



Modelling Resilience, a proof of concept

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2025



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EU Science Hub

JRC140046

EUR 40256

PDF ISBN 978-92-68-25484-4 ISSN 1831-9424 DOI: 10.2760/4529903 KJ-01-25-169-EN-N

Luxembourg: Publications Office of the European Union, 2025

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How to cite this report: European Commission: Joint Research Centre, Montanari, E., Mara, T. and Rosati, R., *Modelling Resilience, a proof of concept*, Sangiorgi, M., Greidanus, H., Piccinini, P. and Galariotis, I. editor(s), Publications Office of the European Union, Luxembourg, 2025, <https://data.europa.eu/doi/10.2760/4529903>, JRC140046.

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Abstract

Enhancing European resilience and security is a European Commission priority for the near, mid, and long- term horizons. The purpose of this report is to introduce a basic statistical model of resilience prediction based on indicators. It also includes an advanced sensitivity analysis using the Shapley method.

Resilience denotes the capacity of a system to withstand shocks and its ability to recover from them. For this reason, resilience is often depicted on a timeline with three specific elements: anticipation, cushioning and adaptation - transformation, wrapping around one or multiple shocks or disturbances (European Commission 2020).

Several European and International institutions track many indicators in the forms of dashboard and trend charts to resilience of such entities. For instance, the Resilience Dashboard at the Joint Research Center (Benczur et al. 2023) has compiled a structured dashboard accounting for 124 quantitative indicators for the past several years while EUROSTAT has been tracking indicators on their resilience dashboard.

This report exploits the continuous progress made within JRC and proposes others drawn from reputable international institutions and institutes such as the World Bank, United Nations and Lloyd's Register Foundation for enhanced prediction purposes.

The application of logistic and linear regression models has shown numerous statistically significant indicators relevant for resilience prediction. It is also evident that more nuanced exploration of continuous measures of resilience, as evidenced by its application to the World Risk Poll data technical report, produces substantial improvements in the statistical significance of indicators. Not least, the deployment of the sensitivity analysis using the Shapley Model has revealed significant benefits for identifying the contribution of individual variables to the variance in resilience outcomes. This method has highlighted the interconnected nature of a restricted number of indicators, such as active citizenship, years of life lost due to PM2.5, antimicrobial resistance, and the degree of specialisation of the economy, providing a more sophisticated understanding of their impact on resilience.

1 Introduction: Why do we need resilience?

The European Security Union Strategy (European Commission 2024a) highlights growing importance of addressing emerging security challenges and enhancing societal resilience in an increasingly complex and interconnected world. As outlined in the seventh EU Security Union Report (EU, 2024), the European Union has implemented a comprehensive approach to security that spans multiple domains and recognizes the evolving nature of threats.

Emerging security challenges, such as cyber-attacks, hybrid threats, and foreign information manipulation, have become more prominent and require innovative responses. The EU has responded by developing new tools and frameworks, like the EU Hybrid Toolbox (Council of the EU 2024) and measures to counter foreign interference, particularly in the context of protecting democratic processes.

Societal resilience has emerged as a crucial aspect of the EU's security strategy, recognising that a robust and adaptable society is key to withstanding and recovering from various threats. This is evident in the adoption of directives like the Critical Entities Resilience (CER) (European Commission 2023a) and the revised Network and Information Security (NIS2) (European Commission 2023b), which aim to strengthen the resilience of critical sectors against both cyber and physical threats.

By prioritising these areas, the EU aims to create a more secure environment for its citizens while maintaining the openness and values that characterise European societies. This balanced approach to security and resilience is crucial in addressing the complex and evolving threat landscape of the 21st century.

The Joint Research Centre (JRC) has outlined new priorities for 2024 (European Commission and Joint Research Centre 2023), with a strong emphasis on societal resilience and preparedness. This focus aims to enhance European societies' capacity to anticipate, adapt to, and effectively respond to multi-faceted and interconnected challenges across sectors such as health, environment, food, water management, and security. The JRC plans to harness anticipatory capabilities to proactively identify and address emerging security risks and vulnerabilities, enabling timely responses to potential crises. Additionally, it will address the interconnected and cascading nature of many threats, while contributing to strengthening the resilience of EU democratic institutions and social cohesion.

The JRC's integrated approach to security and defence reflects a "whole-of-society" perspective, encompassing critical infrastructure protection, public spaces/people protection, border security, and hybrid threats. It also aims to strengthen research on technology permeability between civil, space, and defence sectors. Other priorities include analysing the social, economic, and territorial impacts of transitions to foster fairness, studying migration patterns and their links to security, and supporting candidate countries in adopting EU standards. These priorities collectively reinforce the JRC's commitment to building a more resilient, secure, and adaptable European Union.

This report used the definition of resilience drawn from the JRC "2020 Strategic Foresight Report": "Resilience is the ability not only to withstand and cope with challenges but also to undergo transitions, in a sustainable, fair, and democratic manner."

1.1 COVID lesson: the resilient response models

The COVID-19 pandemic and geopolitical instability demonstrate three key resilience aspects:

1) Anticipation through horizon scanning

- 2) Cushioning via emergency policies
- 3) Adaptation through systemic reforms

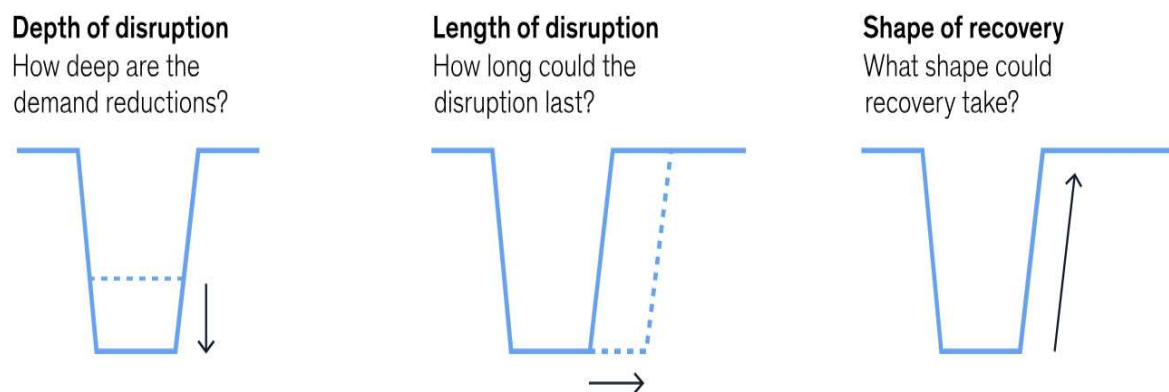
The need for developing resilience is becoming compelling in the face of the so-called emerging volatile, uncertain, complex and ambiguous scenarios (VUCAS) exposing weaknesses in the ability to withstand unpredictable existential threats to the socio-economic fabric of the EU.

1.2 Resilience views across corporations and individuals

Resilience is often invoked by think tanks and consultancies as one of the key factors to improve response to a variety of threats including security ones in the medium and longer term.

The three shock quantification parameters (depth, length, shape) correspond to Figure 1's resilience phases: 1) Depth maps to anticipation, 2) Length to cushioning, 3) Shape to adaptation.

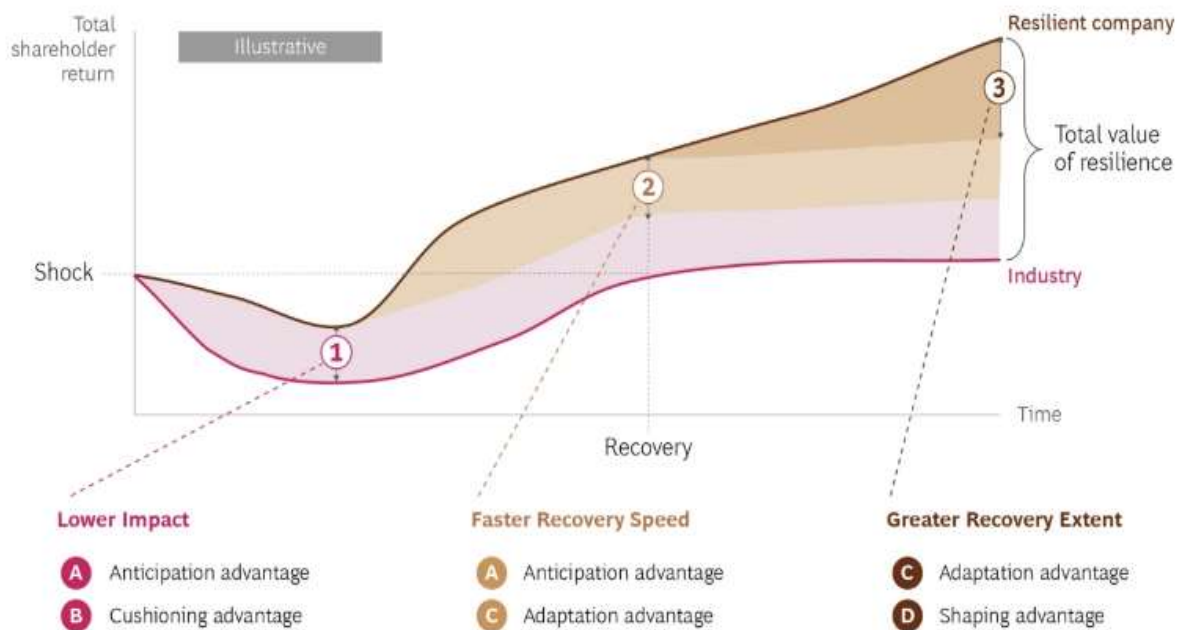
Figure 1. Key parameters for shock quantification.



