The rise of populist attitudes: using supervised machine learning to identify their main determinants

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Abstract

The rise of populism has recently gained significant attention and is widely regarded as a topic of concern. Populism is characterized as a thin-centered ideology that divides society into two distinct groups and is hostile towards those outside the category of "ordinary people." The thin-centered approach allows for measuring populism as an attitude and provides a framework for measuring it among citizens. Moreover, a large amount of research has examined the concept of populism, its theories, and its impact on political parties through diverse methods such as qualitative coding, content analysis, and computerized techniques. However, the study of populist attitudes at the individual level remains under-explored. This dissertation investigates the correlation between populist attitudes and social characteristics, developing a machine-learning framework to identify the key determinants of populist attitudes through the Populist Attitudes Scale (POP-AS).

The findings of this dissertation indicate that individuals who exhibit higher levels of populist attitudes tend to show low agreement with statements related to the behaviour of government officials. Moreover, higher education levels are associated with lower values of populist attitudes, while men tend to display higher levels of populist attitudes. Additionally, younger participants tend to have lower levels of populist attitudes compared to older individuals. Regarding the machine learning models, tree-based algorithms outperformed others. For instance, in the regression approach, the XGBoost and Gradient Boosting regression algorithms demonstrated the best performance among the models tested. The XGBoost and Random Forest classifier outperformed other algorithms in the classification task. These findings shed light on the relationship between populist attitudes and various social characteristics, contributing to a better understanding of populism at the individual level. The machine-learning framework employed in this dissertation offers valuable insights into the determinants of populist attitudes, allowing for a more nuanced analysis of this complex phenomenon.

Keywords: Populism; Populist attitudes; people; ideology; populist scales; machine learning

Resumo

Recentemente, a ascensão do populismo tem recebido significativa atenção e por consequente é considerado um assunto alarmante. O populismo é caracterizado por uma ideologia de fraca consistência, a designada ideologia *"thin-centered"*. Neste tipo de ideologia, a sociedade é dividida em dois grupos distintos onde existe uma hostilidade inerente aqueles que estão fora da categoria de "pessoas comuns". A abordagem *thin-centered* permite medir o populismo como uma atitude entre os cidadãos. Além disso, existe um grande número de investigações descritas literatura onde o conceito de populismo, as suas teorias e o impacto que tem sobre partidos políticos são explorados. Para esse efeito, recorre-se a métodos distintos como codificação qualitativa, análise de conteúdo e técnicas computacionais. No entanto, o estudo das atitudes populistas a nível individual continua ainda por explorar. Esta investigação visa apurar a correlação entre atitudes populistas e características sociais, e eventualmente desenvolver um modelo de *Machine Learning* de modo a identificar os principais determinantes de atitudes populistas através da Escala de Atitudes Populistas (POP-AS).

Os resultados desta dissertação revelam que indivíduos com níveis mais elevados de inclinação para o populismo tendem a demonstrar menor concordância com declarações relacionadas ao desempenho dos líderes governamentais. Além disso, níveis mais altos de educação estão associados a uma menor propensão de atitudes populistas, enquanto os homens tendem a exibir uma maior inclinação para as mesmas. Além disso, participantes mais jovens tendem a exibir uma menor tendência a atitudes populistas em comparação com indivíduos mais velhos. No que diz respeito aos modelos de *Machine Learning*, os algoritmos baseados em árvores superaram os restantes. Por exemplo, no problema de regressão, os algoritmos XGBoost e Gradient Boosting demonstraram o melhor desempenho entre os modelos testados. Na tarefa de classificação, o classificador XGBoost e o Random Forest também superaram outros algoritmos. Estes resultados abrem portas sobre a relação entre atitudes populistas e várias características sociais, contribuindo para uma melhor compreensão do populismo ao nível individual. O quadro de *Machine Learning* utilizado nesta dissertação oferece insights valiosos sobre os determinantes das atitudes populistas, permitindo uma análise mais refinada desse fenómeno complexo.

Keywords: Populismo; atitudes populistas; cidadãos; ideologia; escalas populistas; *machine learning*

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Contents

Chapter 1

Introduction

The French Revolution in 1789 represented the triggering event for the beginning of modern democracy. Despite several political attempts for democracy to settle down, it was only in 1970's that the situation stabilized (Huntington (1991)). Prior to it, there were more dictatorships than democracies in existence. Moreover, with the collapse of the Soviet Union in 1989-1990, democracy faced no ideological competitors and by 2008 the number of democracies had reach an all-time high.

However, this political ideology began to disintegrate after reaching its peak, impacting worldwide. Democracy is dwindling in Eastern Europe and Latin America. Additionally, in Asia, the largest democracy in the world, India, as well as the Philippines, Thailand, Bangladesh, and other countries have all experienced a democratic backsliding. In addition, places where democracy is well-established, like the United States and western Europe, have seen significant democratic erosion (Berman (2021)).

Undertows have followed all previous democratic waves, however, the present situation is especially unique: Today's democracies are more likely to deteriorate than to pass away swiftly. Instead of *coup d'etats*, populists who win elections through the ballot box pose the biggest threat to democracy. Therefore, many scholars have started to refer to this period as the "age of populism" (Berman (2021)).

Being that said, it is crucial to define 'populism'. However, this controversial idea has been used to describe numerous movements, parties, and individuals across time (e.g., Taggart (2004)). Whether populism should be seen as an ideology or body of beliefs is a topic of debate among academics (e.g., Mudde (2004); K. A. Hawkins (2009)), seen as a form of political mobilisation or organisation (e.g., Weyland (2001)) or as a political style (e.g., Jagers and Walgrave (2007); Moffitt and Tormey (2014)). It is still true that there is no widespread agreement on the definition, nature, or consequences of populism (cf., Bale, Van Kessel, and Taggart (2011); Aslanidis (2016)).

Although this description is not accurate, populism is typically seen as a thin-centered ideology that is rounded in a Manichean worldview of good against evil in which the elites conspire against the populace (K. A. Hawkins (2009); Mudde (2004)). Ordinary people, who are sometimes characterized as good, pure, and uniform (Akkerman, Mudde, and Zaslove (2014); Jagers and Walgrave (2007)), represent a silent majority whose general will should be the deciding element in political decision-making but is instead suppressed by a corrupt elite. The term "elite" is commonly used ambiguously and might refer to those in the political or economic realms, officials, philosophers, writers, or the media in general (Jagers and Walgrave (2007)). In addition, populists are known for being hostile to anyone who does not belong to the category of "ordinary people" (Jungkunz, Fahey, and Hino (2021)).

Most of the research focuses on the theory, conceptualization, and impact of populism on party politics. However, recent studies have found that populism can also manifest itself differently. In other words, people have what are referred to as populist attitudes, which reflect how people's levels of populism have changed over time and throughout nations. They are the basis for populist tendencies and prospective votes. Researchers can now examine populism's genesis from both the supply and demand sides, thanks to the ideational definition of populism. This can be achieved by examining the populist content of political party manifestos, political actors' speeches, and general popular sentiments (Akkerman et al. (2014); Kaltwasser and Van Hauwaert (2020)).

To this end, and despite various measurement scales being proposed, in this work, the Akkerman et al. (2014) scale is the elected one as it is widely acknowledged as one of the most reliable scales within the literature.

By using supervised machine learning, a model can be trained on a labelled dataset of populist attitudes and the factors that may contribute to them. The model can then be used to predict populist attitudes based on the presence or absence of certain determinants. (Akkerman et al. (2014); Van Hauwaert, Schimpf, and Azevedo (2020)).

This dissertation aims to develop a Machine Learning framework to identify the main determinants of populist attitudes through the Populist Attitudes Scale (POP-AS), developed by Akkerman et al. (2014), consisting of survey questions and measurement models of these attitudes. The questions focus on the three core features of populism: sovereignty of the people; opposition to the elite; and the Manichean division between "good" and "evil." The survey questions were conceived to capture populism's ideology and conception of democracy, especially its focus on the will of the people (their sovereignty) and the line between the people and the elite.

The structure of this dissertation is as follows: Section 2 presents a literature review, including definitions, historical background, sources, and methods for measuring the concept of populism, the so-called thin-centered ideology. Section 3 outlines the data set available and its preprocessing phase, the scale that will be utilized to measure populist attitudes and a descriptive analysis of the variables. Section 4 presents the data modelling process, where various models are developed based on the available data. The section discusses the performance measures of these models, comparing their effectiveness in capturing the concept of populism. In addition, it provides an in-depth analysis of the inference results, predictions, and diagnosis of the explored models, shedding light on their strengths and weaknesses. By examining the data modelling process, this section contributes to a comprehensive understanding of the populism phenomenon and its measurement within the framework of a thin-centered ideology. In conclusion, Section 5 encapsulates the main findings, possibilities, and future research opportunities that have emerged through the exploration undertaken in this dissertation.

Chapter 2

Literature Review

Political scientists, sociologists, and psychologists have all researched populism extensively because it is a multidimensional and complex concept. There has been significant discussion surrounding the definition of populism, with numerous academics offering differing conceptualizations of the phenomenon. Scholars have also been interested in the historical development of populism, studying the origin and evolution of populist movements and parties over time. The causes of populism have also been contested; some researchers have emphasized the influence of economic considerations, while others have emphasized the influence of sociocultural elements. Finally, significant discussion has been about quantifying populism at the individual level. Researchers have developed and tested various techniques for determining how the general public feels about populism. This literature review seeks to present an overview of the existing state of knowledge on these many populism-related topics and to point out any remaining research gaps.

2.1 Populism Definition

Previously, in the introduction, it was stated that populism could be viewed as an ideology or set of ideas, a form of political mobilization or organization, or a political style. Still, all definitions agree on two main components: people-centrism, and anti-elitism or an anti-establishment attitude.

People-centrism is a belief that emphasizes the importance of the common, everyday individuals intending to implement their perceived "general will" in politics. This view portrays the "people" as a unified, homogeneous group with moral virtues and common interests. In contrast to this idealized view, populism opposes the "people" against an elite group of powerful individuals who are seen as exploiting and controlling politics for their gain and are perceived as morally corrupt. According to populists, politics is a battle between these two groups, one being good and the other evil. This is known as the Manichean aspect of populism (K. A. Hawkins (2010)).

In this dissertation, populism is defined as a "thin-centered ideology" as proposed by Akkerman et al. (2014); Akkerman, Zaslove, and Spruyt (2017); Mudde (2004). This definition includes three main components: elites, "the people", and the criteria for inclusion and exclusion within "the people". The distinction between left-wing and right-wing populism can be seen in their differing views on who should be included or excluded from "the people", with right-wing versions often excluding immigrants and left-wing versions defending against economic threats to workers' rights (Schroeder (2020)).

The "thin-centered" approach has plenty of advantages as it is versatile and has been widely used by scholars to study populism in various regions such as Europe and Latin America, as demonstrated in works by Mudde and Kaltwasser (2013). Second, it provides a framework for measuring populism, as scholars like Akkerman et al. (2014) demonstrate. This has been done through the analysis of speeches, newspapers, and party platforms, such as the work of K. A. Hawkins (2009); Pauwels (2011); Rooduijn, De Lange, and Van Der Brug (2014). Lastly, and of particular significance for this study, the thin-centered ideology approach enables social scholars to measure populism among citizens, as exemplified by research conducted by Akkerman et al. (2014); K. A. Hawkins, Riding, and Mudde (2012); Spruyt, Keppens, and Van Droogenbroeck (2016).

According to this dissertation's definition of populism, society should be divided into two different and antagonistic groups: the good people and the corrupt elite. This viewpoint contends that politics ought to represent the popular sentiment as a whole. This definition was proposed by Mudde (2007), and focuses on populism's three major tenets: people-centeredness, populist opposition to the elite, and framing of this opposition as antagonistic. The elite is considered corrupt and evil, while the people are perceived as decent. This thin-centered strategy has the benefit of making populism measurable since it is seen as a collection of ideas (see K. A. Hawkins (2009); K. A. Hawkins et al. (2012); Mudde (2004)), being possible to measure populism among individuals as an attitude. Building upon previous work on measuring populism at the individual level (mainly Akkerman et al. (2014)), it is possible to operationalize the thin-centered definition of populism to capture the people centered, anti-elite, and antagonistic notion of populism.

The thin-centered ideology approach is beneficial, yet it is based on the fallacious notion that populism is a fairly stable trait of political actors. It allows us to categorize some politicians or parties as populist and others as non-populist. A party or candidate's understanding of politics through the anti-elite/pro-people binary divide can be determined by carefully reading party manifestos or campaign platforms, which is how this is usually done.

The notion that populism is a stable ideology is untrue since it downplays the idea's dynamic nature. Politicians frequently employ populist rhetoric carefully, tailoring their message to the audience and the situation, according to studies. For instance, Clinton did so in 1992 but not in 1996, and Eisenhower actively embraced populism in 1952 but not in 1956. This variant implies that populism is not a rigid ideology but rather a political rhetorical device or "framing" (Bonikowski and Gidron (2016)).

It is possible to investigate which political actors are more inclined to employ populist language in specific circumstances and why by seeing populism as a discursive frame utilized by political actors rather than an inherent quality of the actors themselves. The audience, the speaker's political objectives and background, and the speaker's and their party's political standing are all important strategic considerations when choosing to be populist. According to Bonikowski and Gidron (2016) research, politicians who have held office for a longer period of time are less likely to make populist claims about being an outsider since they may be viewed as less sincere. Additionally, social, political, and economic factors such as economic downturns, risks to national security, or political scandals may impact the decision to utilize populism. As an illustration, the terrorist incidents in Paris and Nice in 2015 and 2016 prompted more politicians to use nationalist populism by criticizing Islam with unambiguous moral judgments and blaming political elites for lax immigration laws. Following the tragedy at the Bataclan, Victor Orban, the president of Hungary, adopted this tactic. Furthermore, while some populist leaders may legitimately believe that elites are morally corrupt, others may only use it for tactical advantages (Robins-Early (2015)).

Another finding made by Bonikowski and Gidron (2016) was that presidential candidates with less experience in politics are more likely to use populist language than those who have held positions of power. For example, George McGovern used populist rhetoric more than Richard Nixon during the 1972 election. Additionally, candidates tend to become less populist throughout successive electoral campaigns, as stated previously in the cases of Dwight Eisenhower in 1952 and 1956 and Bill Clinton in 1992 and 1996. Generally, incumbent candidates use populism less frequently than challengers. Similar patterns are observed in the European Parliaments.

2.2 Populism and its History

It is a common misconception that populism is a new phenomenon in today's academic and public debates. While some analysts acknowledge the presence of populism in the past, many believe we are experiencing an unprecedented rise in populism worldwide. The current research focuses mainly on contemporary cases and can give the impression that populism did not exist in the past or was not politically significant. Some of the earliest examples of populist leaders include Andrew Jackson in the United States in the 1820s and 30s and Juan Manuel de Rosas in Argentina in the 1840s (Lowndes et al. (2017); Shumway (2004)). Other notable early populist leaders include William Jennings Bryan in the United States in the 1890s, and Huey Long in the 1930s (Lowndes et al. (2017)).

A few years later, viewing the 1980s as a more radical subset of the larger conservative movement is possible. Most of its adherents were from the middle class, particularly those who experienced both cultural and economic insecurity. However, as it focused on the demands of the New Left, such as those concerning minorities and individual lifestyles, this new populist wave signalled a change in party rivalry in Western Europe. The radical right had established a new political space characterized by economic and cultural alienation, with a new political identity fuelled by anti-establishment populism (Chryssogelos (2013)).

The political identity of the radical right was further enhanced by the collapse of the Soviet Union and the acceleration of globalization. The loss of national control in a world of free flow of people, products, and services exacerbated the feeling of cultural detachment (Taggart (1998)). Although not particularly noticeable in the 1980s, the radical right's hostility to European integration grew to symbolise their opposition to the nation-deterioration state's. Their anti-elite populism was also motivated by the widespread perception that elected governments have little influence in a united Europe and a globalised society. Traditional political identities weakened as a result, but the populist right managed to preserve support by integrating anti-establishment themes into a larger political movement that still had authoritarian-conservative foundations but was steadily gaining new supporters (Chryssogelos (2013)).

While the new radical right's emphasis on anti-immigrant and anti-elite themes persisted during the 1990s, other facets of their viewpoint shifted. Right-wing populists started to gain support outside of the core of the authoritarian middle-class right in some nations, including France and Austria. They began focusing on law and order, sovereignty, and racial and cultural alienation to win over the working class and young voters. They maintained their economic policy of minimal government intervention in the marketplace, allowing market forces to operate with little to no interference. Traditional far-right ideals were giving way to a general disillusionment with politics as the populist movement, while still predominantly on the right, grew more varied in both its membership and ideology (Chryssogelos (2013)).

Radical right populists started to link their discourse with the widening gap between those who profited from globalisation and those who did not by the early 2000s. This required populist leaders in France and Austria to stray from their usual support base of weak middle-class authoritarianism and focus on immigration, law enforcement, and public order concerns while also taking a more protectionist posture on economic issues (Kriesi et al. (2006)). Although cultural and ethnic authoritarianism remained the essence of populism in these nations (Azmanova (2011)), populist leaders grew more overt in courting people who were adversely affected by economic openness (Bornschier (2010)). Parties like the National Front in France and the Freedom Party in Austria had given up their prior neo-liberal economic ideas by the middle of the 2000s, which helped them win over voters from the working class and people who were fed up with traditional politics (Knapp (2004)).

Beyond the conventional left-right division, populist parties started to forge a new axis of conflict that pitted those favouring openness against those who advocated cultural and economic protection. Discussions on whether the National Front had changed France's political landscape resulted from this (Grunberg and Schweisguth (2003)). The Freedom Party's departure from Austria's government in 2006 signalled the culmination of its shift from a neo-conservative, authoritarian party to a populist protest movement that included demands for working-class protection (Luther (2008)).

The economic crisis in Europe has brought about both continuity and change in the rise of populist politics. On the one hand, it has given populist politicians who were already anti-elite, anti-EU, and protectionist the chance to emphasise these points and win over a bigger share of an electorate growing increasingly disenchanted with politics. On the other side, the magnitude of the crisis has caused some to question the principles of liberal representative democracy (Chryssogelos (2013)).

Election results in the eurozone after 2010 have shown that populist potential is currently predominantly mobilised by opposing traditional political parties. Although the radical right first shaped the populist potential and still contains significant cultural and economic protectionist aspects, it now also contains significant anti-elite and system-critical discourse that makes a coherent anti-system message. Depending on the leader's ideologies, this message is slightly modified. In nations where both right-wing and left-wing populist parties exist, the two sides frequently place more emphasis on competing with the centre than with one another to appeal to the same target demographic of disgruntled middle-class, alienated working-class, and excluded young (Chryssogelos (2013)).

Regardless of their earlier ideological beliefs, new actors can use populism to their advantage and generate support for new issues. The successful campaign of Italian comedian Beppe Grillo in the 2013 elections serves as an illustration of this. His movement reflects a lack of faith in conventional political systems and a broad disgust with the whole political class. Additionally, former US President Donald John Trump, a businessman, television personality, and author, gained popularity partly because of his racially insensitive language toward immigrants, Latinos, Muslims, and African Americans as well as his efforts to undermine democratic institutions and the people who run them. As previously stated, populism is not limited to the right, being increasingly clear that left-wing populism is becoming a significant aspect of politics in the United States. Just as significant as Donald Trump's election victory was the growth of Bernie Sanders and his campaign. This holds true for their precursor movements as well, including the Tea Party and Occupy Wall Street (Bonikowski (2016)).

The European far-right parties, which frequently mix anti-EU sentiment with Islamophobia and nationalism that excludes particular groups, frequently combine populism with discriminatory nationalism. Taggart (2017) observes that national, ethnic, and regional identity problems are frequently the subject of populist parties in Western Europe (minority nationalism). As referendums are a way to give power back to the people and it's a significant tool for populism, Brexit became a symbol for expressing frustrations and anxieties in the UK that were often only indirectly related to the EU. It soon becomes apparent that the promised illusions of fulfilment were not realised. In a populist manner, Nigel Farage soon after the referendum outcome proclaimed it a triumph for genuine people, regular people, and good people. Additionally, he proposed that the country should now celebrate June 23 as its new Independence Day. This fuelled the myth that Brexit would bring fulfilment and meant that Britain had finally emancipated itself from the colonial EU. Despite these assertions, there are significant differences between post-Brexit reality and Commonwealth illusions (Browning (2019)).

On the other hand, a distinct form of populist party that is more centrist and not always anti-European has emerged in Central and Eastern Europe, as noted by Stanley (2017). Left-wing populist movements like Greece's Syriza and Spain's Podemos, which include ethnic minorities, refugees, and migrants in an inclusive picture of society, are becoming more popular in Europe, similar to how it is in the US (Bonikowski (2016)).

This is not to claim that populism is the same everywhere. Mudde and Kaltwasser (2013) point out that, although populism in Europe tends to be right-wing, identity-based and exclusive, in Latin America it tends to be left-wing, economic, and inclusive (K. A. Hawkins et al. (2012)).

2.3 Populism Source

There is a disagreement between supply-side and demand-side theories about the origins of populism. Demand-side or bottom-up, theories attribute populism to citizens' shifting grievances or desires, while supply-side, or top-down, theories see the root of populism in changes to democracy's fundamental principles, particularly the failure of elites and institutions to respond to public demands. Demand-side explanations focus on society or individuals, while supply-side explanations focus on the shortcomings of governments, legislators, policy makers, parties, and other actors (Berman (2021)).

Demand-side explanations of populism refer to the idea that the demands or needs of the public drive populism. There is a division between scholars who believe that economic demands are the main driving force behind populism and those who believe that sociocultural demands are more important.

Economic explanations focus on how globalization, neoliberalism, and technological change have created insecurity and divisions among citizens, leading to discontent and a desire for populist leaders. For instance, income and wealth inequality over the last decades of the twentieth century (Piketty (2014)) and economical development have created deep divisions between countries and people. As all crises tend to attack the already marginalised, the subprime crisis of the late 2000s accelerated the political consequences of democracies (Berman (2021)). This can also lead to flawed conclusions about the causes and effects of populism. For example, Judis (2016) argues that the Great Recession led to a "populist explosion." However, it is unclear why past economic crises, such as the "Long Recession" of 1974-1982, did not have similar results and why countries that were heavily impacted by the Great Recession, such as Portugal, did not see a rise in populist forces during that time. The work of Kriesi and Pappas (2015) suggests no clear correlation between the Great Recession and the emergence of populism in Western Europe.

Sociocultural grievance-based explanations for populism, such as those popular among political scientists studying the advanced industrial world and American politics (e.g. Abramowitz and McCoy (2019)) as well as sociologists, argue that social and cultural trends, such as rising immigration (Caldwell (2009); Murray (2017)), the decline of traditional values, and the mobilization of minority groups (Outten, Schmitt, Miller, and Garcia (2012); Tajfel (1970)), are the main causes of populism. These trends are believed to have challenged existing power dynamics and hierarchies (Craig and Richeson (2014b)), leading to a counterreaction among certain groups, particularly white men, who support right-wing populists to defend their interests (Dodd and Lamont (2017); Hochschild (2017)). In the United States, high levels of immigration and the potential for the country to become majority nonwhite in the future have been linked to group-based identity threats among white Americans and a tendency to favour their group and demonize others (Craig and Richeson (2014a); Gest (2016)). Concerns about the deterioration of European culture and identity and a willingness to support populist politicians and parties that pledge to defend them have arisen in Europe due to immigration from non-Western and non-Christian backgrounds leading to terrorism fears US (2018). A sense of loss and disempowerment among certain white people is thought to have contributed to the perception of an attack on traditional values in both the United States and Europe, which in turn sparked a nativist, nationalist, and populist backlash.

Scholars have increasingly sought to combine aspects of both economic and sociocultural explanations for populism. Inglehart and Norris (2017), who have examined data from the World Values Survey, claim that while sociocultural complaints are the direct cause of right-wing populist voting, they are also a result of rising economic uncertainty and the deterioration of traditional values. Other studies have suggested that shifting economic circumstances, such as the loss of blue-collar jobs and the consequent loss of social standing and financial stability for manual labourers, might lead to mobilisation through anger towards professional elites and minorities. (Bonikowski (2017)).

Demand-side explanations of populism, which focus on social or economic change and grievances (Evans, Rueschemeyer, and Skocpol (1985)), have limitations and biases. Economic and social changes alone don't create populism. They only make citizens angry and susceptible to populism when mainstream politicians and governments fail to address them. These theories assume economic and social trends influence citizens' political demands and choices. Still, supply-side explanations (Longstreth, Steinmo, and Thelen (1992)) argue that these trends are filtered through institutions that determine how they are translated into political outcomes. Supply-side explanations attribute the cause of populism to the decline in responsiveness and effectiveness of political institutions (Berman (2018)), which has made many citizens willing to vote for anti-establishment politicians and parties. These explanations have a long history among students of the developing world, dating back to Huntington's Political Order in Changing Societies, which argued that political disorder stems from a disjuncture between a country's challenges and the strength of its political institutions. In the advanced industrial world, scholars (Berman (2017, 2018)) have focused on how gerrymandering, the Electoral College, and campaign finance have made the U.S. political system less responsive to citizens and contributed to the rise of populism. In Europe, the decline of traditional parties (Berman (2017)) and the growth of technocracy (Berman (2018)) have been identified as factors that have made the political system less responsive to citizens and led to the rise of populism.

2.4 Measuring Populism

As demonstrated by (K. A. Hawkins (2009)), who developed preliminary statistics based on the textual analysis of political speeches made by 215 chief executives from 66 countries, populism can be measured despite being a thin-centered ideology composed of ideas about democracy and political representation. Using a discursive definition of populism and computerised text analysis, Bonikowski and Gidron (2016) examined the speeches of US presidential candidates from 1952 through 1996.

Machine learning and automated techniques have recently been used to analyse content to measure populism (K. A. Hawkins and Silva (2018)). They used 154 speeches and manifestos to categorise using machine learning techniques, training the algorithm using a human-based "holistic grading" method. To find texts that are populist, their statistical algorithm compares word frequencies. The findings aligned with those attained through human coding and indicate that populism can be accurately detected using computerised text analysis if sufficiently large data sets are available for model training.

Using textual analysis of political party manifestos, Di Cocco and Monechi (2022) employed supervised machine learning algorithms to produce populist scores. They created a continuous measure of populism for six European nations between 2001 and 2019 based on an ideational concept. Machine learning methods still have a lot of potential for measuring political populism, though.

Another method for measuring populism is through surveys, which can be divided into two main types: "surveys of political elites," which gather information on the populist attitudes of party members (Bailer (2014)), and "expert surveys," which use expert opinions to classify parties based on a set of predetermined issues.

Besides speeches, surveys and manifestos, populism can be measured through blogs, websites, leaders' tweets, posts and newspapers (Aslanidis (2016); Bracciale and Martella (2017); Engesser, Ernst, Esser, and Büchel (2017); K. Hawkins and Littvay (2019); K. A. Hawkins et al. (2012); Herkman and Matikainen (2019); Jagers and Walgrave (2007)).

As previously stated, various techniques have been used, from holistic qualitative coding, paragraph coding to computerized content analysis. However, measuring populist attitudes at the individual level is less explored.

According to several scholars, populism can be conceptualized as a set of attitudes held by individuals about politics. These scholars have developed various methods for measuring populist attitudes in different contexts and regions, including Europe and the Americas.

Concerning the demand side, the first attempt to measure populist attitudes at the individual level was published by Axelrod (1967) some time ago. However, it was based on a highly American-centric and out-of-date understanding of populism. Recent years have seen the publication of only a few new empirical investigations (Elchardus and Spruyt (2012); K. A. Hawkins et al. (2012); Stanley (2011)).

