

**Department of Mathematics**

Master in Data Science

*Is Our House on Fire?*

*Analysis and Prediction of European Attitudes towards Climate Change.*

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Chapter 1

# Literature Review

In recent years, scholars have increasingly paid attention to public opinion about environmental issues in the United States (Brulle et al., 2012; Driscoll, 2019; Egan & Mullin, 2017; O’Connor et al., 1999; Shwom et al., 2015), in the European Countries (Lorenzoni & Pidgeon, 2006; Vainio & Paloniemi, 2013) and around the world (Lee et al., 2015; Sun & Han, 2018). “Public opinion on climate change[[1]](#footnote-1) is multidimensional, dynamic, and differentiated. […] It includes, among others, beliefs about anthropogenic climate change, perceptions of climate change risks, concern about its seriousness, and thoughts on what, if anything, should be done to address it” (Shwom et al., 2015, p. 269). Public opinion changes over time and space due to individual, socio-cultural, political, economic, habitat factors (Shwom et al., 2015). We use the term “climate change public opinion” to report attitudes, beliefs, concerns, and worries of people in the environmental field. Besides, a complimentary issue of public opinion is behaviour. Scholars have found an important relationship between an individual’s “green behaviours”, and therefore all actions to safeguard the environment, and his/her attitudes regarding climate change (Lacasse, 2015; O’Connor et al., 1999; Vainio & Paloniemi, 2013). Lacasse (2015), a professor of Environmental Psychology, suggests that beliefs could not be always the reason for the actions performed, but on the contrary attitudes could be used to justify the behaviour.

Climate change is a complex, uncertain, and abstract phenomenon, most citizens get information from mass media, and they do not experience it directly (Vainio & Paloniemi, 2013). This uncertainty makes opinions even more ambiguous since people have difficulty evaluating the consequences of their actions and solutions or understanding risks. According to the Special Eurobarometer 91.3 entitled ‘Climate change’, only 20% of citizens in Europe claim that climate change is the single most serious problem facing the world (European Commission, Brussels, 2019). Climate change is considered less important than hunger and poverty in the world. On the one hand, 20% of Europeans perceived the seriousness of climate change; on the other hand, 80% of them take place some environmental-friendly actions to reduce the phenomenon. Therefore, there is a discrepancy between concern and behaviour (Lacroix & Gifford, 2018; Vainio & Paloniemi, 2013). Probably, an individual takes place action only whether he/she knows that he/she can make a difference and if he/she knows that other citizens and governments are moving in the same direction as a safe planet (Lorenzoni & Pidgeon, 2006). Therefore, the relationship between action and attitude also becomes very complex and not obvious.

To sum up, the following chapter focuses on presenting the topic of the research: environmental-friendly behaviour. Also, we evidence the important and complicated relationship between pro-environmental behaviour and attitudes toward climate change, focusing on climate change risk perception. Lastly, scholars suggest other relevant variables for comprehension of risk perception and behaviour in environmentalism, particularly demographic information, such as gender, age, education, and political orientation.

* 1. **Climate Change Risk Perception** 
     1. **The Concept of Risk Perception**

Slovic (1987), a psychology professor at the University of Oregon, affirms that risk perception varies according to inter and intrapersonal, geographical, cultural, and social influences. In this way, an “objective” risk perception does not exist (Yu et al., 2019). Nevertheless, some factors define perception risk, such as “dread risk” and “unknown risk”: the more a phenomenon is considered unpredictable, uncontrollable, with catastrophic consequences, and mostly it is invisible, the more perceived hazard or risk increases (Slovic, 1987). For example, people judge nuclear technology as riskier than car accidents, since the first has catastrophic consequences and it is uncontrollable and invisible (Slovic, 1987). According to the professor, perceived risk is a mental and social construction, created to help people tackle uncertainty or danger (Slovic & Weber, 2002). “It does not exist “out there,” independent of our minds and cultures” (Slovic & Weber, 2002, p. 4).

Risk perceptions are shaped and influenced by different environmental field factors, which can be grouped into four categories, suggested in van der Linden’s (2015) Climate Change Risk Perception Model (CCRPM): sociodemographic, cognitive, experiential, and socio-cultural. All these dimensions lead to change and shape the individual level of risk perception. In the next sections, these categories are explained in detail.

The utility of that overview is to comprehend the precursors to climate change risk perception. This variable, used as a predictor in the pro-environmental behaviour model, is fundamental in our study, and therefore it is important to theoretically describe what causes and conditions could be related to individual risk perception.

* + 1. **Sociodemographic Dimension**

Sociodemographic factors are related to climate change risk perception, such as gender, education level, age, marital status, city/town size, income, and political orientation.

In literature, females tend to have more concerns than males for many hazards (Finucane et al., 2000) also in environmental issues (Davidson & Haan, 2012; Goldsmith et al., 2013; O’Connor et al., 1999; Zhou et al., 2020). One explanation of the gender gap could be that women are more likely to have “a stronger sense of social responsibility and affinity for taking others’ perspectives” (Goldsmith et al., 2013, p. 6), and for this reason, they are more concerned than male.

Also, some studies find that education level is positively correlated with risk perception (Meyer, 2015). The reason why more educated people tend to be more informed on the topic and more aware of the consequences of their actions (Meyer, 2015; Sun & Han, 2018).