Source: (McKinsey 2020)

Today's government and corporate leader's mantra is to improve resilience to cope with a multitude of unknown and unpredicted threats by anticipating and establishing cushioning that introduces future advantage at recovery. For example, Boston Consulting Group shows how resilient corporations have the merit to protect total shareholder returns as well as lives and livelihoods.

Figure 2. Crisis' Phases and Resilient Response.



Source: (Boston Consulting Group 2021)

Improving resilience is also the mantra of the insurance business, “World Risk Poll” (Lloyd’s Register Foundation 2024) by Lloyd’s Register Foundation goes into many details of the constituents of resilience at various levels and dimensions.

The World Risk Poll found that the U.S. ranks high for resilience on an individual basis. However, the country ranks lower for societal resilience, which measures confidence in U.S. institutions, like courts and elections, among other things. The poll found that no other country in the world has such resilient individuals living in a society perceived to be so fragile.

Individual resilience measured two things: a person’s level of agency, or their perceived ability to protect themselves or their family from a future disaster, and their education level. Societal rankings, on the other hand, measured reported discrimination and perceptions about the government’s care for individuals’ wellbeing and the standings of its institutions, like the military, courts and elections.

While looking at the outcomes from Lloyd’s study, this research will address only country level resilience based on the dashboard data available (Benczur et al. 2023) aiming to address multi-level resilience in future publications.

1.3 The importance of modelling to forecast resilience: a health-related example

This report provides modelling of predictive analysis as described in the framework below focusing on the most significant subset of dashboard indicators (Benczur et al. 2023) to help and inform any future policy that may be determinant to build resilience in the most efficient way.

Table 1. Analysis Objective linked to Modelling

Descriptive Analysis  "What happened?" Descriptive analysis is the foundation for other forms of analysis. The simplest form, it summarizes data in words or visuals, helping improve understanding and identify trends. Example applications - Financial statements comparing a company's recent profits to historical performance. - Engagement reports highlighting the most popular social media posts. - Survey reports displaying the results of customer polling.	Diagnostic Analysis  "Why did that happen?" Diagnostic analysis finds correlations among data points and establishes the causes of trends. Organizations often use it to test hypotheses about patterns they've identified with descriptive analysis. Example applications - Market-demand analysis examining why monthly sales spiked or fell. - Customer research explaining the factors driving purchase decisions. - Maintenance reports drawn from sensor data on why equipment is breaking down.
Predictive Analysis  "What will happen next?" Predictive analysis uses historical data to predict future trends. It allows organizations to anticipate potential risks and identify new opportunities, though the analysis doesn't dictate what actions an organization should take. Example applications - Forecasts of transit costs for a shipping company, based on prior fuel prices, weather conditions, and maintenance needs. - Advance warnings of malfunctioning equipment, based on sensor data and historical lifespans. - Early detection of illness, helping healthcare workers react more quickly to symptoms.	Prescriptive Analysis  "What should happen next?" Prescriptive analysis uses data to directly guide decision-making, with the aim of optimizing results. It suggests potential solutions for users to accept or reject. When paired with AI algorithms, it can even automatically take action. Example applications - Recommendation engines for new purchases based on a user's shopping history and other related data. - Algorithms adjusting prices for real-time demand to maximize profits. - Detection systems alerting banks of potential fraud based on purchase anomalies.

Source MIT Horizon

Prediction modelling is the basic technique to forecast future trends and identify potential risks or opportunities in our field using historical data. Predictive analysis, as outlined in the image, serves as our primary methodological approach because it enables us to anticipate potential shifts in our subject matter without prescribing specific actions.

A notable example of predictive analysis occurred in 1948 after Roosevelt's death from cardiac arrest, the Framingham Heart Study (framingham heart study 2024).

This long-term, ongoing cardiovascular cohort study started with 5,209 adult participants from Framingham, Massachusetts. The study has continued for multiple generations, with new cohorts added over time to maintain its relevance and expand its scope.

The key points about the study's timeline:

- 1948: The original cohort study began.
- 1971: The Offspring Study (second generation participants) was initiated.
- 2002: The Third Generation Study began, enrolling grandchildren of the original participants.

The risk prediction model based on the Framingham study data has been updated several times since its initial development. The first major risk prediction model was published in 1998, using data collected over the decades since the study's inception.

While the study began in 1948, the risk prediction models and tools derived from its data have been developed and refined over time, incorporating new findings and adapting to changing health landscapes.

Today and using 6 easily measurable indicators i.e. age, gender, cholesterol, blood pressure, smoking status, diabetes status, it is possible to predict whether the patient would develop cardiovascular disease over the next 10 years. Notably, blood pressure retained as a leading indicator of cardiovascular risk that was previously considered a sign of strength.

This example shows that it is possible to make meaningful predictions when the appropriate set of indicators is accurately identified and effectively incorporated into a statistical model.

2 Literature & Data Review

This report focused on the wealth of data derived from JRC Resilience Dashboard (European Commission 2020).

This report also compares specific databases and indicators from other European or International institutions to identify any potential future opportunity and gap in the well-developed data universe.

2.1 Resilience Dashboard Indicators (Benczur et al. 2023) - EU27

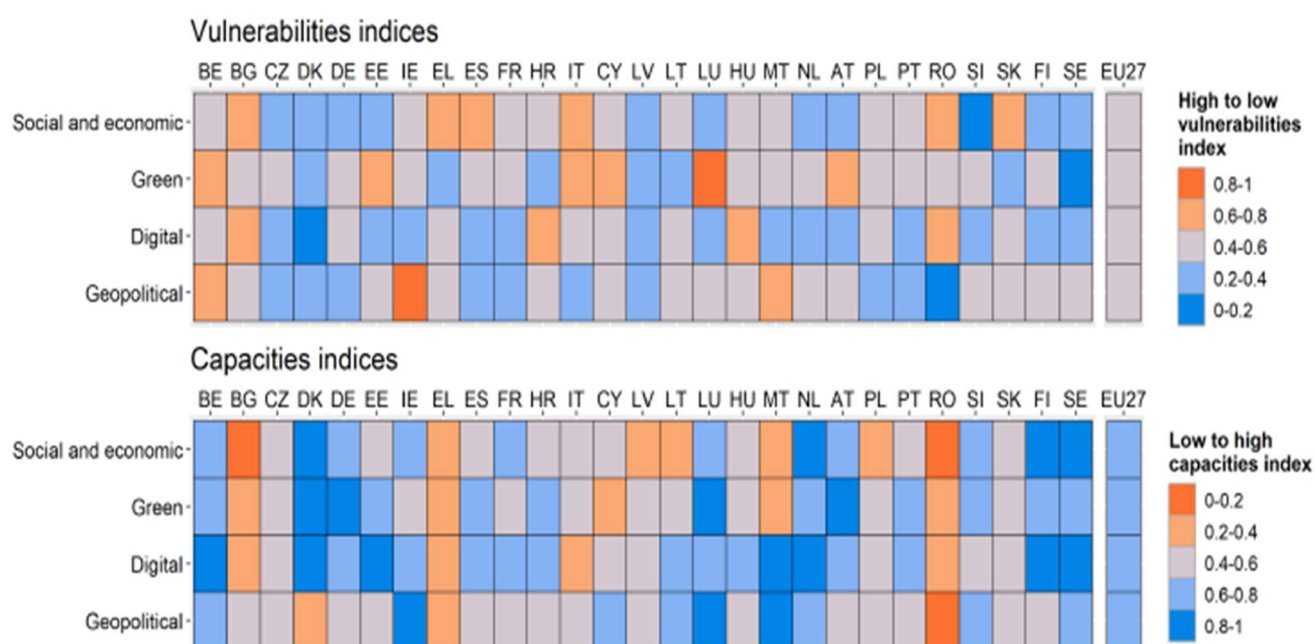
This data originated from the European Commission's Resilience Dashboard with data collection inception in 2021.