Stanley (2011) looked at various populist items from a post-election Slovakia survey. However, this approach does not find that populist sentiments significantly influence voting behaviour. Social and economic issues are better at explaining voting patterns than other variables. These insignificant outcomes could have a variety of explanations. First, populist parties were in power at the time of the study, which may have made it difficult for respondents to distinguish the populists from the elite. Second, given the post-communist environment of Slovakia, it would have been challenging to distinguish between the populist message and more fundamental concerns about national interests and economic and social cohesiveness. Third, it's possible that the questions didn't adequately capture the idea of populism (Stanley (2011)).

In Flanders, Elchardus and Spruyt (2012) conducted their research. Along with indications of one's financial status, level of satisfaction in life, anomie, relative deprivation, and assessment of society, their survey included four populism questions. Although the study discovered some intriguing connections between authoritarian sentiments and populism, as well as between relative deprivation and perceptions of unjust treatment, it is less clear if the authors are genuinely evaluating populism per se. Each of the four populism questions received a comparatively high percentage of affirmative responses, indicating that these questions are more likely to tap into broader anti-establishment sentiments Elchardus and Spruyt (2012).

A different approach is used in the research conducted by K. A. Hawkins et al. (2012), which aims to develop a battery of six survey items that intended to capture three dimensions of populist attitudes: anti-elitism, the prominence of the general will, and the Manichean outlook on society. Their method offers a stronger validity check of populism because it produced these three unique political views based on a combination of preexisting and new questions. The authors rely on linguistic and textual qualities rather than making overt assertions or taking a position on a subject (like tone and metaphors). To address criticisms of the English formulation of these items, the authors also reduced the original 6-item battery to a 4-item version with more populist rhetoric. They used them in two US surveys, and the results were consistent. Therefore, the study by K. A. Hawkins et al. (2012) is a crucial first step in developing a set of inquiries that measure populism and pluralism, while also making crucial improvements in developing inquiries that measure elitist attitudes.

The authors of this study demonstrated that populist attitudes are widespread in the United States, where they differ in predictable ways: they are more prevalent among those with lower levels of education, are weakly correlated with low income, strongly associated with affiliation with outside groups and ideological radicalism (especially strong conservatism) and are correlated with anti-immigrant sentiment. Results are also valid nationwide, not just in a region with a conservative bent. Finally, they demonstrate that these sentiments are not always correlated with gender or age K. A. Hawkins et al. (2012).

The initial 4-item scale created by K. A. Hawkins et al. (2012) serves as the basis for additional scale development, according to Akkerman et al. (2014). They suggest four more populist measures, partly to adapt the initial item-battery to a European setting. They analyse populist attitudes in the Netherlands specifically and discover empirical proof favouring a populist component comprising six (out of eight) items. The two removed items do not capture aspects of the populism dimension. It's intriguing that the two metrics that the authors omitted from the populist item were, in fact, something that American researchers found. Given everything, it's probable that decisions made in the Americas don't necessarily apply to circumstances in Europe (Akkerman et al. (2014)).

According to Van Hauwaert et al. (2020), populist attitudes are significant predictors of support for populist parties. They found that high populist attitudes are particularly important in leading individuals with moderately left or right-wing preferences towards left or right-wing populists, regardless of their economic positions. This is supported by the findings of Andreadis, Hawkins, Llamazares, and Singer (2018); Loew and Faas (2019), who also found that populist attitudes tend to sort individuals within ideological camps, driving individuals with more of those attitudes towards the most populist option on the ballot.

It is important to note that while there is a growing consensus in the academic community that populist attitudes play a significant role in shaping electoral outcomes, recent data from cross-national surveys suggest that these attitudes may not be as influential as previously thought. In particular, studies such as the one conducted by Anduiza, Guinjoan, and Rico (2019), which looked at public opinion in nine European countries, found that the average agreement with populist attitudes was relatively high across the board, with slight variation between countries. Similar findings were also reported in studies by K. Hawkins and Littvay (2019) and Rovira Kaltwasser, Vehrkamp, and Wratil (2019), which looked at data from 11 and 12 countries, respectively. These findings raise questions about how populist attitudes influence vote choice. They suggest that further research is needed to fully understand their role in shaping electoral outcomes.

Intriguingly, populist attitudes are prevalent among the public in many countries, yet populist parties do not receive a majority of votes in these countries. According to K. Hawkins and Littvay (2019), this discrepancy can be explained by the fact that populist attitudes only significantly impact vote choice when there is a viable populist candidate. In addition, the context in which these attitudes are held plays a role in determining their impact on vote choice. For example, in countries with widespread corruption or state failure, populist attitudes may be more likely to influence voting behaviour. This idea is supported by recent experimental evidence suggesting that mainstream parties' representation failures can trigger populist attitudes (B. C. Silva and Wratil (2021)).

Deciding which questions to use to measure a concept can be challenging for researchers.

This is especially true in populism studies, where multiple scholars have used different methods to measure populist attitudes among individuals. Castanho Silva, Jungkunz, Helbling, and Littvay (2020) applied several techniques to seven scales measuring populist attitudes: Akkerman et al. (2014); Elchardus and Spruyt (2016); Oliver and Rahn (2016); Schulz et al. (2018); B. C. Silva et al. (2018); Stanley (2011) and the module of the wave five questionnaire of the Comparative Study of Electoral Systems (CSES) (Hobolt, Anduiza, Carkoglu, Lutz, and Sauger (2016)).

There are two basic methods for creating questions to evaluate populism due to its complexity. The first strategy is to produce specific items that capture each aspect of populism independently, such as praising common people without mentioning the elite. Researchers like Oliver and Rahn (2016); Schulz et al. (2018); B. C. Silva et al. (2018); Stanley (2011) have used this approach. The second approach is to use a single scale that captures all dimensions of populism simultaneously, including items that refer to multiple dimensions. Researchers like Akkerman et al. (2014); Elchardus and Spruyt (2016); Hobolt et al. (2016) have used this approach. Most projects differentiate between three subcomponents: people-centrism, anti-elitism, and anti-pluralism. These dimensions are measured in different ways, for example, by focusing on the importance of one's national group or dividing people into good and evil. The increase in the number of populist governments in Western democracies today makes it necessary to rethink the connection between theoretical anti-elitism and its operationalization.

There is little overlap between items in studies on populism unless scales are directly built on each other. Some studies craft a few items based on theory (e.g., Akkerman et al. (2014); Elchardus and Spruyt (2016); Stanley (2011)) and justify how their selection differs from other projects. However, most scale development is at least partially empirically driven, with items that do not load strongly on latent variables or principal components being deleted. Schulz et al. (2018) and B. C. Silva et al. (2018) have taken this approach further by combining theoretical considerations with exploratory analyses to define a small number of core items. Indices also vary in the number of items, with some including between twelve and fifteen (e.g., Oliver and Rahn (2016)) and most ranging from six to nine (e.g., Akkerman et al. (2014); Hobolt et al. (2016); Schulz et al. (2018); B. C. Silva et al. (2018); Stanley (2011)) or even only four (e.g., Elchardus and Spruyt (2016)). The number of items is related to the number of dimensions, with multidimensional scales including more items than single-dimensional ones. However, longer scales may be more prone to poor operationalization if the selection of items is not careful (Elkins (2000); Hayduk and Littvay (2012)). Wording, framing, and response alternatives are also considered while designing a questionnaire. Some scales may overestimate the average levels of agreement with a construct because they lack negative-worded items. This can be seen on three scales: Akkerman et al. (2014); Elchardus and Spruyt (2016); Schulz et al. (2018). Oliver and Rahn (2016) have only one subdimension with a negative-worded item. B. C. Silva et al. (2018) and Stanley (2011) have negative-worded items for every subdimension. The CSES module has one negatively worded item among seven questions. Akkerman et al. (2014); Elchardus and Spruyt (2016); Hobolt et al. (2016); Schulz et al. (2018) use Likert-type agree-disagree with five categories, while B. C. Silva et al. (2018) and Stanley (2011) use seven-point scales. Oliver and Rahn (2016) use a mix of two, five, and seven categories for their questions.

Castanho Silva et al. (2020) assessed three key characteristics of each scale: internal consistency, cross-cultural validity, and the concept's scope covered.

They start by asking whether each scale measures the latent construct(s) it was designed for. This is accomplished by performing root mean square error (RMSE), standardized root-mean-square residual (SRMR), comparative fit index (CFI), Tucker–Lewis index (TLI) and confirmatory factor analysis (CFA).

Based on a CFA assessment, only three scales were found to have a good fit on almost all fit indices, no poor-performing items, and high average loadings: Akkerman et al. (2014); Schulz et al. (2018); B. C. Silva et al. (2018). Other scales had at least one problematic item in capturing the construct they were designed to measure (Elchardus and Spruyt (2016); Hobolt et al. (2016)).

Cross-national validity, or measurement invariance, was found in only two scales: Elchardus and Spruyt (2016); B. C. Silva et al. (2018), with the latter having poor internal validity. Other scales had poor fitting models when factor loadings were constrained to be the same across countries, indicating low cross-national validity.

In terms of conceptual breadth or capturing high levels of information across the range of the dependent variable, none of the scales tested had broad information curves. Akkerman et al. (2014); B. C. Silva et al. (2018); Stanley (2011) had the widest information curves. Only Oliver and Rahn (2016); B. C. Silva et al. (2018); Stanley (2011) captured more than mere anti-elitism. Most scales had moderate to high correlations with known populist attitudes and could predict populist party identification in at least two of three countries: Italy, France, and Spain, indicating that they are not ideologically skewed to one side or the other.

The analysis of B. C. Silva et al. (2018) shows that these scales should be used with caution, as many have poor psychometric properties or fail to capture the proposed construct. Additionally, most have limited cross-cultural validity, which is a concern for their use in large-scale cross-national surveys. B. C. Silva et al. (2018) performed well in all psychometric properties tested but did not predict populist party support as well as the other scales. Akkerman et al. (2014); Schulz et al. (2018) had acceptable or good performance on most tests but failed on cross-national validity. As Akkerman et al. (2014) is currently the most widely used scale and performed relatively well in all tests, it is considered a good option to take into consideration.

Additionally, according to Falcão, Jalali, and Costa (2023a), the POP-AS is a trustworthy and effective tool for measuring how Portuguese people think about populism. The POP-AS in Portuguese has a good level of consistency and validity: it has one main factor that reflects its concept; it works similarly for different educational levels and for most of the country; All the questions in the POP-AS are clear and relevant for the overall score of the scale, which shows its internal validity. Hence, POP-AS is the chosen scale for this dissertation.

Chapter 3

Methodology

This section provides an overview of the data set available for this dissertation and the transformation of several features to harmonize data from the two distinct surveys in hand. Data preprocessing techniques were applied to ensure consistency and to avoid any potential interference with future analysis and results.

Lastly, univariate descriptive analysis results for all variables are explored. The section then presents and discusses the findings of the bivariate analysis.

3.1 Data

Data for this study come from two online samples. Firstly, it was used the database "Political Participation of Youth in Portugal, 2020" - APIS0094 - which consists of a survey of a representative sample of the Portuguese population, with oversampling of the young (age 15-24), on attitudes about the economic and pandemic situation, political efficacy and populist attitudes, as well as social, civic and political involvement of them. This survey has 1464 respondents (Costa et al. (2022)).

The second database "Changing European Elections (CEE) The impact of Eurozone bailouts on European Parliament election campaigns" consists of to what extent the bailout context shaped the European election campaigns in the 'bailout countries' (P. Silva and Jalali (2018)). Combining two different dimensions, it sought to empirically assess the impact of the bailouts on the 2014 European Parliament (EP) election campaigns; and, secondly, the effects of these post-bailout campaigns on citizens' attitudes towards the EU and European integration. To achieve objectives, a comparative study comparing the 2014 European Parliament election campaign with the previous campaign in 2009 was conducted and compared the bailout countries to those in which bailouts did not occur. This research also used a quasi-experimental design with a control group, treating the bailouts as the experimental treatment (Portugal and Ireland) and using a sample of non-bailout European countries as the control group (Austria and Finland). This survey has 1510 respondents, totalling 2974 respondents together with the first survey.

3.2 Original data

The two surveys available for this study contained overlapping questions, addressing certain aspects while differing in others. Questions that were already similar included demographic factors such as age, sex, political efficacy and populist attitudes. The variables collected and their discretization strategy from both surveys are described in table 3.1.

There were discrepancies in the educational background section, as the APIS survey consisted of six levels while the CEE survey had 14 levels. To ensure compatibility, the CEE survey responses were harmonized to fit within the six APIS survey levels as seen in the table 3.1.

Concerning political orientation, the APIS survey allowed participants to position themselves on a scale ranging from 0 to 10, representing left-leaning and right-leaning ideology. Conversely, the CEE survey only provided a question concerning party affiliation. To address this disparity, we converted the party preference variable into two binary variables: Left and Right. For the APIS survey, responses ranging from 0 to 4 were categorized as Left (1) while responses of 5 were categorized as neither Left nor Right (0). Responses from 6 to 10 were categorized as Right (1). As for the CEE survey, we assigned values to party preferences based on the information provided by Jolly et al. (2022). If a chosen party was considered left-leaning, the Left variable was assigned 1 and the Right variable 0. Conversely, if the chosen party was considered right-leaning, the Left variable was assigned 0 and the Right variable 1.

With respect to voting behaviour, one binary variable wes created to address whether or not the respondents participated in the legislative elections of 2019.

Regarding the nine items of perceived political self-efficacy (PPE-S) the mean of three dimensions of political efficacy was performed:

- **Internal personal political efficacy**, which expresses the participants' beliefs about their part in political decision-making, evaluating laws, and predicting electoral outcomes;
- **Internal collective political efficacy**, which expresses the respondents' ideas regarding the role of citizens in the aforementioned concerns;
- **External political efficacy**, which reflects the participants' ideas concerning the role of people in government on these topics (Falcão, Jalali, and Costa (2023b)).

By aligning the surveys in this manner, we aimed to ensure consistency and facilitate meaningful comparisons between the collected data.

Table 3.1: Study variables description and transformation

<table>
<tr><th colspan="2">Original variables</th><th>Transformed variables</th></tr>
<tr><td>APIS</td><td>CEE</td><td></td></tr>
<tr><td>A1.Sex
1. Male
2. Female</td><td>Q7_1.Sex
1. Male
2. Female</td><td>Sex
0 = Male
1 = Female</td></tr>
<tr><td>A2. Age</td><td>Q7_2. Age</td><td>Age [15 - 95]</td></tr>
<tr><td>A5. Education
1. None
2. 1st cycle of basic education (4th grade)
3. 2nd cycle of basic education (5th and 6th grades/preparatory)
4. 3rd cycle of basic education (9th grade/5th year of high school)
5. Secondary education (12th grade/7th year of high school or equivalent/preparatory/ civic service)
6. Higher education</td><td>Q7_3. Education
1. None
2. Primary school
3. 6th grade
4. Preparatory cycle
5. Former 5th grade
6. Industrial/Commercial School
7. Unified 7th, 8th, 9th grades
8. Former 7th grade/Preparatory
9. Unified 10th, 11th, 12th grades
10. 2/3-year courses starting after 5th/9th grades
11. College/University (complete or incomplete)
12. Courses starting after the unified 11th/12th grades or former 7th grade
13. Master’s degree
14. Doctorate</td><td>Education
1 = None
2 = 1st cycle of basic education - 2 from A5; 2 from Q7_3
3 = 2nd cycle of basic education - 3 from A5; 3 and 4 from Q7_3
4 = 3rd cycle of basic education - 4 from A5; 5, 6 and 7 from Q7_3
5 = Secondary education - 5 from A5; 8, 9 and 10 from Q7_3
6 = Higher education - 6 from A5; 11, 12, 13 and 14 from Q7_3</td></tr>
<tr><td>Q3. Perceived Political Self Efficacy (PPE-S)
Internal personal political efficacy
Q3_1. I can influence the enactment of new laws and political decisions
Q3_2. I can facilitate the election of a political leader whose views I share
Q3_3. I can successfully demand that existing laws and political decisions be observed</td><td>Q6_5. Perceived Political Self Efficacy (PPE-S)
Internal personal political efficacy
Q6_5_1. I can influence the enactment of new laws and political decisions
Q6_5_2. I can facilitate the election of a political leader whose views I share
Q6_5_3. I can successfully demand that existing laws and political decisions be observed</td><td>Auto_Political_Efficacy
The mean of three internal personal political efficacy</td></tr>
<tr><td>Internal collective political efficacy
Q3_4. Together citizens of my country can influence the enactment of new laws and political decisions
Q3_5. Together citizens of my country can facilitate the election of a political leader whose views they share
Q3_6. Together citizens of my country can successfully demand that existing laws and political decisions be observed</td><td>Internal collective political efficacy
Q6_5_4. Together citizens of my country can influence the enactment of new laws and political decisions
Q6_5_5 Together citizens of my country can facilitate the election of a political leader whose views they share
Q6_5_6 Together citizens of my country can successfully demand that existing laws and political decisions be observed</td><td>Collective_Political_Efficacy
The mean of three internal collective political efficacy</td></tr>
</table>

External political efficacy Q3_7. The people in charge of government are willing to provide information on how political decisions are made Q3_8. The people in charge of government are interested in ensuring equal rights for all political parties and groups Q3_9. The people in charge of government are interested in carrying out the lawful demands of the citizens 1. Strongly disagree 2. Disagree 3. Neither agree nor disagree 4. Agree 5. Completely agree	**External political efficacy** Q6_5_7. The people in charge of government are willing to provide information on how political decisions are made Q6_5_8. The people in charge of government are interested in ensuring equal rights for all political parties and groups Q6_5_9. The people in charge of government are interested in carrying out the lawful demands of the citizens 1. Strongly disagree 2. Disagree 3. Neither agree nor disagree 4. Agree 5. Completely agree	External_Political_Efficacy The mean of three external political efficacy
Q17. Usually, when talking about politics, the terms “left” and “right” are used. On a scale of 0 to 10, where 0 represents the far left position and 10 represents the far right position, where would you place yourself? Use any value between 0 and 10 on the scale.	Q7_5. Do you consider yourself close to a particular political party? 0. No 1. Yes Q7_6. Which Party 1. CDS - Partido Popular (CDS-PP) 2. Partido Comunista Português (PCP) 3. Partido Social Democrata (PSD) 4. Bloco de Esquerda (BE) 5. CHEGA (CH) 6. Iniciative Liberal (IL) 7. Livre (L) 8. Partido Socialista (PS) 9. Pessoas-Animais-Natureza (PAN) 96. Other	Creation of 2 binary variables L (Leftist) and R (Rightist) L = 0 R = 0, if Q17 = 5 or Q7_5 = 2. No or Q7_6 = 96. Other L = 1 R = 0, if Q17 = [0, 4] or Q7_6 = 2, 4, 7, 8 or 9 L = 0 R = 1, if Q17 = [6, 10] or Q7_6 = 1, 3, 5 or 6

Q19. Did you vote in the legislative elections of 2019, or on the contrary, did you choose not to vote or were you unable to do so? 1. Yes 2. Didn't want or couldn't vote 3. Doesn't know/Doesn't remember 4. Doesn't want to answer	Q6_1. The following questions are related to the recent elections for the Republic Assembly, which took place on October 4, 2019. Of the following statements, which one best describes your case? 1. You didn't vote in the 2019 legislative elections because you couldn't 2. You thought about voting this time but didn't do it 3. You usually vote but didn't this time 4. You voted in the 2019 legislative elections	Creation of binary variable: 0. No, if Q19 is 2, 3 or 4 or if Q6_1 is 1, 2 or 3 1. Yes, if Q19 is 1 or if Q6_1 is 4

Participants were also required to respond to inquiries regarding attitudes towards populism. The survey questions and measurement model of populist attitudes are based on the definition of populism, previously mentioned. The questions focus on the three core features of populism: the sovereignty of the people, opposition to the elite, and the Manichean division between "good" and "evil":

- POP1 - The politicians in the [country] parliament need to follow the will of the people;
- POP2 - The people, and not politicians, should make our most important policy decisions;
- POP3 - The political differences between the elite and the people are larger than the differences among the people;
- POP4 - I would rather be represented by a citizen than by a specialized politician;
- POP 5 - Elected officials talk too much and take too little action;
- POP 6 - What people call 'compromise' in politics is really just selling out on one's principles.

The survey questions are aimed at measuring the full ideology of populism, with a focus on its conception of democracy, particularly the concept of the will of the people (their sovereignty) achieved with questions POP 1, POP2, and POP4 and the distinction between the people and the elite with POP 3 and POP 5. The Manichean nature of the distinction between the people and the elite is also captured in the survey questions through statement POP6, which highlights the battle between good and evil. Participants were asked to rate their agreement with the six populism questions on a Likert scale, with options ranging from 1 (I very much disagree) to 5 (I very much agree).

As Falcão et al. (2023a) proved that the POP-AS developed by Akkerman et al. (2014) is a valid and reliable measure for evaluating populist attitudes in Portugal and, since these questions were shared between the two surveys, the target variable of this study comprised the average of the six populist attitudes: (POP 1 + POP 2 + POP 3 + POP 4+ POP 5 + POP 6)÷6

3.3 Data treatment

After aggregating all the data, it is necessary to process and treat the data. This involved examining and reducing the available data, retaining only the relevant information.

The original dataset contained invalid values for certain questions related to PPE-S and populist attitudes (POP). To address this, the following steps were taken:

For the three questions related to each political efficacy, it was verified if there were more than one invalid value. If there were more than one, the participant's record was removed. If there was only one invalid value, the mean was calculated using the remaining two valid answers. If there were no invalid answers, the mean was calculated.

For the six populist attitudes, the respondent's record was removed if there were more than three invalid values. The mean was then calculated based on the number of valid values.

As a result of this preprocessing action, the dataset, which originally had 2974 rows, was reduced to 2930 rows. In conclusion, the dataset is composed of 2930 records and ten columns: Sex, Age, Education, Auto_Political_Efficacy (mean of internal personal political efficacy), Collective_Political_Efficacy (mean of internal collective political efficacy), External_Political_Efficacy (mean of external political efficacy), L, R, Vote and the target variable: Pop_Mean.

3.4 Exploratory data analysis

The exploratory data analysis should be the first step of any analysis. It consists in the search for patterns and trends in a specific dataset.

As observed earlier, the dataset for this study comprises two surveys and encompasses five categorical variables, namely Sex, Education, L, R and Vote along with five numerical variables, including Age, Auto_Political_Efficacy, Collective_Political_Efficacy, External_Political_Efficacy and the target variable Pop_Mean. The numerical variables are described in table 3.2.

Table 3.2: Descriptive Statistics of numerical variables

	Age	Auto_Political_Efficacy	Collective_Political_Efficacy	External_Political_Efficacy	Pop_Mean
count	2930	2930	2930	2930	2930
mean	43.05	3.22	3.57	2.76	3.59
std	16.05	0.70	0.73	0.78	0.70
min	15.00	1.00	1.00	1.00	1.00
25%	29.00	2.67	3.00	2.33	3.00
50%	43.00	3.33	3.67	2.67	3.50
75%	56.00	3.67	4.00	3.33	4.00
max	95.00	5.00	5.00	5.00	5.00

Sex is a binary variable that was attributed to 1 for males and 2 for females: 1432 (48.9%) females and 1498 (51.1%) males have answered the surveys.

Age is a discrete numerical variable which ranges from 15 to 95. The mean and median of the variable Age are both close to 43, which indicates that the distribution of Age is approximately symmetrical. This means that there are equal numbers of people above and below the average age and that there is no skewness in the data. Symmetrical distribution of Age suggests that the sample is representative of the population and that there are no significant biases or errors in the data collection process.

Education is an ordinal categorical variable which identifies the level of education of each respondent and goes from 1 (lower education) to 6 (higher education). As can be seen in the bar chart of figure 3.1, the number of respondents decreases as the level of education decreases as well.

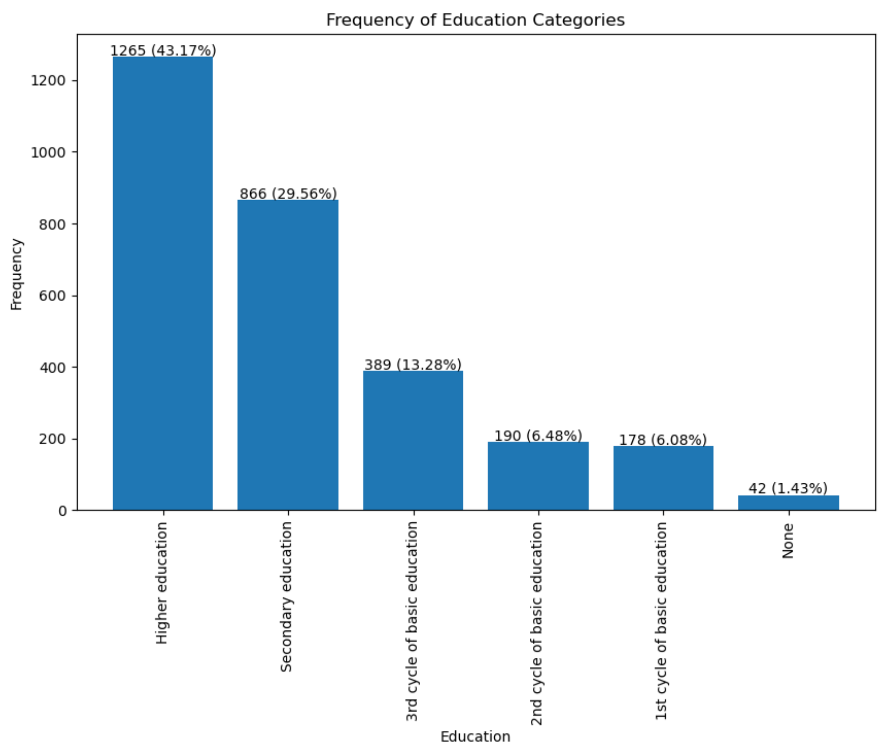

Figure 3.1: Bar chart of variable Education

The variables Auto_Political_Efficacy, Collective_Political_Efficacy and External_Political_Efficacy are numerical variables with a mean of 3.22, 3.57 and 2.76 as seen in the figure 3.2.

For Auto_Political_Efficacy, the second quartile (Q2) is positioned higher than the center of both the first quartile (Q1) and the third quartile (Q3), indicating a positive skewness. Additionally, this feature exhibits an extreme lower outlier, suggesting the presence of exceptionally low values.

In the case of Collective_Political_Efficacy, the Q2 is positioned higher than the centers of both Q1 and Q3, indicating a similar positive skewness as observed in Auto_Political_Efficacy. Furthermore, Collective_Political_Efficacy demonstrates the highest Q2 value among the three features, suggesting a relatively higher central tendency. Notably, two extreme lower outliers indicate a few data points with unusually low values.

On the other hand, External_Political_Efficacy exhibits a different pattern. The Q2 is positioned lower than the centres of Q1 and Q3, indicating a negative skewness. Additionally, External_Political_Efficacy has a lower median (Q2) than the other two features. Moreover, an extreme high outlier is observed, indicating the presence of an exceptionally high value.

Despite the presence of outliers in the three variables, it was decided to retain these records for further analysis and modelling.