Recent studies demonstrated that younger adults are more worried about the consequences of climate change than older (Echavarren et al., 2019; Sun & Han, 2018; Weber, 2016). However, the reasons for this divergence could be two: the *ageing effect* and the *cohort* *effect*, which are the result of being at a certain age point or belonging to a particular generation (Torgler & García-Valiñas, 2007). This last option could explain the difference in attitudes between two different generations due to generational variations in socialization and lifestyle (Torgler & García-Valiñas, 2007). Scholars have begun to alert and mobilize citizens about climate change in the last few decades.

Regarding marital status, the literature suggests that it may influence environmentalism, especially married individuals and/or with children are more worried about climate change since they think about children’s future than single (Torgler & García-Valiñas, 2007).

Additionally, the relationship between the place where individual lives and risk perception is not clear. On one side, citizens who are located in rural should be more in contact with nature, and therefore they should have more environmental values, on the other side, those who live in a city are more active in the environmental policies (Torgler & García-Valiñas, 2007).

The economic situation is also correlated with environmental attitudes and therefore, with risk perception. In general, wealthier people expect a clean and healthy planet (Torgler & García-Valiñas, 2007).

Lastly, political ideology. American literature suggests that Democrats and Liberals are more likely to believe and to concern about climate change than Republicans and Conservatives (Davidson & Haan, 2012; Egan & Mullin, 2017; Fielding et al., 2012; Liu et al., 2014; McCright, 2011). McCright, Dunlap, and Marquart-Pyatt (2016), some of the most important sociologists in Environmental Sociology, extend these findings in the European Union. However, in Europe, the distinction between Democrats (left) and Republicans (right) is not clear and uniform. In Western Europe, the left is related to change and equality, instead of in former Communist countries, this identification cannot be found (McCright et al., 2016). They extend the same findings, thus a polarization of climate change, in only Western countries: citizens on the right are unlikely to recognize the phenomenon as a serious issue than those on the left (McCright et al., 2016). Even though “the effect of left-right ideology in Western Europe is considerably weaker than the effect of political ideology (and party identification) in the USA” (McCright et al., 2016, p. 13). Instead, citizens of Eastern Europe are not divided from an ideological point of view on that topic, due to the irrelevance of political issues and then the difference ideologization and identification of left-right (McCright et al., 2016).

To summarize more educated and liberal young women are more likely to show a higher risk perception level than older and conservative men (Xie et al., 2019).

* + 1. **Cognitive Dimension**

Knowledge is the main factor in the cognitive dimension related to climate change risk perception (Bradley et al., 2020; Hidalgo & Pisano, 2010; O’Connor et al., 1999). Van der Liden (2015), professor of Social Psychology at the University of Cambridge, suggests that knowledge about the causes or impact of climate change can improve individuals’ concerns. The professor empathizes that we cannot make this critical distinction “between an individual's “subjective” knowledge (i.e., what people think is true) and the actual “evidence” (insofar a clear scientific consensus exists, e.g., that burning fossil fuels contributes to climate change) (van der Linden, 2015, p. 114). However, people with accurate knowledge of the phenomenon seem to perceive it as a serious problem and, at the same time, they want to fight it (Bradley et al., 2020; Hidalgo & Pisano, 2010).

* + 1. **Experiential Dimension**

This section points to the importance of emotions or affects and personal experiences with natural disasters in risk perception.

Firstly, emotion. “Risk as feeling” refers to an instinctive reaction to danger: people immediately judge a potential problem as positive or negative feelings (Slovic & Peters, 2006). More the immediate feeling is negative, more risk perception increase. When an individual begins to use this feeling as the first influencer of behaviour, it means that emotion is called “the affect heuristic” (Slovic & Peters, 2006). Some researchers evidence that affect is a predictor of climate change risk perception, and therefore negative feelings increase concern (van der Linden, 2015). On the contrary, Taylor et colleagues (2014) declare that extreme negative emotions can create the opposite effect: fear and anxiety can lead to greater psychological distance and apathy towards climate change.

Secondly, personal experiences with a hazard or extreme weather events, such as extraordinarily hot or cold weather, storms flooding, and forest fires, can increase perceived risk (van der Linden, 2015). Nevertheless, direct climate change experiences are not always possible, but all information is influenced by mass media (van der Linden, 2015). Nevertheless, familiarity with extraordinary weather events makes risk more concrete and real, increasing concern and decreasing the distance from danger psychologically (Akerlof et al., 2013; Bradley et al., 2020; Taylor et al., 2014; van der Linden, 2015).

* + 1. **Socio-cultural Dimension**

One of the most important approaches to risk perception is the cultural theory defined by Mary Douglas in the 1960s. According to theory, risks are a social construction, and they depend on: “(a) the form of social relationships people maintain; (b) cultural biases such as shared values ​​and beliefs including views on human nature, views on society, risk perceptions, and so-called myths of nature, which especially refer to biases toward environmental risks; and (c) preferred behavioural strategies” (Steg & Sievers, 2000, p. 251). Cultural theory suggests that people can be divided into four groups based on their worldview and values: fatalists, hierarchists, individualists, and egalitarians, based on their attitudes and perception (Steg & Sievers, 2000). Fatalists perceive the reality as the product of chance, and it is out of human control, hierarchists appreciate hierarchies and institutional values, and for them, nature can be safeguarded by regulations; individualists focus attention on personal freedom and they see nature as benign, lastly, egalitarians emphasize group welfare, and for them nature is fragile (Taylor et al., 2014; Wildavsky & Dake, 1990).

