European Union Societal Resilience Prediction

Harnessing Data Science to Forecast Public Response in Europe

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1. Preface

"To the children, creating a better living circumstance for them, served as my inspiration to study data science."

Statement of Technology

The data for this study was acquired from the open source ESS Data Portal (https://ess.sikt.no/en/?tab=overview) through an online request. The obtained data is anonymized, and no human participants or animals were involved in data collection. The original owner of the data and code used in this thesis retains ownership of the data and code during and after the completion of this thesis. However, the institution is referenced (NSD – Norwegian Centre for Research Data 2023) in the bibliography section of this thesis as per is mentioned in the portal.

All figures in this thesis belong to the author. In terms of writing, the author used assistance with the language of the paper. The generative language models (ChatGPT 3.5 - https://chat.openai.com/) and (Google Bard - https://bard.google.com/) were used to improve the author's original content, for paraphrasing, spell checking, grammar, and debugging the programming code. No other typesetting tools or services were used.

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In the face of increasing crises and uncertainties, the capacity of European societies to maintain societal resilience is of critical importance. The primary research question of this study is to utilize machine learning techniques to predict the Societal Resilience indicator, examining the interplay of demographic and attitudinal factors. Drawing upon the profound societal impacts of recent challenges such as the COVID-19 pandemic, migration pressures, and economic instability, this research constructs a societal resilience indicator based on emotional attachment to Europe, trust in parliamentary institutions, and perceptions of trustworthiness within people. Leveraging data science and machine learning techniques, the study aims to predict the Societal Resilience indicator using data from the European Social Surveys Wave 10.

The research design encompasses a multifaceted analysis, involving data selection based on theoretical reviews, feature engineering to construct the target and encode variables, and comparison the performance of various predictive models. The models in their evaluation process and along with hyperparameter tuning achieved F1 scores of LightGBM 0.781, Logistic Regression 0.773, Neural Network (MLP) 0.769, and Random Forest 0.769, which significantly surpassed the baseline Decision Tree model with a F1 of 0.689. Sociological findings reveal that demographic factors have a minimal impact on societal resilience prediction, while trust in political institutions plays a substantial role in assessing resilience levels. The study underscores the symbolic capital of institutions like the United Nations in fostering societal resilience.

In light of the growing prevalence of societal challenges, this research makes a timely and significant contribution to the understanding of societal resilience. Compared to other studies, this research contributes novel perspectives to machine learning paradigms for predicting societal resilience and illuminating the intricate social dynamics of European societies in an up-to-date dateset. The findings provide valuable insights for policymakers and civil society organizations seeking to enhance societal resilience in Europe.

2. Introduction

In an era marked by increasing uncertainty and the ever-present possibility of conflicts and emergencies, the resilience of societies and their capacity to respond effectively to crises is of paramount importance.

Resilient communities are characterized by their capacity to survive, recover, and improvement through adaptive and flexible reactions to continuous challenges (Rochira, De Simone, and Mannarini 2023). Researchers have identified civil society organizations' vital contribution to the development of community resilience (Teräs and Kartoglu 2023). A measure of a society's resilience is its capacity to resist, respond to, and overcome unforeseen difficulties.

European societies have faced various crises in recent years, including the COVID-19 pandemic, migration crisis, and economic challenges(Arcese and Traverso 2021) (Sefer 2022) (Consoli, Fernández-Esquinas, and Papadopoulos 2022) (Bartoszewicz 2016) (Marinus and Ossewaarde 2013). These crises have had significant social impacts, leading to changes in societal arrangements, institutions, and political dynamics (Zanfrini 2019). Therefore, some study focuses on vulnerable groups and broadens the definition to take into account things like gender, income, immigration status, home ownership, and history of infection or exposure (Seo 2023). Overall, trust and social attachment are essential foundations for cooperation and resilience in communities. In this regard, understanding and predicting how European social resilience is a multifaceted puzzle demands innovative approaches.

This study embarks on a journey to explore the intricate web of trust, social attachment, and resilience in European societies. Leveraging the wealth of data science tools and machine learning approaches to analyze the data from the European Social Surveys Wave 10, we seek to unravel the underlying patterns and dynamics that govern the resilience of European communities. Although these approaches have been applied to extract the social pattern of political voting behavior of European citizens (Pessini 2021), here, as the scientific contribution of the thesis, 1) we use these methods on the most updated wave of the dataset, and 2) applying the methods to a different and more complicated social indict of the European Union Societal Resilience. Specifically, we aim to predict the Societal Resilience indicator, and the belief in the trustworthiness of fellow citizens—using advanced data science and machine learning techniques.

This study on societal resilience in European societies, also, holds significant relevance in addressing contemporary challenges, informing policy decisions, nurturing social cohesion, advancing scholarly knowledge, and contributing to global resilience efforts. By examining the multifaceted dynamics at play in European communities, we hope to offer insights that can empower societies to navigate an uncertain future with greater resilience and unity. This part of the work provides us with the basement of the Societal Resilience construction, which we use as the target factor in machine learning models.

2.1 Research Questions

The following research questions will be addressed by this study:

1. To what extent do machine learning models predict Societal Resilience based on demographic and attitudinal data from the European Social Survey?

2. How do social and attitudinal factors contribute to the prediction of societal resilience in European countries?

3. Related Work

The European continent has confronted a multitude of crises in recent years, ranging from economic downturns to public health emergencies. Understanding the factors that contribute to societal resilience in the face of these challenges is essential for effective crisis response and preparedness. This literature review explores the intricate relationship between public and institutional trust, social attachment, and resilience in European societies, drawing from a wealth of academic material. Also, the application of machine learning models in social datasets will be explored.

3.1 Trust and Social Attachment as Determinants of Societal Resilience

At the heart of societal resilience lie several critical factors, including social trust, social attachment, and institutional trust (Elran 2017). Trust, which involves the belief in others' positive intentions, has significant implications for cooperation, governance, and collective action. It influences individuals' willingness to engage in social interactions and contribute to the well-being of their communities. Social attachment, on the other hand, refers to the emotional bonds individuals form with their communities, fostering a sense of belonging and identity. It has a vital role in promoting social cohesion and resilience when facing challenges. Understanding the dynamics of trust and social attachment is essential for building resilient societies and fostering positive social relationships (Wang and Li 2020) (Brück et al. 2020). In continuation, we will delve into a more detailed examination of the theoretical foundations of the relationship between social trust and social attachment as constructive factors of social resilience.

- **Public and institutional Trust and Societal Resilience:**

Trust facilitates cooperation among individuals and institutions, which is crucial for building resilience. Fornale and Armiero emphasize the emergent and contingent nature of resilience, shaping societal relationships in unexpected way(Fornalé, Armiero, and Odasso 2023). Yang and Bae focus on the role of trust in promoting psychosocial recovery from disasters, including emotional resilience (Nemeth, Kuriansky, and Onishi 2021). These studies suggest that trust is a key factor in fostering resilience and supporting the well-being of individuals affected by disasters. Living in a high-trust environment has been found to make people more resilient to adversity(Wang et al. 2023b). Trust, too, is a key component of social capital, influencing economic stability and social well-being. Research has shown that trust-building factors in organizations can increase efficiency and reduce indirect costs(Akberdiyeva and Antczak-jarzĄBSKA 2022). Trust is seen as a reinforcement for the progress of small industrial businesses and a recommendation for women to remain a mainstay for family economic resilience(Chamola et al. 2022). Overall, trust plays a crucial role in various contexts, impacting work performance, economic stability, and social well-being. Social trust, a component of the overall climate of trust measured in ESS, has been linked to well-being and resilience. Living in a high-trust environment has been found to make people more resilient to adversity(Helliwell, Huang, and Wang 2016). Other study also highlights the importance of trust in building an atmosphere of trust in organizations, leading to increased work efficiency and decreased corrupt practices(Tuominen and Haanpää 2022). Additionally, trust has been identified as one of the three dimensions of social capital that is significantly associated with well-being in young people (Kimbal and Maru 2021).

Trust in institutions is also a crucial aspect of societal resilience. Institutional trust and social resilience interact to shape collective responses to crises. Trust is crucial in all dimensions of disaster resilience, as it affects risk perceptions and cooperative behaviors. Multi-stakeholder partnerships and collaboration can increase institutional resilience during moral crises, leading to joint action(Fornalé, Armiero, and Odasso 2023). The trust-built environment plays a significant role in enhancing social resilience, and understanding the relationship between people and places is crucial (Rashidfarokhi and Danivska 2023). Also, Maintaining social cohesion and collective efficacy is essential for the effectiveness of public health measures during crises, while social distancing is practiced(Elcheroth and Drury 2020). Trust between citizens and institutions, as well as among different levels of governance, is crucial for cooperation and resilience in communities (Bakker 2019) (Ţăranu and Ţăranu 2013). These factors not only shape the way individuals and communities respond to crises but also influence their ability to cooperate and work together in times of need.

In this regard, The European Social Survey (ESS) has emerged as a valuable resource for studying trust and societal well-being in Europe(García-Crespo, Fernández-Alonso, and Muñiz 2021). ESS data has been used to examine trust in various contexts, including political trust(Bešić 2021), trust in institutions, and social trust's impact on well-being. The ESS offers a rich dataset for exploring trust dynamics and their implications for resilience in European societies. ESS data has also been used to analyze trust in institutions among EU citizens, revealing differences among countries and individual-level determinants of trust(Mingo and Faggiano 2020).