In its simplest form the Resilience Dashboard (RDB) comprises eight synthetic indicators derived from the full set of 124 quantitative indicators selected by their capability to describe an element of resilience or being a proxy of the same.

The synthetic resilience indicators are split into four vulnerabilities and four capacities and aggregated across the following main thematic dimensions i.e. Social and economic, Green, Digital and Geopolitical.

Below is the rendering of the synthetic vulnerabilities and capacities per thematic dimension and split across the 27 EU member states.

Figure 3. Synthetic Index Dashboard



Source (Benczur et al. 2023)

The RDB colour coding observed in **Figure 3** is linked to the normalised quintile indicators values in Table 2 as following.

Table 2. Resilience Quintiles.

	Vulnerability (V)	Capacity
(C)Blue	1	0
Light Blue	0.75	0.25
Grey	0.5	0.5
Orange	0.25	0.75
Red	0	1

Source (Benczur et al. 2023) and own elaboration

A member state demonstrates resilience when $\geq 60\%$ of indicators show blue (quintile 4-5), indicating superior performance across capacities and vulnerabilities.

One of the initial issues in assessing the outcome through such inference is the endogeneity of the dashboard derived resilience outcome. Endogeneity refers to a situation where the indicators used in the analysis affect both the outcome variable and other indicators used to derive the outcome variable as it is shown in the multicollinearity analysis further below and as it is the case for the dashboard derived resilience.

2.2 Special mention for the “World Risk Poll 2024” (Global)

When researching for an independent source of resilience measure, this report found in the world risk poll 2024 (Lloyd’s Register Foundation 2024), a suitable input: this global survey provides an external perspective on resilience that is particularly useful because it offers data from beyond the European Union, allowing researchers to validate and expand their correlations across a wider geographical context. Such resilience measure will be indicated as exogenous further in this report as it extends the opportunity of correlation verification.

Lloyd’s conducts its poll on global resilience every two years through a third party, Gallup. The biennial reporting cycle (2022, 2024) publishes analysed data collected during preceding years (2021, 2023 respectively). Having two reports lets us track trends over time, in addition to drawing conclusions about global resilience for 2022 and 2024 separately. Future reports will enable longitudinal analysis of global resilience evolution between reporting periods.

Figure 4. World Risk Poll



Source: (Lloyd's Register Foundation 2024)

The World Risk Poll reports use a bottom-up data collection approach that makes it ideal to derive an exogenous measure for resilience. The process summarised is:

- Large-scale global survey: The 2022 report was based on 125,911 interviews in 121 countries and territories, while the 2024 report expanded to nearly 147,000 interviews in 142 countries and territories.
- Multilayered resilience measurement: Both reports assess resilience at four levels - individual, household, community, and societal. This type of multilevel analysis has great potential to enhance the granularity of the resilience modelling and analysis.
- Resilience Index: Both reports compile the various indicators into a global Resilience Index, scoring countries between 0 and 100.

A few analysis points are here extracted from the World Risk Poll 2024 shows significant findings when resilience is measuring a multiple levels or granularity e.g. country vs. individual levels:

- Individual resilience fell globally, with significant drops in over a third (42) of countries measured in both years.
- The 2024 report measures 120 of the same countries surveyed in 2021, allowing for trend analysis.
- The 2024 report shows a slight increase in global resilience, with the average Resilience Index score rising from 55 in 2021 to 57 in 2023. While the 2022 report provided baseline data, the 2024 report reveals that three-quarters of countries (90 of 120) saw no significant change in Resilience Index scores.
- Disaster experience: The 2024 report shows an increase in people experiencing disasters related to natural hazards, rising from 27% in 2021 to 30% in 2023.
- While the 2022 report focused more on regional differences, the 2024 report highlights employment status, household income, and age as strongly associated with resilience.

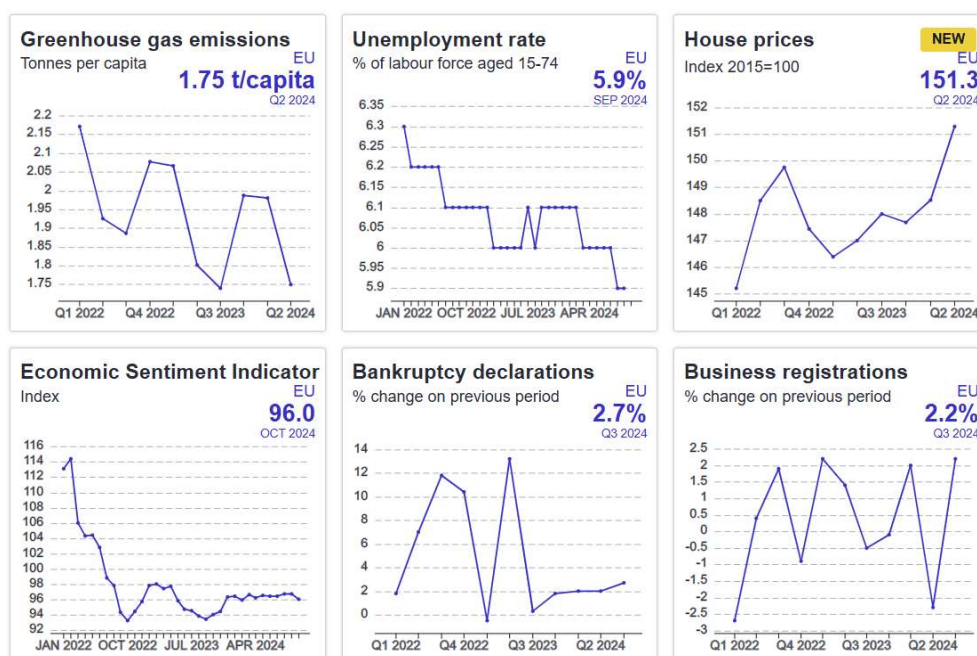
In this report, the resilience index outcome for 2024 is used to correlate with the Resilience Dashboard Indicators.

2.3 EUROSTAT COVID-19 Dashboard & Indicators (EU27, (EUROSTAT 2024))

The EUROSTAT COVID-19 dashboard is also an excellent framework for measuring societal resilience through multiple interconnected indicators. Beyond the classic econometrics indicators well represented in the Resilience Dashboard (Benczur et al. 2023), the EUROSTAT dashboard offers unique insights through its diverse economic and social metrics. The inclusion of dynamic indicators like business registrations, bankruptcy declarations, and economic sentiment provides real-time signals of economic resilience, while mobility indicators such as flight numbers and tourism nights capture the recovery patterns in cross-border activities.

This multifaceted approach enables a more nuanced understanding of systemic resilience across different societal dimensions and the list keeps growing.

Figure 5. European Statistical Monitor



Source (EUROSTAT 2024)

Several additional indicators to be modelling in future research that could enhance the resilience assessment framework in future research iterations. Here are the indicators from this report comparison that are not explicitly represented in the current Resilience Dashboard:

- GDP
- Industrial production
- Inflation
- Economic Sentiment
- Business Registrations
- Bankruptcy declarations

- Number of Flights
- Production in services
- Retail Trade
- Production in construction
- Government Debt
- Labour Market Slack
- Tourism Nights
- From Unemployment to Employment, From Unemployment to Inactivity, From Employment to Inactivity
- Excess Mortality

2.4 OECD, IEA and World Bank Indicators (Global)

The Organisation for Economic Co-operation and Development (OECD), the International Energy Agency (IEA), and the World Bank are paramount international organisations that collect, analyse, and maintain comprehensive datasets vital for understanding global socio-economic and environmental dynamics.

The OECD, comprising 38 member countries, centres on economic cooperation and development, providing standardised metrics across areas such as education, inequality, and infrastructure (OECD 2024). The IEA, an autonomous intergovernmental organisation within the OECD framework, specialises in energy-related data and analysis, particularly in tracking renewable energy adoption and energy security (International Energy Agency 2024). The World Bank, through its extensive data collection efforts including the Worldwide Governance Indicators, offers crucial insights into governmental effectiveness, regulatory quality, and various development indicators across nations. These organisations' indicators serve as fundamental tools for policymakers, researchers, and institutions in assessing and building resilience across economic, social, and environmental dimensions (World Bank 2024).

Several crucial indicators that could enhance the resilience assessment framework warrant consideration for future research. A comprehensive analysis of resilience would benefit from the inclusion of the following indicators.

Table 3. International Organisations' Relevant Indicators.