Various studies have found a significant relationship between “cultural worldview” and attitudes toward climate change (Steg & Sievers, 2000; Taylor et al., 2014). For example, the values of egalitarians are positively correlated with environmentalism, while individualists’ values are negatively correlated with it (Steg & Sievers, 2000).

* 1. **Pro-environmental Behaviour**

“Pro-environmental behaviour is most commonly defined as ‘intentionally reducing the negative impact that an action can have on the environment” (Dono et al., 2010, p. 178). Generally, scientists mean pro-environmental behaviour like walking, recycling, energy saving. It is an intent-oriented definition, which is different from an impact-oriented one: the first highlights the action as such, it may not produce an environmental impact, the second must necessarily have a sustainable effect (Stern, 2000). When scholars focus on individual attitudes or motives to understand behaviour, as in this case, they adopt an intent-oriented definition (Stern, 2000).

* + 1. **Types of Pro-environmental Behaviour**

According to Stern (2000), president and senior scholar of the Social and Environmental Research Institute, there are four different environmental behaviour types: environmental activism, nonactivist behaviours in the public sphere, private-sphere environmentalism, other environmentally significant behaviours.

Environmental activism concerns citizens' active involvement in manifestation and organizations (Dono et al., 2010; Stern, 2000).

Nonactivist behaviours in the public sphereconcern individuals who support public policies or environmental citizenship, their actions have a positive, but indirect, impact on the environment (Stern, 2000).

Private-sphere environmentalismrefers simply to green consumers in the home and personal field. (Stern, 2000).

Lastly, other environmentally significant behaviours refer to individuals who positively impact the environment even if other behaviours, such as a worker, can influence pro-environmental actions of the organization to which he/she belongs (Stern, 2000).

* + 1. **Factors influencing Pro-environmental Behaviour**

Sociologists suggest that pro-environmental behaviour is not only motivated by environmental attitudes (Stern, 2000). There are also psychological, social, and economic factors that can influence and mitigate behaviour (Whitmarsh & O’Neill, 2010). We can organize these factors into three main groups: internal, external factors, and again, sociodemographic.

***Internal Factors***

Internal factors are motivation, environmental knowledge, attitudes, emotion (Kollmuss & Agyeman, 2002). One of the most important theories which aim to predict behaviour is the theory of planned behaviour (TPB). It affirms behaviour is determined by attitudes towards that action, subjective norms, and perceived behavioural control (Oreg & Katz-Gerro, 2006; Whitmarsh & O’Neill, 2010). Therefore, actual behaviour is determined by behavioural intention, which has its turn is influenced by both attitudes and social, or normative, pressures (Kollmuss & Agyeman, 2002).

Generally, as just shown with the theory, motivation, values, knowledge are interconnected. Motivation (unconscious or conscious) drives action and it could be shaped also linked by environmental knowledge and awareness (Kollmuss & Agyeman, 2002). Also, values, influenced by social networks (family, peer-groups, education), shape motivation and behaviour. “The more strongly individuals subscribe to values beyond their own immediate interests, that is, self-transcendent, prosocial, altruistic or biospheric values, the more likely they are to engage in pro-environmental behaviour” (Steg & Vlek, 2009, p. 311). Finally, emotions. Emotional involvement is shaped by knowledge about the topic since as we have already shown, climate change is an abstract and complex problem (Kollmuss & Agyeman, 2002). However, some individuals experience climate change (extreme atmospheric phenomena) directly and then they feel fear, anger, guilt (Kollmuss & Agyeman, 2002). These extreme negative feelings can lead to refusal to accept reality, rational distancing from the problem, apathy, and delegation of personal responsibility (Kollmuss & Agyeman, 2002). Therefore, whether the emotion is too strong and extreme can prevent and block behaviour.

We can summarize that mainly attitudes, values, or experiences have a powerful influence on behaviour. An extraordinary conception is that they are not always positively related to pro-environmental action. Sometimes, whether the perceived risk is too high or whether the lived experience is extremely negative, the opposite effect is obtained.

***External Factors***

It is also important to take into account the context where individuals are embedded. According to Kollmuss & Agyeman (2002), institutional, economic, and socio-cultural factors influence individuals’ behaviour. Firstly, “many pro-environmental behaviours can only take place if the necessary infrastructure is provided (e.g. recycling, taking public transportation)” (Kollmuss & Agyeman, 2002, p. 248). It is evident that if there is no public transport, an individual can not take place an environmental-friendly action. Then, economic factors are essential in the decision-making process. People could be partially influenced by monetary motives to behave pro-environmentally, and therefore vice-versa for expensive ones and consequently the lack of pro-environmental action. Lastly, cultural norms and cross-cultural differences represent an influential role in shaping people’s performance (Kollmuss & Agyeman, 2002; Oreg & Katz-Gerro, 2006). Socially accepted behaviour vary by country and culture and can impact behavioural patterns at the individual level.