- **Social Attachment and Community Resilience:**

Meiyi Ruan's research explored how social capital, information exchange, location attachment, and community resilience are related (Ruan 2022). Moreover, this is elaborated in the study by Wang et al. (Wang and Li 2020), which looks at the functions of environment perception, social justice, and community attachment in subjective well-being (SWB) during urban emergencies. They discover that environmental perception and SWB are mediated by community connection, while social justice and community attachment directly influence SWB(Wang et al. 2023a). Trust in the European Union is influenced by emotional attachments and connections that citizens have with the Union. This highlights the significance of emotional factors in shaping trust (Giorgio et al. 2021) (Brosius, van Elsas, and de Vreese 2020).

In summary, our literature review highlights the critical roles of trust and social attachment in shaping societal resilience. It emphasizes their relevance to European societies, particularly in the context of the EU's response to various crises. The empirical foundation provided by the European Social Survey data has provided us with a valuable resource for investigating these dynamics. This research builds upon and extends this literature by employing advanced data science techniques to predict trust and social attachment indicators, contributing to a deeper understanding of European societal resilience.

3.2 Machine Learning

Application of ML in social science: According to Lazer et al. (2020), social scientists are using computational social science methods more and more(Lazer et al. 2020), especially machine learning (ML). A class of flexible algorithmic and statistical techniques for prediction and dimension reduction" is how one can characterize methods falling under machine learning (ML)(Grimmer, Roberts, and Stewart 2021). Machine learning models also can be used to improve the accuracy of social surveys by applying predictive modeling methods that can adapt to complex relationships between outcomes and predictors. (Talathi and Vartak 2019) By using machine learning algorithms and techniques, social surveys can benefit from improved prediction performance and more efficient feature subset selection(Takahashi, Asahara, and Shudo 2019) (Gunnalan et al. 2003). Given the features mentioned in machine learning and data science tools, new studies have been conducted by adopting a new machine learning paradigm instead of traditional statistical paradigms in the field of applying machine learning models to social surveys(Skopek 2023)(Chen, Yang, and Lin 2022).

Chen et al. (Chen, Yang, and Lin 2022), in their study, applied Ordinal Logistic Regression (OLR) and Artificial Neural Network (ANN) to predict the happiness levels of European immigrants and natives. In this study, the European Social Survey Wave 9 dataset was used, which was selected from 13 variables with a focus on data from 15 countries for analysis and application in machine learning models. This study also defines happiness into three levels: Unhappy (values ranging from 0 to 3), Neutral (values ranging from 4 to 6), and Happy (values ranging from 7 to 10). As regards the performance of prediction models, the overall F1 scores of the OLR and ANN baseline models in both immigrant groups and native groups are less than 0.66.
Skopek (Skopek 2023) used data from the European Social Survey round first (2002) to predict attitudes towards immigration. As the target variable, "rejecting immigration" is constructed as a mean index consisting of three variables. The target variable is dichotomized by setting a threshold at the mean value of the scale for binary classifications. A value of 1 reflects negative opinions towards immigration. To select variables based on theoretical foundations, they first created two constructs of conservation and self-transcendence based on 10 variables from the question set in their study. They also used six demographic variables to predict the target. The sample size used was N = 27,164 respondents, and logistic regression and random forest models were used, resulting in F1 scores of 0.735 and 0.728, respectively.
Based on the literature review conducted, the present study seeks to apply the machine learning paradigm to the conventional social science dataset of social surveys, with a focus on the research problem of predicting Societal Resilience. In this regard, it should be noted that the use of this paradigm in this area of social analysis is new, and limited research has been done in this field. In addition, in this study, a variety of models were investigated and compared, some of which, such as the LightGBM Classifier, have not been used in previous studies. Also, the dataset reviewed, namely ESS round 10, has not been used for such purposes until the time of this study, given that it is the most up-to-date wave of the survey. On the other hand, the topic of Societal Resilience, which is the issue of this research, has not been studied in this collection, i.e. with a machine learning approach and in the present dataset. Therefore, the present study seeks to cover the existing gap in addition to research on its main issue. Continuing, we will delve into the examination of the experimental setup used for in this research.

4. Experimental Setup

This chapter aims to give a thorough explanation of the experimental setup used for this investigation. The dataset and its features that were employed, as well as the dataset's characteristics, are explained. A thorough explanation of the preprocessing stage is given. The key findings from the examination of the exploratory data are showcased. The experimental method and models are described in the next section. Also, the experimental setup's tools and packages are explained.

4.1 Dataset Description

The European Social Survey, or ESS, stands as a goldmine of data for researchers and policymakers seeking to unravel the intricate dynamics of European societies(Kolarz et al. 2022). Since 2002, ESS has been a research-driven survey carried out throughout Europe. The poll examines the attitudes, convictions, and actions of various people across over thirty countries(Consortium 2023). ESS10(NSD – Norwegian Centre for Research Data 2023), the tenth wave of this comprehensive survey, offers a rich and diverse dataset that serves as an invaluable resource for tackling the pressing problem of predicting societal resilience in Europe through machine learning (ML) models. For the ML analysis aimed at predicting European societal resilience indicator, ESS10 offers a treasure trove of variables that can play a pivotal role in predictive models. There were 706 characteristics and 59685 occurrences in the original dataset. However, considering the research objectives and the theoretical foundations discussed, 26 variables were selected from various variables (Table 1) which were collected from 31 European Union countries (Appendix 1).

As mentioned earlier, Chen (Chen, Yang, and Lin 2022) and Skopek(Skopek 2023), in their studies on the implementation of machine learning on the European Social Survey dataset, have selected the number of variables used based on the theoretical foundations of their research problem. In this way, some of the variables, including demographic variables such as age, gender, income level, and education, and other attitudinal variables, are selected based on the research problem, which in the end the number of variables used in their studies has been less than 25 questions.

As another reason for the significant reduction in the number of variables used in this study compared to the raw variables in the dataset, it should also be noted that the dataset contains many variables that are related to questions that are repeated for each country, or that have different options for each country due to differences in the subject matter. However, the dataset also contains integrated variables for comparative analysis, which were used in this study. For example, the questions about the respondent's educational level are considered separately for each country based on the country's educational system. However, there is also a standard variable that allows you to compare educational level in a consistent way without considering nationality. In other words, the dataset contains many variables that are redundant or irrelevant to the research problem. By using integrated variables, the number of variables is reduced while still retaining the information that is most relevant to the study.

The mentioned subset of columns from the original dataset was chosen to focus the analysis on key variables. These columns include demographic information (such as age and gender), measures of well-being (happiness and health), and resilience-related questions (trust in people, EU parliament, and attachment feeling to the EU). Additionally, the 'cntry' column was retained to account for the country of origin, allowing for country-specific analysis. In this study, "atcherp" (emotional attachment to Europe), "trstep" (trust in the European Parliament), and "ppltrst" (trust in fellow citizens) are pivotal factors for creating the resilience indicator.

4.2 Pre-processing

Preprocessing is essential to a model's predictive behavior since it allows for the making of several decisions that have an impact on the model's functionality (Zelaya 2019). Thus, the raw dataset underwent a number of data transformations and cleaning procedures. Because it was important to obtain the participants' actual replies, the records in which they had marked "Not applicable," "Refused to answer," "No answer," or "I don't know" at the variables were imputed. For instance, in the 'agea' column, missing values encoded as 999 were replaced with NaN (Not a Number) to facilitate subsequent analysis. Furthermore, a label mapping dictionary was applied to several columns to handle special codes (e.g., 77, 88, 99) representing missing or undefined values. It should be noted that after the unification of the non-response codes, the observed non-response cases (Appendix 2) were approximately one percent. Missing values in selected features were imputed to ensure data completeness and accuracy. Given the low percentage of

Table 1: Dataset Selected Variables

	Labels	Variabels	N	
			Valid	Missing
1	cntry	Country	59685	0
2	ppltrst	Most people can be trusted or you can't be too careful	59411	274
3	stfdem	How satisfied with the way democracy works in country	58478	1207
4	stfeco	How satisfied with present state of economy in country	58623	1062
5	stfedu	State of education in country nowadays	57578	2107
6	stfgov	How satisfied with the national government	58435	1250
7	stfhlth	State of health services in country nowadays	59196	489
8	stflife	How satisfied with life as a whole	59138	547
9	trstep	Trust in the European Parliament	56893	2792
10	trstlgl	Trust in the legal system	58768	917
11	trstplc	Trust in the police	59180	505
12	trstplt	Trust in politicians	58902	783
13	trstprl	Trust in country's parliament	58644	1041
14	trstprt	Trust in political parties	58727	958
15	trstun	Trust in the United Nations	56288	3397
16	atcherp	How emotionally attached to Europe	58804	881
17	brncntr	Born in country	59408	277
18	ctzcntr	Citizen of country	59302	383
19	happy	How happy are you	59331	354
20	health	Subjective general health	59419	266
21	rlgdgr	How religious are you	58772	913
22	gndr	Gender	59050	635
23	agea	Age of respondent, calculated	58347	1338
24	eisced	Highest level of education, ES - ISCED	58602	1083
25	hincfel	Feeling about household's income nowadays	57859	1826
26	implvdm	How important for you to live in democratically governed country	58903	782

missing data and the fact that other imputation strategies, such as mean or multivariate feature imputation, do not provide us with integer values for data replacement, the median imputation strategy was employed. It is worth noting that, considering the types of machine learning models applied and the ordinal nature of the data, the use of other imputation approaches would have introduced unnecessary complexity to the dataset, which was therefore avoided. The method that is applied for imputing missing values was provided by the SimpleImputer class. In this method, missing values can be imputed using a fixed value that has been supplied or by utilizing the statistics (mean, median, or most common) of each column that contains the missing data. Additionally, this class supports several encodings for missing data (scikit-learn contributors 2023).