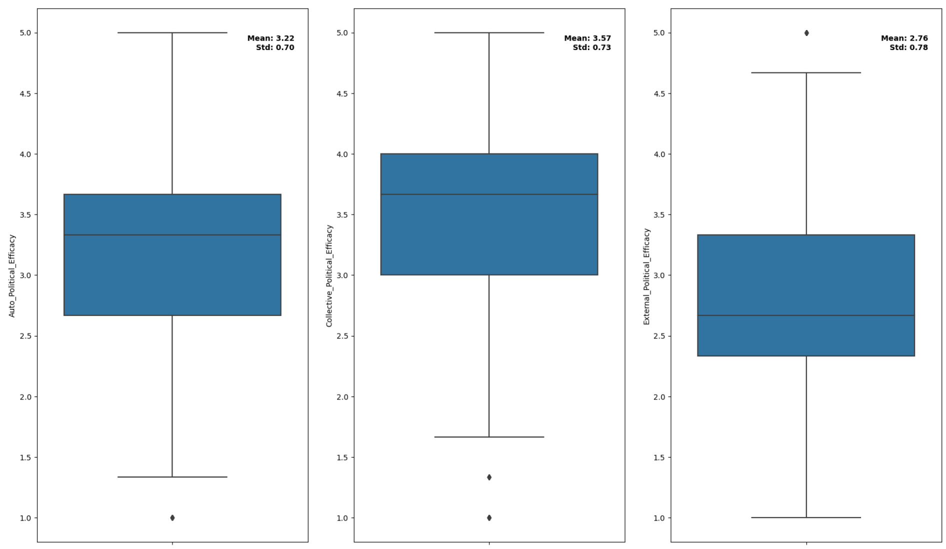

Figure 3.2: Box Plots of variables Auto_Political_Efficacy, Collective_Political_Efficacy, External_Political_Efficacy

The variable L consists of 2295 respondents who do not identify with the leftist political side (value = 0), while 635 respondents identify as leftist (value = 1). Similarly, variable R includes 2290 respondents who do not identify with the right-wing and 640 respondents who identify as rightists (value = 1). It is worth mentioning that some respondents do not identify with either the left or right, which provides a possible explanation for the high frequency of value 0.

Finalizing the overview of the univariate analysis, we can observe the histogram of the variable Pop_Mean in Figure 3.3. The histogram seems to show a normal distribution.

Prior to modelling the data, it is essential to examine the relationships between the variables. As the dataset consists of numerical, ordinal, and binary data, various coefficients were computed to capture these associations. Pearson, Point-Biserial and Spearman coefficients were utilized for this purpose.

Pearson's correlation coefficient was utilized when examining associations between pairs of continuous numerical variables; The point-biserial correlation was applied when exploring associations between a binary variable and a continuous numerical variable; Spearman's rank correlation coefficient was employed when analyzing relationships involving ordinal data, making it suitable for ordinal vs. continuous numerical data.

The findings of this bivariate analysis are summarized in figure 3.4.

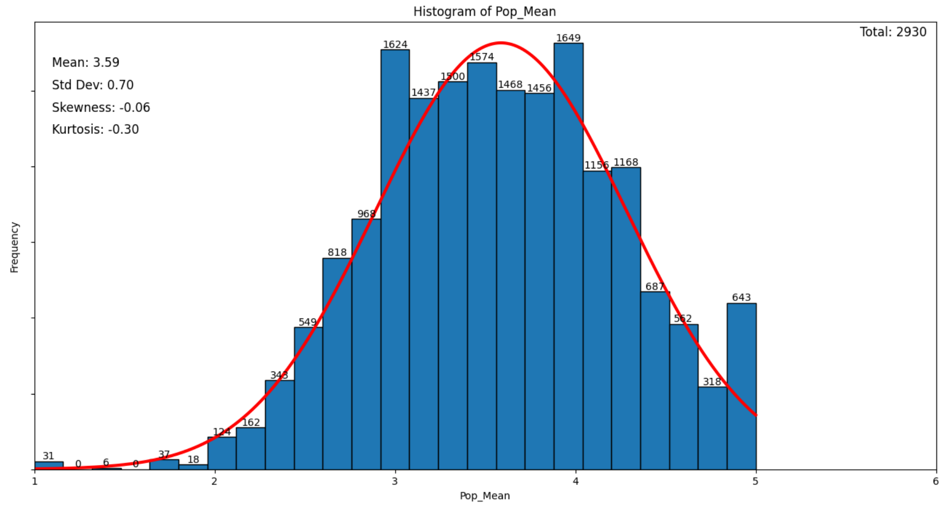

Figure 3.3: Histogram of target variable Pop_Mean

There are no significant correlations observed among the variables. However, a negative correlation of -0.40 between Age and Education can be observed. This implies that as Age increases, the level of education tends to decrease.

In terms of the Mean_efficacy variables, positive correlations ranging from 0.31 to 0.48 can be observed among them.

As expected, variables L and R exhibit a negative correlation of -0.28, indicating an inverse relationship between left-wing and right-wing identification.

Regarding the variable Pop_Mean, negative correlations can be observed with Sex, Education, and External_Political_Efficacy, with coefficients of -0.12, -0.16, and -0.22, respectively. This suggests that males, respondents with lower levels of education, and lower values of External_Political_Efficacy tend to have higher populist attitudes.

These findings will be further explored and analysed in detail in Chapter 4 of this dissertation.

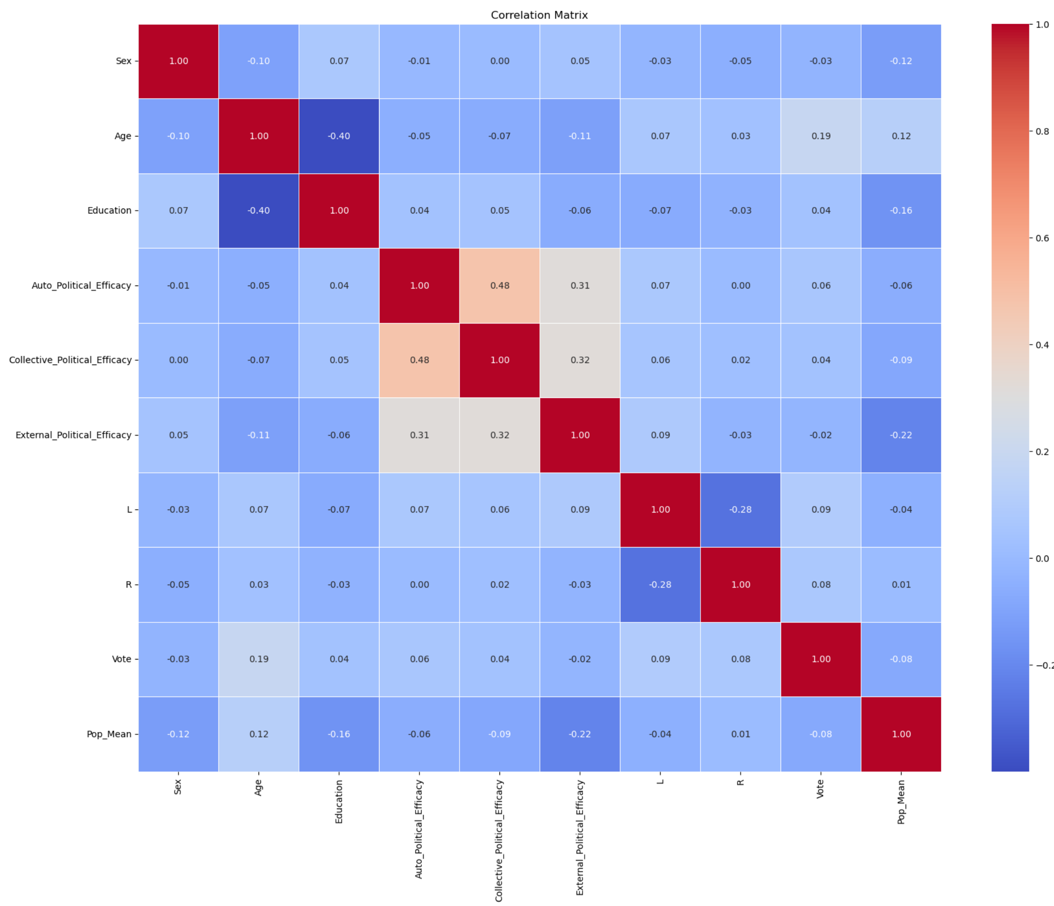

Figure 3.4: Pearson, Point-Biserial and Spearman correlations

3.5 Software

This dissertation's data analysis and experimentation were conducted using Jupyter Notebook, a web-based interactive computing environment. Python, along with various libraries and packages for data manipulation, visualization, statistical analysis, and machine learning, were employed to support the research process.

Data manipulation and analysis were conducted using the "pandas" and "numpy" libraries, respectively, facilitating data structuring and statistical computations. Informative visualizations were crafted with the assistance of the "seaborn" and "matplotlib.pyplot" libraries, enabling a clear graphical representation of outcomes (McKinney et al. (2010), Harris et al. (2020), Hunter (2007), Waskom (2021)).

In regards to the regression and, in addition to linear regression models, more complex models were explored, such as "DecisionTreeRegressor", "GradientBoostingRegressor", and "RandomForestRegressor" from the "sklearn.ensemble" library (Pedregosa et al. (2011)).

Metrics such as mean squared error, mean absolute error, and coefficient of determination (R^2) were assessed to gauge regression model performance.

Moreover, the classification approach modules such as "RandomForestClassifier,", "LogisticRegression," "SVC," and "XGBClassifier" facilitated the exploration of predictive models. Performance metrics, including accuracy, recall, precision, and F1-score were measured using the "accuracy_score," "recall_score," "precision_score," and "f1_score" functions (Pedregosa et al. (2011)).

For both types of algorithms, "GridSearchCV" was performed in order to optimize models. Moreover, model interpretation was enhanced with the "SHAP" library, facilitating analysis of feature importance analysis in predictions (Pedregosa et al. (2011)).

Statistical analyses extended to methods such as the Friedman Chi-Square test, made possible by the "friedmanchisquare" function from the "scipy.stats" module. Post-hoc analysis was conducted using the "posthoc_nemenyi_friedman" function from the "scikit_posthocs" library, enabling further insights into the results (Virtanen et al. (2020)).

Chapter 4

Results and Discussion

In this chapter, the data modelling process is described as well as the comparison between the models. Furthermore, this section presents and discusses the explored models' inference results, predictions, and diagnosis.

In the next sections, the train_test_split function from the sklearn.model_selection module in Python was employed. This function is a component of the scikit-learn library. Initially, a test size of 0.25 was chosen, allocating 25% of the data for testing purposes, while the remaining 75% was used for training the model.

Various regression models will be examined, including linear models such as linear regression, ridge regression, lasso regression, and elastic net regression. These models assume a linear relationship between the predictors and the response variable. Furthermore, a comprehensive investigation into tree-based models is to be undertaken.

Through exploration of these regression techniques, the aim is to assess their performance and evaluate their effectiveness in capturing the underlying patterns in the data.

Moreover, the target variable will undergo a transformation, thereby framing the problem as a classification one to achieve superior model performances.

4.1 Regression

4.1.1 Linear regression

In the initial phase, a linear regression algorithm was employed to analyse the relationship between the features and the target variable (Pop_Mean). The coefficient estimates of each feature were examined to assess their impact on the target variable. To ensure fair comparison and enhance interpretability of the estimates, a standardization technique called StandardScaler was applied, and it transforms the data by subtracting the mean and dividing it by the standard deviation, resulting in a distribution with a mean of 0 and a standard deviation of 1. This process converts the data into a z-score distribution, where values are expressed in standard deviations from the mean. Standardization is a widely used preprocessing step in machine learning to normalize numerical features and facilitate comparison across different scales (Pedregosa et al. (2011)).

The coefficient estimate indicates how a unit change in the predictor variable affects the target variable, holding other variables constant. The height of the coefficient estimates bars represents the magnitude of impact a particular feature has on the target variable. The visual representation in figure 4.1 demonstrates the influence of the features “External_Political_Efficacy” and “Education” on the target variable, Pop_Mean. The bar representing “External_Political_Efficacy” is the largest, indicating its significant influence, as well as the bar representing “Education”.

Besides the magnitude, reflecting the strength of the relationship between the predictor and the target variable, it’s possible to state that a positive coefficient indicates that an increase in the predictor variable is associated with an increase in the target variable (it’s the case of variables age and Auto_Political_Efficacy). While a negative coefficient suggests a decrease in the target variable with an increase in the predictor variable. In this case, the increase in variables like sex, Education, Collective_Political_Efficacy, External_Political_Efficacy, L, R and Vote leads to lower Populist attitudes (Pop_Mean) from people.

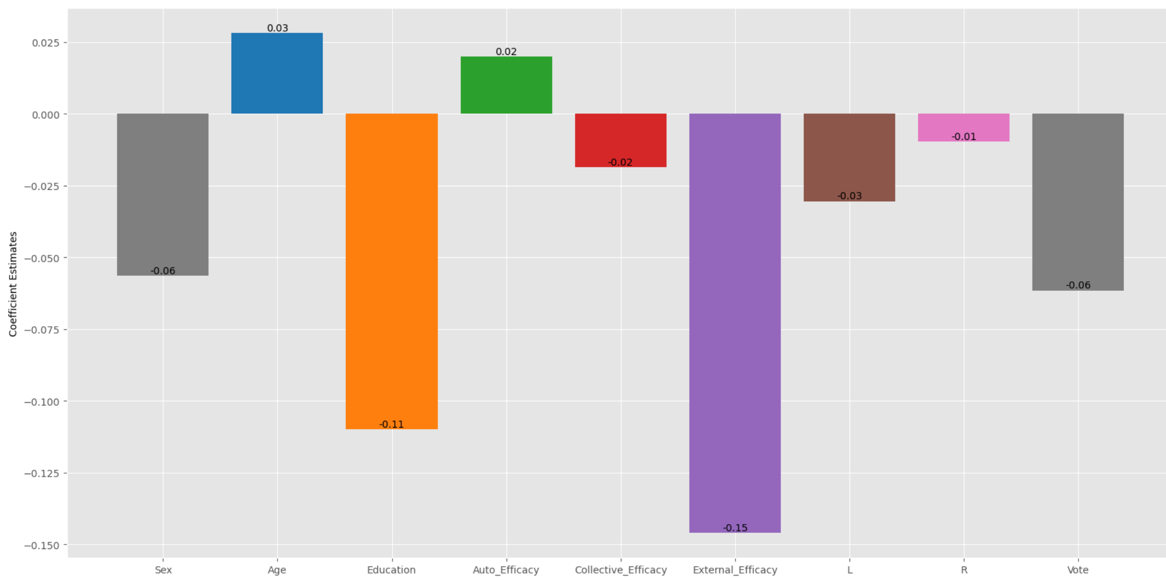

Figure 4.1: Feature coefficients estimates towards target variable Pop_Mean for linear regression

SHAP values plots are used in explainable artificial intelligence to understand the contribution of individual features in a predictive model. These plots offer valuable insights into the impact of input features on model predictions. Visualizing the Shapley values provides the relationships between features and predictions. They can uncover unexpected relationships, enabling the identification of model errors or biases. Additionally, these plots aid in recognizing irrelevant or redundant features that have minimal impact on predictions. Moreover, they facilitate feature importance comparison across various models or algorithms, facilitating model selection and enhancing comprehension of their distinctions (Lundberg and Lee (2017), Molnar (2020)).

In figure 4.2 the SHAP values of each feature and their values are reflected in the output target variable. The analysis of feature importance revealed that External_Political_Efficacy had the most significant impact on the model’s predictions, while variable R was found to be the least influential. Moreover, a more detailed understanding of the model’s behaviour can be obtained from Figure 4.2. The following insights can be derived:

- Lower values of External_Political_Efficacy have a positive impact on Pop_Mean, indicating that as External_Political_Efficacy decreases, the tendency towards populism in Pop_Mean increases;
- Individuals with higher levels of education tend to score lower on Pop_Mean, suggesting that higher education is associated with lower levels of populism;
- Gender differences play a notable role in Pop_Mean. Men, represented by low values of Sex, tend to exhibit higher levels of populism compared to women;
- People who voted - high feature level - tend to have lower populist values opposing those who didn't vote - low feature level;
- Those who identify with leftist (value 1 on L) and rightist ideologies (value 1 on R) have lower populist values than those who do not identify with any ideology (value 0 on both L and R). Nevertheless, the highest value of L indicates lower populist attitudes than the highest value of R as can be seen by the red values for both features. This indicates that people who identify with left ideology tend to have less populist attitudes than those who identify with right ideology;
- Younger people also tend to have lower populist values;
- Although the impact is not as strong, higher values of Auto_Political_Efficacy and lower values of Collective_Political_Efficacy are associated with higher levels of populism.

From the SHAP values, it's possible to reveal some insights through the variables' impact towards the model output.

Notably, individuals who exhibit higher levels of populist attitudes tend to show low agreement with the statements related to the behaviour of the people in charge of the government.

The first statement of External_Political_Efficacy, "The people in charge of government are willing to provide information on how political decisions are made," receives low agreement scores that the government lacks transparency and openness in sharing information about political decision-making processes. The findings indicate a possible disconnect between the government and citizens, leading to decreased trust in the decision-making mechanisms.

Similarly, the second statement, "The people in charge of government are interested in ensuring equal rights for all political parties and groups," received low agreement scores from individuals with high populist attitudes value. This implies that these individuals perceive a lack of fairness and equal treatment in the government's approach to different political parties and groups.

The third statement, "The people in charge of government are interested in carrying out the lawful demands of the citizens," also received low agreement scores from individuals with high populist attitudes. This indicates a perception among these individuals that the government fails to address the lawful demands put forth by the citizens. It suggests a disconnect between the government's actions and the perceived needs and expectations of the populace.

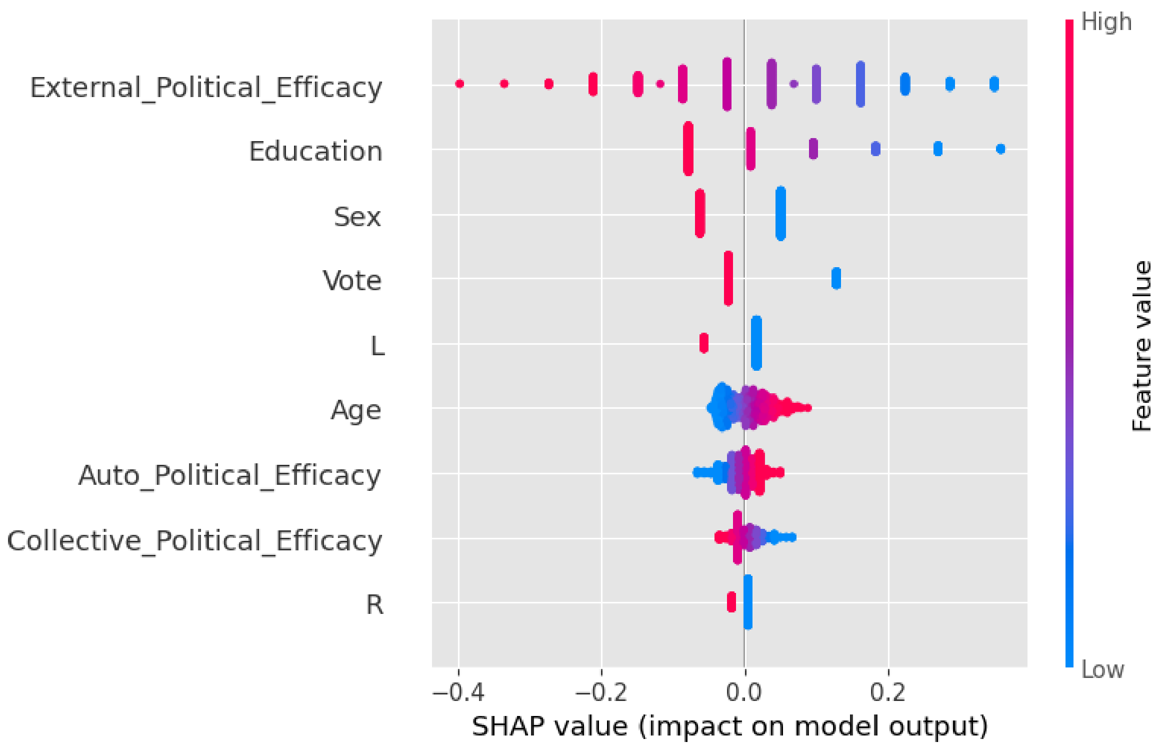

Figure 4.2: Shap Values of features towards target variable Pop_Mean for linear regression

These findings reflect a general sentiment of mistrust, dissatisfaction, and a perceived lack of alignment between the government's actions and the expectations of individuals with high levels of populist attitudes (Spruyt et al. (2016)).

Spruyt et al. (2016) stated that education level and support for populism are related, and it's clear that through figure 4.2, people with higher education tend to have low values of populist attitudes. These results are in line with some previous studies (Rico, Guinjoan, and Anduiza (2017); Spruyt et al. (2016)). This can be attributed to their increased awareness and critical thinking skills, which may make them more discerning and resistant to the influence of populist appeals. On the other hand, individuals with lower levels of education may be more susceptible to populist messaging, potentially due to various socio-economic factors that can contribute to their vulnerability. It is important to note that the relationship between education level and support for populism is multifaceted and influenced by many factors beyond education alone (K. A. Hawkins et al. (2012)).

Regarding variable Sex, males are represented by the low value (blue) and females are represented by the high value (red) in figure 4.2. That said, men show higher populist attitudes. Over the past few decades, extensive research has provided insights into the factors driving voter support for populist parties, particularly those aligned with populist radical right ideologies (Elchardus and Spruyt (2016); Immerzeel et al. (2015); Ivarsflaten (2008)).

First, Spierings and Zaslove (2015) showed that women feel less threatened by immigration and thus hold weaker anti-immigrant attitudes.

The socio-economic perspective posits that women's employment patterns, such as their higher representation in the public sector and lower presence in labour-intensive industries, contribute to their reduced vulnerability to the effects of deindustrialization. As a result, women are less prone to perceive a direct threat to their economic well-being, which diminishes their inclination to support Populist Radical Right (PRR) parties (Harteveld, Van Der Brug, Dahlberg, and Kokkonen (2015)).

Also, Spierings and Zaslove (2017) state that populist attitudes have been associated with opposition to European integration, suggesting that the resistance may stem from a perceived divide between the 'political elite' and the 'people,' rather than solely targeting the EU. This finding holds relevance from a gender perspective, considering the EU's role in promoting women's empowerment and advancing the rights of LGBT individuals across Europe.

Looking at variable Vote, it seems that people who voted 2019 general elections tend to have lower populist attitudes score in opposition to those who didn't vote.

Low values of Age (younger participants) also tend to have lower populist attitudes in opposition to older people. Age seems to correlate positively with populist attitudes, thus confirming empirical analyses conducted in Southern European countries (Rico et al. (2017); Teperoglou, Andreadis, Tsatsanis, et al. (2016)). However, it's important to be cautious because age appears to have a stronger association with right-wing indicators like ethnic nationalism and xenophobia. Consequently, the relationship between age and populist attitudes may be confined to the realm of right populism exclusively (Bernhard and Hänggli (2018)).

Although the Auto_Political_Efficacy and Collective_Political_Efficacy variables do not show great impact in the model output, their impact can bring some insights. It's clear that low values of Collective_Political_Efficacy tend to have a positive impact on populist attitudes. This variable is the mean value of internal collective political efficacy which consisted in these sentences:

- PPE-S4. Together citizens of my country can influence the enactment of new laws and political decisions.
- PPE-S5. Together citizens of my country can facilitate the election of a political leader whose views they share.
- PPE-S6. Together citizens of my country can successfully demand that existing laws and political decisions be observed.

One possible reason why people who strongly disagree or disagree with the statement tend to have more populist attitudes could be a perception of limited political influence and a belief that the existing political system is unresponsive or unrepresentative of their interests.

When individuals feel that they have little to no influence over the enactment of new laws and political decisions (PPE-S4), the election of a political leader whose views they share (PPE-S5), or the enforcement of existing laws and political decisions (PPE-S6), they may become disillusioned with the current political establishment. This frustration and disillusionment can lead to a stronger attraction towards populist ideologies that promise to give power back to the people and challenge the perceived elite or establishment.

The opposite happens with Auto_Political_Efficacy - internal personal efficacy - where higher values (agree, completely agree), represent higher populist attitudes value. The sentences regarding this variable are the following:

- PPE-S1. I can influence the enactment of new laws and political decisions.
- PPE-S2. I can facilitate the election of a political leader whose views I share.
- PPE-S3. I can successfully demand that existing laws and political decisions be observed.

Although can be contradictory with Collective_Political_Efficacy, one possible explanation for this pattern is that individuals who strongly believe in their ability to influence political processes and outcomes may feel a sense of empowerment and confidence in their own agency. They may view themselves as active participants in the political system and believe that their actions and demands can bring about meaningful change. This belief in their own influence and efficacy may align with populist narratives that emphasize the power and voice of the people.

In order to assess the effectiveness of the regression models, various metrics were computed. While an initial test size of 25% was employed, different test sizes were also examined to observe the performance of the metrics across varying test sizes in table 4.1.

The evaluation of the linear regression model using the test set of 25% allowed the following performance metrics: Mean Squared Error (MSE) of 0.458, Mean Absolute Error (MAE) of 0.543, and Mean Absolute Percentage Error (MAPE) of 0.169. Also, changing test sizes doesn't make a considerable impact on the obtained metrics - table 4.1.

As the average squared difference between the predicted and actual values increases, the MSE value also increases. The MAE represents the average absolute difference between the predicted and actual values, and a lower value indicates better accuracy. As a result of this model, a moderate level of accuracy and precision was achieved with an MSE of 0.458 and an MAE of 0.543. Although MSE and MAE may not provide comprehensive information on their own, comparing them to other models offers valuable insights and serve as effective evaluation criteria.

The MAPE, representing the average percentage difference between predicted and actual values, is useful for assessing relative errors. A lower MAPE value indicates a better match between predicted and actual values. In this study, the MAPE was calculated as 0.169, suggesting that, on average, the model's predictions were within approximately 16.9% of the true values.

Among the test sizes evaluated, it was observed that a test size of 25% resulted in the largest R-squared value of 0.1, indicating that approximately 10% of the variance in the target variable could be explained by the linear regression model. Even though the R-squared value remains relatively low, this result suggests a moderate association between the model and the target variable. It is important to note that R-squared values closer to 1 indicate a better fit of the model to the data.

In regression analysis, residuals and predicted values play a fundamental role in evaluating the performance and validity of the model. Residuals represent the discrepancies between the actual observed values and the values predicted by the model. These differences are crucial in understanding how well the model fits the data and whether it captures the underlying relationships between the variables.

Table 4.1: Different test sizes Metrics obtained in linear regression

Metrics	Test size				
	0.2	0.25	0.3	0.35	0.4
Mean Squared Error (MSE)	0.467	0.458	0.461	0.455	0.443
Mean Absolute Error (MAE)	0.549	0.543	0.545	0.542	0.536
Mean Absolute Percentage Error (MAPE)	0.168	0.169	0.169	0.168	0.165
R-squared	0.094	0.100	0.091	0.099	0.099

As seen in figure 4.3, the linearity assumption is not supported due to the residuals vs. predicted values plot showing a negative slope. However, it appears to have homoscedasticity (even distribution of points around zero), suggesting that the model might be capturing the average behaviour well. Still, it underestimates the variability (spread) of the errors (Penn State Eberly College of Science (2021)).

In this case, the negative slope typically indicates that the model overestimates the target variable's value for lower predicted values and underestimates it for higher predicted values. However, the spread of the residuals (the magnitude of the errors) is consistent across the range of predicted values.

