stratified by EU-SILC proportions for country, income, gender, tenancy, and disability). Full results, including cross-sector patterns, will be reported after data completion.

4. Discussion

The predictive model converts perceptual surveys into probabilistic forecasts for anticipatory governance in the twin transition. Its strengths include EU-SILC-aligned stratification, multi-country harmonization across six use cases, and an explainable AI pipeline (Naive Bayes, logistic regression, ANOVA). It addresses uncertainty and highlights inequalities, particularly the effects on low-income groups in housing and transport.

Reliability is affected by sampling bias on platforms like Prolific, which attract digitally skilled participants. The FITTER-EU design uses quota controls to address this, but self-selection may still skew estimates for rural groups. A sample size of around 456 per sector balances feasibility.

Future efforts should address self-report bias and incomplete analyses by incorporating hybrid sampling, real-time data, and sector expansion (e.g., agriculture), while also integrating into the FITTER Digital Platform for automated policy briefs.

5. Conclusion

This paper introduces a predictive hazards assessment framework using survey data and Bayesian Network modeling to support an inclusive twin transition. It identifies high-risk DG-hazards and simulates policy impacts, providing actionable insights for policymakers. Enhancing the evolutionary tree framework from Kapoor et al. (2025), it offers quantitative tools for vulnerability mapping in the FITTER-EU ecosystem, addressing technological developments and final functionalities. This work advances just transition research and foster scalable anticipatory governance tools across Europe.

Future work will involve integrating the nowadays collected data into the brain of Dr. Transition, as the FITTER Digital Platform, making actionable all these algorithms. It is also expected to extend the scope of Dr. Transition to other sectors and other EU countries to strengthen anticipatory governance for a fair and inclusive transition.