It should be noted that, as the dataset included around 60,000 samples, the sampling weights strategy was not applied in this research. Sampling weights are employed in survey research to compensate for the varying probability of selection for different units within the sample. Each respondent is allocated weights which are utilized to appropriately adapt the data to represent the target demographic. Sampling weights are usually used when calculating cross-country differences in the context of comparative analysis. They reflect the inclusion probabilities within each nation, ensuring that the estimates are representative of the population (Kaminska and Lynn 2017). However, the study of MacNeil (MacNell et al. 2023) on the impacts of accounting sampling weights in gradient boosting provided insights that emphasized the difficulties in applying machine learning methods to complicated survey data. This study noted that the influence of sampling weights varies depending on factors such as sample size and other analytical characteristics. However, The article's experimental study scenarios demonstrated that for sample sizes exceeding 10,000, there was no significant difference between applying the weighted sampling approach or not. Given the substantial sample size and specific attributes of the dataset, a deliberate choice was made to forego the incorporation of sampling weights in the machine-learning models. Instead, a focus was placed on addressing the research objectives using alternative analytical methods, with nuanced considerations regarding the impact of sampling weights on model outcomes.

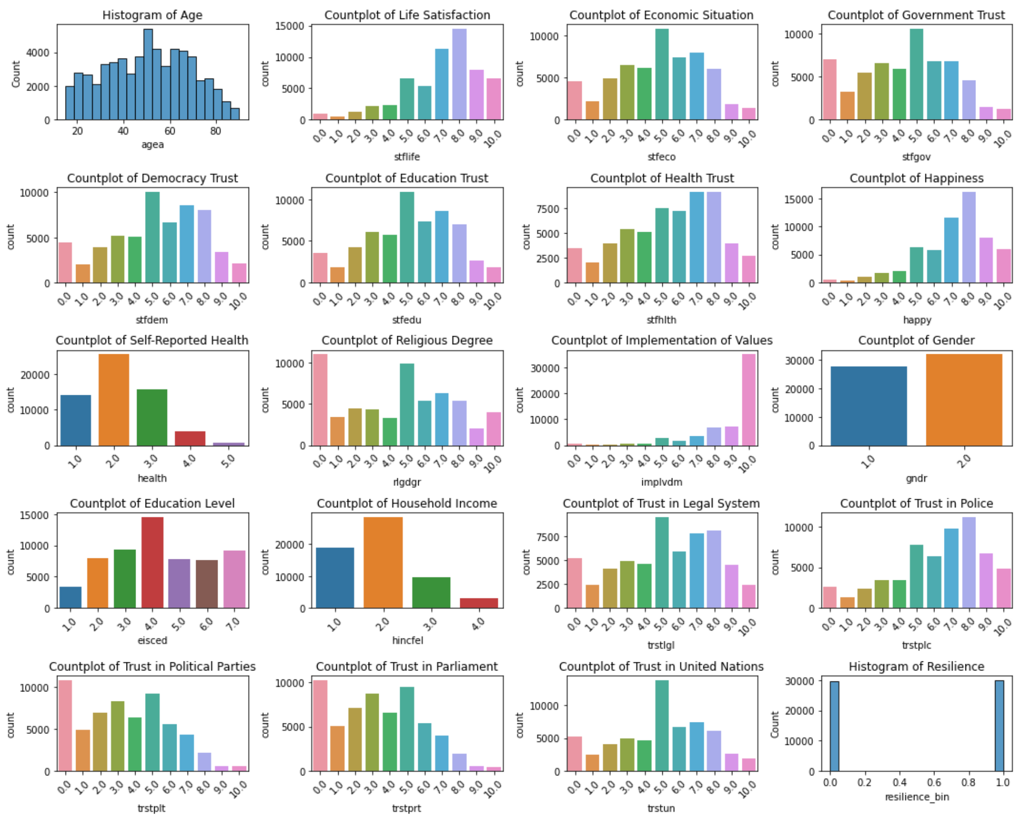
In the process of feature engineering for the aim of this thesis, a new indicator named "resilience" was derived from existing variables following the approach suggested by Skopek (Skopek 2023). This approach involves constructing a composite variable by averaging three separate variables and then dichotomizing the resulting mean value at a predetermined threshold. In this case, the three variables used to construct the "Resilience" indicator were "atcherp" (emotional attachment to Europe), "trstep" (trust in the European Parliament), and "ppltrst" (trust in fellow citizens). The mean value of these variables was then compared to a threshold of 5, and respondents were classified as either "resilient" (mean value 5) or "non-resilient" (mean value < 5) with two labels: 0 for non-resilient and 1 for resilient. This approach aligns with Skopek's method of constructing a binary indicator representing attitudes towards immigration. Skopek used a mean index of three variables to measure "rejecting immigration". The variables used by Skopek also loaded strongly on a single dimension in a confirmatory factor analysis.
After creating the target variable, to ensure that the resilience indicator was not biased by the original variables, the three constituent variables (atcherp, trstep, and ppltrst) were removed from the dataset before training the machine learning models. This was done to prevent the models from simply memorizing the relationship between the resilience indicator and the original variables.

4.3 Exploratory Data Analysis

Any study analysis must include an exploratory investigation of the data. It facilitates comprehension of the dataset, uncovers hidden patterns, and yields new insights(Hodeghatta and Nayak 2023). The objectives of any exploratory data analysis (EDA) are to determine the data's quality, compute descriptive statistics, and investigate feature distributions(Chatfield 1986). To get an understanding of the features of the dataset, descriptive statistics were calculated (Appendix 3). Summary statistics, such as mean, quantiles, standard deviation for continuous variables, and frequency counts for categorical variables, were calculated and illustrated in histograms. These statistics offered an initial understanding of the data's central tendencies and distributions.

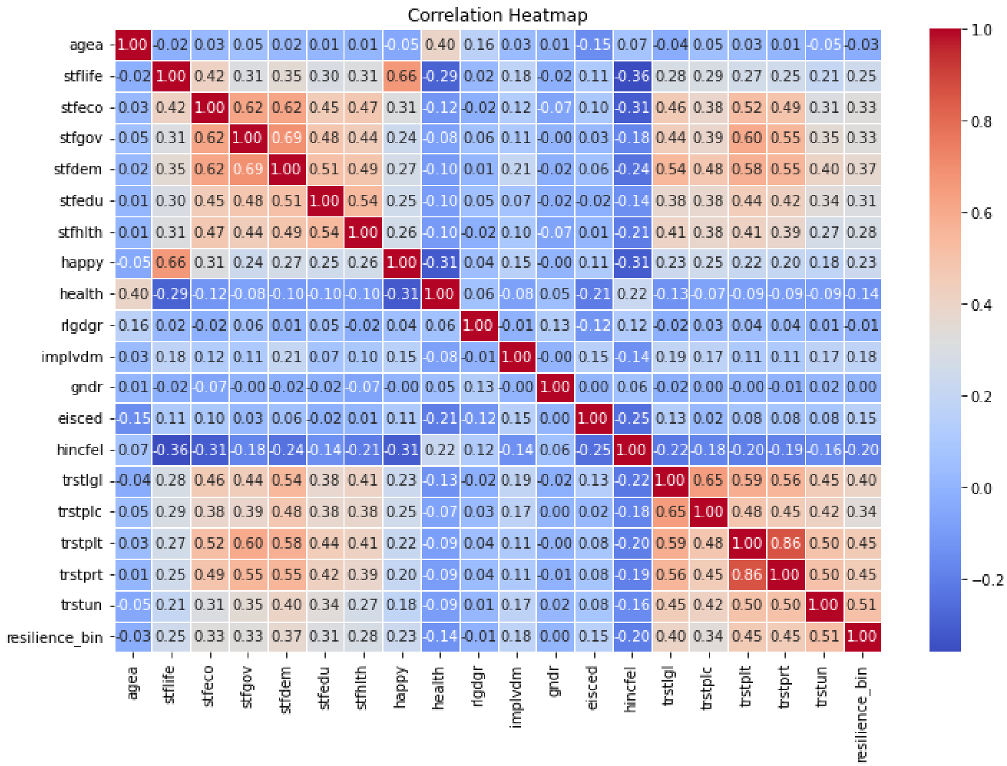
In the Exploratory Data Analysis (EDA) phase of the report, a grid of subplots is created, with each subplot dedicated to a selected variable, and the dataset's key variables are visualized using various plotting techniques. In figure 1, countplots are generated for categorical features to display the frequency distribution of categories, while histograms are plotted for numerical variables to visualize the distribution of values. This systematic approach allows the exploration and assessment of central tendencies, variabilities, and patterns within each variable, supporting critical insights into the dataset's characteristics. As evident in the figure 1, the demographic variable of age follows a normal distribution. The gender distribution is balanced. Most attitudinal variables also exhibit normal distributions. However, the variable of "How important for you to live in a democratically governed country?" tends to skew positively. Lastly, the target variable, social resilience, is distributed evenly.

Figure 1: Descriptive Statistics Count Plots and Histograms



A correlation heatmap, figure 2, is produced when the chosen variables are passively analyzed through the construction of a correlation matrix. In order to identify underlying links and dependencies within the dataset, pairwise correlations between the selected variables are computed in this procedure. These correlations are visually represented in the resultant heatmap, which uses a color-coded system to indicate the direction and intensity of the associations. This passive analytical approach effectively conveys insights about potential associations between variables by using a cool-to-warm color palette and displaying correlation coefficients as annotations. This helps identify relevant patterns and trends within the data by enabling an initial understanding of which variables may influence one another. According to Figure 3, as expected, there is a strong relationship between trust in politicians and trust in political parties. Additionally, satisfaction with the country's economic situation, the national government, and the functioning of democracy shows strong associations with each other. Feeling happy with life satisfaction also has a mutual relationship. However, demographic variables such as age, religiosity, and education level, as well as income satisfaction, display weak relationships with other variables.