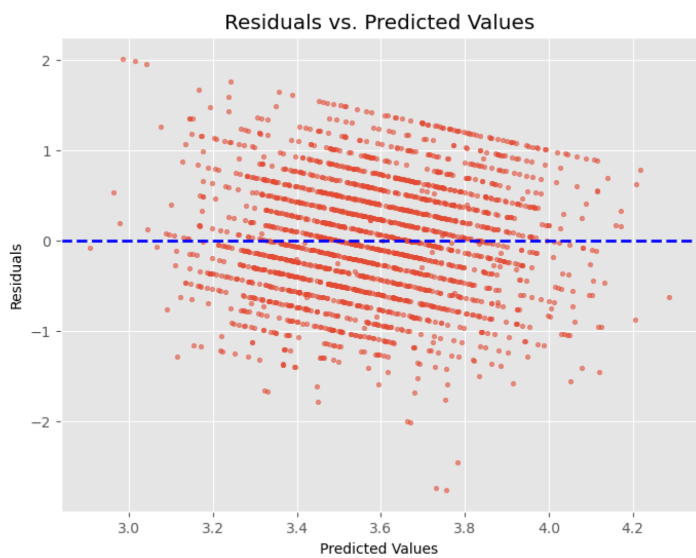

Figure 4.3: Residual plot analysis

Moreover, by the QQ plot of the residuals presented in figure 4.4, the residuals follow a reasonably straight line (with deviations at the tails, which is normal), suggesting that the normality assumption is met.

Despite the negative slope in the residuals vs. predicted values plot, the residuals seem to be well-distributed around zero, and the QQ plot exhibits a reasonably straight line, indicating that the model's residuals have homoscedasticity and approximate normality (Statology (2020)).

Overall, the results indicate that the linear regression model shows some level of predictive

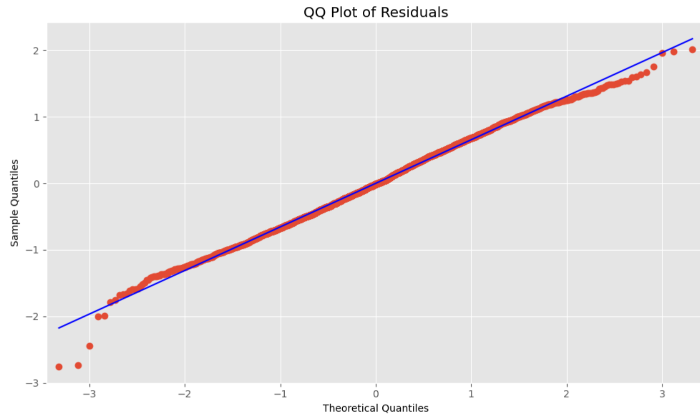

Figure 4.4: QQ Plot of Residuals

capability. Nevertheless, performance metrics should be evaluated within the context of the specific problem domain and the acceptable error tolerance level. Additional analysis, model refinement, and comparison with other models will be necessary to improve predictive accuracy and assess the model's suitability for practical use.

4.1.2 Ridge regression

Linear regression is a widely used statistical technique for modelling the relationship between a dependent variable and one or more independent variables. It aims to find the best-fit line that minimizes the sum of squared differences between the observed and predicted values. However, linear regression can be susceptible to overfitting when dealing with high-dimensional datasets or multicollinearity among the independent variables (Skiena (2017)).

In contrast to linear regression, where coefficients can be large and prone to overfitting, ridge regression provides a more robust and stable solution by balancing the trade-off between model complexity and accuracy. The ridge algorithm is particularly useful when working with datasets containing highly correlated predictors or when there is a need for better generalization performance (Skiena (2017)).

Firstly, cross-validation was performed, being tested a list of alphas in RidgeCV [0.0001, 0.001, 0.01, 0.1, 1, 10, 20, 30, 40, 50, 60, 70]. The obtained alpha was 50, being the optimal regularization parameter for the Ridge regression model. It consists of the level of regularization applied to the model by influencing the shrinkage of the coefficients. It helps balance the trade-off between model complexity and fitting the data well, ultimately aiming to improve the model's generalization performance.

In figure 4.5 it's possible to see the coefficient estimates for the ridge algorithm. They show similar values as in linear regression. For Ridge, standardization was also applied.

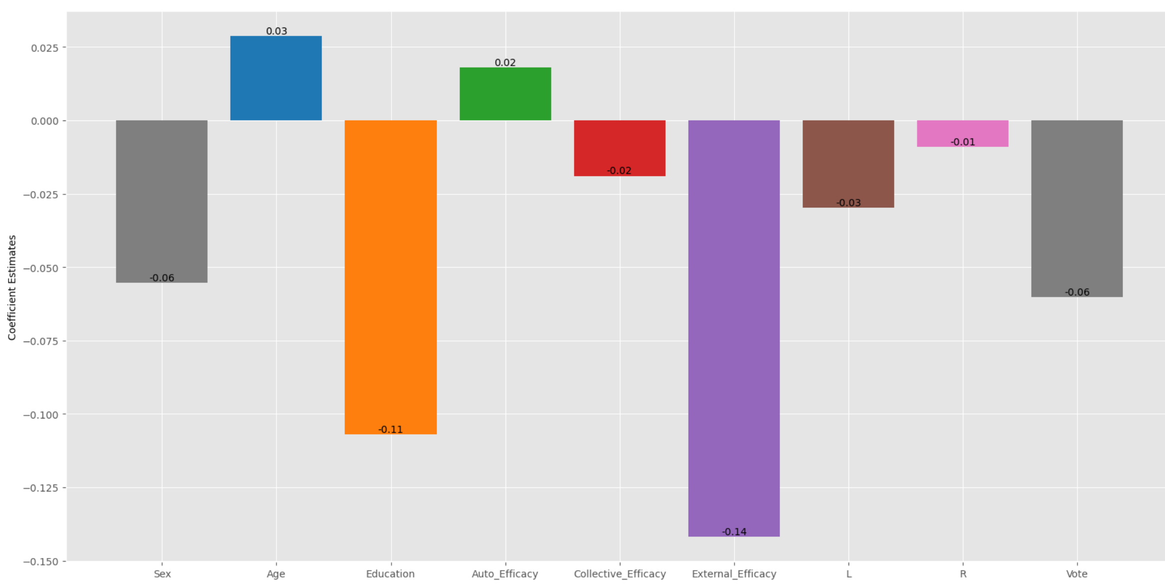

Figure 4.5: Feature coefficients estimates towards target variable Pop_Mean for ridge regression

The SHAP values are very similar to Linear Regression so the previous explanations are applied to ridge regression - figure 4.6.

Testing several test sizes the metrics obtained are explained in table 4.2.

Compared to linear regression, the Ridge regression model results are similar. However, when increasing the test size, there is a notable improvement in the coefficient of determination

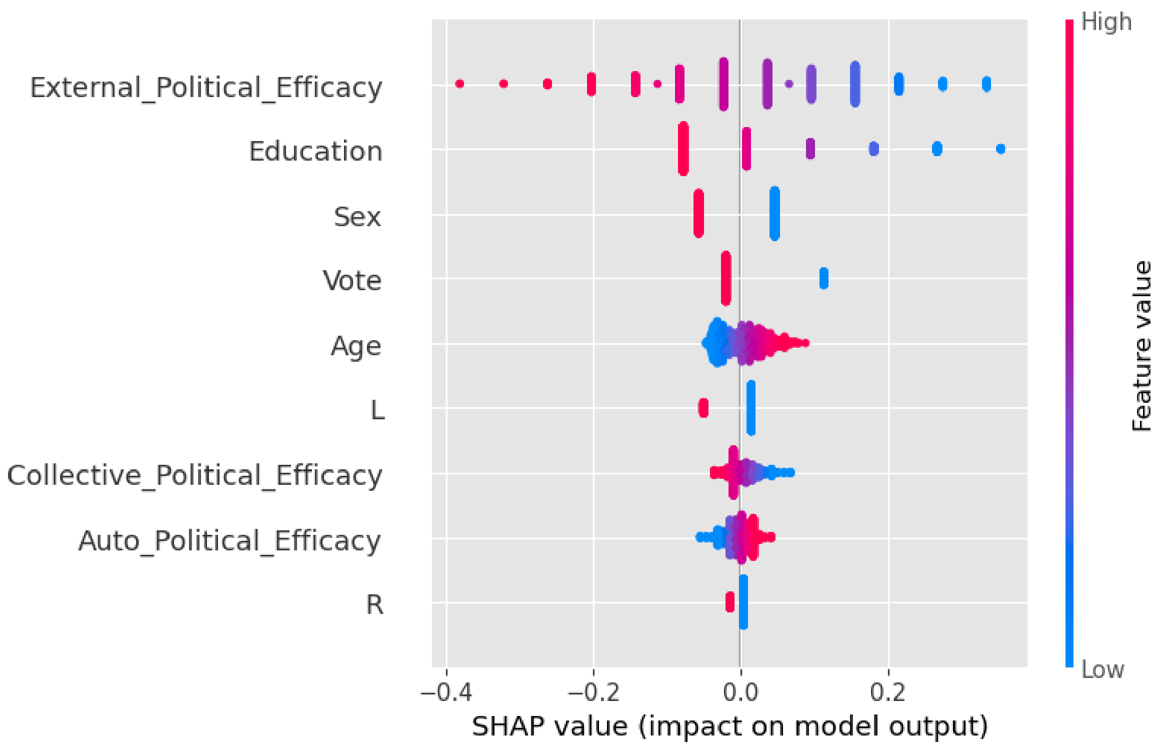

Figure 4.6: SHAP Values of features towards target variable Pop_Mean for ridge regression

(R^2), which reaches a value of 0.102. Considering the performance metrics, particularly for the error measures, it was observed that with a test size of 0.4, the model exhibited slightly smaller errors compared to a test size of 0.25.

Table 4.2: Different test sizes Metrics obtained in ridge regression

Metrics	Test size				
	0.2	0.25	0.3	0.35	0.4
Mean Squared Error (MSE)	0.466	0.458	0.459	0.453	0.453
Mean Absolute Error (MAE)	0.548	0.543	0.543	0.542	0.535
Mean Absolute Percentage Error (MAPE)	0.168	0.169	0.169	0.168	0.164
R-squared	0.095	0.100	0.095	0.102	0.102

4.1.3 Lasso regression

Lasso regression, short for "Least Absolute Shrinkage and Selection Operator," is a regression technique that combines both feature selection and regularization. It is an extension of linear regression that addresses multicollinearity and helps identify the most relevant features for predicting the target variable (Skiena (2017)).

While ridge regression uses L2 regularization, which adds the squared magnitude of the coefficients to the model's objective function, lasso regression utilizes L1 regularization. L1 regularization adds the absolute values of the coefficients to the objective function, resulting in a sparsity-inducing effect (Skiena (2017)).

Performing cross-validation, among the alpha values tested ([0.0001, 0.001,0.01, 0.1, 1, 10]), it was found that the best value for the lasso algorithm was 0.0001.

The resulting estimates were calculated and visualized in figure 4.7 following the standardisation and computation of coefficient estimates.

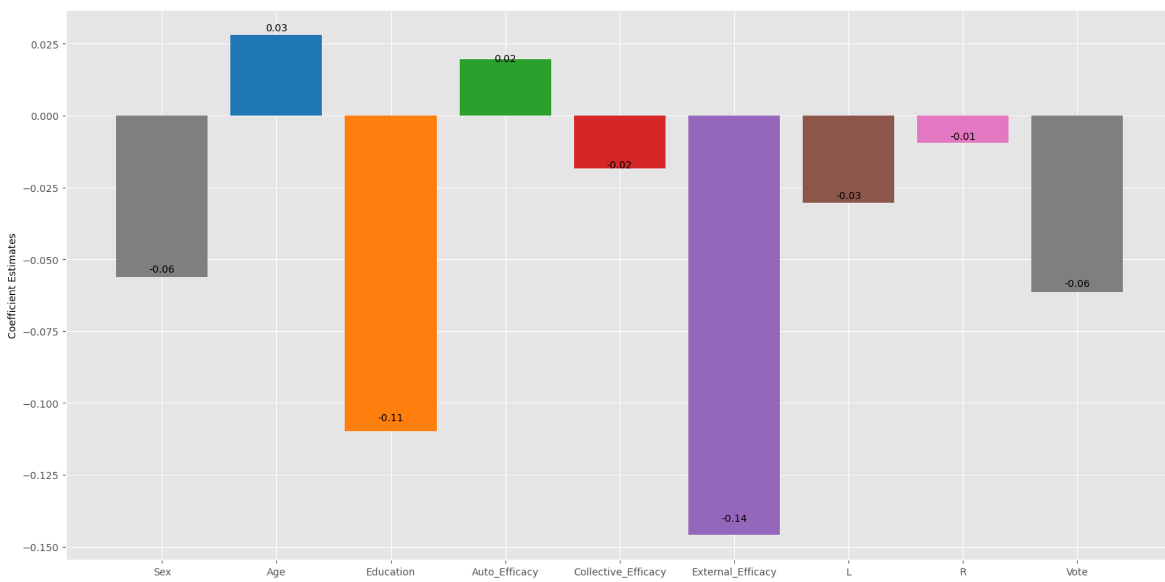

Figure 4.7: Feature coefficients estimates towards target variable Pop_Mean for lasso regression

The SHAP values for lasso regression are very similar to the previous linear models as can be seen in figure 4.6.

In order to assess the performance of the lasso algorithm under different test sizes, a comprehensive analysis was conducted. The results of this analysis, including the evaluation metrics, are presented in a table 4.3.

Like ridge regression, increasing the test size tends to result in slightly lower error and higher R^2 values. While this improvement is notable, a test size of 40% appears to be a suitable choice.

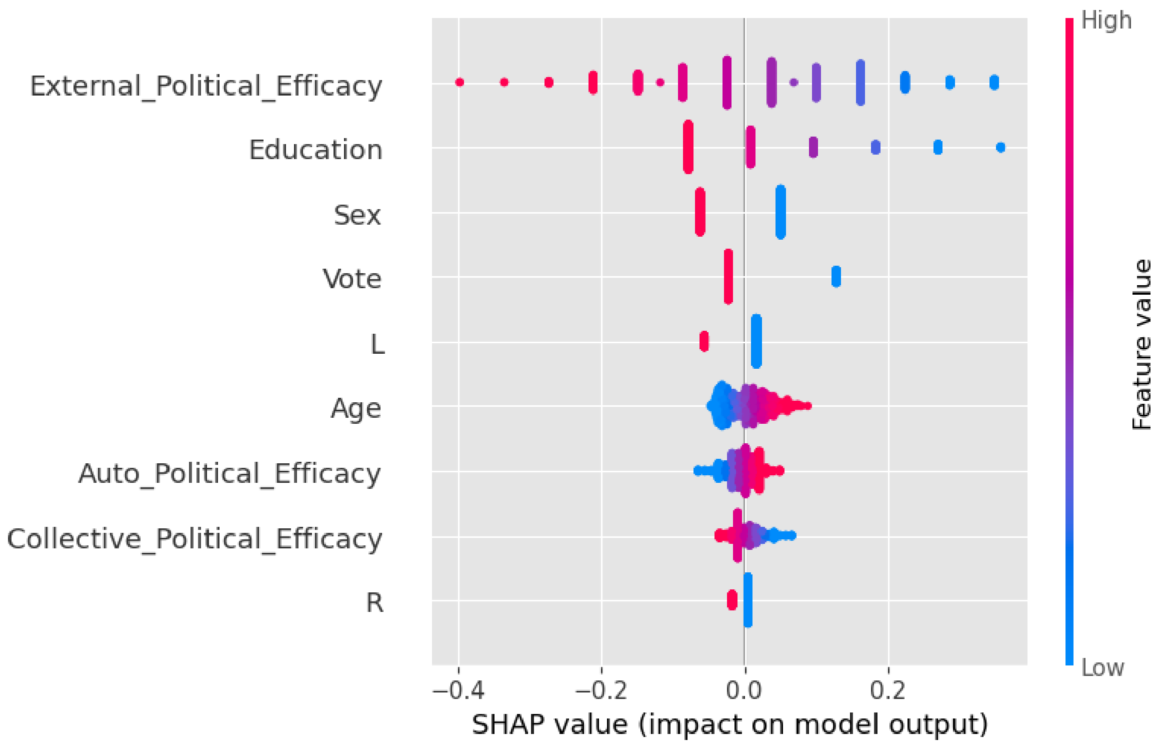

Figure 4.8: SHAP Values of features towards target variable Pop_Mean for lasso regression

Table 4.3: Different test sizes Metrics obtained in lasso regression

Metrics	Test size				
	0.2	0.25	0.3	0.35	0.4
Mean Squared Error (MSE)	0.466	0.457	0.459	0.453	0.441
Mean Absolute Error (MAE)	0.548	0.542	0.543	0.540	0.534
Mean Absolute Percentage Error (MAPE)	0.168	0.168	0.168	0.168	0.164
R-squared	0.096	0.102	0.096	0.103	0.103

4.1.4 Elastic net regression

Elastic net regression is a combination of ridge regression and lasso regression. Its objective function incorporates both L1 (lasso) and L2 (ridge) regularization penalties. By tuning the weighting parameter, it's possible to control the balance between the L1 and L2 regularization, allowing the model to select variables (like lasso) and shrink coefficients towards zero (like ridge) (Skiena (2017)).

A cross-validation was performed where the following list of alphas and L1 were tested:

- alphas = [0.0001, 0.001, 0.01, 0.1, 1, 10, 20];
- L1_ratio = 10 number of evenly spaced values were generated between 0.01 and 1. The l1_ratio parameter determines the balance between L1 and L2 regularization. An l1_ratio of 1 corresponds to pure L1 regularization (lasso), while an l1_ratio of 0 corresponds to pure L2 regularization (ridge). Intermediate values between 0 and 1 combine both types of regularization.

The elastic net model is created with an alpha of 0.01 and an l1 ratio of 0.1 being fit into the training data and tested on the test data. This allowed us to obtain the following coefficient estimates after performing variables standardization - figure 4.9.

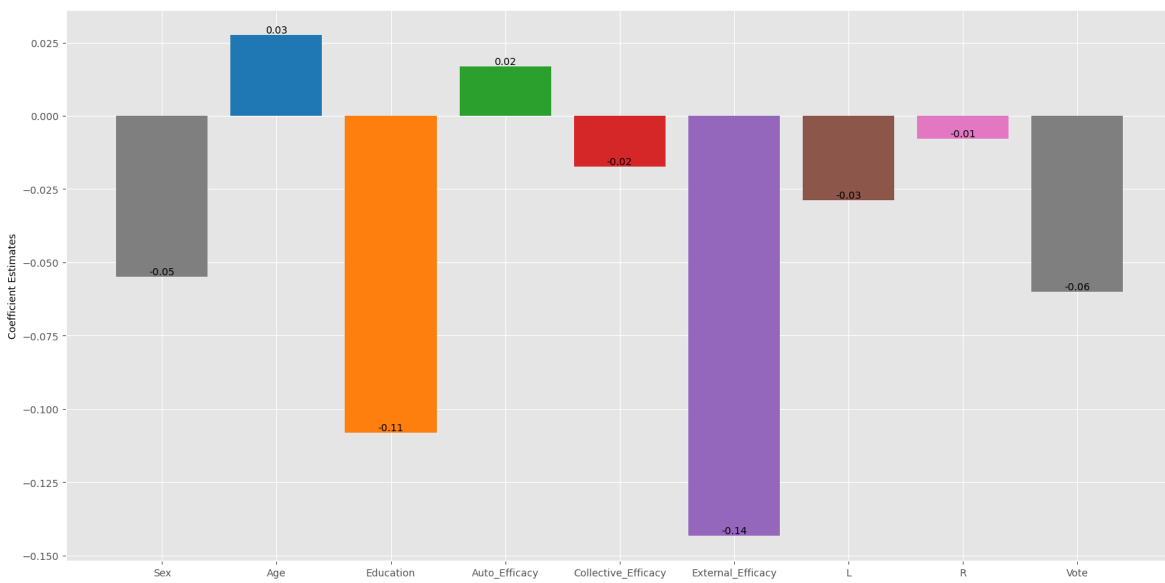

Figure 4.9: Feature coefficients estimates towards target variable Pop_Mean for elastic net regression

The SHAP values for elastic net regression can be seen in figure 4.10.

Finally, the metrics for elastic net for different test sizes can be seen in table 4.4.

The results didn't show any improvements relative to lasso and ridge regressors. These three algorithms are particularly useful when there are many correlated variables in the dataset, as they can help identify important variables while handling multicollinearity. This is not the case as previously seen on the correlation matrix - figure 3.4.

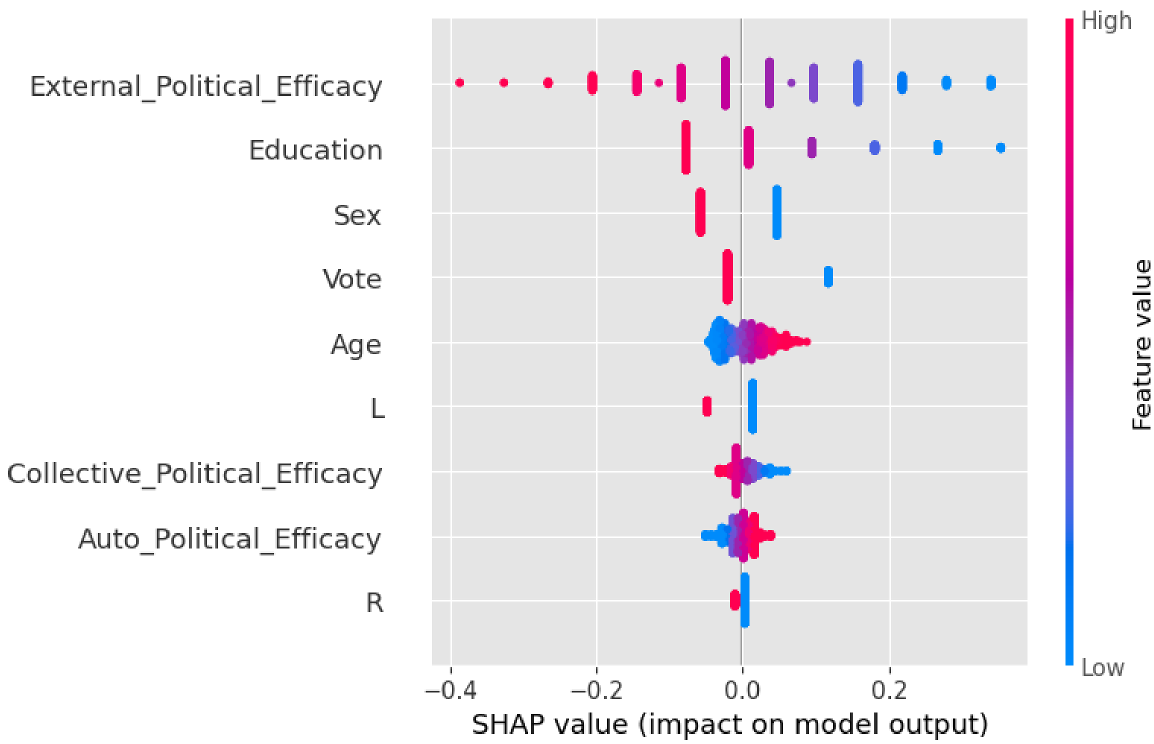

Figure 4.10: SHAP Values of features towards target variable Pop_Mean for elastic net regression

Table 4.4: Different test sizes Metrics obtained in elastic net regression

Metrics	Test size				
	0.2	0.25	0.3	0.35	0.4
Mean Squared Error (MSE)	0.466	0.458	0.459	0.453	0.441
Mean Absolute Error (MAE)	0.548	0.543	0.544	0.541	0.534
Mean Absolute Percentage Error (MAPE)	0.168	0.169	0.169	0.168	0.164
R-squared	0.096	0.101	0.095	0.103	0.103

4.1.5 Support vector machine regression

Support Vector Machine (SVM) regression is a machine learning algorithm used for regression tasks.

Unlike traditional linear regression, which focuses on minimizing the sum of squared errors, SVM regression is a more flexible model that can handle non-linear relationships and outliers by finding optimal hyperplanes that maximize the margin while allowing a certain error tolerance. This allows the algorithm to handle outliers and focus on finding a general solution (Skiena (2017)).

Before analysing any features impact on the target variable, cross-validation was performed with the following grid:

- kernel determines how the algorithm transforms the input data into a higher-dimensional space to find optimal decision boundaries. The linear kernel might be sufficient if the data is nearly linearly seperable. For more complex relationships, polynomial or RBF kernels can be used. The sigmoid kernel is less commonly used and often requires careful tuning: ['linear', 'poly', 'sigmoid', 'rbf'];
- C is the parameter that controls the regularization strength. It determines the trade-off between allowing training errors and maintaining a simple decision boundary. Higher values of C result in a smaller margin and a more complex model that tries to fit the training data more accurately: [0.1, 1, 10];
- epsilon sets the margin around the regression line. It defines a range within which errors are considered acceptable. It is used to control the tolerance for errors in the training data: [0.5, 0.1, 0.01, 0.001];
- degree is a parameter specific to the polynomial kernel and defines the degree of the polynomial used in the transformation. Higher values of degree allow the SVM to capture more complex polynomial relationships in the data: [2, 3, 4];
- gamma: This parameter is specific to the polynomial, RBF, and sigmoid kernels. It determines the influence of individual training samples on the decision boundary. A low value of gamma means a larger influence, and vice versa: ['scale', 'auto', 0.1];
- coef0 is a parameter specific to the polynomial and sigmoid kernels. It controls the independent term in these kernel functions and can affect the shape of the decision boundary: [0.0, 0.1, 1.0];
- shrinking is a boolean parameter that turns on or off the use of the shrinking heuristic. When set to True, it speeds up the training process by removing support vectors that are far from the decision boundary: [True, False];
- tol: The tolerance for stopping criterion. It determines the tolerance for the stopping criterion. The training process will stop when the optimization reaches a tolerance of tol: [1e-3, 1e-4, 1e-5];

- max_iter is the maximum number of iterations allowed for the solver to converge and find the optimal solution: [100, 500, 1000].

The best parameters obtained were C: 10, coef0: 0.0, degree: 2, epsilon: 0.5, gamma: scale, kernel: 'rbf', max_iter: 1000, shrinking: True, tol: 0.001.

In the context of the rbf kernel, the SVR model does not have easily interpretable coefficients for each feature. Instead, it relies on the support vectors and their corresponding weights to make predictions for new data points. The support vectors are a subset of the training data that are crucial for defining the decision boundary and determining the model's behaviour in the higher-dimensional space.

To get some insights into feature importances for the rbf kernel, these importances from tree-based models are used and can be seen in figure 4.11.

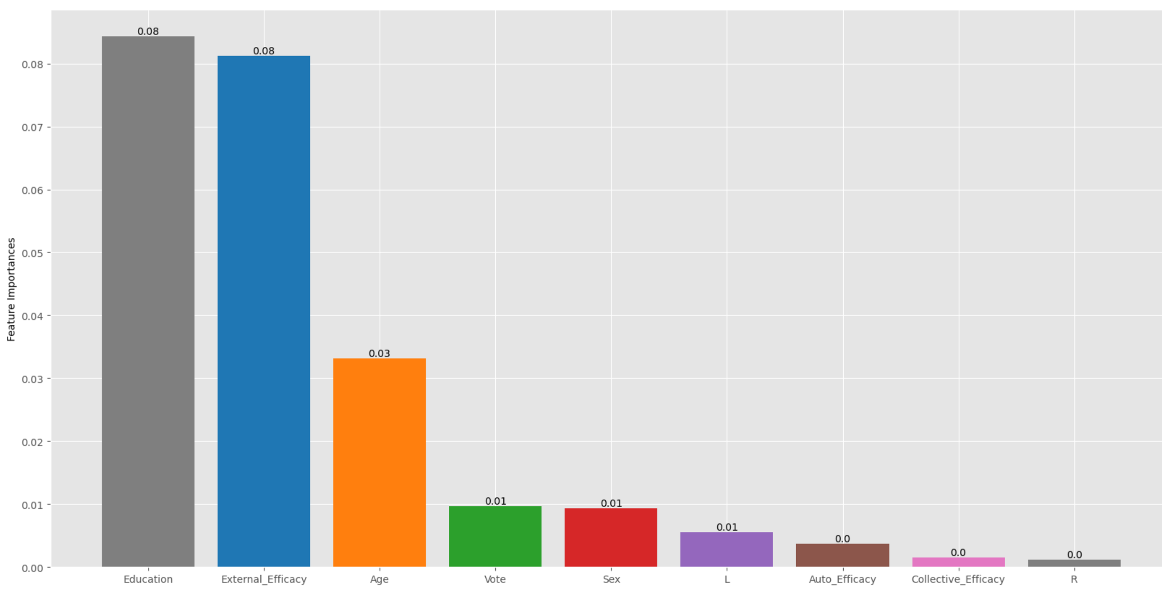

Figure 4.11: Feature importances towards target variable Pop_Mean for SVM

The SHAP values for SVM regression can be seen in figure 4.12.