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References

1. Kapoor, A., Molero, G. D., Santarremigia, F. E., Malekzadeh, M. Z., Malviya, A. K., & Flynn, T. (2025). An Evolutionary Tree Framework for a Fair and Inclusive Twin Transition in Europe. Extended abstract submitted to ERSA Special Session 88: Twin Transition and its Unequal Geography. https://airdrive.eventsair.com/eventsairwesteuprod/production-ersa-public/f75d8e4e57864d449bd11f855774df60
2. Eurostat. (2024). Methodological guidelines and description of EU-SILC target variables: 2024 operation. European Commission.
3. Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2018). *Advanced issues in partial least squares structural equation modeling*. Sage.
4. Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*(3), 607–610.
5. Santarremigia, F. E., Molero, G. D., et al. (2025). *Deliverable 4.1: Report on the hazards' probability rates and negative impacts' severity rate*. FITTER-EU Project.
6. Kelly, J. A., Clinch, J. P., et al. (2020). Enabling a just transition: A composite indicator for assessing home-heating energy-poverty risk. *Energy Policy, 146*, 111791. https://doi.org/10.1016/j.enpol.2020.111791
7. Verhorst, T., Fu, X., & van Lierop, D. (2023). Definitions matter: Investigating indicators for transport poverty. *European Transport Research Review, 15*, 21. https://doi.org/10.1186/s12544-023-00596-z
8. Aiello, L. M., et al. (2025). Bayesian insights on digitalization and environmental sustainability practices. Towards the twin transition in the EU. *Business Strategy and the Environment*. https://doi.org/10.1002/bse.3985
9. Methodology | FITTER-EU, https://fitter-eu.com/page/methodology, Accessed: 2026-02-16.
10. Fair and inclusive twin transitions for a stronger social Europe | FITTER-EU | Project | Fact sheet | HORIZON | CORDIS | European Commission, https://cordis.europa.eu/project/id/101132546, Accessed: 2025-02-16
11. FITTER-EU – AITTEC, https://www.aitec-intl.com/fitter-eu/, Accessed: 2026-02-16.
12. Kapoor, A., Zarehparast Malekzadeh, M., Molero, G. D., Santarremigia, F. E., Bjegojevic, B., MacNamara, N., & Salomón, O. (2026, August 25–28). Anticipating the future: A pedagogical policy-making process guided by AI. 65th ERSA Congress, Sofia, Bulgaria (under review).
13. Molero, G. D., Santarremigia, F. E., Kapoor, A., Zarehparast Malekzadeh, M., Leva, M. C., & Clavero, S. (2026). *A methodological framework for a fair and inclusive twin transition in the transport sector*. Transportation Research Arena (TRA) 2026.
14. Memon, Mumtaz & Ting, Hiram & Cheah, Jun-Hwa & Ramayah, T. & Chuah, Francis & Cham, Tat-Huei. (2020). Sample Size for Survey Research: Review and Recommendations. Journal of Applied Structural Equation Modeling. 4. i-xx. 10.47263/JASEM.4(2)01.
15. Sirwan Khalid Ahmed, How to choose a sampling technique and determine sample size for research: A simplified guide for researchers, Oral Oncology Reports, Volume 12, 2024, 100662, ISSN 2772-9060, https://doi.org/10.1016/j.oor.2024.100662. (https://www.sciencedirect.com/science/article/pii/S2772906024005089)
16. Hair, Joseph & Risher, Jeff & Sarstedt, Marko & Ringle, Christian. (2018). When to use and how to report the results of PLS-SEM. European Business Review. 31. 10.1108/EBR-11-2018-0203.
17. Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2018). Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks, CA: Sage. https://doi.org/10.3926/oss.37
18. Hsieh, G., & Kocielnik, R. (2016). You get who you pay for: The impact of incentives on participation bias. In "Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing (CSCW '16)" (pp. 823–835). Association for Computing Machinery. https://doi.org/10.1145/2818048.2819278
19. Mao, A., Kamar, E., Chen, Y., Horvitz, E., Schwamb, M. E., Lintott, C. J., & Smith, A. M. (2013). Volunteering versus work for pay: Incentives and tradeoffs in crowdsourcing. In "Proceedings of the First AAAI Conference on Human Computation and Crowdsourcing (HCOMP 2013)". Association for the Advancement of Artificial Intelligence.
20. Rosenthal, R., & Rosnow, R. L. (1975). "The volunteer subject". Wiley.
21. Singer, E., & Ye, C. (2013). The use and effects of incentives in surveys. The ANNALS of the American Academy of Political and Social Science, 645(1), 112–141. https://doi.org/10.1177/0002716212458082
22. Slonim, R., Wang, C., Garbarino, E., & Merrett, D. (2013). Opting-in: Participation bias in economic experiments. "Journal of Economic Behavior & Organization", 90, 43–70. https://doi.org/10.1016/j.jebo.2013.03.002

23. Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. “Journal of Experimental Social Psychology”, 70, 153–163. https://doi.org/10.1016/j.jesp.2017.01.006
24. Göritz, A. S. (2015). Incentive effects in surveys. In “Handbook of survey methodology for the social sciences” (pp. 313–328). Springer.
25. Williamson, K. (2002). “Research methods for students, academics and professionals: Information management and systems” (2nd ed.). Centre for Information Studies, Charles Sturt University.
26. Molero, G. D., Poveda-Reyes, S., Malviya, A. K., García-Jiménez, E., Leva, M. C., & Santarremigia, F. E. (2021). Computational Solutions Based on Bayesian Networks to Hierarchize and to Predict Factors Influencing Gender Fairness in the Transport System: Four Use Cases. Sustainability, 13(20), 11372. https://doi.org/10.3390/su132011372
27. Meinshausen, N. and Bühlmann, P. (2010), Stability selection. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 72: 417-473. https://doi.org/10.1111/j.1467-9868.2010.00740.x
28. Cohen, J. (1994). The earth is round (p < .05). American Psychologist, 49(12), 997–1003. https://doi.org/10.1037/0003-066X.49.12.997