Field	Indicator
Digital Resilience Metrics	- Cybersecurity preparedness indices - Digital infrastructure robustness measurements - Digital literacy and adoption rates
Climate Adaptation Indicators	- Specific adaptation measures effectiveness - Climate-related disaster recovery capabilities

	- Climate-resilient infrastructure assessments
Social Cohesion Metrics	- Social trust indices - Community engagement levels - Cultural diversity and integration measures
Supply Chain Resilience	- Trade partner diversity indices - Critical resource availability tracking - Supply chain redundancy measures
Mental Health and Wellbeing	- Population-level mental health metrics - Access to mental health services - Work-life balance indicators
Urban Resilience	- City-level adaptive capacity measures - Urban infrastructure flexibility - Smart city implementation metrics
Financial System Stability	- Market stress indicators - Financial inclusion metrics - Alternative finance accessibility
Ecosystem Resilience	- Biodiversity indices - Natural capital assessments - Ecosystem services valuations
Innovation Ecosystem	- Patent diversity metrics - Startup survival rates - Innovation adoption speed
Intersectional Vulnerabilities	- Multidimensional poverty indices - Social vulnerability assessments - Cross-system risk measures

Source: (OECD 2024; World Bank 2024), and Own elaboration

These additional indicators would provide a more nuanced understanding of systemic resilience and better capture the interconnected nature of modern societal challenges in future research.

2.5 The United Nations Sustainable Development Goals (SDGs, Global)

Not least, the United Nations SDG indicators were reviewed and compared to the Resilience Dashboard and found well-represented for what concerns resilience.

2.6 The INFORM Risk Index (Global) ((JRC) 2024)

The INFORM Risk Index is a tool that uses composite indicators to simplify complex crisis risk data and aid policymaking for crisis anticipation and preparedness. It highlights countries at high risk of humanitarian emergencies and disasters that may exceed their national response capacities, potentially needing international assistance. The index has three main components: hazard and

exposure, vulnerability, and lack of coping capacity. Among these, vulnerability and lack of coping capacity are particularly important for identifying indicators of resilience.

Vulnerability: This measures what makes a population more vulnerable to hazards. Vulnerability is often linked to unmet basic needs and limited self-protection, focusing on:

- The ability of individuals or households to afford safe living conditions and maintain well-being.
- Factors like housing safety, access to healthcare, nutrition, and preventive medicine to reduce health risks during disasters.
- Beyond income, addressing vulnerabilities requires improved development, education, and cultural awareness to enhance resilience.

Lack of Coping Capacity: This evaluates how well a country can handle disasters through:

- Government actions to increase societal resilience.
- Success in implementing disaster response measures.
- Existing infrastructure and organized efforts to reduce disaster risks.

3 Methodology

3.1 Resilience: Capturing the target variable

The first step in policy-making analysis is to clearly and precisely define the objective, i.e. what we aim to understand, analyse, and address with policy recommendations. In statistical analysis, this requires defining the target variable(s) with clarity and precision. This step is crucial for understanding the study's purpose and determining the best approach to model it effectively.

The term "resilience" is inherently complex, making it challenging for researchers, analysts, and policymakers to define a clear target variable for accurate analysis and predictions. The 2020 Strategic Foresight Report offers not only a useful definition but also divides resilience into four key dimensions: a) social and economic, b) geopolitical, c) green, and d) digital. This approach is also followed in the 2021 Resilience Dashboards Report in which the resilience dashboards developed by the European Commission are presented in detail. By aligning with these dimensions and identifying relevant datasets, we can establish four distinct target variables corresponding to these categories. Therefore, one approach would be to define four target variables corresponding to the dimensions of resilience:

1. social and economic resilience;
2. geopolitical resilience;
3. green resilience and
4. digital resilience.

Afterward, we can develop a single, comprehensive target variable for resilience that combines all the previously mentioned target variables into one. This structured approach allows for a more detailed and comprehensive analysis of the multifaceted nature of resilience.

3.2 Resilience: In search of the predictor variables

The predictor variables could be identified through a deep literature review to determine the factors influencing resilience, the contexts in which they operate, and the levels of analysis they apply to. The 2021 Resilience Dashboards Report provide a strong foundation for identifying factors that may influence resilience. It presents 124 quantitative indicators representing vulnerabilities or capacities that could impact future societal, economic, digital, and green transformations or help manage potential new shocks. These indicators could be considered potential factors influencing resilience and warrant thorough exploration to determine their relevance and effectiveness as drivers of resilience.

This step is crucial in the modelling phase because identifying the predictor variables will guide the search for relevant and reliable datasets. It will also help in selecting the most suitable models for making inferences and predictions about resilience.

3.3 Modelling challenges

Level of analysis: An essential aspect of modelling resilience is comprehensively defining the level of analysis. Resilience operates at multiple levels, each with distinct characteristics and implications. For this report, we have identified three levels of analysis:

1. **Individual:** Focuses on personal adaptability and mental health support.
2. **Community:** Centers on local networks and support systems.
3. **Institutional:** Examines the strength of governance, legal frameworks, and crisis management mechanisms.

Clarifying the level of analysis is crucial as it guides the selection of an appropriate modelling framework to make inferences and predictions about resilience. This multi-layered approach ensures a comprehensive understanding of the concept across different contexts.

Data management: A key step in analysing resilience is understanding and preprocessing the available data. Once suitable data for the target and predictor variables is identified, the next steps involve data collection, exploratory data analysis and data cleaning and preparation.

1. **Data Collection:**
 - (a) Priority is given to open-source databases for unrestricted access.
 - (b) For proprietary survey data, collaborations with private companies may be necessary to obtain access.
 - (c) It is essential to store the collected data in a robust IT infrastructure to ensure easy and immediate access for researchers and policy analysts.
2. **Exploratory Data Analysis (EDA):** After collection, exploring the data helps uncover patterns, trends, and anomalies. This involves:
 - (a) Creating visualizations such as histograms, scatterplots, and other graphical representations.
 - (b) Summarizing data using descriptive statistics.
 - (c) Detecting inconsistencies, errors, and outliers, which informs the data-cleaning process.
3. **Data Cleaning and Preparation:**
 - (a) Correct errors and handle missing or incoherent data.
 - (b) Identify and address outliers.
 - (c) Apply transformations to predictor variables, such as normalization or rescaling, to ensure consistency and suitability for modelling.

These steps are crucial for ensuring the data's reliability and readiness for the subsequent modelling phases.

Missing data: Resilience modelling will rely on open-source data for known resilience drivers to estimate future societal risks and threats. The precision and performance of statistical models heavily depends on the quality and coverage of the data used. However, datasets often face significant challenges with missing data, which can undermine model reliability:

1. **Bias in Estimates:** Missing data is rarely random, which can lead to biased model estimates if not properly addressed (Honaker and King 2010).

2. **Incomplete Data for Predictions:** Predictions require complete data for all predictor variables in a given year, making missing data a critical issue.

A common solution to missing data is **imputation** (Rubin 1987), which involves estimating missing values based on the distribution of observed data. While imputation is effective with small amounts of missing data, it becomes less reliable as data gaps increase. Whether using single or multiple imputation techniques, careful consideration of the dataset's characteristics is necessary to apply a robust and reliable imputation method for addressing missing data challenges.

3.4 Statistical modelling reflections

The selection of a suitable statistical model depends primarily on the objectives set by policymakers—whether for inference, prediction, or both. A statistical model should be based on clear assumptions about the relationships between indicators and the model outcome.

In this report, we propose a prototype statistical model as a foundational approach to:

1. Demonstrate how to model the effect of resilience drivers on resilience.
2. Provide policymakers with predictions based on these relationships between resilience and the drivers of resilience.

A prototype model serves as the starting point for identifying the relationships between target and predictor variables and determining which variables are relevant to retain in the analysis. Once the prototype model is finalized, it can be expanded to incorporate greater complexity by employing advanced techniques, such as:

- **Time Series Models:** To analyse trends over time.
- **Longitudinal Models:** To study changes in resilience across different time points.
- **Multilevel Models:** To account for the hierarchical structure of data (e.g., individual, community, institutional levels).
- **Machine Learning Models:** For handling large datasets and uncovering non-linear patterns.
- **Stochastic Models:** Agent-based or Brownian motion dynamic modelling techniques may enable the creation of system that can adapt and learn much like the community or societies it models.

This progression ensures both a robust understanding of resilience and actionable insights for policymakers.

3.5 Analysis approaches

This report utilises the logistic and linear regression t-stat approach and the Global Sensitivity Analysis (GSA) in steps of growing model complexity for analysing and determining the correlation and the most significant indicator(s) for any potential policy recommendation about resilience.

The following considerations apply between t-stat and GSA applications:

1. There are complementary strengths between logistic/linear regression t-stat, providing immediate statistical significance for indicators, and GSA, capturing complex interactions and non-linear effects.
2. The combination of the two methods offers a more comprehensive analysis with statistical validation using t-stats and broader system-wide understanding using GSA.
3. Each method has better field complexity applications, and, in this way, this report can address both simple and complex relationships between indicators and their interacting nature.