Figure 2: Correlation Heatmap: Identifying Relationships and Dependencies

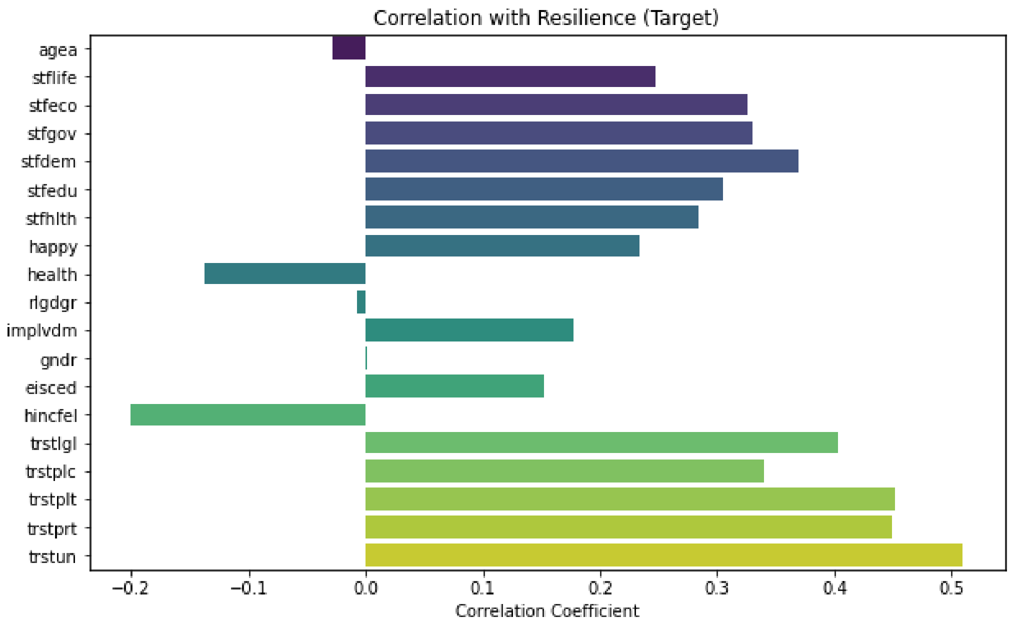


During our data exploration, an analysis was performed to understand the factors affecting an individual's resilience. Correlation coefficients were computed between various features and the target variable 'resilience_bin.' These coefficients offer insights into the strength and direction of relationships between each feature and resilience.

Figure 3 displays our findings in a bar plot, where bar length represents the strength of the relationship: Longer bars indicate stronger correlations, whether positive or negative. Positive correlations imply that an increase in these features corresponds to higher resilience, while negative correlations suggest decreased resilience.

The key takeaway is the identification of influential features. These insights guide subsequent modeling and inform parameter decisions. They also provide context for understanding dataset patterns and feature contributions to resilience predictions. As evident in the figure, variables such as trust in the United Nations, politicians, political parties, and the government are the most important factors with strong relationships with the social resilience variable, even more so than variables like life satisfaction, healthcare, education, or happiness. Some demographic variables continue to show weak relationships. In other words, the structure of social resilience should be evaluated in harmony with political trust rather than being solely assessed based on its social context. Income satisfaction and perceived health have negative associations with the social resilience index. It can be inferred that the higher individual autonomy, the more negative the position regarding factors contributing to social resilience, such as trust in others, trust in the European Parliament, and a sense of belonging to Europe.

Figure 3: Correlation with Resilience (Target): Identifying Influential Factors



In summary, our Exploratory Data Analysis (EDA) has provided essential insights into our dataset. We've examined descriptive statistics, visualized feature distributions, and analyzed correlations between variables. These findings will inform our modeling approach and parameter choices while enhancing our understanding of the dataset.

4.4 Method

The primary objective of this study is to develop a classification model for predicting the binary target variable "resilience" based on a comprehensive set of socio-demographic and attitudinal factors. For the dataset, a train and test set split needs to be made in order to feed the models and let them train. The 59685 observations will be randomly split by using the sklearn package and the `train_test_split` function from the `sklearn.model_selection` library, where 80% is placed in the train set and 20% is placed in the test set. The random seed being set to 42 for consistency across experiments. Grid searches were applied for each model (Dummy Classifier, Decision Tree, Logistic Regression, Random Forest, LightGBM, and Neural Network) using 5-fold cross-validation. This setup followed the instructions suggested by Skopek (Skopek 2023). A set of hyperparameters and their potential values were defined for each model. Given the novelty of the models implemented and the data source in this study, and as a result of the limited scientific resources on the appropriate parameters for tuning the aforementioned models, the set of parameters for this study are selected through a recursive, feedback, and trial-and-error process, which are presented in the report below. The optimal hyperparameters are identified by systematically exploring these combinations. Specifically, the Three-Dimensional Loss Surface Visualization of Hyperparameter Optimization for LightGBM Classifier (Figure 6) is utilized to visualize the performance of the models across different hyperparameter combinations, allowing for more informed parameter adjustments. After training each model with the optimal hyperparameters, predictions were made on the test set, and their performance was evaluated using metrics like accuracy, recall, and F1-score. The results allowed for the comparison of model performance and the selection of the best model for the specific problem. This methodology aims to select the best-performing model that can effectively classify individuals' resilience levels based on socio-demographic and attitudinal factors, thus contributing valuable insights to the field of predictive analytics in the social sciences.

4.5 Models

In this section, we evaluate a variety of models to predict public response patterns in Europe. We begin with baseline models, including the Dummy Classifier and Decision Tree Classifier, to establish performance benchmarks. Subsequently, we explore advanced models, such as Logistic Regression, Random Forest Classifier, LightGBM Classifier, and a Neural Network (NN) Classifier. Each model is thoughtfully configured and fine-tuned to optimize its predictive power. We'll also discuss key hyperparameters for these models. Our goal is to identify the best-performing model for precise and accurate forecasting without repeating the details covered in the subsections.

- Baseline Models (Dummy Classifier and Decision Tree Classifier):

1. **Dummy Classifier:** The most basic foundation model is the Dummy Classifie which here serves as the simplest baseline model. It adopts a `'most_frequent'` strategy, which predicts the class that appears most frequently in the training data. This model establishes a fundamental reference point for performance evaluation. Although it undergoes a training process, the Dummy Classifier relies on straightforward rules for predictions. The most common class in the training data is used to create predictions for the test set. This model shows the most basic knowledge of the target distribution and a good primary sense for getting a better understanding of the matrix evaluation results of the other models.
2. **Decision Tree Classifier:** The Decision Tree Classifier is another baseline model, characterized by its ability to partition the feature space into regions and assign labels to these regions. We employ the base Decision Tree model and train it using the fit method with the training data. Decision trees are known for their ease of interpretation and for providing illuminating details on the factors affecting public opinion. As per the other main Models, Random Forest and LightGBM, which are decision tree based algorithms, this model is selected as a baseline for a better possibility of tuning comparison among the models.

- Main Classifier Models:

1. **Logistic Regression:** There are various benefits of using logistic regression for binary classification. To begin with, it is a predictive model that may be applied in situations where the response variable is binary, enabling the modeling of the likelihood of a specific result(Wilson et al. 2015). Because logistic regression is resilient, it can produce meaningful findings even in situations where the model's assumptions are not met(Sperandei 2014).

However, logistic regression is not without its drawbacks. It may not always be appropriate because it presupposes a linear relationship between the predictor factors and the outcome's log-odds(Ranganathan, Pramesh, and Aggarwal 2017). Additionally, logistic regression's versatility may be limited in some situations because it necessitates the specification of a link function(Pepe, Cai, and Zhang 2004).
Configuring Logistic Regression and performing a grid search over predetermined hyperparameters like regularization strength (`C`), penalty type (`penalty`), and maximum iterations (`max_iter`) are both done. The best hyperparameters have been found with the use of grid search cross-validation:

```
Regularization Strength (C): [0.1, 1, 10]
Penalty Type (penalty): ['l1', 'l2']
Maximum Iterations (max_iter): [100, 200, 300]
```

In this case, the hyperparameters being tuned are 'C', which controls the regularization strength, 'penalty', which specifies the type of regularization (L1 or L2), and 'max_iter', which determines the maximum number of iterations for the logistic regression algorithm to converge(Pedregosa et al. 2011).

2. **Random Forest Classifier:** When it comes to binary classification, random forests have a number of benefits and drawbacks. Compared to a single decision tree, they can produce forecasts that are more consistent and dependable, which is one benefit(Audemard et al. 2022). But because random forests' forecasts rely on a majority vote across several decision trees, their interpretability is less than that of decision trees(Hanika and Hirth 2023). Positively, random forests can handle nonstandard training data formats and identify behavioral patterns(Chen, Gallego, and Tang 2019). The Random Forest Classifier, an ensemble learning method, is utilized. Similar to Logistic Regression, a grid search is performed over hyperparameters, including the number of estimators (`n_estimators`) and maximum tree depth (`max_depth`). The optimal hyperparameters are identified through grid search cross-validation:

```
Number of Estimators (n_estimators): [10, 50, 100]
Maximum Tree Depth (max_depth): [None, 10, 20]
```

In this context, the hyperparameters being tuned are 'n_estimators', representing the number of decision trees in the random forest, and 'max_depth', which determines the maximum depth of each decision tree(Pedregosa et al. 2011).