***Sociodemographic factors***

According to Larson and colleges (2011), the effect of sociodemographic characteristics on pro-environmental behaviour has not been satisfactorily investigated, instead of the relationship on attitudes, as widely discussed above with perceived risk. Traditionally, poor, and uneducated citizens show lower pro-environmental behaviour than rich and highly educated ones (Larson et al., 2011). Being more concerned, women more likely to behave sustainably (Larson et al., 2011; Vicente-Molina et al., 2018). As we have already explained, this gap could be due to gender socialization theory: women should be more cooperative, empathic, and protective (in this case towards nature) than men (Vicente-Molina et al., 2018). Therefore, similar to risk perception, green consumers, or more in general environmentally activists, are “young, female, well educated, liberal and wealthy” (Gilg et al., 2005, p. 484).

### **Self-reported Behaviour**

In social research, a standard measurement of pro-environmental behaviour is based on respondents’ self-reports through questionnaire items (Steg & Vlek, 2009). Self-reported data reports what individuals believe they have done, and it is in contrast with behavioural data (Veltri, 2019). A problem arises due to individuals may not give an accurate and truthful answer to their actual behaviour (Gatersleben et al., 2002). “Self-reported behaviour reflects perceptions or beliefs about people’s behaviour rather than their actual behaviour. Factors such as social desirability and other types of (conscious or unconscious) response bias may result in inaccurate reports of actual behaviour” (Gatersleben et al., 2002, p. 337). Therefore, when an interviewer asks about behaviour, it is probably that interviewee refers his/her intention rather than his/her concrete behaviour (Chao & Lam, 2011). Social responsibility and social desirability can lead to provide inaccurate information of behaviour (Chao & Lam, 2011; Veltri, 2019). Whether on one side the amount of individuals’ pro-environmental behaviour could be overestimated and not entirely precise, on the other side dichotomized questions about self-reported behaviours (“I do” or “I don’t”) result more accurate and reliable (Kaiser et al., 2003).

* 1. **From Climate Risk Perception to Pro-environmental Behaviour**

In the previous sections, we described two main concepts of research: climate change risk perception and pro-environmental behaviour. These two concepts are partially separated from each other. One does not automatically involve the other. Literature is not clear about their relationship. Some research demonstrates the importance of climate change risk perception to predict pro-environmental behaviour (Xie et al., 2019; Yu et al., 2019; Zhou et al., 2020). Greater risk perception is positively correlated with pro-environmental action, becoming the main predictor and intermediary on behavioural (Xie et al., 2019). When people became aware and then concerned about the issue, they are more likely to behave eco-sustainably to mitigate and fight the environmental problem (Zhou et al., 2020). Instead, Stern (2000) and O’Connor and colleagues (1999) suggest that risk perception could fail to conduct pro-environmental behaviours. Two individuals who have the same level of concern may react by having completely divergent behaviour (Zeng et al., 2020). The reason is that other factors influence the decision-making process. Eco-friendly behaviour may be motived simply by financial interests and not by a high risk perception (Stern, 2000). Otherwise, as we have seen in the paragraph above, high risk perception may lead to apathy or to reject reality and therefore no pro-environmental actions are implemented (Kollmuss & Agyeman, 2002). This discrepancy is called the value-action gap (Lacroix & Gifford, 2018).



Figure 1:A schematic overview of Protection Motivation Theory (explained by Bubeck et al., 2018)

An explanation for this value-action gap is provided by the protection motivation theory (PMT), explained by Bubeck end colleagues (2018) and shown in figure 1. It has become popular to explain “the risk-reducing behaviour of residents against natural hazards” (Bubeck et al., 2018, p. 1239). According to the theory, the decision of pro-environmental behaviour or not is driven by two different cognitive processes: threat appraisal (or referred to as “risk perception”) and coping appraisal (Bubeck et al., 2018). When a threshold of risk perception (threat appraisal) is exceeded, the individual begins to adopt a possible measure to reduce the threat, called coping appraisal (Bubeck et al., 2018). This latter includes three factors: “the perceived effectiveness of a certain measure (response efficacy), the perceived ability to implement the respective measure (self-efficacy), and the perceived costs associated with its implementation (response cost)” (Bubeck et al., 2018, p. 1240). The interaction between risk perception and coping appraisal affects behaviour. If an individual has deep concern and high coping appraisal, then he/she will have pro-environmental behaviour, otherwise, if he/she has high-risk perception but low coping appraisal then he/she will nonprotective response (Bubeck et al., 2018). However, nowadays, there is the revised theory introduced by Rogers, who adds some variables that influence risk perception and coping appraisal: environmental and intrapersonal sources (Bubeck et al., 2018). Prior experiences, sociodemographic, personal attitudes, and contextual factors may influence and modify these two dimensions, affecting the behavioural response.