The following comparative table provides a comprehensive review of the methods to be used in this report:

Table 4. Comparative analysis of regression and sensitivity methods.

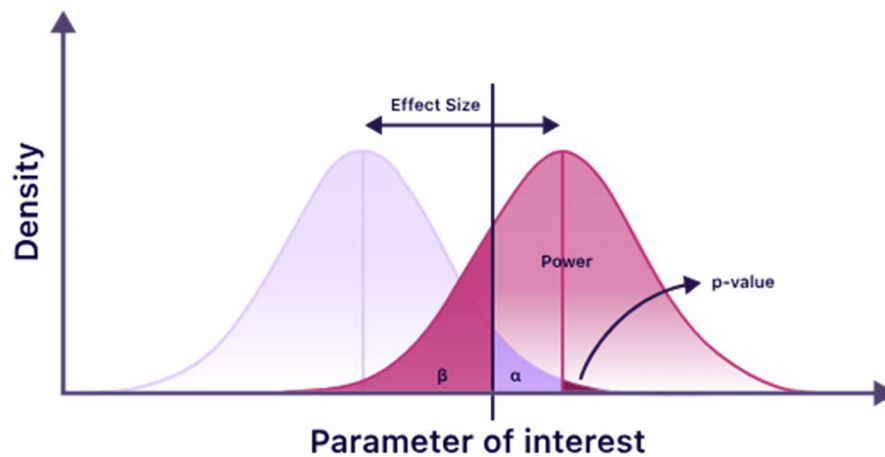
Method	Pros	Cons	Best Used For
t-statistics in logistic & linear regression	- Simple to interpret - Tests specific hypotheses - Well-established statistical significance - Works well for comparing means	- Only for single variables - Assumes normal distribution - Limited to linear relationships - Can't handle interactions	- Comparing means between groups - Testing specific hypotheses - Simple before/after comparisons
GSA	- Captures non-linear relationships - Analyses multiple variables simultaneously - Identifies interaction effects - Quantifies importance of variables	- Computationally intensive- Requires more data - More complex to interpret- May need multiple methods	- Understanding variable interactions - Ranking variable importance - Analysing complex systems- Model validation

Source: (Duflo, Glennerster, and Kremer 2006), (Iooss and Priour 2019), and own elaboration

In addition to the t-stat approach and the GSA, Principal Component Analysis (PCA) may be used to reduce dimensionality and to identify patterns in data. This method handles multicollinearity and is computationally efficient while it assumes linearity and is sensitive to outliers. It was already proposed and reviewed in the literature hence not pursued further.

Furthering the explanation on the logistic and linear regression t-stat approaches, this report measures the statistical significance of the hypothesis (H1) that any indicator is predictive of resilience where null hypothesis (H0) being no significance. The measure takes the name of p-value and it is compared to a maximum value of 5% to reduce the chance that the correlation occurs by chance.

Figure 6. Hypothesis test with p-value



Source: (TestView 2024)

3.6 Synthetic Indicators logistic & linear regression with endogenous Resilience

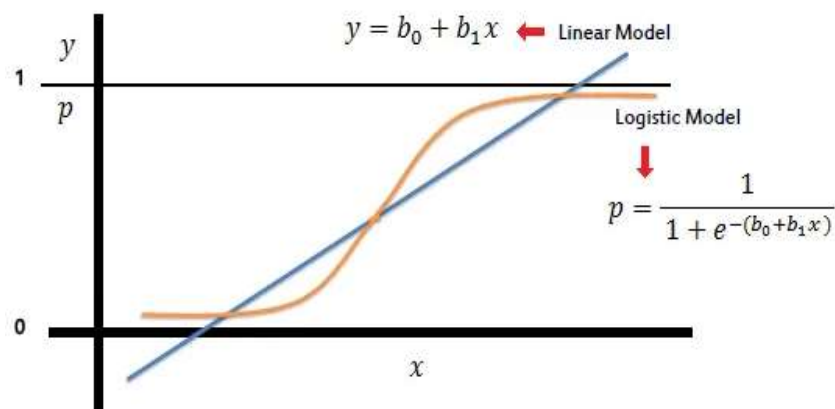
This report employs logistic regression as the first step and as the extreme simplified analysis to determine the relationship between binary resilience outcomes and various synthetic indicators. This statistical technique allowed us to estimate the probability of a positive (or negative) resilience outcome based on one or more predictor variables.

Logistic regression is often used to model “expert assessment” with binary outcomes 0 or 1 while it has limited modulation of the outcomes and assumes independence among independent variables requiring multicollinearity verification (Williamson 2024).

When using the data of the Resilience Dashboard, the logistic regression models the binary “resilience” using the eight indicators, be it vulnerability or capacity.

The logistic regression equation is represented in the picture below in comparison to the classic linear regression.

Figure 7. Regressions



Source: (Sayad 2024)

Predictivity of each indicator is assessed through its statistical significance at 5%.

This first logistic regression is performed using the following R code:

```
# logistic regression model  
model <- glm(Resilience ~ Indicator, data = data, family =  
"binomial")  
# Summary of the model  
summary(model)
```

R Simplified Logistic Regression. Source: Own elaboration

Similarly, this report attempted to run multivariate regression using all synthetic indicators. The logistic regression of such procedure is:

$$P(Y=1|X) = 1 / (1 + e^{-(\beta_0 + X_i X_j \dots + \epsilon)})$$

Where $P(Y=1|X)$ is the probability of the outcome given the input indicators

X_i and X_j are the paired predictor variables

β_i are the regression coefficients.

The results of such regression will not be presented in this report because inconclusive.

3.7 Full Set of Indicators Linear regression with exogenous Resilience

To complement our logistic regression analysis, this report has applied linear regression to examine continuous resilience measures from the World Risk Polls (Lloyd's Register Foundation 2024). This method establishes correlations between quantitative resilience outcome and the full list of Resilience Dashboard indicators.

Linear regression provides further insights into the direction and magnitude of relationships between variables, allowing to create better predictive models and identify the most influential factors contributing to resilience.

Linear Regression is therefore a more nuanced method to understand of relationships between various resilience indicators and system outcomes (Brandon 2016) , quantified by:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 USSR + \beta_3 PIIGS + \epsilon$$

Where Y is the outcome variable resilience

X_i are the predictor variables

β_i are the coefficients

USSR¹ and PIIGS² are dummy variables, i.e., they are categorical variable with value either 0 or 1.

ϵ is the error term.

The linear regression assumes independence among independent indicators, so it requires multicollinearity verification. The linear regression is performed using the following R code:

```
# Linear regression model
model <- glm(Resilience ~ Indicator + USSR + PIIGS, data = data,
family = "gaussian")
# Summary of the model
summary(model)
```

R Linear Regression. Source: Own elaboration

This report also applied a multivariate linear Regression for pairs of indicators, the general formula for it is:

$$Y = \beta_0 + \beta_1 X_i X_j \dots + \epsilon$$

Where Y is the outcome variable

X_i and X_j are the paired predictor variables

β_i are the coefficients

ϵ is the error term.

The results of such regression will not be presented in this report because inconclusive.

3.8 Global Sensitivity Analysis and Shapley application

When analysing complex systems, it is important to understand how different input factors or variables contribute to the overall output or outcome. Global sensitivity analysis is a powerful technique that helps us do this. It goes beyond just looking at the individual impact of each variable - it must also consider how the variables interact with each other to influence the result i.e. resilience.

As described in the result further down, this report did not find conclusive results with multivariate regressions thus, we resorted to an advanced approach called the Shapley method and part of global sensitivity analysis. The Shapley method is named after the mathematician Lloyd Shapley, who developed this concept in the field of game theory. The key idea behind Shapley is to calculate a "fair"

¹ USSR takes value 1 if the country is Bulgaria, Czechia, Poland, Romania or Slovakia else 0

² PIIGS takes value 1 if the country is Portugal, Italy, Ireland, Greece or Spain else 0

contribution for each input variable, considering both its individual impact and how it interacts with the other variables.

When trying to predict each country's overall resilience there might be many different factors that contribute to resilience, like the strength of the economy, the quality of infrastructure, the level of social cohesion, and so on. These factors do not act in isolation - they are all interconnected and influence each other in complex ways and in a non-linear way.

The Shapley method allows us to break down the overall resilience score and assign a numerical "importance" value to each contributing factor. It does this by systematically considering all the possible combinations of factors and measuring how the resilience score changes when each factor is added or removed. For example, this report will show four significant factors effecting resilience: A, B, C, and D. The Shapley method allow us to assess at the resilience outcome when only A is present, then when A and B are present, then A, B, and C, and so on, up to all four factors. In the context of our resilience example, the Shapley analysis might reveal that while factor A has the largest individual impact, the combination of factors B, C, and D together actually contributes more to the overall resilience score. This kind of nuanced insight can be extremely valuable for policymakers and researchers trying to understand and improve the resilience of socioeconomic systems.

