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Investigating Socioeconomic Inequalities and Public Attitudes in Europe:

Evidence from the European Values Study and World Values Survey

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Abstract

Political trust constitutes one of the fundamental pillars of democratic governance, influencing institutional legitimacy, political participation and citizens' willingness to comply with public policies. Understanding the socioeconomic and political determinants of institutional confidence has therefore become an increasingly important area of research within political science, particularly in the context of growing political polarization, economic inequalities and declining confidence in democratic institutions across. The present study investigates the determinants of political trust by examining citizens' confidence in governments, parliaments and political parties using the harmonized European Values Study (EVS) and World Values Survey (WVS) dataset. Following a comprehensive data preprocessing procedure, three binary classification models—Binary Logistic Regression, Random Forest and Extreme Gradient Boosting (XGBoost)—were implemented to predict institutional confidence. Model performance was evaluated using multiple metrics, including Accuracy, Area Under the Receiver Operating Characteristic Curve (AUC), Sensitivity, Specificity and Precision. Furthermore, SHapley Additive exPlanations (SHAP) were employed to enhance model interpretability and identify the most influential predictors of institutional confidence. The empirical findings indicate that satisfaction with democracy, political interest, generalized social trust, age and household income constitute the most important determinants of political trust across all three institutional outcomes. Random Forest and XGBoost achieved slightly superior predictive performance compared with Binary Logistic Regression; however, all three approaches identified remarkably similar sets of influential variables, demonstrating the robustness of the empirical findings. The integration of explainable machine learning techniques further enhanced the interpretation of complex predictive models while preserving high predictive accuracy. Overall, the study demonstrates that political trust is shaped by a multidimensional interaction between socioeconomic characteristics, political attitudes and democratic evaluations. Positive relations were observed with several independent variables like Satisfaction with Democracy, Age and Political Interest and the 3 dependent variables while others like Urbanization tend to not have much of a relation. Beyond its substantive contribution to the literature on political trust, the research illustrates the value of combining conventional statistical methods with explainable artificial intelligence to improve both predictive performance and model transparency. The findings contribute to the growing field of computational political science and provide evidence that may support the development of evidence-based policies aimed at strengthening democratic legitimacy and institutional confidence within contemporary European democracies.

Keywords: Political Trust; Socioeconomic Inequalities; Explainable Artificial Intelligence; Machine Learning; Logistic Regression; Random Forest; XGBoost; SHAP; European Values Study; World Values Survey

1. Introduction

1.1 Socioeconomic Inequalities in Contemporary Europe

Over the past several decades, socioeconomic inequalities have emerged as one of the defining challenges facing contemporary democratic societies. Although economic growth has substantially improved living standards across Europe, the benefits of this growth have not been distributed equally among citizens. Globalization, technological progress, demographic changes, labor market transformations, and successive economic crises have contributed to increasing disparities in income, wealth, employment opportunities, and social mobility. These developments have intensified public debates regarding social justice, equality of opportunity, and the capacity of democratic institutions to respond effectively to citizens' needs.

The growing concern surrounding socioeconomic inequalities extends beyond purely economic outcomes. A substantial body of literature suggests that inequality affects not only material living conditions but also social cohesion, interpersonal trust, political participation, and institutional legitimacy. According to Piketty (2014), rising economic inequality has fundamentally reshaped the relationship between citizens and democratic institutions by increasing perceptions of unfairness and unequal political influence. Similarly, Wilkinson and Pickett (2009) argue that societies characterized by greater inequality tend to experience lower levels of social trust, weaker civic engagement, and poorer institutional performance. These findings suggest that inequality should not be viewed solely as an economic phenomenon but also as a broader social and political issue affecting the functioning of democratic systems. Concerns regarding inequality have become particularly pronounced following the global financial crisis of 2008, the COVID-19 pandemic, and the recent geopolitical instability resulting from international conflicts and rising inflation. These events have exposed substantial differences in economic resilience among countries, while simultaneously increasing people's expectations regarding the role of governments in promoting economic security and social protection.