Chapter 2

# Data and Method

## **2.1 Research Questions**

The first chapter explores the main theoretical aspects that are related to attitudes towards climate change. Many elements are presented: climate change risk perception, pro-environmental behaviour, and their respective factors that influence them. All these concepts are interconnected with each other. Thus, firstly it is important to understand the aim of the research. The study focuses on the prediction and classification of pro-environmental behaviour in European countries. As explained in the literate review, external and internal conditions, such as sociodemographic characteristics, beliefs, and concerns towards climate change can lead to encouraging eco-friendly behaviour. The aim is to focus on an individual level, macro-variables are not considered in the analysis due to computational reasons. Therefore, the study wants to understand what of these factors and predictors directly influence pro-environmental behaviour. In this case, the research examines intent-oriented behaviour since attitudes and motivation are investigated and not the real environmental impact. Another important point to highlight is that there is no distinction between different types of pro-environmental behaviours. All actions, from activism to environmentalists in the private sphere, are taken into account.

According to the literature, the selected sociodemographic features are gender, age, education level, residence location, economic and marital status, political orientation, and country where the individual belongs. Climate Change risk perception, types of green identities and cultural schemas (more details on these two concepts in the next section) are added as predictors.

This model chooses these predictors to primarily test the role of climate change risk perception due to its ambivalence. Overall, the next chapter wants to answer the following questions: what are the most significant characteristics of those who behave environmentally? What is the role of climate change risk perception?

Therefore, according to the existing literature, it is assumed that:

Hp1: higher individual climate change risk perception positively influences and predicts pro-environmental behaviour;

Hp2: citizens’ positive attitudes towards climate change positively influence their pro-environmental behaviour;

Hp3: different citizens’ cultural schemas towards climate shape contrasting behaviour;

Hp4: Demographic characteristics effect on pro-environmental behaviour, in particular:

1. Higher education has a positive effect on pro-environmental behaviour;
2. Women are more likely to take place pro-environmental behaviour;
3. Higher-income has a positive effect on pro-environmental behaviour;
4. Youngers are more likely to take place pro-environmental behaviour;
5. left-wing individuals are more likely to take place pro-environmental behaviour.

In the second part of the analysis, we still want to understand the main factors to predict behaviour, but separately between two groups of those who worry about climate change and those who not. The illustrated literature especially shows the importance of risk perception in predicting action. However, no study has tried to understand what variables influence and vary behaviour whether the level of risk perception changes. Some controversial examples are explained to evidence that a causal relationship between risk perception and behaviour does not exist. This part aims to denote what features and factors emerge in predicting behaviour, but among those who have the same level of climate change risk perception. Therefore, the next questions are: what are the most significant features that classify and predict the behaviour of those with a high climate change risk perception? And those of those who have a low perception of risk? The relevance of the investigation is to cover the existing gap in the literature answering these questions.

It is assumed that:

Hp5: different features classify behaviour in the two subgroups.

## **2.2 Methodology**

As already explained, the research mainly consists of two different parts: in the first, unsupervised learning algorithms are adopted to obtain citizens' profiles, and in the second, supervised learning algorithms are used to classify and predict pro-environment behaviour.

### **2.2.1 Unsupervised Machine Learning Algorithms**

The first set of methods focuses on identifying some citizens' profiles using different types of unsupervised learning techniques: Partition around medoids (PAM) clustering and Correlational Class Analysis (CCA). Unsupervised learning techniques look for unknown and hidden patterns.

PAM is a type of clustering, used primarily for categorical features (Shendre, 2020). It seeks to identify a finite set of clusters or subgroups to describe data (Fonseca, 2013; James et al., 2013). This method creates some subgroups to maximize both the similarity within clusters and the differences among other groups. This algorithm adopts Gower distance which calculates the distance between two objects whose properties are a mix of categorical and quantitative values (Shendre, 2020). Clustering is used to obtain profiles of citizens with similar attitudes toward climate change.

Correlational Class Analysis (CCA) identifies such “cultural schemas” in survey data, in particular in public opinion data (Boutyline, 2017; Rossoni et al., 2020). This technique is an implementation of Relational Class Analysis (RCA) developed by Goldberg (2011) and it “seeks to parse out groups, or classes, of like-minded individuals. Unlike these methods, however, it uses relationality to compare these individuals not on their attitudes per se but on the patterns of relations between their attitudes” (p.1399). Therefore, the goal of RCA is to partition individuals into groups that shared “cultural classes” (Rossoni et al., 2020). The shared “cultural schemas” “does not imply having identical attitudes or behaviours. Rather it suggests agreeing on the structures of relevance and opposition that make actions and symbols meaningful” (Goldberg, 2011, p. 1402). Therefore, it tries to find patterns of associations between attitudes or behaviours in terms of “relationality”. It tries to find relationships both between individuals and between variables, combining clustering analysis and multidimensional scaling or factor analysis (Goldberg, 2011). The difference between RCA and CCA lies in the concept of “relationality”. While Goldberg (2011) uses linear dependency between two singular vectors of answers to find the shared cultural schemas, CCA suggests adopting Pearson’s correlation (Boutyline, 2017). Boutyline (2017) demonstrated that CCA produces more accurate results. In this case, there is no relationship between cases as in clustering, rather than between variables.