The insights from the previous SHAP values models are according to the SVM SHAP values. However, the complex and non-linear nature of the decision boundaries learned by SVM with an RBF kernel can lead to more continuous and intricate SHAP value patterns. In contrast, linear models' simplicity results in more interpretable and well-defined SHAP values, making it easier to understand the feature contributions for each prediction.

For instance, for the variable Age it can be seen in figure 4.12 that there are red points (older people) in both extremes of the SHAP value, but it can be stated that, in overall, younger people (strong blue dots) have a negative impact in populist attitudes.

Finally, the performance of the model is explained by the table 4.5, where a test size of 40% allowed to get satisfactory results within the SVM model.

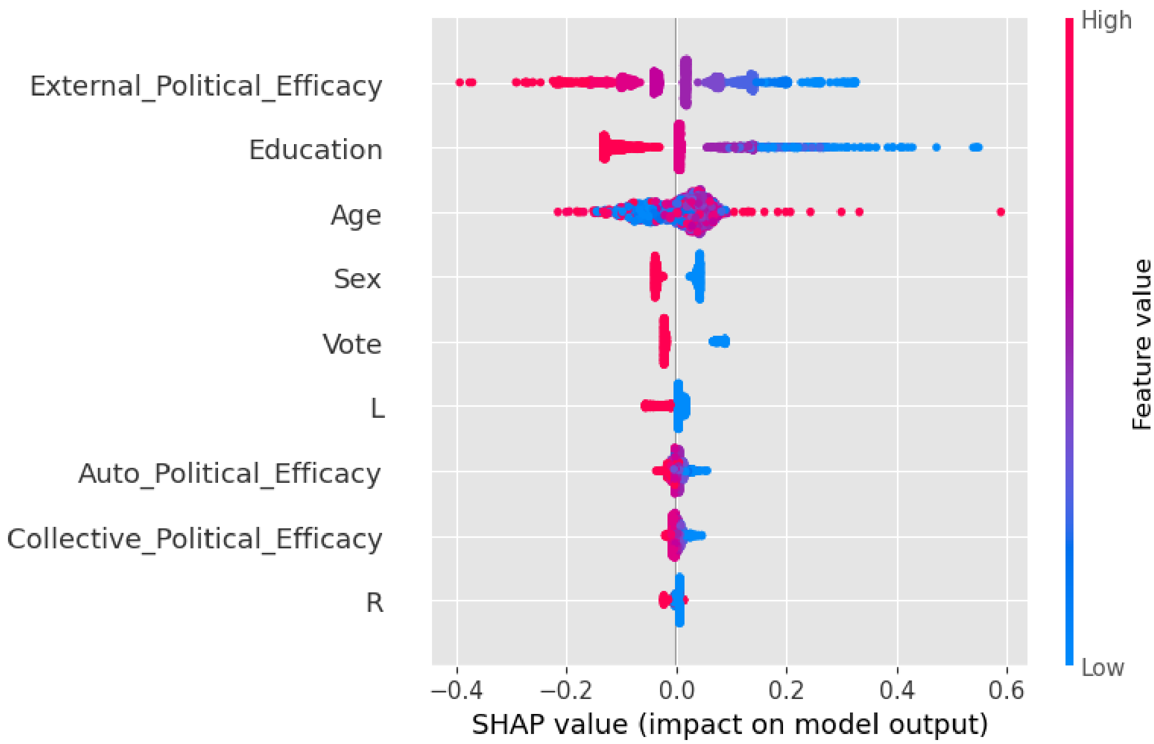

Figure 4.12: SHAP Values of features towards target variable Pop_Mean for SVM regression

Table 4.5: Different test sizes Metrics obtained in SVM regression

Metrics	Test size				
	0.2	0.25	0.3	0.35	0.4
Mean Squared Error (MSE)	0.459	0.452	0.455	0.449	0.438
Mean Absolute Error (MAE)	0.545	0.540	0.541	0.539	0.531
Mean Absolute Percentage Error (MAPE)	0.167	0.167	0.168	0.167	0.163
R-squared	0.110	0.112	0.104	0.110	0.109

4.1.6 Random forest regression

Random forest regressors have the ability to capture non-linear relationships between the features and the target variable. The linear model assumes that there is a linear relationship, which may not apply to many real-life scenarios like those in the social sciences. Also, a random forest regressor is less prone to overfitting than linear models, especially when the dataset has complex relationships or many features (Breiman (2001)).

Performing cross-validation, some parameters must be defined:

- n_estimators that specifies the number of decision trees to be used in the Random Forest ensemble: [100, 200, 300];
- max_depth which determines the maximum depth of each decision tree in the Random Forest. A higher value allows the tree to capture more complex relationships in the data: [None, 2, 5, 7, 10];
- min_samples_split sets the minimum number of samples required to split an internal node in the decision tree. It helps control the tree's complexity and overfitting: [2, 5, 10];
- min_samples_leaf specifies the minimum number of samples required to be at a leaf node. Similar to min_samples_split, it helps prevent overfitting by setting a threshold for the minimum number of samples at a leaf node: [1, 2, 4];
- max_features is the maximum number of features to consider when looking for the best split at each node. The "None" option means all features are considered, while 'sqrt' and 'log2' limit the number of features to the square root and logarithm of the total number of features, respectively: [None, 'sqrt', 'log2'].

After the cross-validation, the best parameters obtained were max_depth: 7, max_features: log2, min_samples_leaf: 4, min_samples_split: 10, n_estimators: 100.

The feature importances for random forest can be seen in figure 4.13, highlighting the key variables that contribute significantly to the prediction. Instead of coefficient estimates, tree models provide feature importances or feature rankings. These metrics evaluate the relative importance of each feature in making predictions within the tree model. Feature importances in tree models are typically based on criteria such as the total reduction in impurity or the total reduction in the criterion used for splitting (e.g., Gini impurity or information gain). The higher the feature's importance, the more influential that feature is in the decision-making process of the tree model.

Notably, External_Political_Efficacy emerge as the top influential features with an importance score of approximately 0.27. Additionally, variables like Age, Education, Auto_Political_Efficacy and Collective_Political_Efficacy demonstrate considerable relevance towards the target variable.

The SHAP values for the random forest in figure 4.14 are quite different from the SHAP plots of the linear models. The variation in importance weights assigned to categories can be attributed to the fact that each tree in the random forest examines different subsets of the data.

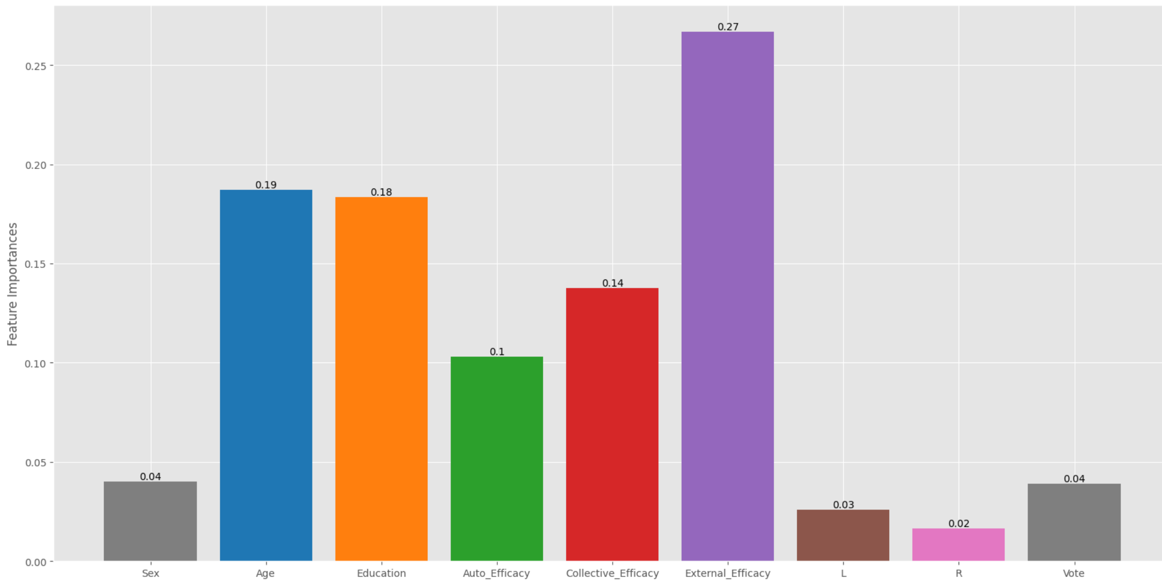

Figure 4.13: Feature importances towards target variable Pop_Mean for random forest regression

As a result, the SHAP values for categorical variables can vary across the trees, leading to a wider spread of points along the x-axis.

On the other hand, in a linear model, the coefficient for categorical variables represents the average effect of that category on the outcome variable. Linear models assume a consistent impact across the data, so the SHAP values for these variables will converge into distinct horizontal lines.

Once again, it is evident that External_Political_Efficacy and Education have the most significant influence on populist attitudes. Moreover, lower values of these features correspond to higher levels of populist attitudes.

The Collective_Political_Efficacy emerges as only the fifth most significant factor within this analysis. As observed in figures 4.8 and 4.12, it was previously noted that lower values of this mean corresponded to higher levels of populist attitudes. This finding is further supported by the evidence presented in figure 4.14.

Curiously, looking at the Auto_Political_Efficacy variable it looks like the most intense blue values (lower values) have a positive impact contradicting the findings in figure 4.8 where high values of internal personal efficacy lead to high values of populist attitudes. In this case, it can indicate possibly disagreement or a lack of belief in one's ability to influence political processes. This aligns with populist attitudes characterized by anti-establishment sentiment, frustration with elites, and a desire for more direct influence and participation in decision-making.

Regarding variables L and R, it's possible to see that respondents who identify themselves with left ideology tend to have lower values of populist attitudes, while right supporters tend to have both low and high values of populist attitudes.

Finally, regarding variables Education, Age, Sex and Vote corroborate the findings previously

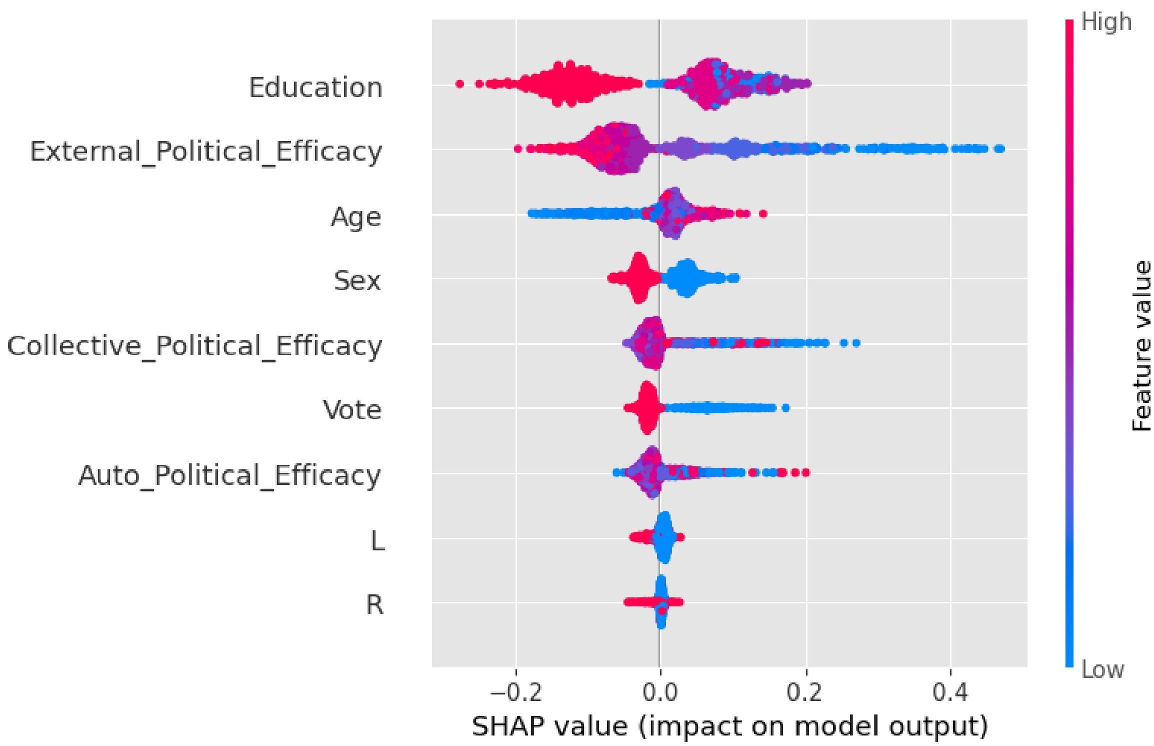

Figure 4.14: SHAP Values of features towards target variable Pop_Mean for random forest regression

stated are confirmed in figure 4.14. Overall, higher levels of education and younger age are associated with low level of populist attitudes, while men and participants who didn't vote in 2019 have higher populist attitude have higher populist attitudes.

Table 4.6 presents the metrics achieved by the random forest model using the best parameters for various test sizes. Notably, the metrics reveal lower error results values and higher R^2. These results suggest that the random forest algorithm exhibits a slight performance improvement compared to the linear models.

Table 4.6: Different test sizes Metrics obtained in random forest regression

Metrics	Test size				
	0.2	0.25	0.3	0.35	0.4
Mean Squared Error (MSE)	0.430	0.427	0.427	0.423	0.430
Mean Absolute Error (MAE)	0.518	0.516	0.515	0.514	0.524
Mean Absolute Percentage Error (MAPE)	0.164	0.164	0.164	0.161	0.164
R-squared	0.128	0.142	0.136	0.130	0.127

4.1.7 Gradient boosting regression

The next type of model to test is gradient boosting regression. While random forest builds multiple decision trees independently and combines their predictions, gradient boosting builds a sequence of models to improve predictions iteratively. Random forest has lower variance but slightly higher bias, while Gradient Boosting has lower bias but can be more prone to overfitting (Breiman (2001)).

The parameters for performing cross-validation are similar to the ones in random forest. In gradient boosting there's also the learning rate parameter which controls the contribution of each tree in the ensemble. Basically, each new tree that is added to the ensemble attempts to correct the mistakes made by the previous trees.

The learning rate parameter determines the step size at which the boosting algorithm learns from the mistakes of the previous trees. It scales each tree's contribution by multiplying that tree's predictions by the learning rate.

The list of hyperparameter values to be searched during the gradient boosting grid search were:

- n_estimators: [200, 300, 400];
- learning_rate: [0.1, 0.01, 0.001];
- max_depth: [2, 5, 10];
- min_samples_split: [2, 5, 10];
- min_samples_leaf: [1, 2, 4];
- max_features: ['sqrt', 'log2'].

The best combination of hyperparameters that maximizes the model's performance were learning_rate: 0.1, max_depth: 2, max_features: 'log2', min_samples_leaf: 1, min_samples_split: 4, n_estimators: 200.

After defining the hyperparameters the calculation of feature importances is made and can be seen in figure 4.15.

The feature importances of External_Political_Efficacy remains the most important, but Education now becomes the second most important, whereas in random forest, Age together with Education held that position (with a small difference of 0.01).

The next step was plotting the model's SHAP values - figure 4.16.

Insights from figure 4.16 are similar to random forest SHAP - figure 4.14. It's possible to see that there are low-value outliers in Auto_Political_Efficacy supporting the findings in figure 4.8. The SHAP values associated with Auto_Political_Efficacy appear to lack consistency across the models. Considering this, removing this variable from the data set might enhance the model's performance in future research.

Table 4.7 shows the performance metrics of the gradient boosting model for different test sizes.

Looking at the errors values and R-squared, the results with best predictability power are obtained through test sizes of 30%, 35% and 40%.

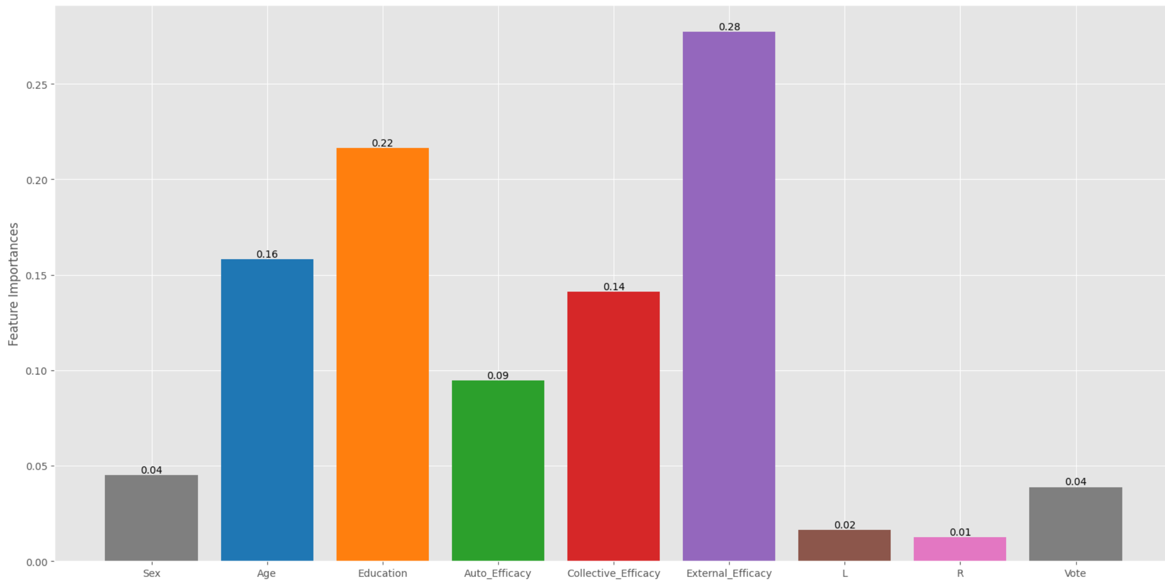

Figure 4.15: Feature importances towards target variable Pop_Mean for gradient boosting regression

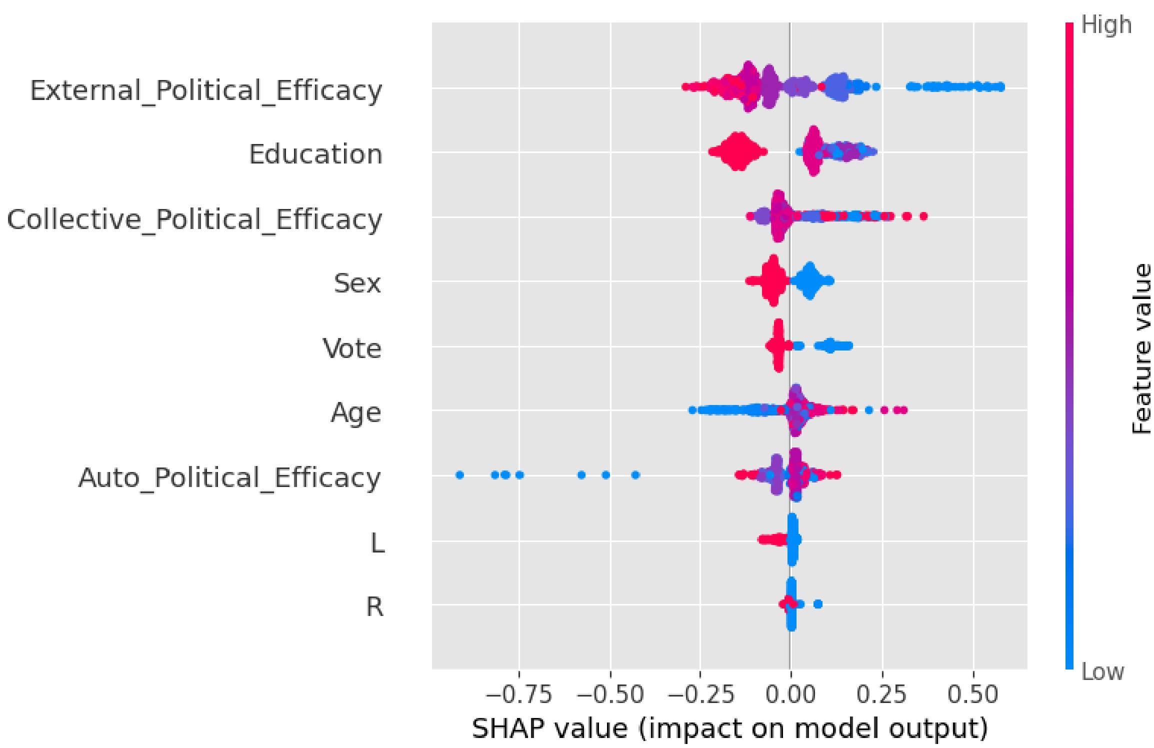

Figure 4.16: SHAP Values of features towards target variable Pop_Mean for gradient boosting regression

Table 4.7: Different test sizes Metrics obtained in gradient boosting regression

Metrics	Test size				
	0.2	0.25	0.3	0.35	0.4
Mean Squared Error (MSE)	0.436	0.433	0.421	0.419	0.421
Mean Absolute Error (MAE)	0.519	0.518	0.510	0.512	0.514
Mean Absolute Percentage Error (MAPE)	0.164	0.164	0.162	0.161	0.161
R-squared	0.117	0.131	0.148	0.138	0.146

4.1.8 XGBoost regression

XGBoost stands for extreme gradient boosting and represents a significant advancement in the realm of ensemble learning algorithms, building upon the foundations of gradient boosting and incorporating novel techniques to achieve exceptional performance, scalability, and versatility. Through the introduction of regularization, tree pruning, and a focus on optimization, XGBoost transcends the capabilities of traditional gradient boosting methods.

Cross-validation is performed and for that several combinations of hyperparamters were tested:

- learning_rate: [0.1, 0.01, 0.001];
- max_depth: [3, 5, 7];
- n_estimators: [100, 200, 300];
- gamma it's the minimum split gain and refers to the minimum loss reduction required to make a further partition on a leaf node during the tree construction process: [0, 0.1, 0.2];
- subsample controls the subsampling ratio of the training instances (rows) when constructing each tree in the ensemble. It randomly selects a fraction of the data points (without replacement) to be used for training each individual tree: [0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 1.0];
- colsample_bytree controls the subsampling ratio of the features (columns) when constructing each tree. It randomly selects a fraction of the features to be used for training each individual tree: [0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 1.0].

The best parameters obtain from cross-validation are the following: colsample_bytree: 0.3, learning_rate: 0.1, max_depth: 2, gamma: 0.2, n_estimators: 200, subsample: 1.0.

A value of 1.0 in subsample indicates that 100% of a portion of training instances will be used, while a value of 0.3 in colsample_bytree indicates that 30% of the features will be used. Based on the subsampling ratio of 30% (specified by 'colsample_bytree') and the feature importance values, it can be inferred that features with lower importance are more likely to have been excluded from the model's performance. In other words, as the importance value of a feature decreases, the probability of that feature not being used in the model increases by establishing this hyperparameter colsample_bytree to low values.

The feature importances with the model trained are plotted in figure 4.17.

The variables Education and External_Political_Efficacy exhibit the highest importances, indicating their significant impact on the outcome similar to gradient boosting. The remaining variables demonstrate comparable importances, with variable L having the lowest importance at 0.07, and R with 0.06.

The SHAP values are plotted in figure 4.18.

The metrics in table 4.8 show the model's performance. Notably, XGBoost is the regression mode that allowed to obtain better performance through the relatively low error values and high value of R^2, especially for a test size of 30%.

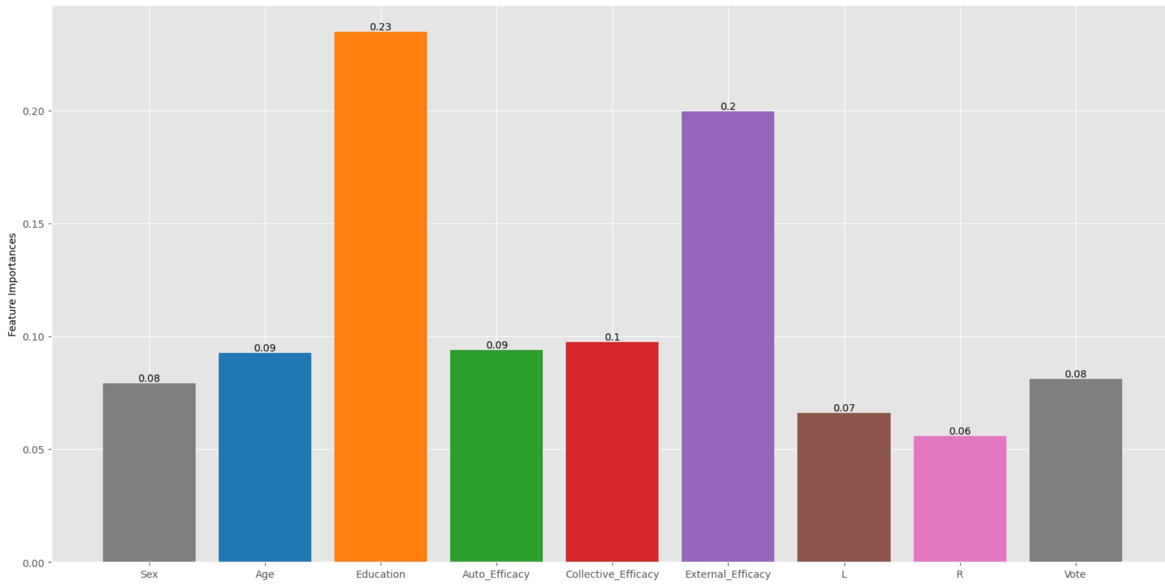

Figure 4.17: Feature importances towards target variable Pop_Mean for XGBoost regression

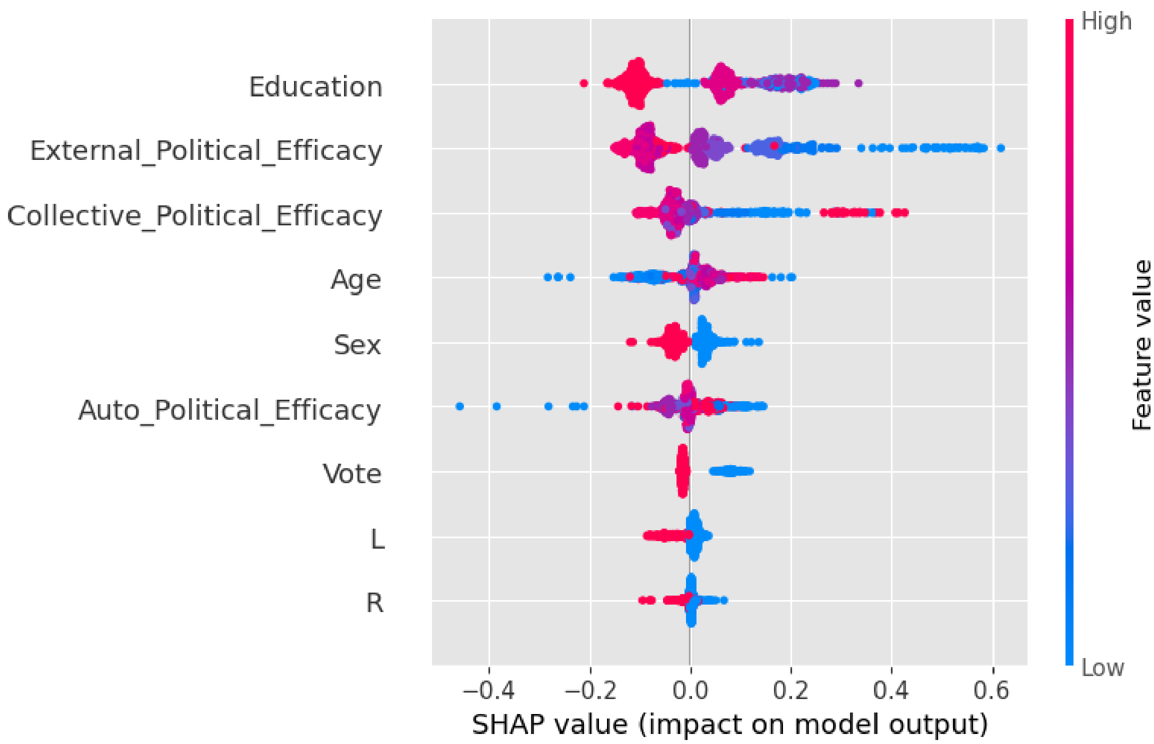

Figure 4.18: Shap Values of features towards target variable Pop_Mean for XGBoost regression

In this section 4.1, various regression models were explored to analyse and predict the target variable. This experimentation revealed that tree-based algorithms, such as random forest and

Table 4.8: Different test sizes Metrics obtained in XGBoost regression

Metrics	Test size				
	0.2	0.25	0.3	0.35	0.4
Mean Squared Error (MSE)	0.432	0.432	0.420	0.420	0.420
Mean Absolute Error (MAE)	0.517	0.515	0.511	0.512	0.516
Mean Absolute Percentage Error (MAPE)	0.164	0.164	0.162	0.161	0.162
R-squared	0.126	0.133	0.149	0.136	0.147

gradient boosting, might reveal slight results with higher predictive accuracy than linear models.