The final Shapley value for each factor represents its average marginal contribution. This gives us a clear understanding of which factors are the most important drivers of resilience, and how much each one contributes, both individually and through its interactions with the other factors.

The key advantages of the Shapley method are:

1. It accounts for interactions between variables. Traditional sensitivity analysis techniques may miss important synergies or antagonistic effects between factors. Shapley captures these complex relationships.
2. It provides a fair and unbiased distribution of contributions. By considering all possible factor combinations, Shapley ensures that each variable's importance is assessed equitably, without favouring any one factor over another.
3. It quantifies the relative importance of each factor. The Shapley values give us a numerical measure of how much each input variable influences the final output. This allows us to prioritise the most impactful factors.
4. It works for both linear and non-linear models. The Shapley method can be applied to a wide range of modelling approaches, from simple linear regressions to more complex machine learning algorithms.

In summary, global sensitivity analysis uses the Shapley method is a powerful tool for understanding how different factors interact to influence system-level outcomes. By quantifying the fair contributions of each variable, it gives us a much richer and more accurate picture of what is driving the behaviour of the system we are studying. For college students and researchers alike, the Shapley method is an important addition to the toolbox of advanced analytical techniques.

In essence, Shapley calculates "fairly" each feature's contribution to the model's prediction by considering all possible combinations of features and assessing how the model's performance changes when each feature is added or removed. The Shapley value for indicator is calculated as:

$$\phi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{(|S|!(n-|S|-1)!}{n!} [v(S \cup \{i\}) - v(S)]$$

Where N is the set of all indicators

S is the set or a subset of indicators

v is the characteristic function

n is the total number of indicators.

(Iooss and Prieur 2019)

The Shapley method addresses limitations of traditional sensitivity analysis techniques by accounting for complex interactions between variables. This advancement not only quantifies individual contributions but also captures the intricate interdependencies among variables, leading to more nuanced insights into system behaviour.

The Shapley value allows for a fair distribution of contributions among indicators, enabling researchers to identify key factors influencing resilience in socio-economic systems. By applying this method, we analyse various resilience indicators. These indicators serve as critical inputs for our model, which aims to predict system responses under different scenarios of external shocks.

4 Results and Findings

4.1 Synthetic Indicators Logistic Regression with endogenous Resilience

Prior to running any regression, this report verifies the collinearity of the synthetic indicators as indicated in this multicollinearity matrix heatmap. A correlation matrix reveals multicollinearity by displaying pairwise correlation coefficients between variables. Correlation values ($|R| > 0.25-0.3$) between indicators suggest multicollinearity thus potential redundancy in the statistical model's independent variables.

The dark colours, either green or red, are indicative of relatively higher collinearity:

Table 5. Synthetic Indicators Multicollinearity in Symmetric Correlation Matrix.

R-values	Green_V	Digital_V	Geopolitical_V	Social.and.economic_C	Green_C	Digital_C	Geopolitical_C
Social.and.economic_V	5%	10%	-14%	13%	21%	50%	46%
Green_V		-27%	10%	2%	37%	21%	-18%
Digital_V			-33%	5%	20%	13%	10%
Geopolitical_V				-5%	-34%	-20%	10%
Social.and.economic_C					40%	54%	11%
Green_C						32%	-26%
Digital_C							31%

Source: Own elaboration

Using t-statistic thus measuring the number of standard deviations an estimated normalised outcome is from zero (in this case resilience), this report essentially quantifies how far the observed relationship deviates from the null hypothesis i.e. no effect of the indicator on resilience. The p-value represents the probability of obtaining test results at least as extreme as the observed results, assuming the null hypothesis is true, with values below 0.05 or 5% typically indicating statistically significant evidence to reject the null hypothesis. By regressing individual indicators, one can find the following summary significance table:

Table 6. Synthetic indicators logistic regression's results.

By Single Indicator	Stat Significance
---------------------	-------------------

Social.and.economic_C	5.00%
Digital_C	5.00%
Green_C	10.00%
Social.and.economic_V ⁴	None
Green_V	None
Digital_V	None
Geopolitical_V	None
Geopolitical_C	None

Source: Own elaboration

4.2 Full Set of Indicators Linear Regression with exogenous Resilience

Prior to running any regression, this report has verified the collinearity of the 124 indicators and for practical purposes, the multicollinearity matrix is included in the report data section. The data frame structure including the added dummies is exemplified here following in picture.

³ C is shorthand for capacity

⁴ V is shorthand for vulnerability

Table 7. Data frame structure for linear regression.

Input: 124 Indicators (Benczur et alia, 2023)				Exo-resilience (Lloyd's, 2023)			
...							
Government expenditures on education, health, and social protection	Self-reported unmet need for medical care	Macroeconomic skills mismatch rate	Years of life lost due to PM2.5	PIIGS	USSR	Resilience_Lloyds	
0.721518987341772	0.896341463414634	0.267705395659447	0.897208985704561	0	0	60	
0.181434599156118	0.939024390243902	0.349762270813402	0.475153165418652	0	1	46	
0.481012658227848	0.981707317073171	0.57176184815093	0.785228046289993	0	1	63	
0.805907172995781	0.920731707317073	0.614615454657205	0.938393464942137	0	0	66	
0.624472573839662	0.99390243902439	0.643969480591069	0.882913546630361	0	0	67	
0.392405063291139	0.50609756097561	0.59178312716995	0.986385296119809	0	1	65	
0.181434599156118	0.878048780487805	0.43545337454126	0.963240299523485	1	0	67	
0.350210970464135	0.609756097560976	0.441577942212131	0.730428863172226	1	0	53	
0.531645569620253	0.932926829268293	0.402611579918313	0.879850238257318	1	0	51	
0.708860759493671	0.829268292682927	0.429263674991577	0.912185159972771	0	0	55	
0.421940928270042	0.896341463414634	0.417816920975535	0.665078284547311	0	1	53	
0.489451476793249	0.890243902439024	0.347544704024894	0.740299523485364	1	0	55	
0.375527426160338	0.99390243902439	0.59529768677185	0.835602450646698	0	0	54	
0.375527426160338	0.75609756097561	0.56581213786404	0.841048332198775	0	1	56	
0.39662447257384	0.853658536585366	0.451294793526951	0.809734513274336	0	1	57	
0.413502109704641	0.939024390243902	0.457720574426697	0.959836623553438	0	0	68	
0.333333333333333	0.932926829268293	0.482481456845549	0.644656228727025	0	1	52	
0.29957805907173	0.99390243902439	0.746411157490316	0.889040163376447	0	0	56	
0.616033755274262	0.98780487804878	0.875804666369115	0.906739278420694	0	0	65	
0.59493670886076	0.981707317073171	0.706144936580438	0.886997957794418	0	0	68	
0.375527426160338	0.835365853658537	0.521824847585976	0.631381892443839	0	1	52	
0.39662447257384	0.859756097560976	0.704540955115863	0.914227365554799	1	0	57	
0.135021097046414	0.731707317073171	0.43493847425621	0.591899251191287	0	0	51	
0.510548523206751	0.707317073170732	0.520205146312904	0.811095983662355	0	1	62	
0.417721518987342	0.823170731707317	0.337069283428188	0.716473791695031	0	1	54	
0.628691983122363	0.731707317073171	0.566993543303168	1	0	0	66	
0.565400843881857	0.920731707317073	0.452924132607289	0.993192648059905	0	0	71	
0.565400843881857	0.878048780487805	0.48416585407411	0.81858407079646	0	0	59	
Dummies				↑	↑		

Source: (Benczur et al. 2023), Own elaboration

Similarly to what it is described in the previous chapter, this report used t-statistic thus measuring the number of standard deviations an estimated normalised outcome is from zero (in this case resilience), this report essentially quantifies how far the observed relationship deviates from the null hypothesis i.e. no effect of the indicator on resilience. The p-value represents the probability of obtaining test results at least as extreme as the observed results, assuming the null hypothesis is true, with values below 0.05 or 5% typically indicating statistically significant evidence to reject the null hypothesis.

By regressing individual indicators, one can find the following summary significance table and the relative correlation measure R^2 :

Table 8. Complete indicators linear regression's results.