Recent comparative studies further demonstrate that citizens occupying different socioeconomic positions often evaluate political institutions differently. Individuals with higher incomes, greater educational attainment, and more stable employment generally report more positive assessments of institutional performance, whereas economically vulnerable groups are more likely to express dissatisfaction and political discontent. However, the mechanisms through which socioeconomic characteristics influence political attitudes remain far from straightforward. Several authors argue that institutional quality, perceptions of fairness, and experiences with public services may mediate or even outweigh the direct effects of economic resources on political trust as suggested by Levi & Stoker (2000) and Hooghe & Zmerli (2011). Consequently, understanding the interaction between socioeconomic inequalities and political attitudes represents an increasingly important area of research within political science, economics, and sociology. Among the various public attitudes influenced by socioeconomic inequalities, political trust has attracted particular attention due to its central role in democratic governance

1.2 Political Trust as a Pillar of Democratic Governance

Political trust constitutes one of the fundamental pillars of democratic governance and has long attracted the attention of political scientists, economists, and sociologists. Broadly defined, political trust refers to citizens' confidence that political institutions and public authorities act competently, fairly, and in the public interest. It reflects the extent to which individuals believe that governments, parliaments, political parties, and other public institutions can represent citizens' interests while maintaining democratic principles and institutional stability. Consequently, political trust is widely regarded as a key indicator of democratic legitimacy and effective governance. The concept of political trust has evolved considerably since the pioneering work of Easton (1965), who distinguished between specific support and diffuse support for political systems. Specific support refers to people's evaluations of the current performance of political authorities, whereas diffuse support reflects a more general and long-term attachment to political institutions and democratic values. This distinction remains highly relevant because citizens may express dissatisfaction with the performance of a particular government while continuing to support the broader democratic system. Conversely, persistent dissatisfaction may gradually erode institutional legitimacy and weaken confidence in democratic governance.

Conversely, declining political trust has been associated with a wide range of political and social challenges. Low institutional confidence may reduce electoral participation, increase political disengagement, encourage anti-establishment attitudes, and contribute to the emergence of political polarization and populist movements. Norris (2011) argues that contemporary democracies increasingly face a phenomenon described as the democratic deficit, in which citizens continue to support democratic ideals while expressing growing dissatisfaction with the institutions responsible for implementing them. This distinction highlights the complexity of political trust as a multidimensional concept influenced by institutional performance, public expectations, and broader social conditions. An extensive body of empirical research further demonstrates that political trust is influenced by both institutional and individual-level factors. Citizens are more likely to trust governments that are perceived as competent, responsive, and capable of delivering public goods efficiently. Similarly, institutional fairness and equal treatment under the law reinforce the legitimacy of democratic institutions and strengthen public confidence.

At the individual level, demographic characteristics, socioeconomic status, education, political interest, generalized social trust, and citizens' satisfaction with the political system have all been identified as important predictors of political trust. In recent years, political trust has become increasingly relevant due to the global crises. These have placed unprecedented demands on governments and public institutions. These developments have altered expectations regarding state capacity, economic management, and institutional responsiveness. As governments were required to implement complex policy responses under conditions of uncertainty, citizens' evaluations of institutional performance became increasingly important determinants of political trust. Consequently, understanding the factors that shape confidence in political institutions has become not only an academic objective but also a practical concern for policymakers seeking to strengthen democratic resilience.

Given its central role in democratic governance, political trust represents the primary outcome examined in this thesis. Rather than treating institutional confidence as a single construct, this study adopts a multidimensional perspective by analyzing confidence in government, parliament, and political parties separately. These institutions perform distinct democratic functions and may therefore be influenced differently by socioeconomic characteristics and political attitudes. Examining each institution individually allows for a more nuanced understanding of the determinants of political trust and provides richer empirical evidence regarding the relationship between socioeconomic inequalities and citizens' evaluations of democratic institutions.