Only categorical ordinal variables are used with these two algorithms, only climate change questions are considered, except for the dependent variable, pro-environmental behaviour, and climate change risk perception.[[2]](#footnote-2) Five questions are selected to fit these methods. The questions proposed are on the type of governance on climate change. The responses were on a 4-point Likert scale, with the following gradations and labels (the latter change according to the questions):

1 = Totally agree/ Very important

2 = Tend to agree/ Fairly important

3 = Tend to disagree/ Not very important

4 = Totally disagree/ Not at all important

The purpose of this part of the analysis is to group some similar types of citizens, called clusters or classes, that better describe the data used. In fact, through these techniques, some new segmentations of citizens could be identified and then they could help to find new explanations to the phenomenon studied. Theoretically, using these two different types of segmentation of citizens, the results should be opposite. On the one side, the traditional clustering profiles the data according to similar attitudes, therefore we will find different types of *green identity*. On the other side, CCA finds shared cultural schemas, structure of thought. Eventually, the classes obtained from PAM clustering and CCA are used as predictors in the subsequent classifications.

### **2.2.2 Supervised Machine Learning Algorithms**

The second set of methods focuses on predicting climate change pro-environment using different types of supervised learning techniques and classifiers. Classification is used when a categorical variable is predicted (James et al., 2013). “The methods used for classification first predict the probability of each of the categories of a qualitative variable” (James et al., 2013, p. 127).

The different techniques of classifiers are briefly presented below. These classifiers randomly split all data into training (70%) and testing sets (30%), and the output labels are *yes* or *no*, depending on whether the environmental action has been taken place.

The pro-environmental behaviour prediction starts with a Logistic Regression. It is a form of binary regression and it explains relationships between a categorical outcome and some continuous or discrete predictors (Peng et al., 2002). It models the probability of being to a particular category (Peng et al., 2002; Stoltzfus, 2011).

The model requires some assumptions:

1. independence of errors;
2. linearity in the logit for continuous independent variables;
3. the absence of multicollinearity among explanatory

variables;

1. the absence of extreme outliers

(Stoltzfus, 2011)

However, some assumptions are violated. There is no present linearity in the logit for the age variable. Furthermore, some outliers are found in climate change risk perception, but they are not so distant from other values.

Despite the robustness of the logistic regression models, data cannot fully satisfy the assumptions, also decision tree models are fitted. Decision Tree is a “flow-chart-like hierarchical tree structure” (Jenhani et al., 2008, p. 786) and it is composed of three elements: nodes, edges, and leaves. Nodes represent attributes or variables, edges match the various potential attribute values and lastly, leaves include items that belong to the same class (Jenhani et al., 2008). The main advantages of the decision tree are that it has not assumptions and especially it produces graphical representation, which makes it easier to read and interpret the model.

The analysis continues with another robust model: Random Forest, which is produced randomized multiple decision trees that work as an ensemble (Belgiu, 2016; Biau & Scornet, 2016). This classifier “can successfully handle high data dimensionality and multicollinearity, being both fast and insensitive to overfitting” (Belgiu, 2016, p.24). Another advantage is that it can be dealing with unbalanced data, as in this case (Belgiu, 2016).

The last classifier used is Gradient Boosting. It is similar to the random forest algorithm, but in this case, each new tree is been created using the previous ones, to correct mistakes made (James et al., 2013). Instead of fitting a large number of trees separately, it learns slowly from previous trees recursively.

The last two tree-based methods, producing multiple trees, have become more popular since they improve prediction accuracy but they lose the immediacy of interpretation (Belgiu, 2016; James et al., 2013).

To sum up, all these classifiers predict pro-environmental behaviour. Figure 2 shows the distribution, unbalanced, of the observations according to the dependent variable. We have 14327 individuals who declared to have taken any action to fight climate change over the past six months and 7651 who have not.



Figure 2: Pro-environmental behaviour distribution

Sociodemographic variables, including country (the only one related to the context), classes created from PAM, and CCA, and climate change risk perception are used as predictors. We want also to investigate the main factors and predictors that influence pro-environmental behaviour. This process is achieved thanks to selected models, logistic regression, and tree-based methods, determining the importance of independent variables. This part is considered quite conventional according to the literature review, above-mentioned: variables selected have already been used previously, even if have mostly used more traditional techniques (and not machine learning techniques). An innovative point is PAM clustering and CCA’s use to create new groups where individuals belong to. Additionally, another originality of this research can be found in the next step.

Due to the theoretical relevance of climate change risk perception, in the pro-environmental behaviour’s prediction, two different analyses, according to the degree of this main explanatory variable, are performed. Two datasets are created: one with only the observations of individuals who declared very worried about the phenomenon (responses with a score greater than or equal to 6 are considered), and one with those who do not care (score less than or equal to 5). The same algorithms, just described, are fitted for the two different subsets. The aim is to discover the divergent variables that predict actions and whether there are relevant differences between those who care and those who do not care.



Figure 3: Pro-environmental behaviour distribution according to Climate Change Risk Perception

Figure 3 indicates the distribution of our dependent variable according to the two created subsets. The subset with the observations of those who worried is greater: 12988 observations of those who have not done any ecological behaviour and 6084 individuals who have done nothing. Instead, the second dataset is composed of the observations of those who do not worry about the environment. We have few cases, but they are balanced: 1339 and 1567, respectively who does environmentally behaviours and who does not.