For each algorithm, the best results can be seen in table 4.9.

Table 4.9: Metrics obtained for each regression model

Models	Metrics				
	Test size	MSE	MAE	MAPE	R^2
Linear regression	0.25	0.458	0.543	0.169	0.100
Ridge regression	0.4	0.453	0.535	0.164	0.102
Lasso Regression	0.4	0.441	0.534	0.164	0.103
Elastic Net regression	0.4	0.441	0.534	0.164	0.102
SVM regression	0.4	0.438	0.531	0.163	0.109
Random Forest regression	0.25	0.427	0.516	0.164	0.142
Gradient boosting regression	0.3	0.421	0.510	0.162	0.148
XGBoost regression	0.3	0.420	0.511	0.162	0.149

In the study presented in Table 4.9, the results alone do not provide sufficient evidence to conclude that certain algorithms outperform others. The Friedman test was conducted to investigate the differences among the algorithms further. This test aims to assess whether there are significant variations among the regressors.

The null hypothesis (H_0) assumes that the regressors are equal, while the alternative hypothesis (H_1) suggests that at least one difference exists between the regressors.

By conducting the Friedman test across all metrics and regression algorithms, a p-value of 0.0004 was obtained. This p-value is below the common significance level of 0.05. Therefore, there's not enough evidence to reject the null hypothesis. The p-value suggests that the algorithms do not perform equally across all metrics, and at least one performs significantly better or worse than the other on average.

Nevertheless, for a precise identification of algorithms displaying statistically significant differences, the Nemenyi test is employed. Performing this test, a p-value lower than 0.05 is obtained between linear regression and Gradient Boosting (0.006) and linear regression and XGBoost (0.003). Also, although the value is above the 0.05 threshold, a value of 0.06 was obtained for the comparison between Ridge and XGBoost.

For further improvement, the problem was approached from a different perspective, considering whether it could be reframed as a classification problem rather than a traditional regression problem. This shift in perspective opened new avenues for exploration and potentially yielded additional insights.

Considering the problem as a classification task enables the utilization of various classification algorithms and techniques to address the challenge. This shift allows for the leverage of the strengths of classification models, including logistic regression, support vector machines, or even more advanced approaches like neural networks. Additionally, this approach yields a clear prediction of the class or category to which an observation belongs, facilitating a more straightforward understanding and explanation of the model's predictions.

In the upcoming chapter, the classification aspect of the problem is explored, including an examination of the suitability of various classification algorithms, an evaluation of their performance, and a comparison of the results with the previous regression-based analysis. This exploration is aimed at gaining a deeper understanding of the problem domain and uncovering potential enhancements in predictive accuracy and interpretability.

4.2 Classification

To convert the problem into a classification task, a transformation was applied to the target variable. The aim was to categorize the values based on predefined split points.

Firstly, the split points were calculated by dividing the range of the populist attitudes target variable into three equal segments: the lower, middle, and upper ranges. These split points served as thresholds for dividing the data into different categories.

Each data point was assigned to one of the three categories based on its original value and relationship to the split points. Data points falling below the first split point were assigned to Category 1 (Low populist attitudes), those falling between the first and second split points were assigned to Category 2 (medium populist attitudes), and those exceeding the second split point were assigned to Category 3 (high populist attitudes).

By applying this transformation, the original continuous target variable was transformed into a categorical variable with three distinct classes. This allows to approach the problem from a classification perspective, enabling the utilization of classification algorithms to predict and analyse the target variable.

A binary classification problem has two possible classes: positive and negative. The confusion matrix consists of four key metrics:

- True Positives (TP): This represents the number of instances correctly predicted as positive by the classifier. These are the cases where the model correctly identifies the positive class;

- True Negatives (TN): This indicates that the number of instances is incorrectly predicted as negative by the classifier. These are the cases where the model correctly identifies the negative class;

- False Positives (FP): Also known as a Type I error, this refers to the instances that are wrongly predicted as positive by the classifier when they are actually negative. In other words, the model falsely identifies negative instances as positive;

- False Negatives (FN): Also known as a Type II error, this represents the instances that are wrongly predicted as negative by the classifier when they are actually positive. In other words, the model fails to identify positive instances correctly.

In a classification problem, a confusion matrix is a table that is used to evaluate the performance of a binary classifier - table 4.10.

Table 4.10: Confusion matrix for binary classifiers, defining different classes of correct and erroneous predictions

		Predicted values	
		Positive	Negative
Actual values	Positive	TP	FN
	Negative	FN	TP

Using the values in the confusion matrix, several evaluation metrics can be derived to assess the classifier's performance, such as accuracy, precision, recall (sensitivity) and F1 score.

- Accuracy: It measures the overall correctness of the classifier and is calculated as (TP + TN) / (TP + TN + FP + FN);
- Precision: It quantifies the proportion of true positive predictions out of all positive predictions and is calculated as TP / (TP + FP);
- Recall (Sensitivity): It represents the proportion of true positive predictions out of all actual positive instances and is calculated as TP / (TP + FN);
- F1 Score: It is the harmonic mean of precision and recall, providing a balanced measure of both metrics and is calculated as 2 * (Precision * Recall) / (Precision + Recall).

However, this problem consists of a 3-class classification. In order to calculate the four key metrics, it's necessary to perform the confusion matrix for each class. The following example shows the confusion matrix for the class of low values of populist attitudes (Pop_Value = 1) - table 4.11.

Table 4.11: Confusion matrix for class = 1 (low populist attitudes)

		Predicted values		
		1	2	3
Actual values	1	TP	FN	FN
	2	FP	TN	TN
	3	FP	TN	TN

For a three-class problem, accuracy can be computed as the sum of true positives for all three classes divided by the total number of instances.

While precision, recall and F1 Score are calculated using weighted averages:

- weighted_precision = (precision_class_1 $\times$instances_class_1 + precision_class_2 $\times$instances_class_2 + precision_class_3 $\times$instances_class_3) / total_instances;
- weighted_recall = (recall_class_1 $\times$instances_class_1 + recall_class_2 $\times$instances_class_2 + recall_class_3 $\times$instances_class_3) / total_instances;
- weighted_f1_score = (F1_score_class_1 $\times$instances_class_1 + F1_score_class_2 $\times$instances_class_2 + F1_score_class_3 $\times$instances_class_3) / total_instances.

In conclusion, another crucial metric to consider is the misclassification rate for each class. This metric provides insights into how effectively an algorithm categorizes instances within each class. It is particularly significant to examine whether a certain algorithm consistently misclassifies instances, and if so, to what extent. For example, in the case of class 1, if the predicted values are mostly assigned to class 2 (medium populist attitudes), the misclassification error is relatively less severe compared to the scenario where all predicted values are assigned to class 3 (high populist attitudes). This analysis helps to gauge the algorithm's performance in accurately assigning instances to the appropriate classes, highlighting potential biases or shortcomings that need to be addressed.

4.2.1 Logistic regression

Logistic regression is a widely used statistical technique that is crucial in predictive modelling and data analysis. It is particularly useful when dealing with classification problems, where the goal is to predict the categorical outcome variable based on a set of independent variables (Skiena (2017)).

Logistic regression is a supervised learning algorithm that models the relationship between the independent variables and the probability of belonging to a particular class. Unlike linear regression, which predicts continuous numerical values, logistic regression is specifically designed for binary or multiclass classification tasks (Skiena (2017)).

As in the regression section, here the cross-validation (cv) also represents an indispensable step for the algorithms' performances. For that reason, different values were explored during the grid search process to find the best combination of hyperparameters:

- penalty: it represents the regularization penalty term to be used in the logistic regression model: ['l1', 'l2', 'elasticnet'];

- C: it represents the inverse of the regularization strength. The grid includes six logarithmically spaced values ranging from 0.001 to 1000. A smaller value of C indicates stronger regularization, while a larger value indicates weaker regularization;

- solver: it specifies the algorithm to be used for optimization. ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']. 'newton-cg', 'lbfgs', and 'sag' are optimization algorithms suitable for both L1 and L2 regularization. 'liblinear' is a solver specifically designed for L1 regularization. 'saga' is an extension of 'liblinear' that supports both L1 and L2 regularization, as well as 'elasticnet' penalty;

- fit_intercept: it is a boolean parameter indicating whether to include an intercept term in the logistic regression model. The grid includes two options: True and False. When set to True, an intercept term is included, and when set to False, it is excluded;

- max_iter: it defines the maximum number of iterations for the solver to converge: [100, 200, 300];

- l1_ratio: it is the mixing parameter for elastic-net regularization, only considered when the 'penalty' is set to 'elasticnet': [0.2, 0.4, 0.6, 0.8]. A lower value of l1_ratio puts more emphasis on L2 regularization, while a higher value puts more emphasis on L1 regularization.

- class_weight: it determines the weights associated with each class. The grid includes two options: None and 'balanced'. None means all classes have equal weight. 'balanced' automatically adjusts the weights inversely proportional to the class frequencies in the input data.

Also, different values of 'cv' were explored [3, 5, 7], being the default value chosen by the GridSearchCV: 5.

That said, the hyperparameters defined after the cross-validation step are: C: 0.015848931924611134, class_weight: None, fit_intercept: True, l1_ratio: 0.2, max_iter: 300, penalty: 'l2', solver: 'sag'.

Moreover, logistic regression provides interpretability by estimating the impact of each independent variable on the predicted probabilities. One useful measure in logistic regression is the odds ratio (OR), which quantifies the change in odds for a one-unit change in an independent variable while holding other variables constant. The odds ratio provides valuable insights into the relative importance of each independent variable and helps identify variables that significantly contribute to the classification task (Szumilas (2010)).

Basically, if OR = 1, it indicates that there is no association between the predictor variable and the outcome. If OR > 1, it suggests a positive association, meaning that as the predictor variable increases, the odds of the outcome also increase. If OR < 1, it indicates a negative association, meaning that as the predictor variable increases, the odds of the outcome decrease.

Prior to calculating the ORs, the variables were standardized. Subsequently, the ORs for logistic regression were computed for each type of output class, and the results are presented in the following table 4.12.

Table 4.12: Odds ratios of independent variables for Pop_Value = 1, 2 and 3

Feature	Odds Ration Pop_Value = 1	Odds Ration Pop_Value = 2	Odds Ration Pop_Value = 3
Sex	1.12	1.03	0.86
Age	0.94	1.02	1.05
Education	1.15	1.03	0.85
Auto_Political_Efficacy	0.94	1.02	1.04
Collective_Political_Efficacy	1.00	1.04	0.96
External_Political_Efficacy	1.32	0.92	0.82
L	1.04	0.99	0.97
R	1.01	1.00	0.99
Vote	1.14	0.95	0.92

Observations reveal that variables such as Sex (females), Education, External_Political_Efficacy, and Vote demonstrate a positive influence on Pop_Value = 1. This implies that these variables positively contribute to low populist attitudes. On the other hand, although it's not a strong relation, variables like Age and Auto_Political_Efficacy have a negative impact on low populist attitudes. As these variables decrease, they contribute to low populist attitudes. Finally, there are variables that have no or very little influence on the Pop_Value = 1. These are the cases of Collective_Political_Efficacy, L and R.

For medium populist attitudes, it seems that none of the variables has a considerable impact on them. Only External_Political_Efficacy has a negative effect on Pop_Value = 2.

Sex, Education, External_Political_Efficacy and Vote have a negative impact on high populist attitudes. The rest of the variables seem to have little impact on the Pop_Value = 3.

The findings regarding Pop_Value = 1 in ORs are confirmed by the SHAP values plot in figure 4.19 where high values of External_Political_Efficacy, Sex (females), Education and Vote contribute positively to low populist attitudes. On the other hand, Age and Auto_Political_Efficacy have a negative impact on low populist attitudes, which corroborates with the SHAP Values of the linear regression models previously seen.

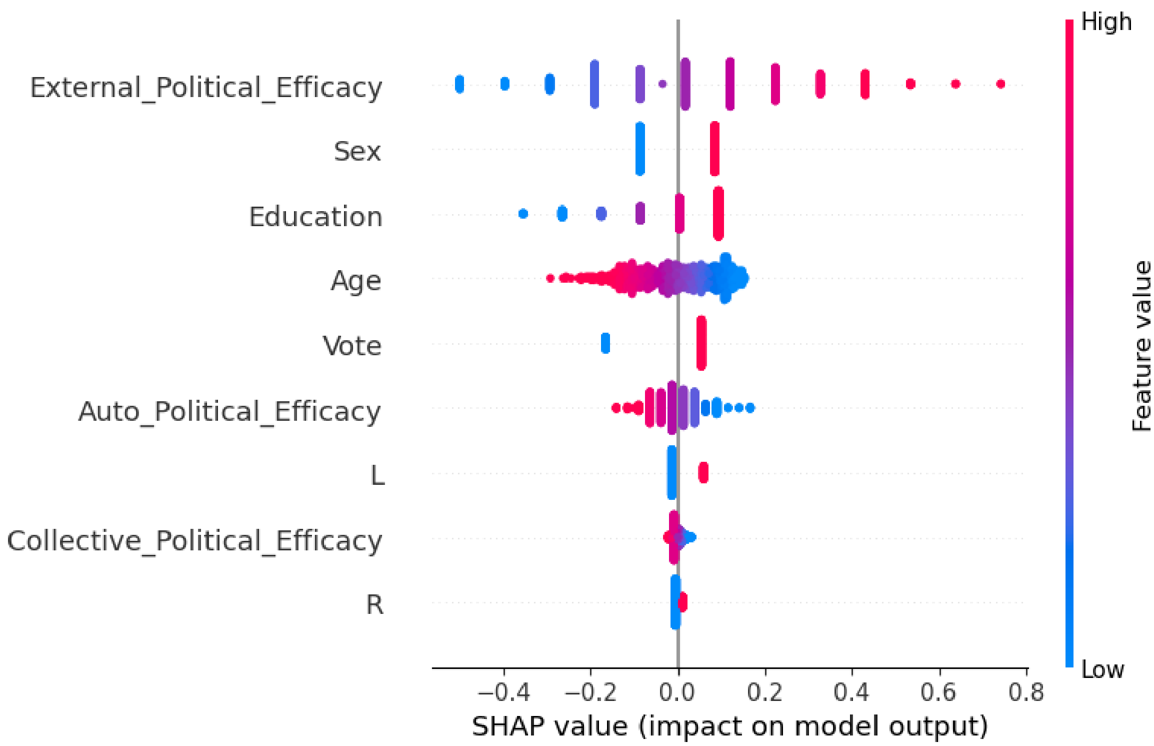

Figure 4.19: SHAP Values of features towards target variable - low populist attitudes - Pop_Value = 1 for Logistic regression

For the medium populist attitudes, the ORs of the different variables didn't show relevant impact and as it can be seen in figure 4.20, the x-axis is zoomed in comparison with figure 4.19. However, some insights can be still retrieved from the following plot.

Females and people that didn't vote tend to have medium populist attitudes compared to their opposites.

Also, individuals who exhibit medium levels of populist attitudes tend to show low agreement with the statements related to the behaviour of the people in charge of the government - External_Political_Efficacy.

In contrast, Auto_Political_Efficacy - internal personal efficacy - where higher values (agree, completely agree), led to medium populist attitudes values.

Also, high values of Collective_Political_Efficacy tend to have a positive impact on medium populist attitudes.

In the high populist attitudes - figure 4.21 -, it is clear that men have a positive impact as well as older people.

Low values of External_Political_Efficacy, Education and Vote (didn't vote) are related to high populist values. This is also applicable, although with low impact, for variables like L and

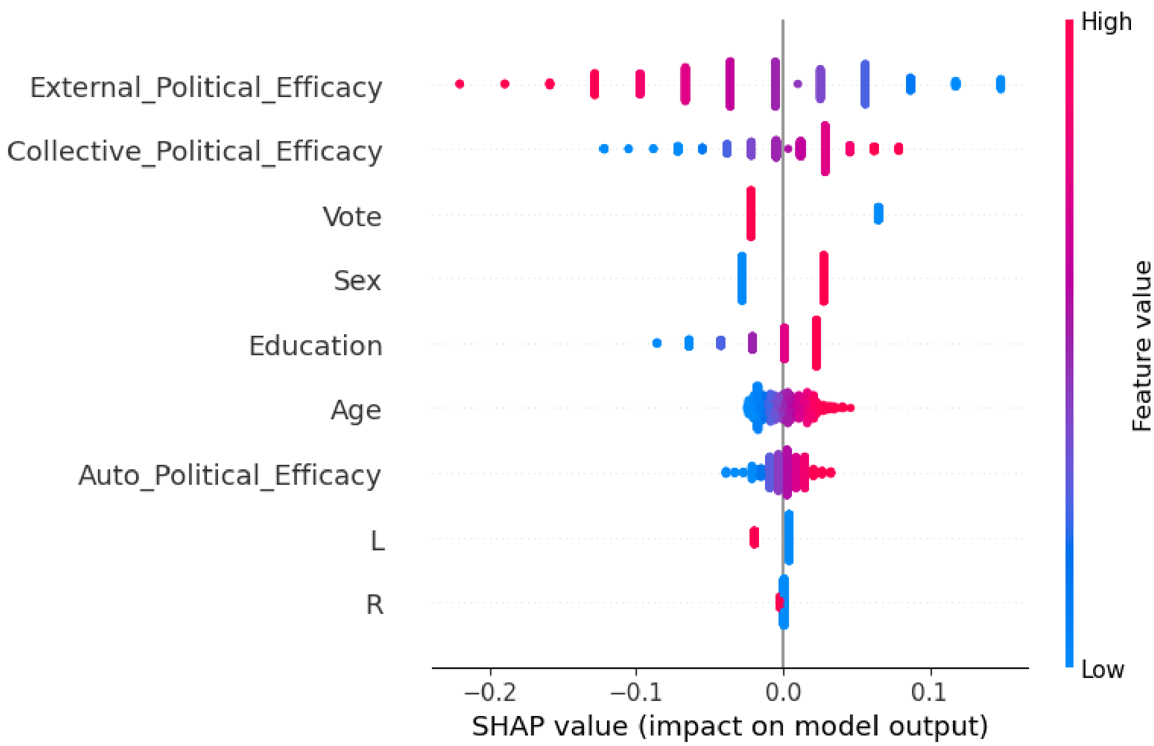

Figure 4.20: SHAP Values of features towards target variable - medium populist attitudes - Pop_Value = 2 for Logistic regression

Collective_Political_Efficacy.

By fitting the classifier to the training data and performing predictions on the test data using the trained classifier, the following results are obtained:

- Accuracy: 44.6%
- Precision: 43.2%
- Recall: 44.6%
- F1 Score 42.5%

The findings indicate that the logistic regression classifier achieved an overall prediction accuracy of 44.6%. Specifically, it accurately classified 44.6% of the correct predictions. The precision, representing the proportion of true positives across the three classes divided by the sum of true positives and false positives, yielded a value of 43.2%. The recall, denoting the ratio of true positive predictions to the total number of positive instances, was 44.6%. Lastly, the F1 Score, a combined metric that balances precision and recall, yielded a value of 42.5%. These results provide insights into the performance and effectiveness of the logistic regression classifier.

Moreover, the error rates for the different classes are the following:

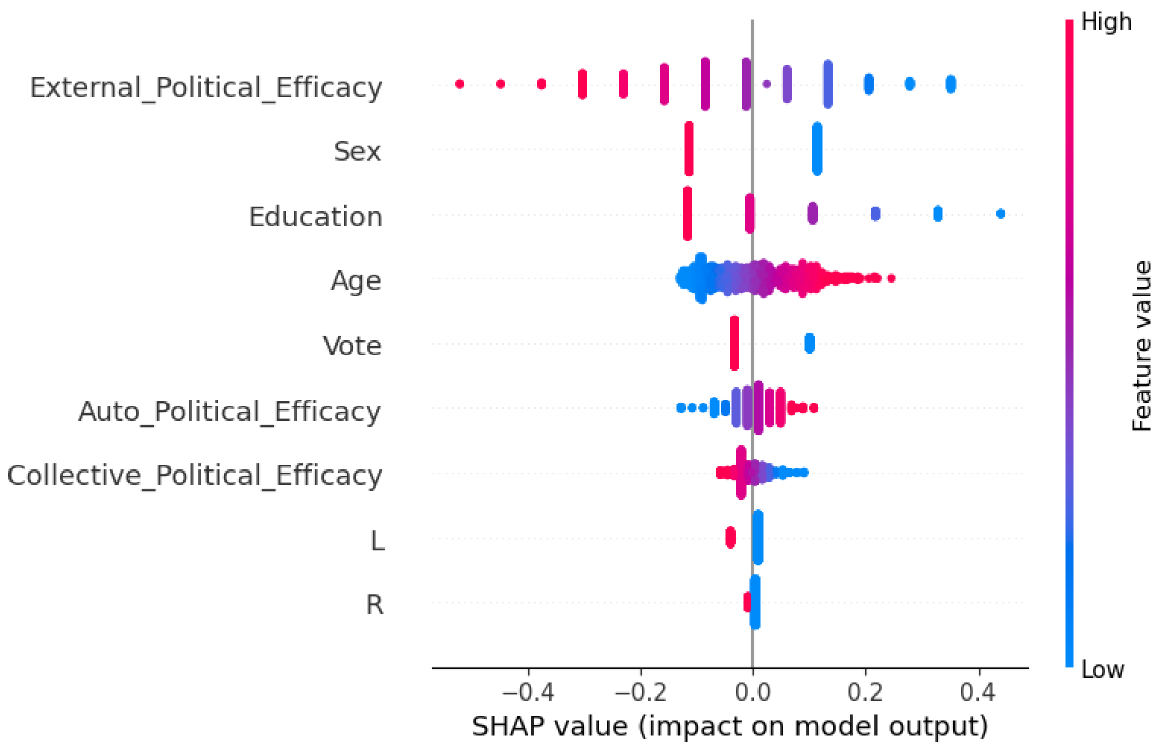

Figure 4.21: SHAP Values of features towards target variable - high populist attitudes - Pop_Value = 3 for Logistic regression

- Pop_Value 1 classified as Pop_Value 2 - 16.8%
- Pop_Value 1 classified as Pop_Value 3 - 23.8%
- Pop_Value 3 classified as Pop_Value 1 - 30.1%
- Pop_Value 3 classified as Pop_Value 2 - 14.1%

Upon analysing the error rates, it becomes evident that the error rates for the extreme classifications, specifically Pop_Value 1 classified as Pop_Value 3 and Pop_Value 3 classified as Pop_Value 1, are relatively high compared to the error rates for the non-extreme classifications (Pop_Value 1 classified as Pop_Value 2 and Pop_Value 3 classified as Pop_Value 2). This observation raises concerns about the model's performance in accurately distinguishing between the extreme classes.

The discrepancy in error rates between extreme and non-extreme classifications highlights the model's difficulty in accurately classifying instances from extreme categories. This indicates a potential limitation or weakness in the model's ability to effectively differentiate between the extreme classes, which could undermine its overall performance and reliability.

To improve the model's performance, exploring strategies such as gathering more representative training data, considering alternative modelling techniques, adjusting the model's hyperparameters, or conducting further analysis to identify potential factors contributing to the higher error rates for extreme classifications may be necessary. Addressing these issues is crucial to ensure a more balanced and accurate classification performance across all classes.

4.2.2 Support Vector Machine classification

This study's subsequent phase involves classifying using the Support Vector Machine (SVM) classification algorithm.

Regarding SVM classification the cross-validation method was also applied:

- C: [0.1, 1, 10];
- kernel: ['linear', 'poly', 'rbf', 'sigmoid'];
- degree: [2, 3, 4];
- gamma: ['scale', 'auto'];
- coef0: [0.0, 0.1, 1.0].

The best hyperparameters obtained were C: 0.1, coef0: 0.0, degree: 2, gamma: 'auto', kernel: 'poly'. Using them for plotting feature importances, it can be seen in figure 4.22 that variables Education, External_Political_Efficacy and Age have the most influence on populist attitudes.

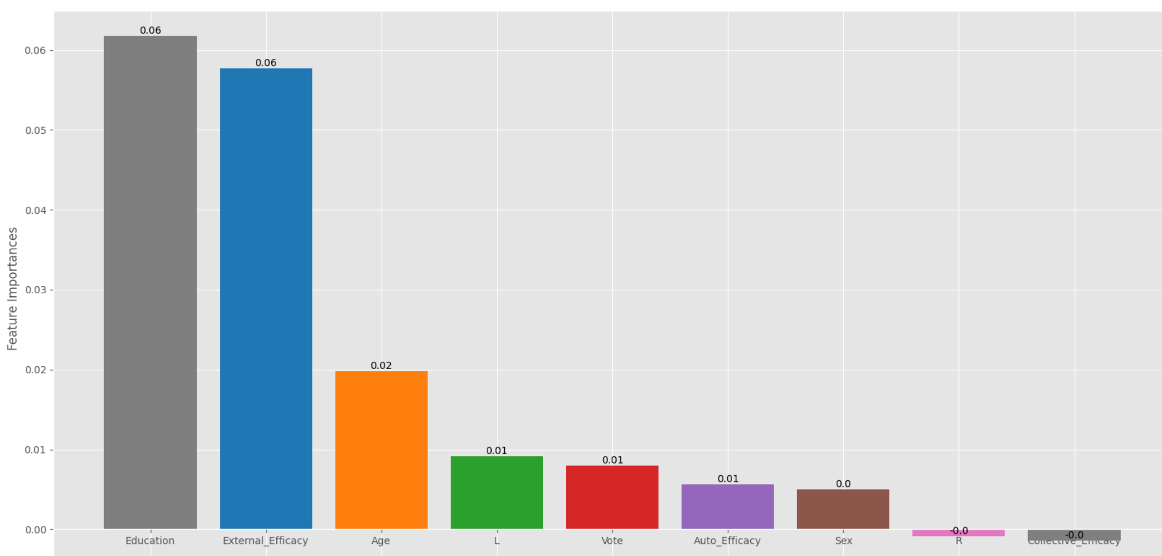

Figure 4.22: Feature importances towards target variable Pop_Value for SVM classification

The SHAP values are plotted in the three figures 4.23, 4.24 and 4.25 and they reveal similar behaviour as logistic regression model.