3. **LightGBM Classifier (Best Model):** LightGBM, short for light gradient-boosting machine, is a distributed gradient-boosting framework for machine learning(Brownlee 2020). It is utilized for classification, ranking, and other machine learning applications and is based on decision tree algorithms. The development approach prioritizes scalability and performance(Ke et al. 2017). A highly efficient decision tree learning technique is implemented by LightGBM, yielding significant improvements in performance and memory consumption(Alsabti, Ranka, and Singh 1998). The LightGBM algorithm runs more quickly while retaining a high degree of accuracy because of the use of two cutting-edge methods dubbed Exclusive Feature Bundling (EFB) and Gradient-Based One-Side Sampling (GOSS)(Ke

et al. 2017). LightGBM, a gradient boosting framework, emerges as the best-performing model following hyperparameter tuning. Grid search cross-validation is utilized for a number of hyperparameters, such as the learning rate (`learning_rate`), maximum tree depth (`max_depth`), number of leaves (`num_leaves`), and number of boosting rounds (`n_estimators`).. The model is trained with the optimal hyperparameters using the `fit` method, and predictions for the test set are made using the `predict` method:

```
Number of Leaves (num_leaves): [31, 63, 127]
Maximum Tree Depth (max_depth): [5, 10, 15]
Learning Rate (learning_rate): [0.01, 0.05, 0.1]
Number of Boosting Rounds (n_estimators): [50, 300, 500]
```

In this context, the hyperparameters being tuned include 'num_leaves,' representing the maximum number of leaves in each decision tree, 'max_depth,' which sets the maximum depth of the trees, 'learning_rate,' controlling the step size for gradient boosting, and 'n_estimators,' indicating the number of boosting rounds (or trees)(Ke et al. 2017).

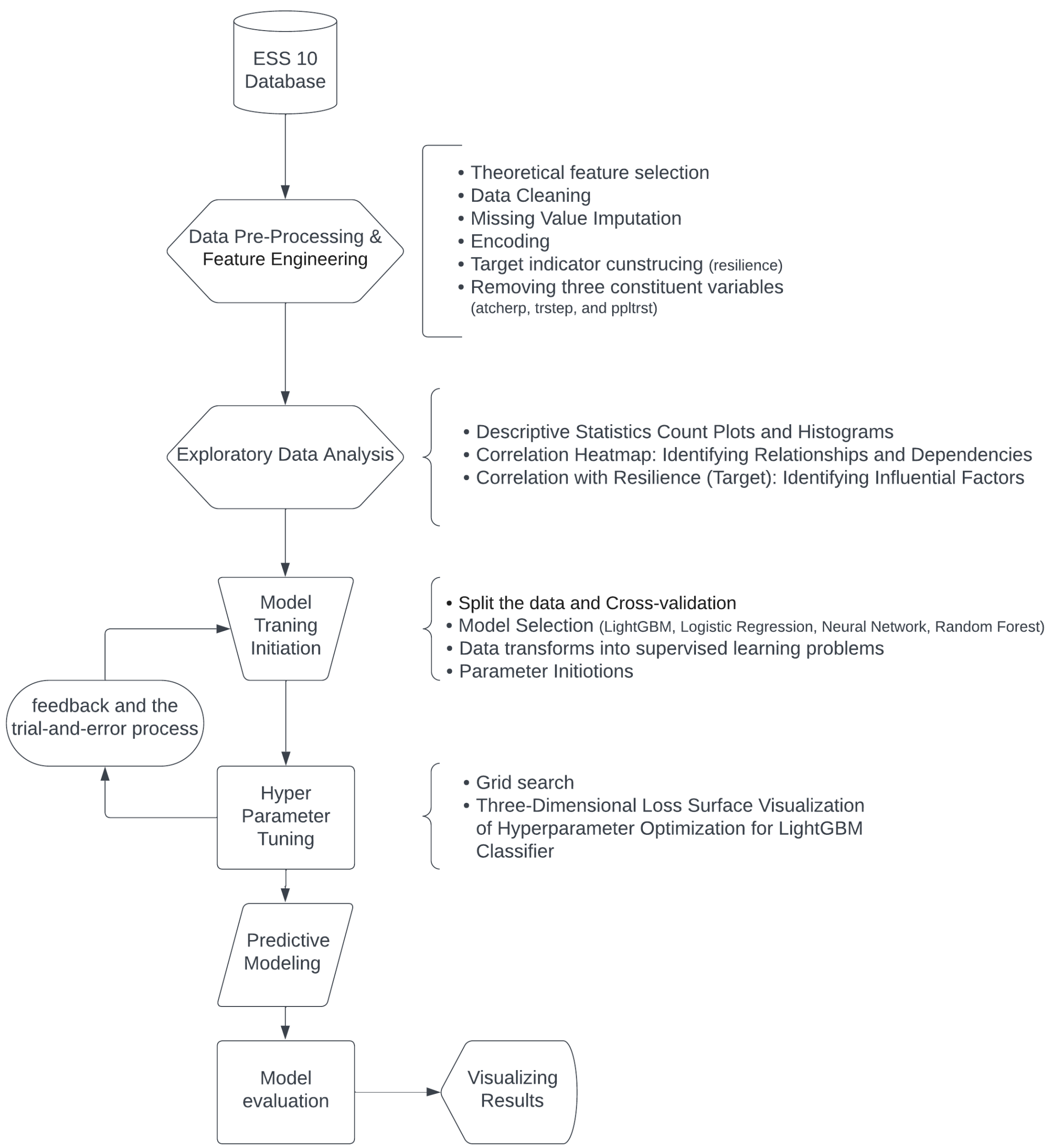
4. **Neural Network (NN) Classifier:** There are a number of benefits and drawbacks to neural networks for binary classification. One benefit over approaches that evaluate variables separately is their capacity to manage intricate interconnections among input variables, which can improve forecast accuracy(Kanemura et al. 2017). Furthermore, neural networks exhibit greater resilience and reduced sensitivity to variations in sample size, group count, variable count, group membership percentages, and group overlap levels(Basioti and Moustakides 2019). But there are a few drawbacks as well. Because of their restricted bit-depth, binary neural networks, which limit the bit-depth of network weights and activations, have a trade-off between accuracy and efficiency(Jeatrakul and Wong 2009). Additionally, when there are few or no interactions between variables, neural networks may overfit the data and represent the input-to-output relationship with a more complex function than is necessary(Subramanian, Hung, and Hu 1993). A Neural Network (NN) classifier is employed, offering the capacity to capture intricate data patterns. In this case, Multi-layer Perceptron classifier (MLPClassifier) is used as the NN model. Hyperparameter tuning is conducted through grid search cross-validation, considering parameters such as hidden layer sizes (`hidden_layer_sizes`), activation functions (`activation`), and the regularization term (`alpha`). The NN model is trained with the below hyperparameters:

```
Hidden Layer Sizes (hidden_layer_sizes): [(20, 10, 4),
(50, 25, 4)]
Activation Functions (activation): ['relu', 'tanh']
Regularization Term (alpha): [0.0001, 0.001, 0.01]
```

The hyperparameters being tuned include 'hidden_layer_sizes,' specifying the architecture of the neural network by defining the number of neurons in each hidden layer, 'activation,' which determines the activation function used in the neurons (either 'relu' for rectified linear unit or 'tanh' for hyperbolic tangent), and 'alpha,' representing the L2 regularization term used to control overfitting by penalizing large weights(Pedregosa et al. 2011).

In summary, each model is trained with its respective hyperparameters using the training data. After training, these models are used to make predictions on the test set, and performance metrics (particularly the F1-score) are calculated to evaluate their predictive accuracy. This comprehensive approach ensures a thorough evaluation of each model's performance and allows for the selection of the best-performing model, which, in this case, is the LightGBM Classifier following its hyperparameter tuning.

Figure 4: Workflow Process for Predicting Societal Resilience



5. Results

In this section, the outputs of various models' executions will be evaluated. The goal is to apply machine learning models to predict the binary resilience index. Table 2 presents the best parameters for each model. Machine learning model optimization input values are explained by hyperparameter settings(Ippolito 2022). these hyperparameter settings are tailored to each respective model type. The choices made reflect strategies to control overfitting, optimize convergence, and balance model complexity with the goal of achieving the best predictive performance on the given dataset.