1.3 Contribution of the Study

Despite the considerable body of literature examining the determinants of political trust, several important limitations remain. First, most empirical studies continue to rely on traditional econometric techniques, such as Ordinary Least Squares (OLS), ordered logistic regression, or binary logistic regression, to estimate the relationship between socioeconomic characteristics and institutional confidence. While these approaches provide valuable insights regarding statistically significant relationships, they generally assume linear or predefined functional forms and may therefore fail to capture complex interactions and non-linear associations among explanatory variables. Recent developments in computational social science have introduced machine learning techniques as complementary tools for analysing large-scale survey data. Compared with conventional statistical models, machine learning algorithms are specifically designed to maximise predictive performance by identifying complex patterns within high-dimensional datasets. Rather than focusing exclusively on statistical significance, these methods allow researchers to evaluate the relative importance of individual predictors while simultaneously modelling interactions that are difficult to specify within traditional regression frameworks like Mullainathan & Spiess (2017).

Among the most widely used machine learning algorithms in contemporary social science research are Random Forest and Extreme Gradient Boosting (XGBoost**)**. Random Forest, originally proposed by Breiman (2001), constructs an ensemble of decision trees and combines their predictions to improve classification accuracy while reducing overfitting. XGBoost, introduced by Chen and Guestrin (2016), further enhances predictive performance through gradient boosting, sequentially improving weak learners to produce highly accurate predictive models. Both algorithms have demonstrated excellent performance across a wide range of applications, including political behaviour, public opinion, electoral studies, and policy analysis. Although machine learning methods provide substantial improvements in predictive accuracy, they have often been criticised for functioning as models whose internal decision-making processes remain difficult to interpret. This limitation has motivated the rapid development of Explainable Artificial Intelligence (XAI**)**, a growing field that seeks to improve the transparency and interpretability of complex predictive algorithms. Among the available explainability techniques, SHapley Additive exPlanations (SHAP) have become one of the most widely accepted approaches for interpreting machine learning models. Based on cooperative game theory, SHAP values quantify the contribution of each predictor to individual model predictions, thereby allowing researchers to identify not only which variables are important but also the magnitude of their influence (Lundberg & Lee, 2017).

The integration of machine learning into political science remains relatively recent. While an increasing number of studies employ predictive algorithms to analyze voting behavior, political participation and public opinion, comparatively few investigations have applied explainable machine learning techniques to the study of political trust using large cross-national survey datasets. Furthermore, existing studies rarely combine conventional statistical inference with predictive modelling within a unified analytical framework. As a result, there remains limited evidence regarding whether the determinants identified through traditional regression models are also those that contribute most strongly to predictive performance.

This study seeks to address these limitations by integrating conventional econometric methods with modern machine learning approaches. Rather than replacing classical statistical analysis, machine learning is employed as a complementary methodological framework that enables a broader understanding of the mechanisms underlying political trust. Binary Logistic Regression is first used to estimate the direction and statistical significance of the relationships between socioeconomic characteristics and institutional confidence. Subsequently, Random Forest and XGBoost are implemented to evaluate predictive performance and identify the most influential variables through feature importance measures. Finally, SHAP values are employed to provide interpretable explanations of model predictions, thereby enhancing the transparency of the machine learning results.

Beyond its methodological contribution, this study also offers a substantive contribution by examining political trust within a large comparative European sample derived from the harmonized European Values Study (EVS) and World Values Survey (WVS). The combined dataset includes more than 150,000 respondents from multiple countries and simultaneously incorporates demographic characteristics, socioeconomic conditions, political attitudes and institutional evaluations. This comprehensive analytical framework makes it possible to investigate not only whether socioeconomic inequalities influence political trust, but also which factors exert the greatest influence across different political institutions. By combining explanatory and predictive perspectives, the present research contributes to the growing literature on political trust while demonstrating the potential of explainable machine learning techniques within comparative political and socioeconomic research. In doing so, the study provides a more comprehensive understanding of institutional confidence than would be possible through the exclusive use of traditional regression models.

1.4 Aim of the Study

The primary aim of this study is to investigate the socioeconomic and attitudinal determinants of political trust by examining citizens' confidence in three core democratic institutions: government, parliament and political parties. Political trust is widely recognized as a fundamental component of democratic legitimacy, yet it remains influenced by a complex interaction of economic conditions, social characteristics and individual political attitudes. Understanding these relationships is therefore essential for explaining variations in institutional confidence across contemporary European societies. To address this objective, the study employs a harmonized dataset combining EVS and WVS, allowing for the analysis of political trust using a large and internationally comparable sample.