## **2.3 Data Description**

As aforementioned, the research studies the pro-environmental behaviour of European citizens. The main data used in this project come from one wave of Eurobarometer survey. The Eurobarometer is a public opinion research institution in the European Union to examine a variety of topics and attitudes. The European Commission conducts Standard & Special Eurobarometer periodically. We used the Special Eurobarometer 91.3 dataset, entitled “Climate Change”, made available by the Eurobarometer Open Data website. This survey is collected in April 2019 using face-to-face interviews. There are 27655 respondents from 28 countries of the European Union. The Eurobarometer data are publicly available from GESIS (European Commission, Brussels, 2019). Eurobarometer 91.3 asks some questions about environmental issues and some sociodemographic information. Some relevant items about climate change and sociodemographic variables are selected.[[3]](#footnote-3)

### **2.3.1 Data Cleaning**

The first step before performing the analysis is data cleaning. To obtain an accurate analysis, some observations are dropped. Missing data or refusal answers of climate change issues are not considered in the final dataset. The missing data of our dependent variables, pro-environmental behaviour (encoded as qb5), is dropped since the analysis is based on the predictions of a dichotomous outcome (coded as 1 = Yes, 0= No). Even if this is a self-reported behaviour, it is considered valid and accurate according to the literature, being a dichotomous variable. Climate change risk perception (qb2) is measured on a 1-10 scale, and no answers are dropped to keep the variables as a metric, as some previous research had done (Echavarren et al., 2019). The question does not directly about the perceived risk but it is referred to the *seriousness* of the phenomenon in the present moment and it is a one-dimension of climate change risk perception (Echavarren et al., 2019). Successively, other questions regarding the topic are selected, all expressed on a 4-point Likert scale, as already mentioned above. Also, in this case, missing or refusal data is removed. The reason why PAM clustering and CCA does not accept missing data and therefore the entire observation must be removed. Instead, sociodemographic variables are for the most part categorical and therefore *refusal* or *dk* (don’t know) are kept among the answer choices. However, some transformations are adopted in these variables. Political orientation (d1) is originally presented in a 10-points Likert scale (1 = left to 10 =right). It is transformed into a categorical variable: the answers 1-2 are become “left”, 3-4 “centre-left”, 5-6 “centre”, 7-8 “centre-right”, 9-10 “right” and *dk* or *refusal* “not positionable”. For the current situation variable (d7), some new categories are created depending on whether an individual has declared that he/she lives with “partner”, “partner and children” or he/she is “single” or “single (and he/she lives) with children”. The education variable (d8), or rather when he/she finished studying, has been converted from continuous to categorical. According to scholars (Abu-Omar & Rütten, 2008; Loyen, 2016), five categories are created: “up to 15 years”, “16-19 years”, “20+years”, “still studying” and “refusal/other”. Gender (d10) and age (d11) are not manipulated since nobody answered with “other” and therefore the first variable is a dichotomous “male” and “female” option, while the second one is maintained as continuous. For residence (d25) and class identity (d63) variables, the categories proposed by the Eurobarometer are kept. Respectively, the first has the following classes: “rural area or village”, “small or middle-sized town”, “large town” and “dk” (don’t know). While the second one has the options: “the working class of society”, “the lower middle class of society”, “the middle class of society”, “the upper-middle class of society”, “the higher class of society”.[[4]](#footnote-4)

Lastly, the country variable is considered. Eurobarometer surveys collected about 1000 interviews on average for each country, except for small nations, such as Malta and Luxembourg. Only manipulation is computed: West and East Germany are combined into one country “Germany”.

To sum up, the final dataset has 21978 respondents (out of 27655).[[5]](#footnote-5)

# 

# **Appendix**

**APPENDIX A. Survey Question Wording and Coding**

|  |  |  |
| --- | --- | --- |
| **Variables** | **Questions** | **Coding** |
|  | ***Question about Climate Change issues*** |  |
| qb2 | And how serious a problem do you think climate change is at this moment? Please use a scale from 1 to 10, with '1' meaning it is "not at all a serious problem" and '10' meaning it is "an extremely serious problem" | 1-10 scale: 1= Not at all a serious problem to 10= An extremely serious problem |
| qb4\_3 | To what extent do you agree or disagree with each of the following statements? Taking action on climate change will lead to innovation that will make EU companies more competitive | 1-4 scale: 1= Totally agree to 4 = Totally disagree |
| qb4\_5 | To what extent do you agree or disagree with each of the following statements? Adapting to the adverse impacts of climate change can have positive outcomes for citizens in the EU | 1-4 scale: 1= Totally agree to 4 = Totally disagree |
| qb5 | Have you personally taken any action to fight climate change over the past six months? | 1= Yes; 0= No |
| qb7 | How important do you think it is that the (NATIONALITY) government sets ambitious targets to increase the amount of renewable energy used, such as wind or solar power, by 2030? | 1-4 scale: 1= Very important to 4= Not at all important |
| qb8 | How important do you think it is that the (NATIONALITY) government provides support for improving energy efficiency by 2030 (e.g. by encouraging people to insulate their home or buy electric cars)? | 1-4 scale: 1= Very important to 4= Not at all important |
| qb9 | To what extent do you agree or disagree with the following statement: We should reduce greenhouse gas emissions to a minimum while offsetting the remaining emissions, for instance by increasing forested areas, to make the EU economy climate neutral by 2050. | 1-4 scale: 1= Very important to 4= Not at all important |
|  | ***Sociodemographic information*** |  |
| d1 | In political matters people talk of "the left" and "the right". How would you place your views on this scale? | 1-10 scale: 1= left to 10= Right |
| d7 | Which of the following best corresponds to your own current situation? | Categorical |
| d8 | How old were you when you stopped full-time education? | Number in actual years |
| d10 | Gender | Female; Male |
| d11 | How old are you? | Number in actual years |
| d25 | Would you say you live in a...? | Categorical |
| d63 | Do you see yourself and your household belonging to…? | Categorical |
| country | Country | Categorical |