Table 2: Best model parameters

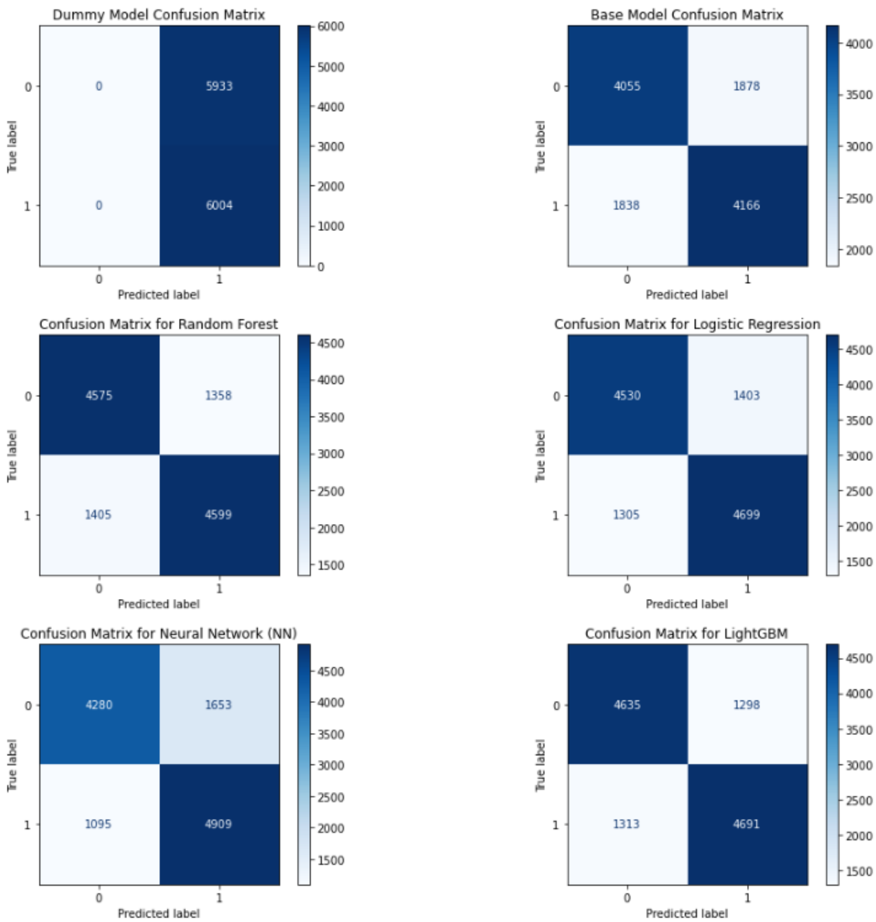
Model	Best model parameters
LightGBM :	{'learning_rate': 0.05, 'max_depth': 5, 'n_estimators': 500, 'num_leaves': 31}
Neural Network :	{'activation': tanh', 'alpha': 0.01, 'hidden_layer_sizes': (20, 10, 4)}
Random Forest :	{'max_depth': 20, 'n_estimators': 100}
Logistic Regression:	{'C': 0.1, 'max_iter': 300, 'penalty': 'l2'}

A confusion matrix, a table that summarises a classification model's performance, is used to evaluate models in binary classification. It offers details on the predictions that the model produced, including true positive, true negative, false positive, and false negative. Numerous assessment metrics, including accuracy and F1 score, may be obtained from the confusion matrix. Accuracy is a measure of the overall correctness of the model's predictions, whereas the F1 score is a measure of the model's accuracy that accounts for both precision and recall. These metrics are frequently employed to evaluate binary classifier performance(Vanacore, Pellegrino, and Ciardiello 2022). The F1 score and accuracy output subsequently indicate the best results based on the confusion matrix. As evident, the best model (Table 3) for predicting the resilience index is the LightGBM model.

Table 3: Model Evaluation

Model	F1 Score	Accuracy
LightGBM	0.781	0.781
Logistic Regression	0.773	0.773
Neural Network	0.769	0.770
Random Forest	0.769	0.769
Base Model	0.689	0.689
Dummy Model	0.337	0.503

Figure 5: Confusion Matrix Results for ML Models



In the continuous pursuit of a better understanding of the selected model's behavior and the fine-tuning of its performance, a comprehensive analysis of hyperparameter combinations was conducted using a 3D loss surface visualization. This approach allowed deeper insights into how variations in two critical hyperparameters, "Learning Rate" from 0.01 to 0.11 and "Number of Estimators" between 50 and 500, were impacted by the model's Log Loss, a pivotal performance metric. The 3D plot presented (Figure 6) illustrates the relationship between these hyperparameters and Log Loss, serving as a valuable guide for selecting optimal hyperparameter values. Minimizing Log Loss is considered essential for enhancing the predictive accuracy of the LightGBM classifier, and this visualization aided in the identification of the most effective hyperparameter settings to achieve this goal. For a deeper exploration, in Appendix 4, the 2-dimensional perspective of Loss Surface contains information about the best hyperparameter tuning region which is indicated by dark-blue area.

Figure 6: Three-Dimensional Loss Surface Visualization of Hyperparameter Optimization for LightGBM Classifier

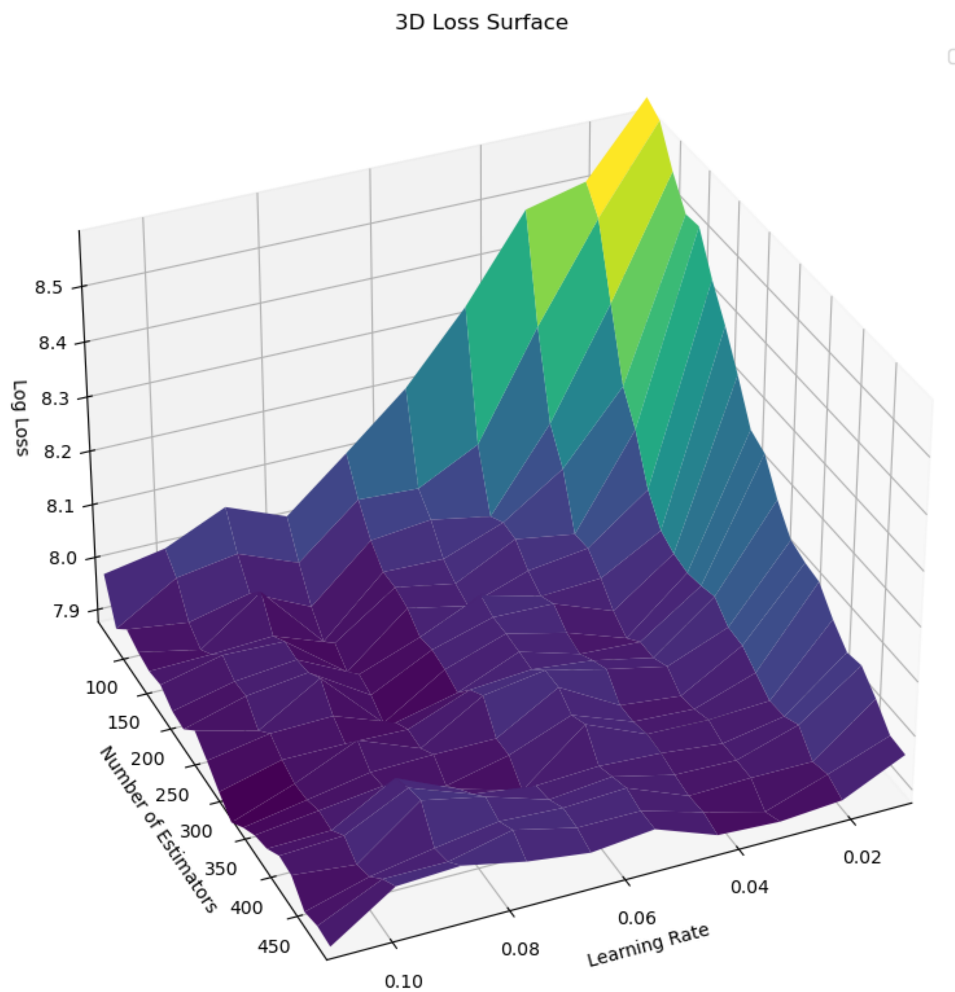
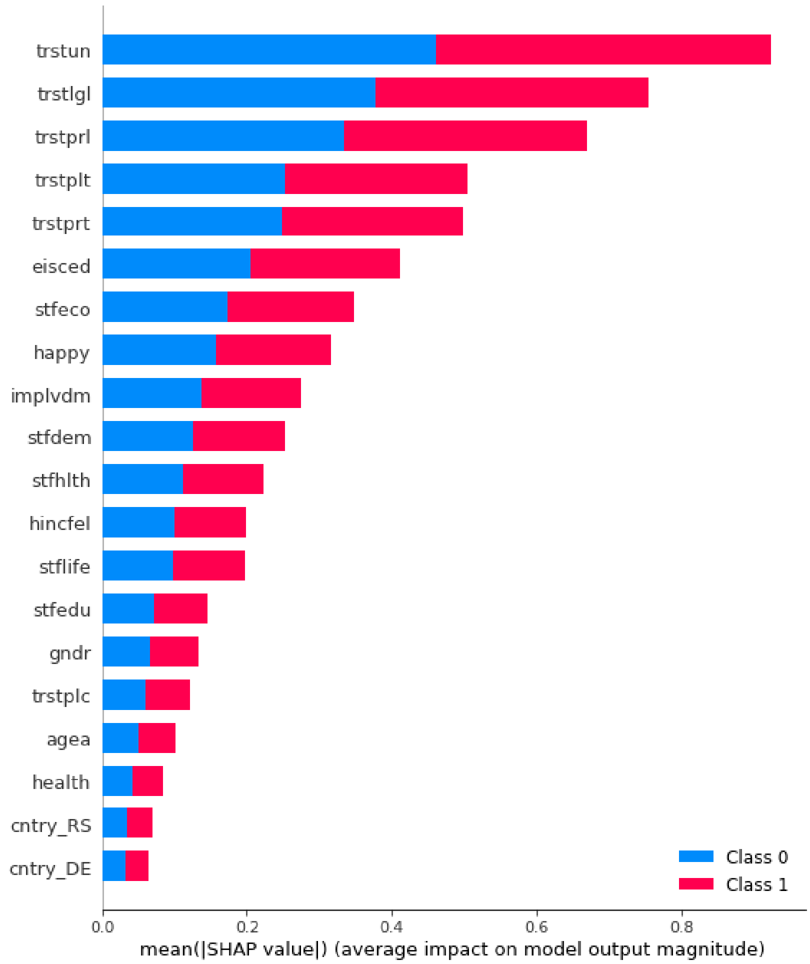


Figure 7 shows the feature importance of the final model by SHAP (SHapley Additive exPlanations) method(Lundberg and Lee 2017). Machine learning models can provide an explanation for their predictions using the SHAP approach. It offers a means of appraising the input characteristics' contribution to model learning and comprehending the model's prediction generation process(Bogdanova, Imakura, and Sakurai 2023). In addition to taking into account a feature's presence, SHAP values consider the feature's relationship to other features as well as how feature values impact model predictions.