A second objective of the study is to compare conventional statistical modelling with modern machine learning techniques to evaluate their relative effectiveness in predicting political trust. Specifically, the study applies Binary Logistic Regression, Random Forest and XGBoost models and compares their predictive performance using multiple evaluation metrics. Furthermore, the implementation of SHAP enables the interpretation of complex machine learning models by identifying the contribution of individual explanatory variables to model predictions. Beyond its empirical contribution, the study also seeks to demonstrate the value of integrating explainable artificial intelligence into quantitative political science research. By combining traditional econometric methods with contemporary machine learning approaches, the research aims not only to improve predictive accuracy but also to enhance the transparency and interpretability of analytical results. In doing so, the study contributes to the growing literature on computational social science while providing evidence that may support the development of evidence-based public policies aimed at strengthening political trust and democratic legitimacy.

Finally, this research contributes to the existing literature by offering a comprehensive comparative analysis of three different predictive modelling approaches within a unified analytical framework. The combination of harmonized international survey data, conventional statistical inference and explainable machine learning provides a robust methodological foundation for examining political trust and offers insights that may inform both academic research and policymaking in contemporary European democracies.

2. Literature Review

2.1 Introduction

The relationship between socioeconomic inequalities and political trust has become one of the most prominent topics in contemporary political science, economics and comparative social research. Over the last several decades, societies have experienced profound economic, demographic and institutional transformations resulting from globalization, technological change, labor-market restructuring, financial crises, migration flows and increasing socioeconomic disparities. These developments have altered not only objective living conditions but also citizens' perceptions of democratic institutions, political representation and governmental performance. A substantial body of literature has investigated the relationship between socioeconomic characteristics and institutional confidence. Previous studies have examined the effects of income, education, employment status, age, political interest and social trust on citizens' evaluations of governments and democratic institutions. While many authors conclude that socioeconomic inequalities play an important role in shaping political trust, others emphasize institutional quality, democratic performance and political culture as equally important explanatory factors. These differing perspectives suggest that political trust emerges from the interaction of multiple economic, social and political mechanisms rather than from any single determinant.

Recent advances in computational social science have introduced machine learning as a complementary methodological approach for analyzing large-scale survey data. Unlike traditional econometric models, machine learning algorithms prioritize predictive performance and can identify highly complex relationships among explanatory variables. At the same time, the rapid development of XAI has substantially improved the interpretability of these algorithms through techniques such as SHAP, allowing researchers to understand not only how accurately models predict political attitudes but also why particular variables contribute to those predictions (Lundberg & Lee, 2017; Molnar, 2022). Our study builds upon these recent methodological developments by integrating conventional statistical inference with explainable machine learning techniques. Using the EVS-WVS dataset the analysis investigates the determinants of confidence in government, parliament and political parties. Rather than relying on a single analytical approach, the study combines Binary Logistic Regression, Random Forest, XGBoost and SHAP values, allowing both explanatory inference and predictive performance to be evaluated within a unified analytical framework.

2.2 Political Trust and Democratic Legitimacy

Political trust has long been recognized as one of the most important indicators of democratic legitimacy and institutional effectiveness. Although scholars have proposed different conceptualizations of political trust over the past decades, there is broad agreement that institutional confidence reflects citizens' expectations regarding the competence, integrity and responsiveness of political authorities. High levels of political trust facilitate democratic governance by encouraging political participation, increasing compliance with public policies and strengthening people’s willingness to cooperate with public institutions. Conversely, persistent declines in institutional confidence may undermine democratic stability by reducing political engagement, weakening institutional legitimacy and increasing support for anti-establishment movements. The theoretical foundations of political trust can be traced to the work of Easton (1965), who distinguished between specific support and diffuse support for political systems. According to Easton, citizens evaluate political institutions on two different levels. Specific support reflects short-term evaluations of governmental performance and policy outcomes, whereas diffuse support represents a more stable and enduring attachment to democratic institutions themselves. This distinction remains particularly relevant because fluctuations in political trust do not necessarily imply rejection of democracy as a political system. Instead, citizens may simultaneously support democratic principles while expressing dissatisfaction with the performance of elected governments or representative institutions.