By Single Indicator	Stat Significance	R^2
Life Years Lost PM2.5	1.00%	75%
Urban Waste Water Treatment	1.00%	62%
Armed.forces.personnel	5.00%	44%
Average.scores.in.the.PISA.test	5.00%	55%
Adult Participation in Edu	5.00%	63%
Antimicrobial Resistance	5.00%	60%
Active Citizenship	5.00%	64%

Source: Own elaboration

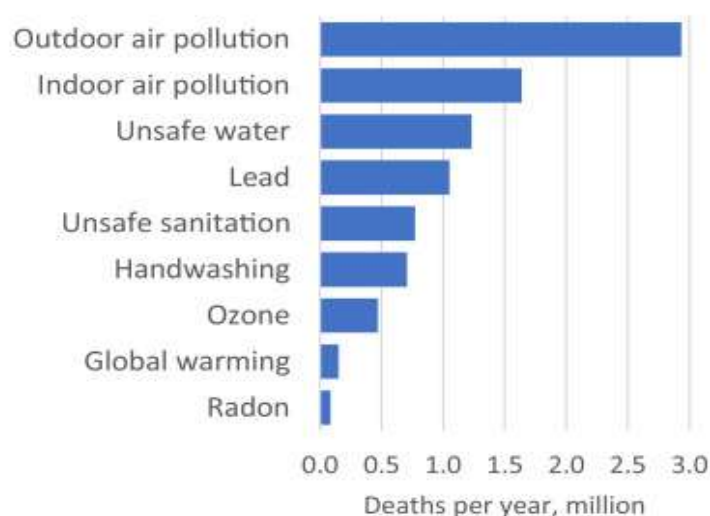
Other statistically significant indicators are cited here for completeness:

— E-waste recycling rate

- E-passenger fleet
- Environmental patents per capita
- Extra EU import partner concentration
- Extra EU export partner concentration
- Fossil Fuel Subsidies
- Gender Employment Gap
- Gross Value added in environmental goods and services
- Import dependence in energy materials
- Net lending-borrowing
- Outward FDI partner concentration
- Organic Farming
- Soil Carbon content
- Water Exploitation

Some of the results will not be surprising, the concept of indoor pollution can be linked to PM2.5 as well as other harmful pollutants created by burning gas include carbon monoxide, benzene, formaldehyde and particulate matter. A new study led by Spain's University Jaume I reveals that gas cookers are a significant source of indoor air pollution, expected to contribute to nearly 40,000 early deaths and hundreds of thousands of asthma cases across Europe each year (EPHA 2024). The research highlights that nitrogen dioxide (NO₂) levels in homes using gas cookers often exceed WHO air quality guidelines, particularly in countries with high gas usage like the UK, France, and Italy. The European Public Health Alliance (EPHA) is urging EU policymakers to introduce stricter regulations and promote cleaner cooking alternatives to address this widespread but overlooked public health issue.

Figure 8. Deaths from environmental issues in 2017.

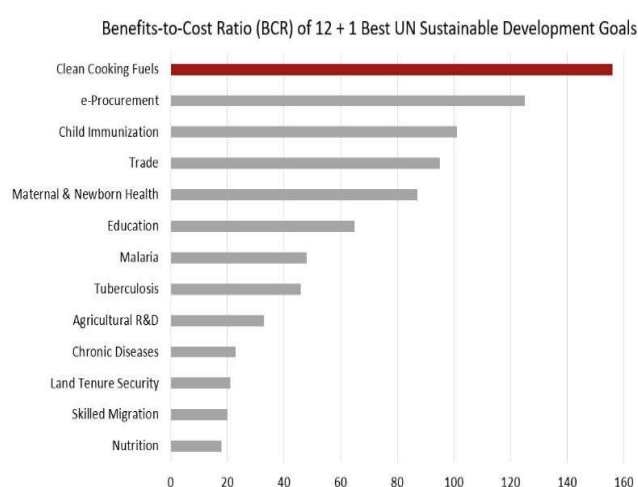


Source: (Stanaway et al. 2017)

This policy focus aligns with WHO (2017) data showing indoor air pollution causing approximately 1.6 million deaths annually, making it the second-largest environmental cause of mortality after outdoor air pollution.

The urgency for action is further supported by Lomborg in his book “Best things first”, who demonstrates that clean cooking fuels investments yield the highest benefit-to-cost ratio among various sustainable development interventions, surpassing even crucial areas like e-procurement and child immunization. This economic efficiency, combined with the substantial mortality burden, presents a compelling case for prioritizing clean cooking initiatives in both policy and development frameworks.

Figure 9. Best Things First.



Source: Lomborg

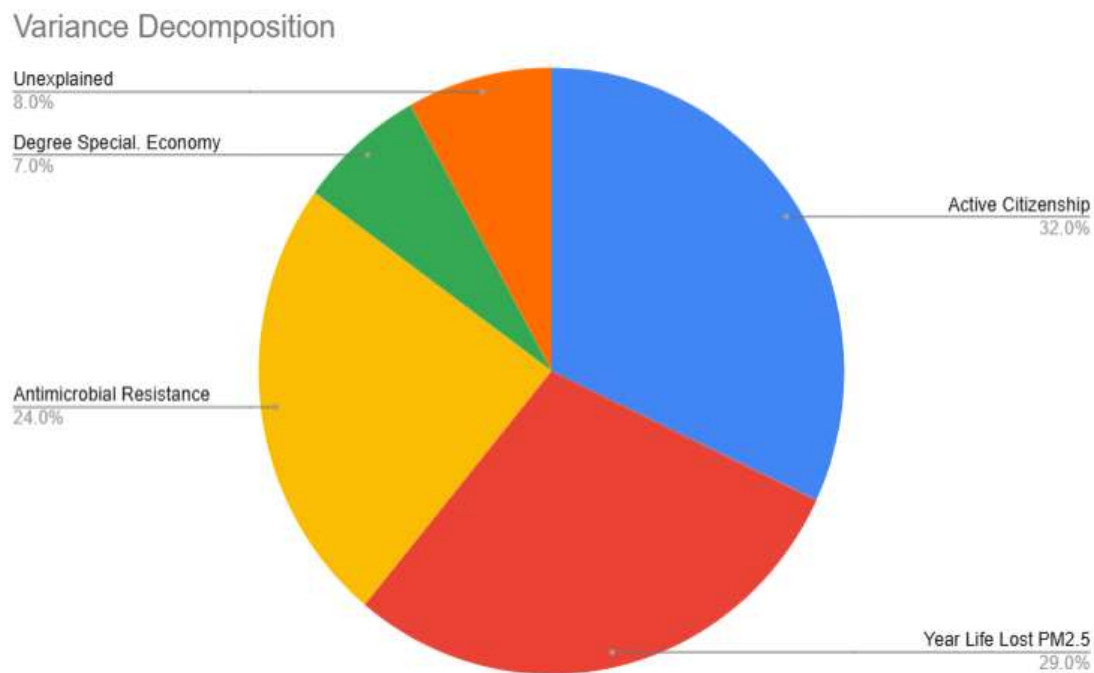
4.3 Sensitivity Analysis with Shapley (Bayesian Sparse Polynomial Chaos Expansion PCE⁵)

This report has conducted a sensitivity analysis on the Full Set of Indicators Linear Regression with exogenous Resilience.

To ascertain the relative significance of the indicators, this report computed Shapley effects to decompose the variance, aggregation all other variables effects in unexplained. The quantitative analysis reveals that active citizenship contributes the highest proportion at 32% of the variance, followed by years of life lost due to PM2.5 at 29%, antimicrobial resistance at 24%, and degree of specialisation of the economy at 7%. Approximately 8% of the variance falls under unexplained. Notably, Shapley analysis highlights substantial correlation amongst the indicators set.

⁵ Bayesian Sparse Polynomial Chaos Expansion (PCE) following Iooss & Prieur (2019)

Figure 10. Variance decomposition via Shapley Effects. Around 8% is left unexplained.



Source. Own elaboration

The four variables demonstrating significant contribution to the exogenous output can be combined in the optimal model below while achieving an R-squared value of 92%:

$$Y = P_0 + P_1(X_{94}) + P_1(X_{61}) + P_1(X_{69}) + P_2(X_{84}) \times P_2(X_{69})$$