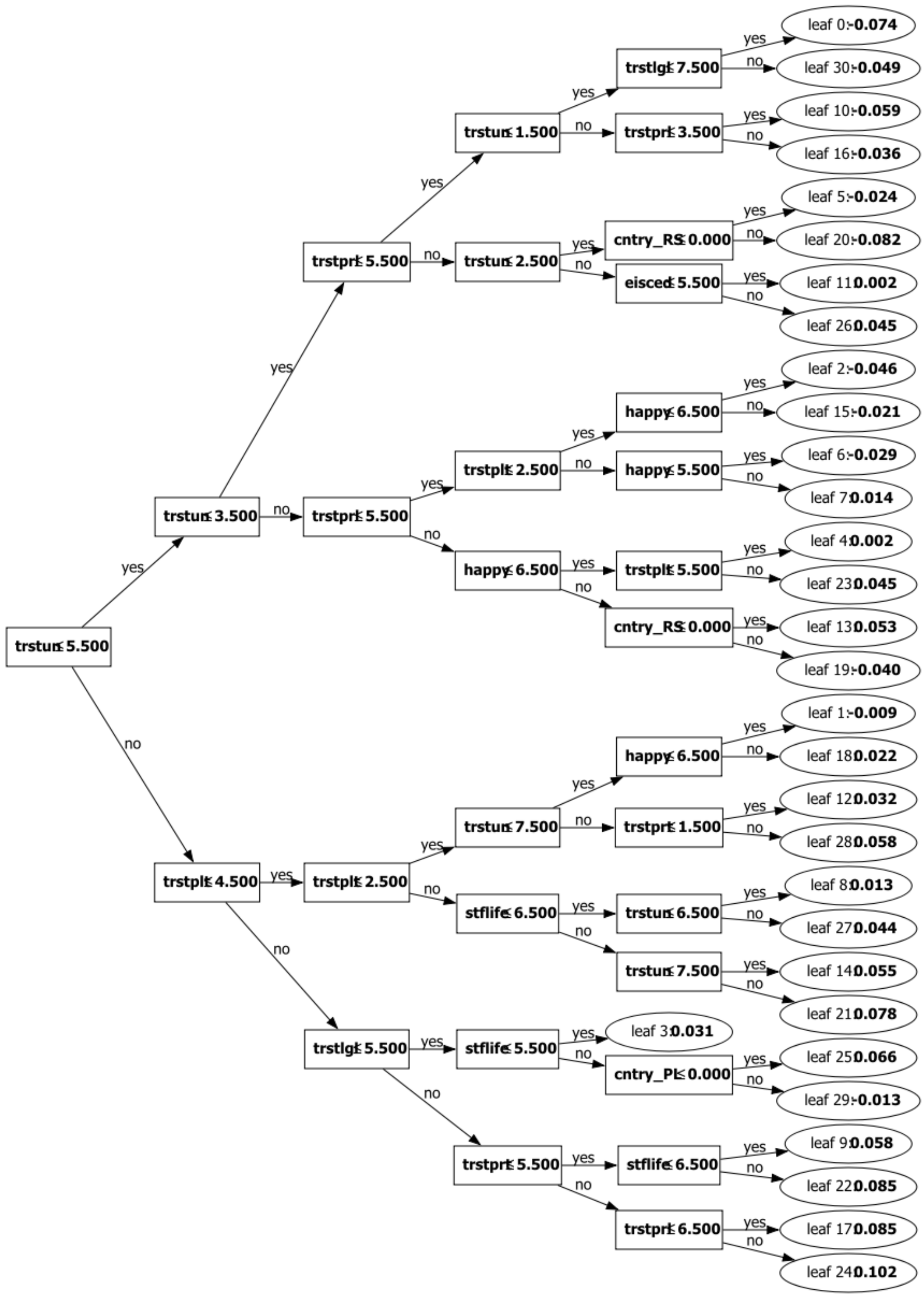
Figure 7: Feature Importance of LightGBM Model Using SHAP (SHapley Additive Explanations) Algorithm



In the final section of LightGBM's tree visualization with Graphviz[1], it was utilized to enhance our understanding of the model's inner workings. Figure 8 provides a clearer interpretation of the data. It is possible to determine which features are considered essential for the model's predictions by looking at the tree structure. Features that are used frequently throughout different trees and at the top of the tree are probably going to be given greater weight. Understanding the model's decision-making process can help with hyperparameter tuning, enabling well-informed choices to be made about variables like tree depth, learning rate, and tree count. Tree visualizations can reveal patterns in the data, such as the relationship between certain feature values and certain predictions. With this goal, based on the main model, LightGBM, a sample of the decision tree model was selected based on the best iteration in the training process and was visualized to have a better understanding of the decision-making process. As is clear in the figure 8, institutional trust still plays a major role in this sample decision tree.

1 https://lightgbm.readthedocs.io/en/latest/pythonapi/lightgbm.plot$_{t}ree.html$

Figure 8: LightGBM Decision Tree Visualization: Understanding the Model's Decision-Making Process



6. Discussion

The study's findings are covered in this section. First, an explanation of the study's goal is given. The study's findings are then described and their interpretation given. Lastly, the study's limitations and recommendations for further study are discussed. The study's contributions round out this part.

6.1 The Goal of the Research

This study set out to investigate if supervised learning approaches may provide novel prospects for understanding and predicting EU societal resilience. To construct a societal resilience index, this study initially delved into theoretical literature in the social sciences. Relevant demographic and attitudinal variables from the ESS Wave 10 social survey were chosen. Following the principles of machine learning methodology, pre-processing and exploratory data analysis were conducted. These stages not only facilitated optimal model application but also enabled a better understanding of the data and their relationships through statistical analysis and data visualization tools. The computation and creation of the societal resilience index, as the target factor for predicting machine learning algorithms, were performed at this stage. Moreover, evaluation metrics such as accuracy and F1 scores were considered for assessing the output of machine learning models, given the binary nature of the target variable. Baseline models like decision trees were utilized, allowing for comparison with the primary models to evaluate the obtained results. Additionally, in the design of primary models, hyperparameter tuning facilitated the identification of appropriate values for model refinement. Utilizing common classifier models, the study involved prediction, examination, and comparison of outputs, aligning with the study's nature and objectives. Simultaneously, data visualization tools and related reports were employed to present a suitable overview of the machine learning implementation stages and executions.

6.2 Findings

The results of this study will be presented in three sub-chapters: findings related to machine learning, sociological findings, and methodological findings.

ML findings: In response to the primary research question concerning the prediction of societal resilience using machine learning models, various algorithms with a set of parameters for tuning were employed. Table 2 presents the best parameters for each of the primary models. The optimal model for predicting societal resilience was the LightGBM model, achieving an F1 score of 0.781. This score was nearly replicated across other tuned models, exhibiting considerable improvement compared to the baseline model.

As highlighted in The study of Erhard and Heiberger(Skopek 2023), implementing machine learning models in social research represents a novel approach. Considering the fact that the data was realised in 2022, limited studies exist for comparing model outputs. Among these is the Shwaming study(Chen, Yang, and Lin 2022), which predicted happiness levels among immigrants or native Europeans using data from the first to ninth rounds of the European Social Survey. The average F1 scale of various models in this study was below 0.66 for both groups, whereas the current study achieved a higher score. Additionally, in models executed by Lucas Berry(Skopek 2023) on Wave 1 of the European Social Survey for predicting dichotomized attitudes towards immigration, the F1 score remains at 0.735, which is lower than the outputs of the tuned models in the present research.

Sociological findings: In response to the second research question on the influence and participation of social and attitudinal factors in predicting societal resilience, both traditional statistical paradigms and machine learning methodologies were applied. The findings of this section, primarily derived from unique social insights, hold significant importance. As previously indicated, the construct of societal resilience, based on social science literature and concepts like individual and institutional social trust and the sense of social belonging, was established. The computation of this construct relied on common methodologies in social sciences. In qualitative research and analysis of social surveys, demographic variables traditionally assume a significant role in analyzing indices. However, the findings in Figure 2 suggest a lesser significance of these variables, such as age, gender, highest educational attainment on the societal resilience index.

Moreover, Figure 3 demonstrates a negative correlation between income satisfaction, health, and societal resilience. In essence, considering income satisfaction and health as indicators of individual independence versus reliance on social institutions, individuals with higher independence may exhibit lower positions in societal resilience and potentially engage less in accepted collective responses during social crises.

On one hand, the findings indicate that while demographic variables, both subjective or objective , do not significantly predict societal resilience, as illustrated in Figure 7, institutional trust, especially trust in entities like the United Nations, the judicial system, or political institutions, plays a crucial role in determining individuals' societal resilience levels. Figure 8, portraying the best decision tree created in the primary model, reiterates the importance of trust in political institutions such as UN and country's parliament. Figure 2 also exhibits a strong correlation between trust in these institutions and satisfaction with the implemented democracy mechanisms in the country.

In other words, these insights suggest that societal resilience has a substantial correlation with democratic mechanisms. Particularly in the LightGBM model, as highlighted in Figure 7 concerning the average impact of factors on the model output, trust in the United Nations holds the highest influence on predicting societal resilience. This finding underscores the symbolic capital of the United Nations in the societal resilience of European Union countries. Essentially, EU countries, particularly in policymaking contexts, especially during crises, should consider the functions and reputation of the United Nations as symbolic capital. EU countries not only as donor nations but also as recipients should prioritize optimizing the functions, roles, and positive reputation of the United Nations, viewing this investment as part of appropriate social intervention mechanisms to address crises.