Building upon this perspective, Almond and Verba (1963) emphasized the importance of civic culture in sustaining democratic governance. They argued that stable democracies require not only formal constitutional arrangements but also citizens who trust political institutions, participate actively in public life and perceive themselves as legitimate members of the political community. Political trust therefore constitutes an essential component of democratic culture because it facilitates cooperation between governments and citizens while reducing political conflict and institutional instability. More recent research has extended these theoretical perspectives by examining the institutional determinants of political trust. Levi and Stoker (2000) argue that citizens' confidence in political institutions depends largely on perceptions of governmental competence, procedural fairness and institutional accountability. Governments that are perceived as transparent, effective and responsive tend to generate higher levels of political trust, whereas corruption, ineffective public administration and unequal treatment substantially reduce institutional confidence. Similarly, Rothstein and Stolle (2008) suggest that institutional quality influences political trust indirectly through its effects on generalized social trust, arguing that fair and impartial institutions promote cooperative behavior and strengthen confidence in democratic governance.

An important development within literature concerns the distinction between political trust and social trust. While political trust refers specifically to confidence in political institutions, social trust reflects individuals' expectations regarding the trustworthiness of other members of society. Hooghe and Zmerli (2011) argue that these two forms of trust are closely interconnected because individuals who exhibit higher levels of interpersonal trust frequently display greater confidence in democratic institutions. Nevertheless, the relationship is not deterministic. Institutional performance may strengthen or weaken political trust independently of broader patterns of social trust, particularly during periods of economic crisis or political instability. The comparative literature further demonstrates that political trust varies considerably across countries and institutional contexts. Norris (2011) argues that many contemporary democracies experience what she describes as a democratic deficit, whereby citizens continue to endorse democratic principles while expressing declining confidence in governments, political parties and representative institutions. This phenomenon has become increasingly visible following the global financial crisis, , the COVID-19 pandemic and the recent cost-of-living crisis, all of which have intensified public scrutiny of governmental performance and institutional responsiveness.

Recent comparative studies also indicate that confidence differs substantially across political institutions. Citizens frequently distinguish between executive institutions, legislatures and political parties when evaluating democratic performance. Governments are primarily judged according to policy outcomes and economic performance, parliaments according to legislative effectiveness and democratic representation, while political parties are often evaluated in terms of political competition, accountability and ideological representation. Consequently, treating political trust as a single homogeneous concept may obscure important differences in the determinants of institutional confidence. This distinction provides an important justification for the empirical strategy adopted in the present study. Rather than constructing a composite indicator of political trust, the analysis examines confidence in government, confidence in parliament and confidence in political parties separately. This approach allows the investigation of whether socioeconomic characteristics and political attitudes influence different institutions in similar or distinct ways, thereby providing a more detailed understanding of the mechanisms underlying political trust across democracies.

2.3 Socioeconomic Inequalities and Public Attitudes

Socioeconomic inequalities have long occupied a central position within the literature on political behavior and democratic governance. Beyond their direct implications for economic well-being, inequalities influence how citizens perceive political institutions, evaluate public policies and participate in democratic processes. As a result, the relationship between socioeconomic status and political trust has become one of the most extensively investigated topics within comparative political science. Among the various indicators of socioeconomic status, income has consistently emerged as one of the strongest predictors of political trust. Individuals with higher incomes generally report greater confidence in political institutions because they tend to experience higher levels of economic security, improved access to public resources and stronger perceptions of political efficacy. Conversely, citizens experiencing financial insecurity often exhibit lower institutional confidence, particularly during periods of economic instability or rising inequality.

According to Solt (2008), increasing economic inequality weakens political trust by reinforcing perceptions that democratic institutions primarily serve the interests of economically privileged groups. In highly unequal societies, lower-income citizens frequently perceive that political influence is distributed unequally, reducing confidence in representative institutions and weakening democratic legitimacy. Similar conclusions are reached by Uslaner (2002), who argues that economic inequality erodes generalized trust by reducing perceptions of fairness, reciprocity and equal opportunity. Since generalized social trust represents an important antecedent of institutional confidence, persistent socioeconomic inequalities may indirectly undermine political trust through broader processes of social fragmentation.