Upon training the classifier with the provided training data and subsequently making predictions on the test data using the trained classifier, the following results are obtained:

- Accuracy: 45.7%
- Precision: 44.6%

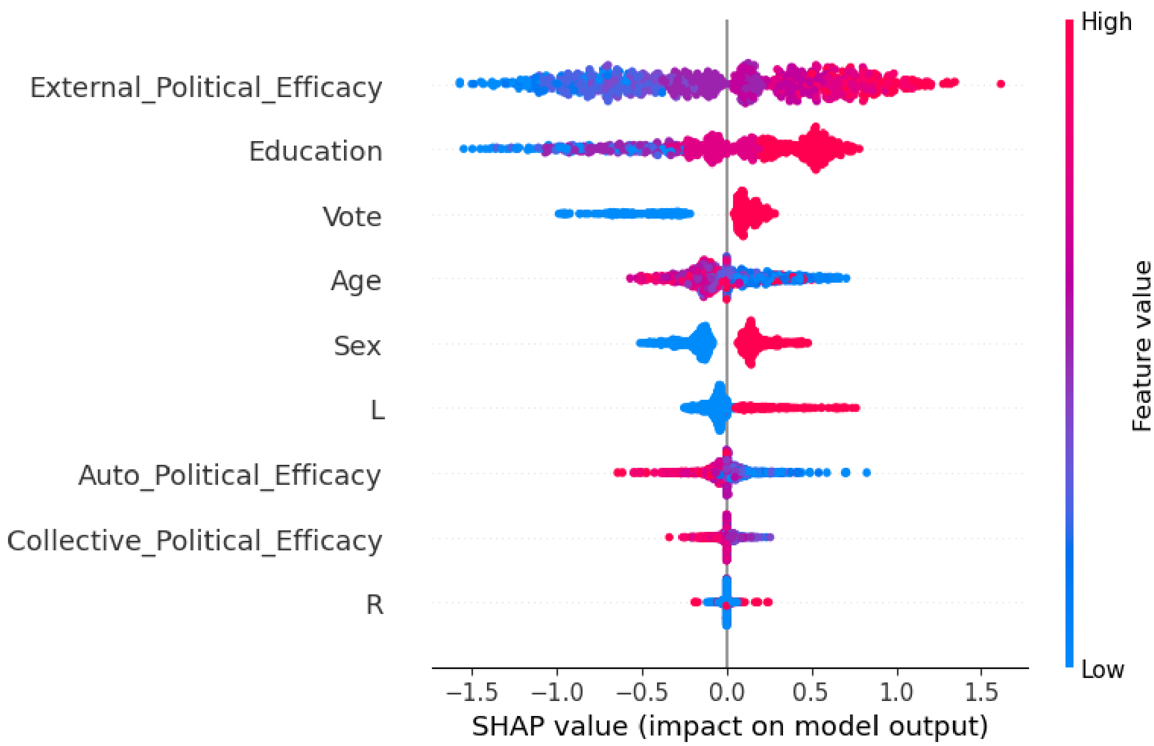

Figure 4.23: SHAP Values of features towards target variable - low populist attitudes - Pop_Value = 1 for SVM classification

- Recall: 45.7%
- F1 Score 44.5%

It shows a slight improvement relative to Logistic regression. Moreover, the error rates for different classes can be seen as well:

- Pop_Value 1 classified as Pop_Value 2 - 21.9%
- Pop_Value 1 classified as Pop_Value 3 - 24.3%
- Pop_Value 3 classified as Pop_Value 1 - 24.1%
- Pop_Value 3 classified as Pop_Value 2 - 17.7%

The error rates also show a slight improvement as the misclassification between extreme classes (Pop_Value 1 and Pop_Value 3).

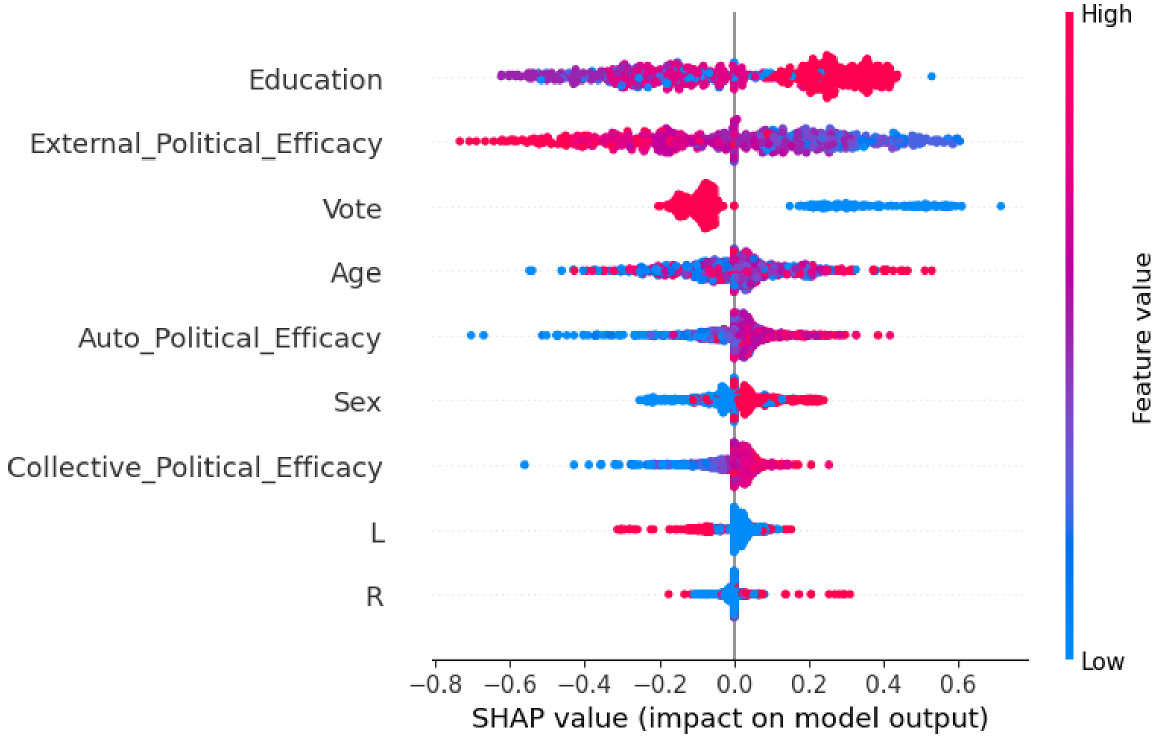

Figure 4.24: SHAP Values of features towards target variable - medium populist attitudes - Pop_Value = 2 for SVM classification

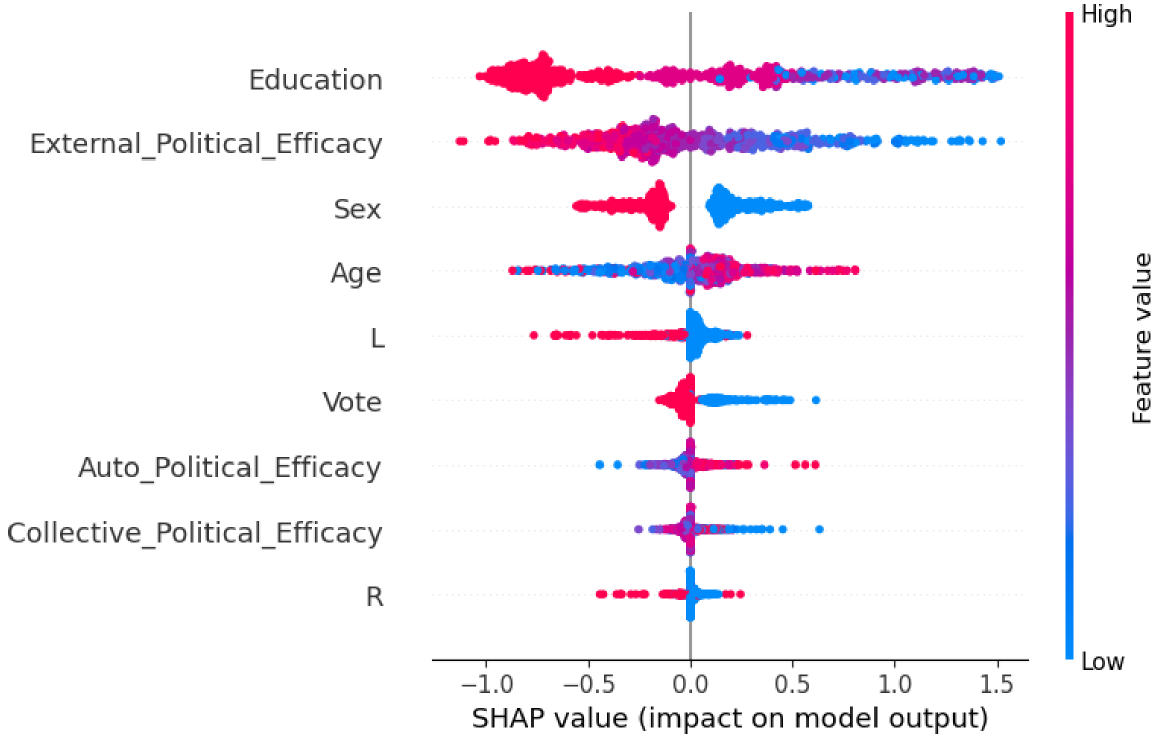

Figure 4.25: SHAP Values of features towards target variable - high populist attitudes - Pop_Value = 3 for SVM classification

4.2.3 Random forest classification

Random Forest classification is another popular algorithm for binary and multi-class classification tasks. It is an ensemble learning method that combines multiple decision trees to make predictions.

Cross-validation was performed for the random forest with the following hyperparameters:

- criterion: ['gini', 'entropy'];
- n_estimators: [100, 200, 300];
- max_depth: [None, 5, 10];
- min_samples_split: [2, 5, 10];
- min_samples_leaf: [1, 2, 4];
- max_features: [None, 'sqrt', 'log2'].

The best hyperparameters obtained were criterion: 'gini', max_depth: 5, max_features: None, min_samples_leaf: 4, min_samples_split: 2, n_estimators: 100.

Gini impurity is a measure of impurity or disorder within a node. It calculates the probability of incorrectly classifying a randomly chosen element in the dataset if it were randomly labelled according to the distribution of classes in the node.

After this step, the feature importances are plotted and seen in figure 4.26 where it is not unexpected to observe that the variable External_Political_Efficacy exhibits a greater impact on the Pop_Value outcome. Subsequently, the variables Age and Education demonstrate notable impacts on the outcome, with respective values of 0.22 and 0.17. Moreover, Auto_Political_Efficacy and Collective_Political_Efficacy exhibit considerable influences as well, with values of 0.12 and 0.13, respectively.

Analysing the SHAP values across the three classes provides a deeper understanding of the data. The visualization in Figure 4.27 reveals that a strong alignment with statements of External_Political_Efficacy corresponds to lower levels of populist attitudes. The positioning of the red dots towards the right side of the plot also indicates a negative association between Education and populist attitudes. While the distribution of colours for Age is not uniform, it can be inferred that younger individuals tend to exhibit low levels of populism. Additionally, individuals who did not vote appear to have a negative impact on the Pop_Value = 1. Notably, in the case of the variable Sex, the SHAP values for high (women) have a positive impact on the target variable.

From figure 4.28, what stands up is that those who didn't vote tend to have medium populist attitudes. Low values of External_Political_Efficacy have a more positive impact on medium populist attitudes, although there are a few strong blue dots that have also a negative impact. Variable Age has not a linear relation with Pop_Value = 2, but it can be said that low values of age tend to have a low impact. Similarly, in Education, it's possible to see that high values, tend to have none or few impact on Pop_Value = 2.

For a high level of populism, it's possible to see that Education and values of agreement with External_Political_Efficacy have a negative impact on it. Although it can be stated that

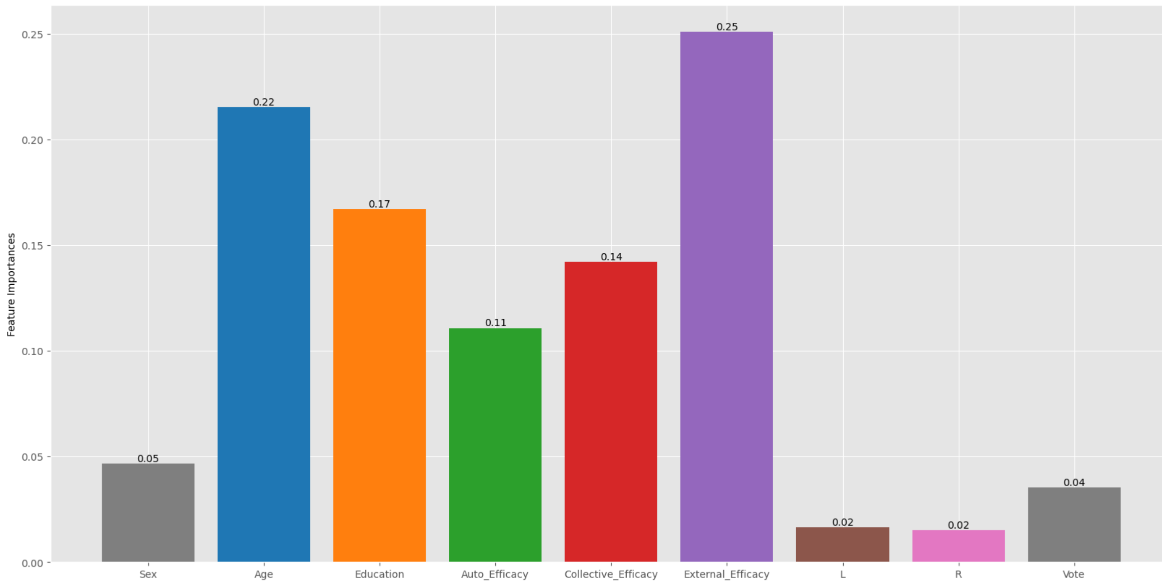

Figure 4.26: Feature importances towards target variable Pop_Value for Random forest classification

low values of agreement with Collective_Political_Efficacy tend to represent populist attitudes, this relationship is not so linear as can be seen in some red dots on the right side of the plot. Similarly, in the case of the variable Age, higher values tend to be associated with a positive impact on populist attitudes. However, it is important to note that this relationship is not linear in the context of random forest classification.

The following metrics were obtained for Random Forest classifier:

- Accuracy: 47.0%
- Precision: 46.8%
- Recall: 47.0%
- F1 Score 46.1%

Moreover, the error rates for the different classes are the following:

- Pop_Value 1 classified as Pop_Value 2 - 24.2%
- Pop_Value 1 classified as Pop_Value 3 - 21.3%
- Pop_Value 3 classified as Pop_Value 1 - 18.1%
- Pop_Value 3 classified as Pop_Value 2 - 22.4%

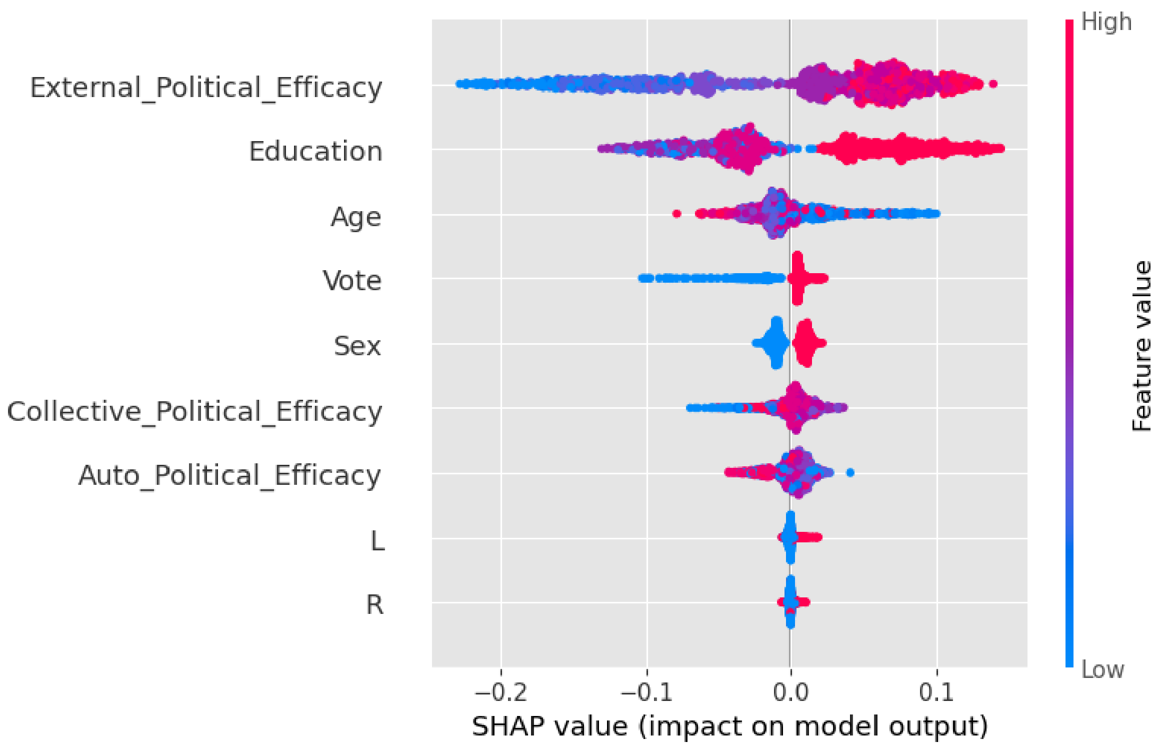

Figure 4.27: SHAP Values of features towards target variable - low populist attitudes - Pop_Value = 1 for random forest classification

When comparing the performance of logistic regression and SVM with the random forest classifier, it is observed that metrics like accuracy, precision, recall and F1 score exhibit better results.

Moreover, the Pop_Value 3 classified as Pop_Value 1 decreases by nearly half when utilizing the random forest classifier. This outcome is indicative of positive progress and improvement.

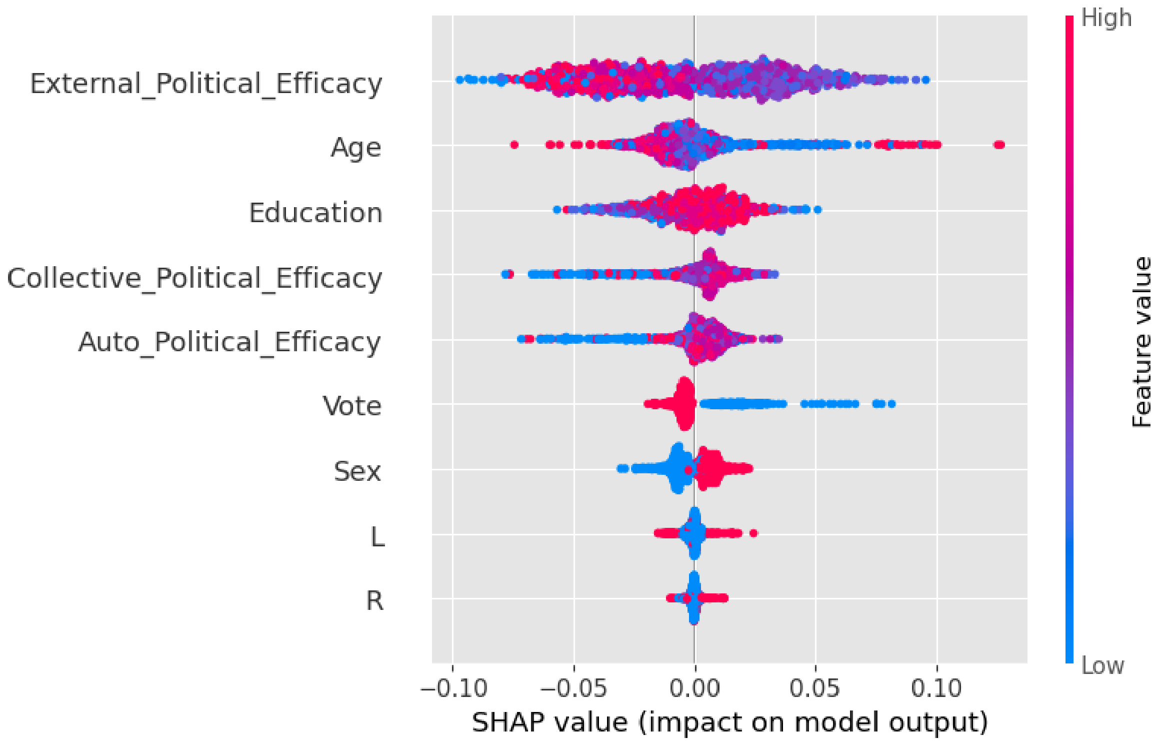

Figure 4.28: SHAP Values of features towards target variable - medium populist attitudes - Pop_Value = 2 for random forest classification

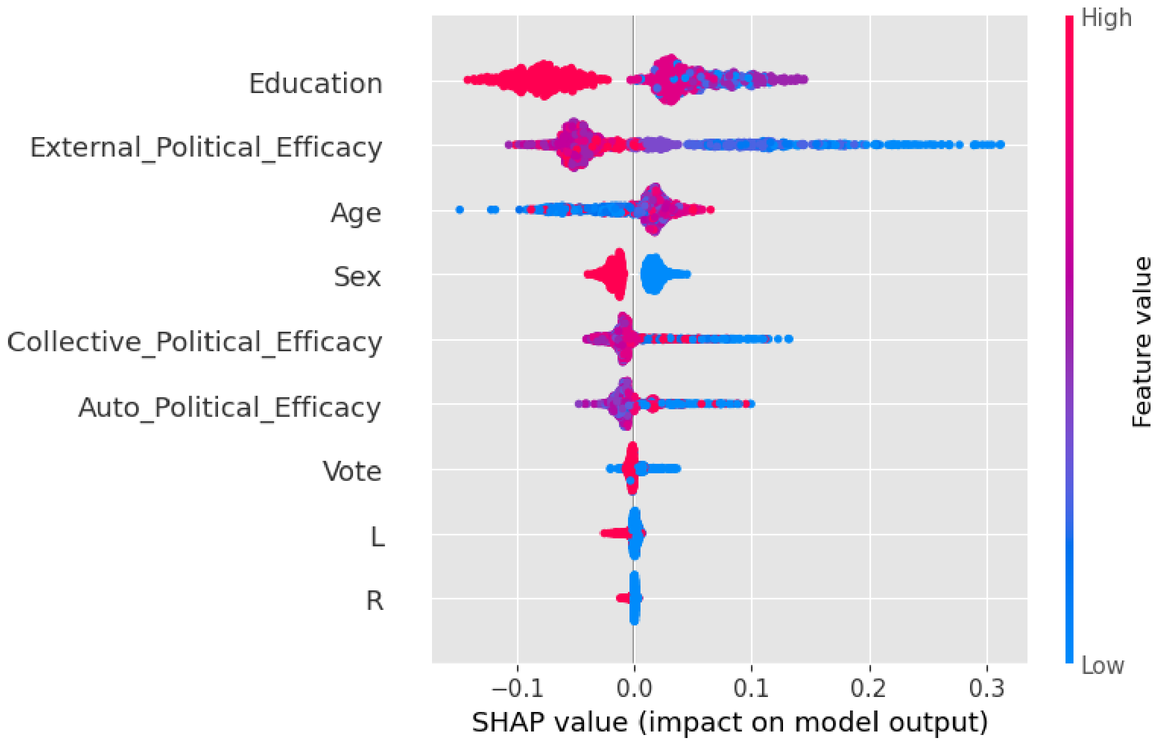

Figure 4.29: SHAP Values of features towards target variable - high populist attitudes - Pop_Value = 3 for random forest classification

4.2.4 Gradient Boosting classification

Among the tree-based algorithms, gradient boosting was also tested in the regression section, and naturally, cross-validation was performed as well:

- n_estimators: [10, 50, 100];
- learning_rate: [0.1, 0.01, 0.001];
- max_depth: [3, 5, 10];
- min_samples_split: [2, 5, 10];
- min_samples_leaf: [1, 2, 4];
- max_features: ['sqrt', 'log2'].

After running the cv process, the best hyperparameters obtained were n_estimators: 100, learning_rate: 0.1, max_depth: 3, max_features: 'log2', min_samples_leaf: 4, min_samples_split: 10.

The feature importances of the gradient boosting classifier after the cv can be seen in figure 4.30. It's clear that variables Age and External_Political_Efficacy are the ones with the biggest impact on Pop_Value, although they represent a lower value compared to the random forest classifier (0.22 and 0.25, respectively). Education, Collective_Political_Efficacy and Auto_Political_Efficacy have also a fair impact on the target variable.

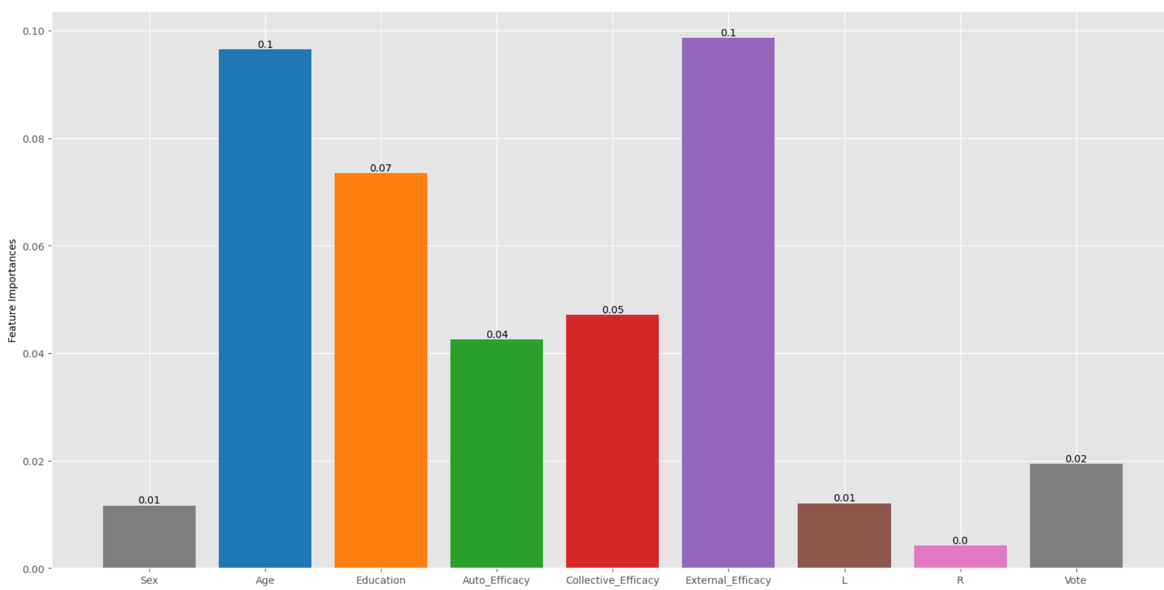

Figure 4.30: Feature importances towards target variable Pop_Value for Gradient boosting classification

The findings through the SHAP values for low populist attitudes in random forest are also confirmed for gradient boosting - figure 4.31.