Methodological findings: Another aspect of the findings in this study pertains to cognitive methodology. At the beginning of the research, during the index preparation phase, efforts were made to construct the target as per of its constituent factors within a Likert scale spectrum ranging from 0 to 10. However, when implementing the models, the outputs did not yield desirable results, likely due to respondents' inclination towards responses focused on the middle of the spectrum. In other words, the responses were somewhat ambiguous, making prediction challenging for the algorithms. As a result, and considering traditional and accepted statistical solutions in social sciences

(MacNell et al. 2023), the target variable was transformed into binary states, leading to more suitable results, as detailed in this research report.

Therefore, considering the inclination of data analysts in social sciences towards utilizing machine learning paradigms, it's suggested that if survey studies aim to predict social constructs, attention should be paid to this matter. While designing the questionnaire structure, it might be beneficial to incorporate spectrums that reduce the potential for ambiguous responses. This would align with the objectives of predicting social structures or constructs in survey-based studies and optimize the compatibility of data collection methods with machine learning approaches.

6.3 Limitations and Future Research

While this study has made significant contributions to the understanding of societal resilience, it is important to acknowledge and address its limitations.

In his study, Nathaniel MacNell(MacNell et al. 2023) highlights the widespread use of complex survey data in social research and the increasing popularity of machine learning techniques. However, there is a lack of machine learning software implementations that can effectively handle complex samples.

Therefore, considering the outcomes of the same study and having a sufficient number of research samples in the dataset, common machine learning algorithms were employed without the utilization of weighted variables. However, it is suggested that in future research endeavors, solutions suitable for weighted variables should also be considered. Especially in cases where the data volume is less than 10,000 instances or when the research encompasses subgroups that have been adjusted by weighted variables in the sampling process. To mitigate this limitation, future research should explore the use of machine learning models that are specifically designed for weighted data, such as exploring the library(survey) in R language programming. This library provides a comprehensive set of tools for analyzing survey data, including methods for handling weighted data. By incorporating these methods into machine learning models, researchers can ensure that the predictions are based on a representative sample of the population and are not biased by the sampling design. This method could potentially improve the accuracy and generalizability of the predictions, especially in situations where the data is not as large or where the sample includes subgroups with different sampling weights. Another option is to explore ensemble methods, which combine multiple machine learning models into a single model that can potentially outperform any individual model. These methods can be particularly effective in dealing with weighted data, as they can help to mitigate the effects of any bias that may be present in the individual models.

Also, current research has primarily focused on cross-sectional data. Future research could conduct longitudinal studies to track changes in societal resilience over time and identify the factors that influence these changes.

Additionally, future research could assess the effectiveness of different interventions aimed at enhancing societal resilience, such as social cohesion programs, community engagement initiatives, and educational programs.

Despite these limitations, the present study contributes to a growing body of knowledge on the use of machine learning in social research and the predictive modeling of societal resilience. The findings offer valuable insights for policymakers and practitioners seeking to enhance societal resilience in Europe. However, by addressing these limitations, future research can further advance the understanding of societal resilience and contribute to the development of more effective interventions for promoting resilience in European societies.

7. Conclusion

In this study, the primary objective was to investigate the potential of supervised learning in unraveling and foreseeing societal resilience within the European Union context. Initially, the study embarked on constructing a resilience index sourced from ESS Wave 10 data. This process involved meticulous exploration of theoretical frameworks in social sciences, aiming to identify pertinent demographic and attitudinal variables crucial for the index's formulation.

Implementing machine learning methodologies, the research engaged in preprocessing and exploratory data analysis, essential for both optimal model application and comprehensive comprehension of data dynamics. Through these stages, a societal resilience index was formulated, serving as the pivotal target for machine learning algorithm predictions.

The findings uncovered several pivotal insights. Notably, the LightGBM model emerged as the most effective predictor, boasting an F1 score of 0.781, demonstrating significant improvement compared to baseline models and earlier research endeavors.

On a sociological front, the study shed light on intriguing patterns. While demographic variables displayed limited influence on societal resilience, trust in institutional entities—particularly the United Nations and political institutions—exerted substantial impact. This correlation underscored the intertwining relationship between societal resilience and democratic mechanisms, advocating for enhanced trust-building during moments of crisis within political institutions.

However, methodological challenges surfaced during the study. The attempt to construct indices within Likert scales faced complications due to respondents' inclination toward middle-range responses, resulting in ambiguous outputs for machine learning models. The adoption of binary states for the target variable ultimately led to more coherent and interpretable results, offering a critical insight for future survey designs.

Acknowledging its limitations, particularly in addressing weighted variables, the study still highlights the pioneering use of machine learning in social research. It illuminates pathways for predicting societal resilience while suggesting avenues for future studies to incorporate weighted variables in machine learning approaches effectively.

In essence, this study not only delved into the forefront of machine learning's application in social research but also unveiled crucial societal dynamics, emphasizing the intertwined relationship between institutional trust, democratic mechanisms, and societal resilience within the EU context.

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1. Appendix: Countries

Country					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	AT	2003	3.4	3.4	3.4
	BE	1341	2.2	2.2	5.6
	BG	2718	4.6	4.6	10.2
	CH	1523	2.6	2.6	12.7
	CY	875	1.5	1.5	14.2
	CZ	2476	4.1	4.1	18.3
	DE	8725	14.6	14.6	32.9
	EE	1542	2.6	2.6	35.5
	ES	2283	3.8	3.8	39.3
	FI	1577	2.6	2.6	42.0
	FR	1977	3.3	3.3	45.3
	GB	1149	1.9	1.9	47.2
	GR	2799	4.7	4.7	51.9
	HR	1592	2.7	2.7	54.6
	HU	1849	3.1	3.1	57.7
	IE	1770	3.0	3.0	60.7
	IL	1308	2.2	2.2	62.8
	IS	903	1.5	1.5	64.4
	IT	2640	4.4	4.4	68.8
	LT	1659	2.8	2.8	71.6
	LV	1023	1.7	1.7	73.3
	ME	1278	2.1	2.1	75.4
	MK	1429	2.4	2.4	77.8
	NL	1470	2.5	2.5	80.3
	NO	1411	2.4	2.4	82.6
	PL	2065	3.5	3.5	86.1
	PT	1838	3.1	3.1	89.2
	RS	1505	2.5	2.5	91.7
	SE	2287	3.8	3.8	95.5
	SI	1252	2.1	2.1	97.6
	SK	1418	2.4	2.4	100.0
	Total	59685	100.0	100.0	

2. Appendix: Missing percentage of Variables

	Variable	Missing Percentage
0	cntry	0.000000
1	stflife	0.916478
2	stfeco	1.779342
3	stfgov	2.094329
4	stfdem	2.022284
5	stfedu	3.530200
6	stfhlth	0.819301
7	happy	0.593114
8	health	0.445673
9	rlgdgr	1.529698
10	ctzcntr	0.641702
11	brncntr	0.464103
12	implvdm	1.310212
13	gndr	1.063919
14	agea	2.241769
15	eisced	1.814526
16	hincfel	3.059395
17	atcherp	1.476083
18	ppltrst	0.459077
19	trstep	4.677892
20	trstlgl	1.536399
21	trstplc	0.846109
22	trstplt	1.311887
23	trstprt	1.605093
24	trstun	5.691547
25	trstprl	1.744157

3. Appendix: Descriptive statistics of Variables

Table 4: Descriptive statistics of Variables

Stat.	stflife	stfeco	stfgov	stfdem	stfedu	stfhlth	trstprl	ctzcntr	eisced
count	59685	59685	59685	59685	59685	59685	59685	59685	59685
mean	6.99	4.84	4.37	5.25	5.16	5.49	4.51	1.05	4.26
std	2.22	2.52	2.64	2.66	2.51	2.67	2.71	0.21	1.78
min	0	0	0	0	0	0	0	1	1
25%	6	3	2	3	3	4	2	1	3
50%	7	5	5	5	5	6	5	1	4
75%	8	7	6	7	7	8	7	1	6
max	10	10	10	10	10	10	10	2	7

Stat.	happy	trstep	trstlgl	trstplc	trstplt	trstprt	trstun	resilience	agea
count	59685	59685	59685	59685	59685	59685	59685	59685	59685
mean	7.13	4.52	5.23	6.24	3.45	3.43	4.95	0.50	50.48
std	2.02	2.59	2.81	2.61	2.50	2.44	2.61	0.50	18.34
min	0	0	0	0	0	0	0	0	15
25%	6	3	3	5	1	1	3	0	36
50%	8	5	5	7	3	3	5	1	51
75%	8	6	8	8	5	5	7	1	65
max	10	10	10	10	10	10	10	1	90

Stat.	health	rlgdgr	hincfel	atcherp	ppltrst	brncntr	implvdm	gndr
count	59685	59685	59685	59685	59685	59685	59685	59685
mean	2.19	4.46	1.95	5.86	4.77	1.09	8.81	1.53
std	0.90	3.13	0.82	2.68	2.67	0.28	1.95	0.50
min	1	0	1	0	0	1	0	1
25%	2	2	1	5	3	1	8	1
50%	2	5	2	6	5	1	10	2
75%	3	7	2	8	7	1	10	2
max	5	10	4	10	10	2	10	2

4. Appendix: 3d Loss Surface - 2 dimensional perspective