Broader economic literature similarly emphasizes that growing income inequality affects not only material living conditions but also the quality of democratic governance. Piketty (2014) argues that sustained increases in wealth concentration contribute to unequal political influence, limiting equal representation within democratic institutions and reinforcing perceptions of institutional bias. Likewise, Wilkinson and Pickett (2009) demonstrate that unequal societies frequently exhibit lower levels of interpersonal trust, weaker social cohesion and poorer institutional outcomes, suggesting that inequality constitutes both an economic and a democratic challenge. While income represents an important determinant of institutional confidence, previous research consistently demonstrates that socioeconomic status alone cannot fully explain political trust. Education constitutes another key explanatory factor because it enhances political knowledge, civic engagement and individuals' capacity to evaluate governmental performance. More educated citizens generally participate more actively in democratic processes and possess greater political efficacy. However, education may also increase citizens' expectations regarding governmental transparency, accountability and institutional effectiveness. Consequently, highly educated individuals may become more critical of political institutions when democratic performance fails to meet these expectations, resulting in an ambiguous relationship between education and political trust (Levi & Stoker, 2000; Hooghe & Zmerli, 2011).

Literature has also increasingly recognized the importance of social trust as a determinant of political trust. According to Rothstein and Stolle (2008), interpersonal trust and institutional trust reinforce one another through broader processes of social cooperation and institutional fairness. Citizens who believe that other people behave honestly and cooperatively tend to perceive public institutions more positively, whereas low levels of generalized trust frequently coincide with institutional skepticism and political disengagement. This relationship has been repeatedly confirmed across European comparative studies and constitutes one of the principal theoretical motivations for including measures of generalized social trust in the present analysis. Recent empirical studies have further demonstrated that socioeconomic status may moderate the relationship between political attitudes and institutional confidence. Albareda and Müller (2025), for example, show that the positive association between political efficacy and political trust is significantly stronger among individuals with higher socioeconomic status, indicating that economic resources influence not only political trust directly but also the way citizens interpret political experiences and institutional performance. These findings suggest that the determinants of political trust interact in complex and potentially non-linear ways, reinforcing the need for analytical approaches capable of modelling such relationships.

Based on the theoretical arguments presented above, empirical analysis incorporates a set of demographics, socioeconomic and attitudinal variables that have been consistently identified in literature as important determinants of political trust. Household income serves as the principal indicator of socioeconomic status, while age, sex, educational attainment and employment status capture demographic and socioeconomic characteristics. Political attitudes are represented through political interest and satisfaction with democracy, whereas generalized social trust and trust toward people of different religions and nationalities reflect broader dimensions of social capital. Finally, respondents' economic and ideological preferences are measured through variables capturing attitudes toward income equality, government responsibility, state ownership, progressive taxation and unemployment assistance. Together, these variables provide a comprehensive framework for examining the multidimensional determinants of confidence in government, parliament and political parties.

2.4 Explainable Machine Learning in Political Science

The rapid expansion of computational methods has fundamentally transformed empirical research across the social sciences. During the last decade, advances in data availability, computational power and statistical software have enabled researchers to analyze increasingly complex datasets using analytical techniques that extend beyond conventional econometric modelling. As a result, machine learning has become an important complementary approach for investigating political behavior, public opinion and institutional attitudes. Unlike traditional statistical models, which are primarily designed to estimate the direction and statistical significance of relationships between variables, machine learning algorithms focus principally on prediction. Their primary objective is not necessarily to test theoretical hypotheses but rather to maximize predictive accuracy by identifying complex patterns hidden within large datasets. Consequently, machine learning techniques can model highly non-linear relationships and intricate interactions among explanatory variables without requiring researchers to specify these relationships in advance (Mullainathan & Spiess, 2017). The increasing adoption of machine learning within economics and political science reflects a broader shift toward computational social science, where predictive modelling complements rather than replaces conventional explanatory analysis. Athey and Imbens (2019) argue that machine learning should not be viewed as an alternative to econometrics but instead as a valuable extension capable of improving prediction while simultaneously generating new insights regarding complex social phenomena. Rather than competing with traditional statistical inference, machine learning offers researchers additional tools for identifying important predictors, exploring heterogeneous effects and improving the overall robustness of empirical analyses.