High values of External_Political_Efficacy, Education and Sex (Females) represent low values of populist attitudes. Also, younger respondents tend to have low values of populist attitudes. In Gradient Boosting it's clearer that low values of Auto_Political_Efficacy represent low values of populist attitudes.

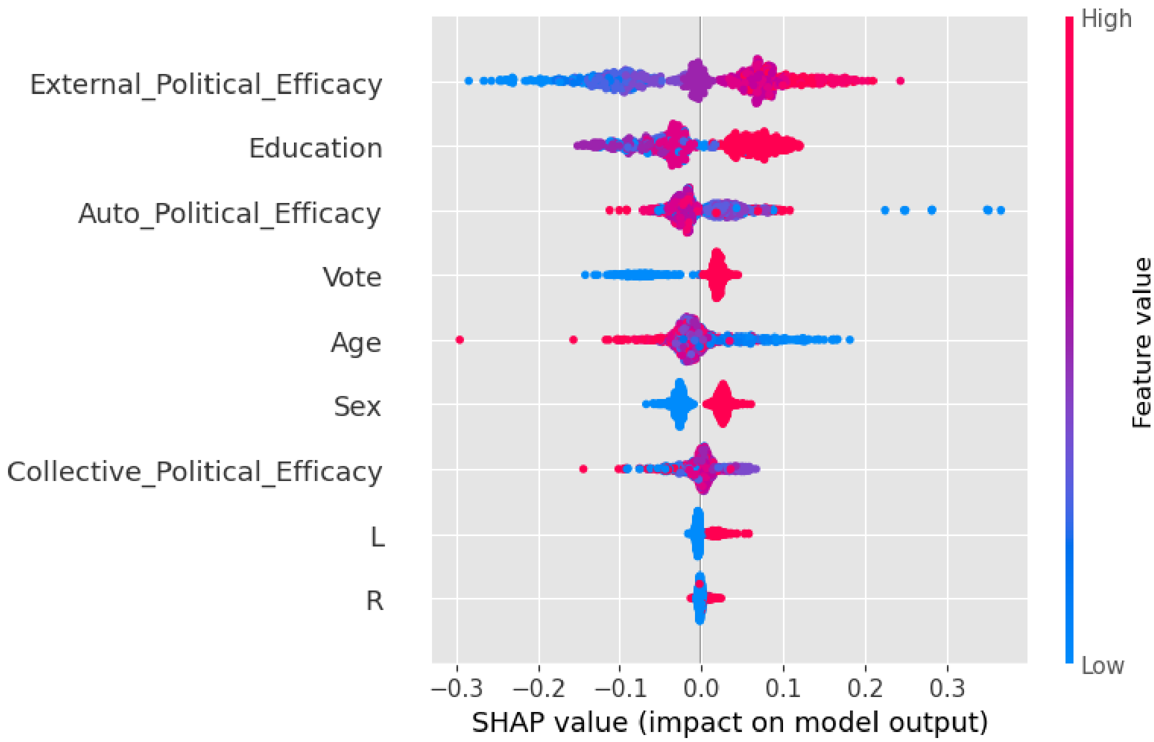

Figure 4.31: SHAP Values of features towards target variable - low populist attitudes - Pop_Value = 1 for gradient boosting classification

The SHAP values for medium populist attitudes can be seen in figure 4.32.

For a high level of populism, from the figure 4.33 it's possible to retrieve the same findings as for random forest classification - figure 4.29. Education and values of agreement with External_Political_Efficacy exert a negative influence on populist attitudes. Higher values of Age and males appear to correlate with a positive impact on populist attitudes.

Performing predictions using the trained gradient boosting classifier the following metrics are obtained:

- Accuracy: 48.2%
- Precision: 47.7%
- Recall: 48.2%

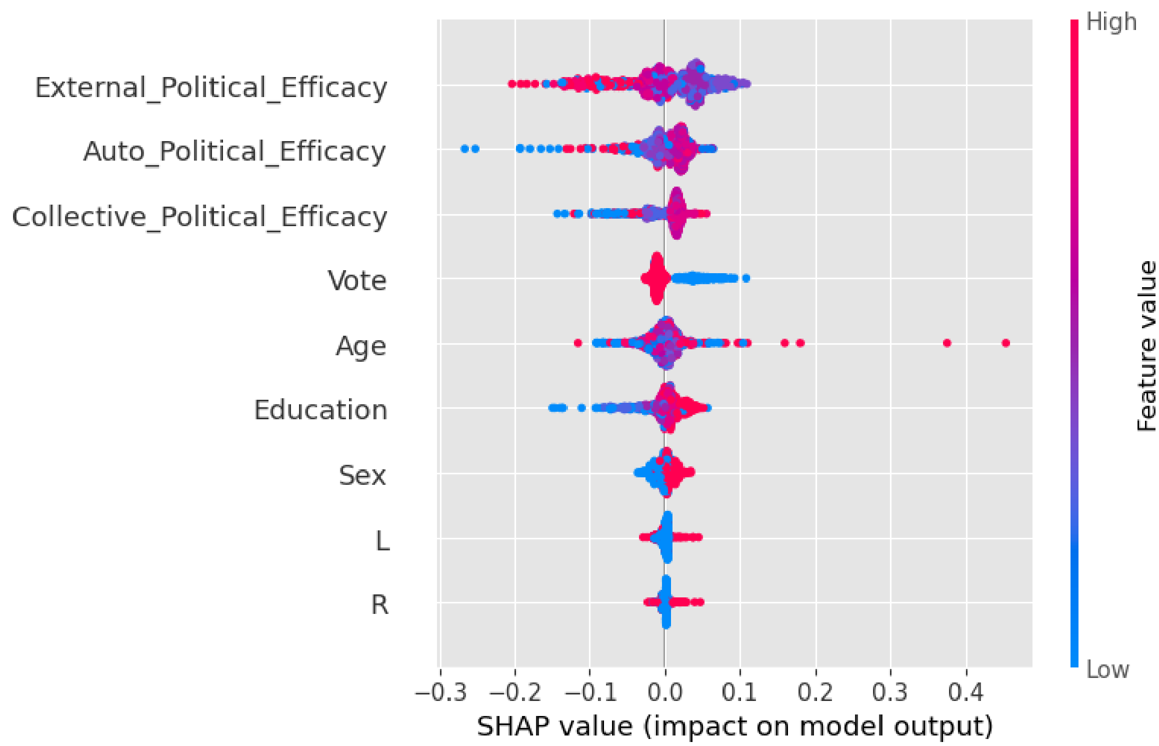

Figure 4.32: SHAP Values of features towards target variable - medium populist attitudes - Pop_Value = 2 for gradient boosting classification

- F1 Score: 47.9%

In general, when evaluating classifier performance, higher values of accuracy, precision, recall, and F1 score indicate better model performance. Compared with random forest, gradient boosting shows slightly higher values for these performance metrics.

- Pop_Value 1 classified as Pop_Value 2 – 28.8%
- Pop_Value 1 classified as Pop_Value 3 - 21.9%
- Pop_Value 3 classified as Pop_Value 1 - 16.7%
- Pop_Value 3 classified as Pop_Value 2 - 23.7%

Comparing the error rates with random forest the Pop_Value 1 classified as Pop_Value 3 are similar, however the Pop_Value 3 classified as Pop_Value 1 decrease from 18.1 to 16.7%.

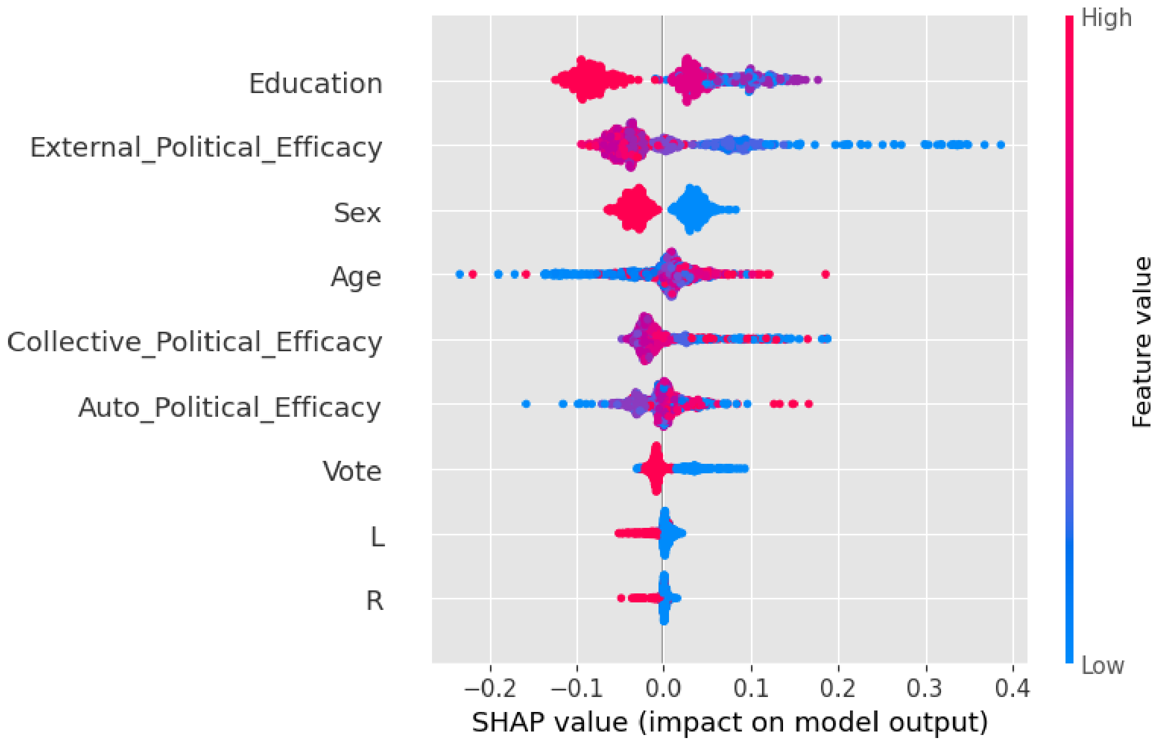

Figure 4.33: SHAP Values of features towards target variable - high populist attitudes - Pop_Value = 3 for gradient boosting classification

4.2.5 XGBoost classification

Lastly, XGBoost classifier will be used for the classification problem. A cross-validation was performed in order to find the best hyperparameters:

- n_estimators: [10, 50, 100];
- learning_rate: [0.1, 0.01, 0.001];
- max_depth: [3, 5, 10];
- gamma: [0, 0.1, 0.2];
- min_child_weight: [1, 2, 4];
- subsample: [0.3, 0.4, 0.5,0.6, 0.7, 0.8, 1.0, 1.2];
- colsample_bytree: [0.3, 0.4, 0.5, 0.6, 0.7, 0.8].

Running the cv process the hyperparameters obtained were n_estimators: 50, learning_rate: 0.1, max_depth: 5, gamma: 0.2, min_child_weight: 1, subsample: 0.3 and colsample_bytree: 0.8.

The feature importances of each variable can be seen in figure 4.34 where all variables have a relatively high importance towards the target variable. Unlike previous algorithms, variables like Vote, L and R reveal higher importance.

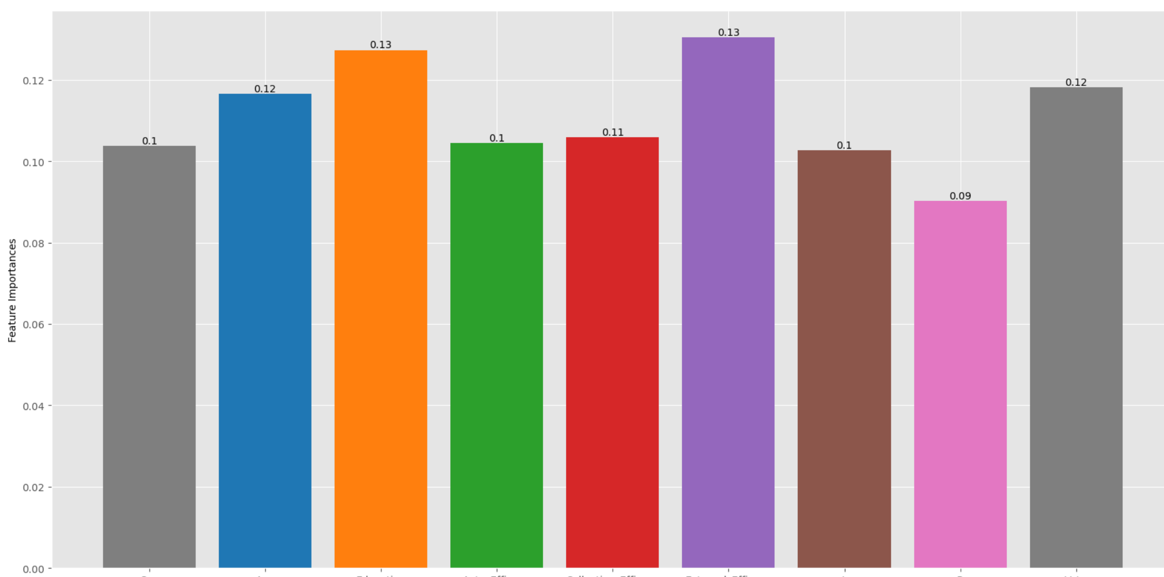

Figure 4.34: Feature importances towards target variable Pop_Value for XGBoost classification

SHAP values of the different variables for the XGBoost algorithm can be seen in figures 4.35, 4.36 and 4.37. The insights retrieved from them align with descriptions provided for other algorithms.

The metrics obtained for XGBoost classifier were the following:

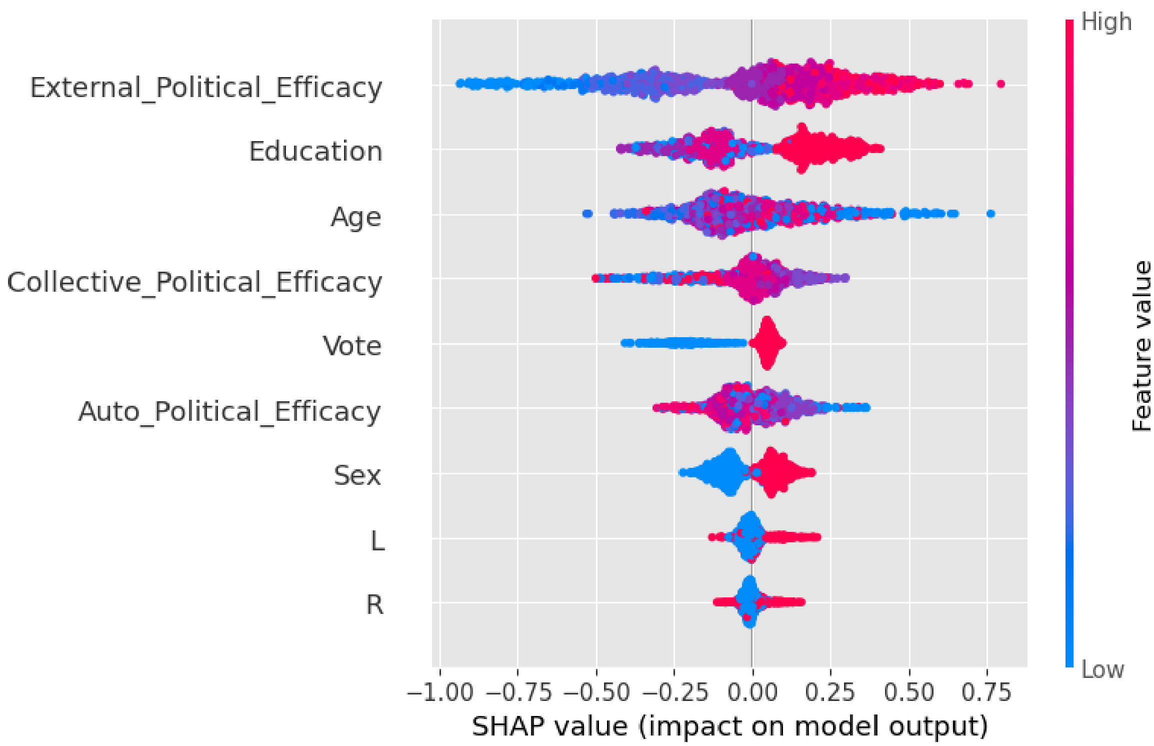

Figure 4.35: SHAP Values of features towards target variable - low populist attitudes - Pop_Value = 1 for XGBoost classification

- Accuracy: 47.3%
- Precision: 47.0%
- Recall: 47.3%
- F1 Score: 47.1%

The metrics acquired through XGBoost exhibit marginally lower values compared to those obtained from gradient boosting.

- Pop_Value 1 classified as Pop_Value 2 – 28.1%
- Pop_Value 1 classified as Pop_Value 3 - 19.7%
- Pop_Value 3 classified as Pop_Value 1 - 19.7%
- Pop_Value 3 classified as Pop_Value 2 - 25.8%

In contrast to gradient boosting, there was a minor reduction in the misclassification of low populist attitudes. However, the misclassification of high populist attitudes demonstrated a general increase of 2% points across both low and medium populist attitudes.

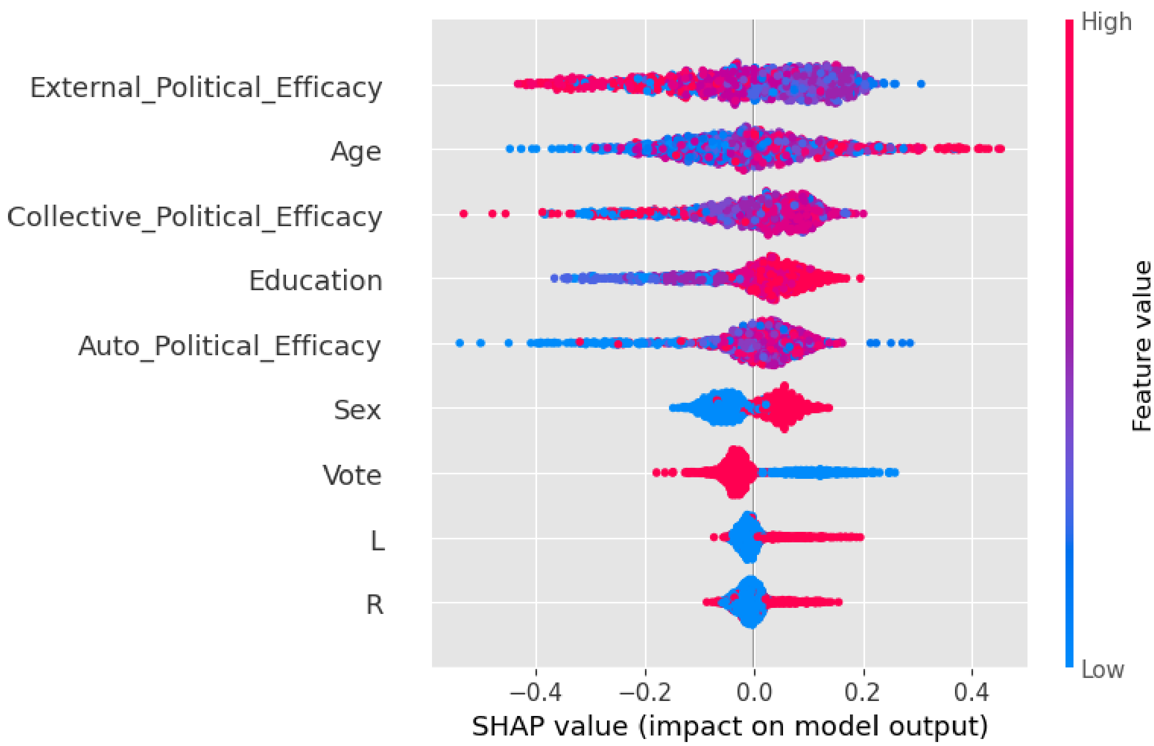

Figure 4.36: SHAP Values of features towards target variable - medium populist attitudes - Pop_Value = 2 for XGBoost classification

As a summary of classification algorithms, table 4.13 encapsulates all performance metrics for each model. Notably, these results reveal a marginal superiority in the results of tree-based algorithms. These algorithms exhibit a slightly higher percentage across the range of metrics evaluated. This suggests their proficiency in capturing intricate data relationships, underscoring their potential for enhanced classification performance.

Table 4.13: Metrics obtained for each classification model

Algorithms	Accuracy	Precision	Recall	F1 Score
Logistic Regression	44.6%	43.2%	44.6%	42.5%
SVM Classification	45.7%	44.6%	45.7%	44.5%
Random Forest Classification	47.0%	46.8%	47.0%	46.1%
Gradient Boosting Classification	48.2%	47.7%	48.2%	47.9%
XGBoost Classification	47.3%	47.0%	47.3%	47.1%

Conducting Friedman's test to assess potential distinctions among various classification algorithms, the analysis yielded a p-value of 0.003, indicating significant variations among them.

Moreover, the Nemenyi post hoc test determines which pairs of classification algorithms have significant differences in their performance based on the results of Friedman's test. The value of 0.003 is obtained between the logistic regression and gradient boosting classifier, and

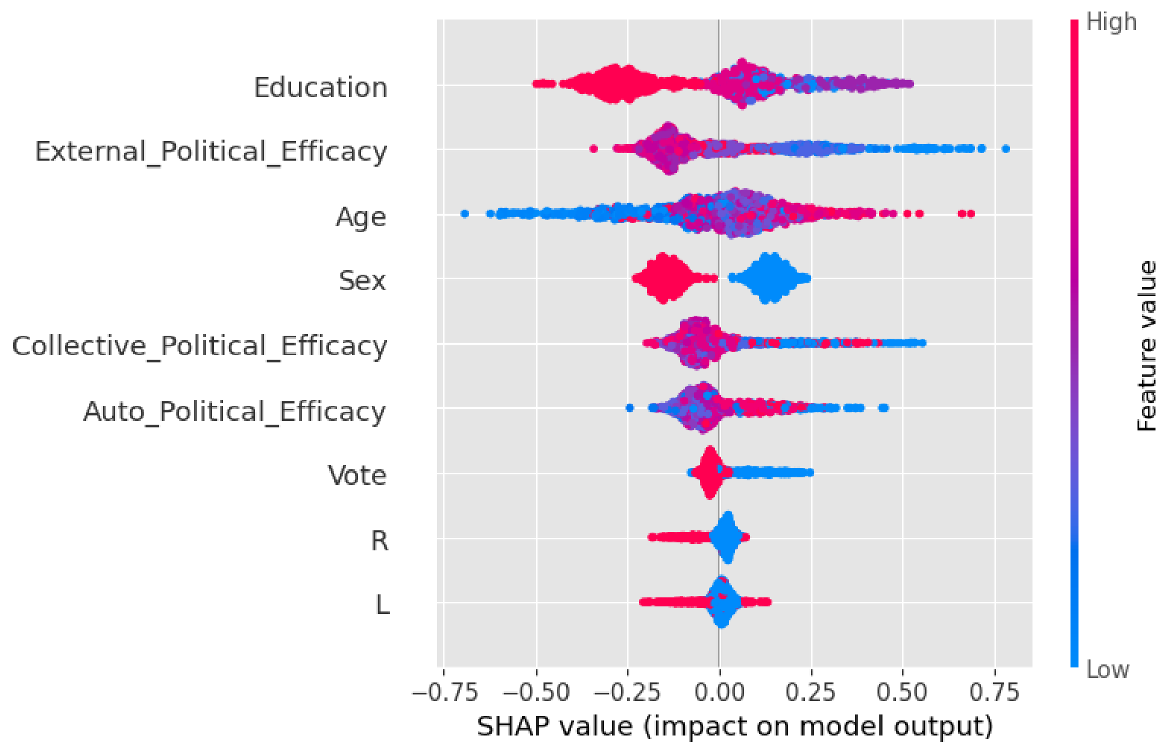

Figure 4.37: SHAP Values of features towards target variable - high populist attitudes - Pop_Value = 3 for XGBoost classification

so, they are statistically significantly different. Even though it is above of the threshold of 0.05, a value of 0.06 was obtained between logistic regression and XGBoost.

Chapter 5

Conclusion

The primary objective of this dissertation was to develop a machine learning model to identify the key determinants of populist attitudes through the Populist Attitudes Scale (POP-AS). Hence, this dissertation has shed light on the key variables pivotal in predicting populist attitudes among individuals. The empirical analysis revealed that several critical factors substantially impact shaping these attitudes.

First and foremost, the research identified External Political Efficacy as a crucial determinant. In a broad sense, this variable exhibited the most significant influence on Populist attitudes across all algorithms. The inverse relationship observed between External Political Efficacy and populist attitudes underscores the significance of citizens' perceptions of the government's transparency and openness. As External Political Efficacy diminishes, the propensity towards populism tends to increase. This outcome underscores the need for governments to enhance communication and information-sharing processes to bridge the gap between decision-making mechanisms and citizens, thus fostering a more trusting relationship.

Moreover, the study highlighted the influence of Education on populist attitudes. Individuals with higher levels of education were inclined to exhibit lower levels of populist attitudes. This finding suggests that education plays a role in equipping individuals with critical thinking skills and a deeper understanding of political processes, which can act as a buffer against populist tendencies.

Sex and Age also emerged as noteworthy variables in shaping populist attitudes. Men were found to have higher levels of populist attitudes than women, and younger participants exhibited lower populist attitudes in contrast to their older counterparts. The positive correlation between age and populist attitudes suggests the importance of considering generational differences when exploring and addressing populist sentiments. Moreover, it's worth noting that the higher levels of populist attitudes among older individuals might partly be attributed to weariness and scepticism that can develop over time towards political processes and the broader system. This weariness could result from years of witnessing political changes and potentially feeling disillusioned with the outcomes, thus influencing their inclination towards populist stances.

Lastly, the analysis delved into the impact of voting behaviour on populist attitudes. Individuals who participated in the 2019 general elections displayed lower levels of populist attitudes, indicating a potential link between political engagement and a more nuanced understanding of political issues. It would be intriguing to investigate whether this voting behaviour might have a distinct impact on populist attitudes in contemporary times, especially considering Portugal's recent emergence of the far-right.

Among the array of regression algorithms explored, it became evident that certain methodologies exhibited a superior capacity to uncover meaningful patterns within the dataset. By observing of lower error metrics and higher R-squared values, the tree-based algorithms, namely XGBoost and Gradient Boosting regressors, emerged as leaders.

In parallel to the findings in the regression analysis, the evaluation of classification algorithms reaffirmed the ascendancy of tree-based methodologies. Notably, the outcomes align with the regression assessment, as tree-based algorithms, exemplified by Gradient Boosting, once again surfaced with superior and improved results in the realm of classification.

One of the notable limitations encountered in this study pertains to the seemingly modest performance metrics achieved by both regression and classification algorithms. Although we recall that this was a multiclassification problem, also, our models struggled to achieve an accuracy rate that did not surpass 50%. However, it is essential to contextualize these outcomes within the framework of the complex and multifaceted nature of the social sciences. The challenges inherent in predicting human behaviour, especially within the realm of political attitudes, are inherently intricate. The human element, influenced by a multitude of sociocultural and psychological factors, introduces a level of unpredictability that machine learning algorithms may find challenging to capture.

Therefore, in future research, expanding the dataset to include more records and additional variables such as income levels, employment types, and other socio-demographic details could enhance the predictive capacity of the algorithms, providing a more comprehensive understanding of the factors driving populist attitudes.

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