Where Y is the outcome variable resilience

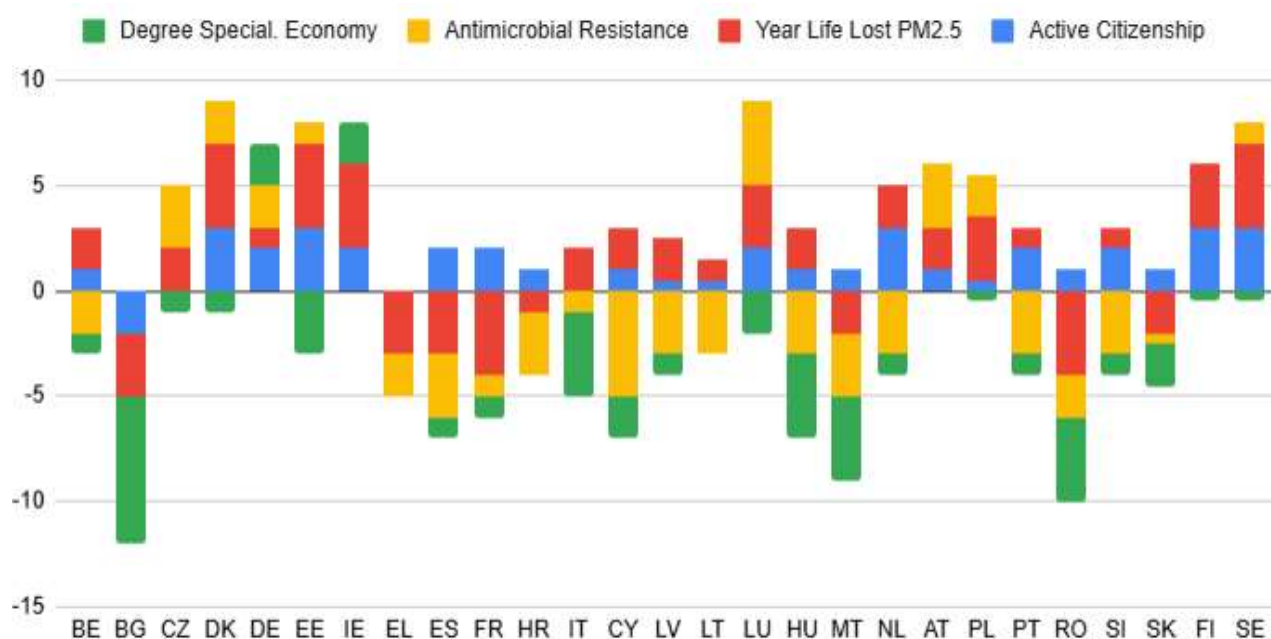
$P_k(X_j)$ denotes a kth-degree polynomial function of indicator X_j .

It is important to note that whilst the remaining indicators appear not to have direct impact on the exogenous resilience, they may exert indirect influence through their correlations with the four identified relevant variables corroborating the idea that the indicators are multicollinear.

Further investigation utilising Shapley values was undertaken to elucidate how different input variables combine to influence the deviation of the resilience from its mean ($y - \text{mean}(y)$) in the following chart. This analysis revealed country-specific variations in the importance of variables. For instance, in one country, active citizenship emerged as the most significant variable, generally increasing its Resilience value above the mean. Conversely, for another country, years of life lost due to PM2.5 proved most influential, contributing to a reduction in Resilience below the mean value.

For instance, for the first country the indicator "Active citizenship" seems to be the most important factor that contributes to increasing its resilience value while for the second country, the value of the "Years of Life Lost due to PM 2.5" variable is the most important negative contribution, meaning it tends to decrease the country's resilience. The chart allows us to see the relative importance and impact of each factor on the resilience value for each of the 27 countries.

Figure 11. Decomposition of Resilience – Mean (Resilience) per key indicator per country.



Source. Own elaboration

This sensitivity analysis illuminates the intricate interplay of indicators contributing to the exogenous resilience. Whilst four key variables have been identified, their high correlation suggests complex relationships within the model. The Shapley value analysis further demonstrates that the importance of these variables can vary markedly between countries, underscoring the necessity for nuanced approaches in resilience planning and policy-making.

5 Conclusions

The comprehensive study undertaken in this paper has underscored the immense value of the wealth of data from current dashboards and their trending indicators in the domain of societal resilience. The utilisation of the European Commission's Joint Research Centre (JRC) resilience dashboards, in conjunction with data from Lloyd's Register Foundation World Risk Poll 2024, has provided a rich tapestry of quantitative measures that are crucial for understanding and improving the resilience of societies.

The application of logistic and linear regression models has shown both benefits and limitations in this context. Logistic regression's simplicity and the ease with which it handles binary outcomes are invaluable for initial assessments of resilience factors. However, its limitations become apparent when addressing the complexity of societal resilience, which involves multiple, often interrelated factors. Linear regression, on the other hand, allows for a more nuanced exploration of continuous measures of resilience, as evidenced by its application to the World Risk Poll data report. However, this technique also assumes independence among predictors and is limited by its inability to capture nonlinear interactions without additional modifications.

The deployment of the sensitivity analysis using the Shapley Model has revealed significant benefits. The Shapley Model, with its roots in cooperative game theory, has proven to be an insightful tool for identifying the contribution of individual variables to the variance in resilience outcomes. This method has highlighted the interconnected nature of variables, such as active citizenship, years of life lost due to PM2.5, antimicrobial resistance, and the degree of specialisation of the economy, providing a more sophisticated understanding of their impact on resilience report.

Moreover, the Shapley Model has unveiled further opportunities available for expanding datasets. The ability to account for the interactions between variables has paved the way for incorporating additional data sources, such as those from EUROSTAT, OECD, IEA, and the World Bank, into resilience models. These expanded datasets could enhance the resilience assessment framework, allowing for a more comprehensive and detailed analysis of resilience at multiple levels, including country and individual scales.

There are burgeoning research opportunities in the field of security when accounting for multilevel resilience. This report's findings suggest that future research should focus on the nuanced differences between country-level and individual-level resilience. The World Risk Poll 2024 has already begun to explore these dimensions, and further work could provide deeper insights into how different levels of resilience interact and influence each other's report.

Lastly, the potential use of a stochastic approach in resilience modelling will be worth considering when aiming to dynamic predictions that reflect the inherent uncertainties and variabilities within societal systems. This approach could complement the static models employed in this study, providing a more robust and comprehensive toolkit for policymakers and researchers aiming to enhance societal resilience in an ever-changing global landscape.

While the current state of resilience modelling provides insights, there remains significant scope for the advancement of methodologies and the integration of richer datasets. The combined use of logistic and linear regression models, sensitivity analysis through the Shapley Model, and the potential for stochastic approaches represents a powerful suite of tools for the ongoing effort to understand and strengthen the resilience of societies worldwide..

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List of abbreviations and definitions

Abbreviations	Definitions
EU	European Union
JRC	Joint Research Centre
OECD	Organisation for Economic Co-operation and Development
IEA	International Energy Agency
NIS2	Directive on measures for a high common level of cybersecurity across the Union
PCA	Principal Component Analysis
PCE	Polynomial Chaos Expansion
RDB	Resilience Dashboard
VUCAS	Volatile, Uncertain, Complex, Ambiguous Scenarios

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Annexes

Annex 1. Synthetic Indicator Data with Endogenous Resilience

	Social econ_V	Green_V	Digital_V	Geopolitical_V	Socialecon_C	Green_C	Digital_C	Geopolitical_C	Resilience
BE	0	-0.75	0	-0.75	0.75	0.75	1	0.75	0
BG	-0.75	0	-0.75	0	0.5	0.25	0.25	0.5	0
CZ	-0.25	0	-0.25	-0.25	0.5	0.5	0.5	0.5	0
DK	-0.25	-0.25	0	-0.25	1	1	1	0.25	1
DE	-0.25	0	0	-0.25	0.75	1	0.75	0.5	1
EE	-0.25	-0.75	-0.25	0	0.5	0.75	0	0.5	0
IE	0	0	-0.25	-0.25	0.75	0.5	0.75	1	1
EL	-0.75	-0.25	0	0	0.25	0.25	0.25	0.25	0
ES	-0.75	0	-0.25	-0.25	0.5	0.75	0.75	0.5	0
FR	0	0	-0.25	-0.25	0.75	0.5	0.75	0.5	0
HR	0	-0.25	-0.75	0	0.5	0.75	0.75	0.5	0
IT	-0.75	-0.75	0	-0.25	0.5	0.5	0.25	0.5	0
CY	0	-0.75	0	0	0.5	0.25	0.5	1	0
LV	-0.25	-0.25	-0.25	-0.25	0.25	0.5	0.5	0.5	0
LT	0	-0.25	0	0	0.25	0.5	0.75	0.75	0
LU	-0.25	-1	-0.25	0	0.75		0.75	1	0
HU	0	0	-0.75	0	0.5	0.5	0.75	0.5	0
MT	0	0	-0.25		0.25	0.25	1	1	1

NL	-0.25	0	-0.25	0	1	0.75	1	0.75	1
AT	-0.25	-0.75	-0.25	0	0.75		0.75	0.5	0
PL	0	0	0	-0.25	0.25	0.5	0.5	0.5	0
PT	0	0	-0.25	-0.25	0.5	0.75	0.75	0.5	0
RO	-0.75	0	-0.75	0	0.5	0.25	0.25	0.5	0
SI	0	0	-0.25	0	0.75	0.75	0.5	0.75	1
SK	-0.75	-0.25	0	0	0.5	0.5	0.5	0.5	0
FI	-0.25	0	-0.25	0	1	0.75	1	0.5	1
SE	-0.25	0	-0.25	0	1	0.75	1	0.75	1
EU27	0	0	0	0	0.75	0.75	0.75	0.75	1

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