**APPENDIX B. Summary Statistics.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variables** | **Obs.** | **Mean** | **Std. Dev.** | **Min** | **Max** |
| **Qb5** | 21978 |  |  |  |  |
| *Yes* | *14327* |  |  |  |  |
| *No* | *7651* |  |  |  |  |
| **Qb2** | 21978 | 7.93 | 2.02 | 1 | 10 |
| **Qb4\_3** | 21978 | 1.74 | 0.71 | 1 | 4 |
| **Qb4\_5** | 21978 | 1.90 | 0.87 | 1 | 4 |
| **Qb7** | 21978 | 1.52 | 0.65 | 1 | 4 |
| **Qb8** | 21978 | 1.56 | 0.68 | 1 | 4 |
| **Qb9** | 21978 | 1.50 | 0.62 | 1 | 4 |
| **D1** | 21978 |  |  |  |  |
| *Left* | *1853* |  |  |  |  |
| *Centre-left* | *3856* |  |  |  |  |
| *Centre* | *7968* |  |  |  |  |
| *Centre-right* | *3470* |  |  |  |  |
| *Right* | *1603* |  |  |  |  |
| *Not positionable* | *3228* |  |  |  |  |
| **D7** | 21978 |  |  |  |  |
| *Partner* | *7791* |  |  |  |  |
| *Partner and children* | *7000* |  |  |  |  |
| *Single* | *5975* |  |  |  |  |
| *Single with children* | *1120* |  |  |  |  |
| *Refusal/Other* | *92* |  |  |  |  |
| **D8** | 21978 |  |  |  |  |
| *Still studying* | 1405 |  |  |  |  |
| *Up to 15 years old* | *2598* |  |  |  |  |
| *16-19 years old* | *9358* |  |  |  |  |
| *20+ years old* | *8298* |  |  |  |  |
| *Refusal/dk* | *319* |  |  |  |  |
| **D10** | 21978 |  |  |  |  |
| *Man* | *10527* |  |  |  |  |
| *Woman* | *11451* |  |  |  |  |
| **D11** | 21978 | 50.51 | 17.88 | 15 | 98 |
| **D25** | 21978 |  |  |  |  |
| *Rural area or village* | *7068* |  |  |  |  |
| *Small or middle sized town* | *8510* |  |  |  |  |
| *Large town* | *6396* |  |  |  |  |
| *Dk* | *4* |  |  |  |  |
| **D63** | 21978 |  |  |  |  |
| *The higher class of society* | *154* |  |  |  |  |
| *The lower middle class of society* | *3456* |  |  |  |  |
| *The middle class of society* | *10942* |  |  |  |  |
| *The upper middle class of society* | *1630* |  |  |  |  |
| *The working class of society* | *5276* |  |  |  |  |
| *Refusal/Other* | *520* |  |  |  |  |

**APPENDIX C. Sample composition**

|  |  |
| --- | --- |
| **Country** | **Obs.** |
| Austria | 830 |
| Belgium | 970 |
| Bulgaria | 626 |
| Croatia | 904 |
| Cyprus | 411 |
| Czech Republic | 729 |
| Denmark | 839 |
| Estonia | 520 |
| Finland | 807 |
| France | 797 |
| Germany | 1200 |
| Greece | 854 |
| Hungary | 900 |
| Ireland | 928 |
| Italy | 905 |
| Latvia | 687 |
| Lithuania | 704 |
| Luxembourg | 399 |
| Malta | 397 |
| Netherlands | 883 |
| Poland | 710 |
| Portugal | 863 |
| Romania | 869 |
| Slovakia | 810 |
| Slovenia | 874 |
| Spain | 820 |
| Sweden | 890 |
| United Kingdom | 852 |
| **Total** | **21978** |

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1. Some lexical clarifications are reported between global warming versus climate change. Global warming refers to temperatures increase on the Earth's surface (Dunlap, 2014). Instead, climate change refers more generally to changing climatic conditions and their effects (Dunlap, 2014). Public opinion and media use these two terms interchangeably (Weber, 2016). In this study, only the climate change term is used, due to it is more adopted (and more accurate) by the scientific community in the last years (Dunlap, 2014). [↑](#footnote-ref-1)
2. See Appendix A for the list of selected variables. Climate change questions are: qb3\_4, qb3\_5, qb7, qb8, qb9. [↑](#footnote-ref-2)
3. See Appendix A for the list of selected variables. [↑](#footnote-ref-3)
4. See Appendix B for the summary statistics. [↑](#footnote-ref-4)
5. See Appendix C for the number of observations by country. [↑](#footnote-ref-5)