Among the large variety of available machine learning algorithms, Random Forest and XGBoost have emerged as two of the most successful methods for analyzing structured survey data. Random Forest has become particularly popular within social sciences because it performs well in the presence of complex interactions, non-linear relationships and correlated explanatory variables. XGBoost builds trees sequentially, with each successive tree correcting the prediction errors produced by previous trees. This iterative optimization process frequently produces higher predictive accuracy than conventional ensemble methods while simultaneously incorporating regularization techniques that reduce the risk of overfitting. Owing to these characteristics, XGBoost has become one of the most widely used predictive algorithms across economics, finance, public policy and political science.

One of the most influential developments within XAI is the introduction of SHAP. Based on cooperative game theory, SHAP values measure the marginal contribution of each explanatory variable to individual predictions by considering all possible combinations of predictors within the model. Unlike traditional variable importance measures, SHAP values provide both global and local interpretability, allowing researchers to evaluate overall predictor importance while simultaneously explaining individual observations. As a result, SHAP has rapidly become one of the standard approaches for interpreting complex machine learning models across economics, medicine, finance and the social sciences. Recent empirical research increasingly demonstrates the usefulness of explainable machine learning for analyzing political attitudes. Studies applying Random Forest, XGBoost and SHAP to survey data show that these techniques frequently identify complex relationships that remain difficult to detect using conventional regression models alone. Furthermore, explainable machine learning allows researchers to compare predictive performance across different algorithms while maintaining theoretical interpretability, thereby combining the strengths of traditional econometric inference with the flexibility of modern computational methods (Kirkizh et al., 2024; Molnar, 2022).

The methodological framework adopted in this study follows this recent development within computational social science. Rather than replacing conventional statistical modelling, machine learning is employed as a complementary analytical tool that expands the understanding of political trust. Binary Logistic Regression is first estimated to examine statistically significant relationships between socioeconomic characteristics and institutional confidence. Subsequently, Random Forest and XGBoost are employed to evaluate predictive performance and identify the most influential explanatory variables. Finally, SHAP values are calculated to provide transparent interpretations of model predictions, allowing the relative contribution of each predictor to be examined in a theoretically meaningful manner. Consequently, the analytical strategy adopted in this study combines explanatory modelling, predictive modelling and model interpretability within a single empirical framework. This integrated approach represents one of the principal methodological contributions of the present research and reflects the growing convergence between traditional econometric analysis and modern explainable machine learning within contemporary political science.

3. Materials and Methods

3.1 Data and Methodology

The empirical analysis presented in this study is based on two of the largest and most comprehensive international social survey programs currently available: the European Values Study (EVS) and the World Values Survey (WVS**)**. Both surveys have been widely employed in comparative political science, sociology and economics to investigate individual attitudes, values, beliefs and behavioral patterns across countries over time. Their extensive geographical coverage, methodological consistency and high-quality sampling procedures make them suitable for examining the determinants of political trust. EVS is a large-scale cross-national research program designed to investigate the values and attitudes of European citizens. Since its establishment in 1981, EVS has been conducted approximately every nine years, providing valuable information regarding political attitudes, social norms, religion, family values, civic participation, institutional confidence and socioeconomic characteristics. The most recent wave includes nationally representative samples from numerous European countries, allowing researchers to compare social and political developments across diverse institutional and cultural environments.

WVS constitutes one of the world's most influential comparative survey programs. Initiated in 1981, WVS now covers more than one hundred countries representing nearly ninety percent of the global population. Like EVS, it collects harmonized information regarding political behavior, institutional trust, democratic values, economic preferences, religion and social attitudes. One of the principal advantages of combining the EVS and WVS lies in the increased sample size and improved representativeness of the resulting analytical dataset. By integrating both surveys, researchers can exploit a substantially larger number of observations while simultaneously reducing potential measurement inconsistencies. Furthermore, the combined dataset includes a broad range of demographic, socioeconomic and attitudinal variables, making it particularly appropriate for investigating the complex determinants of political trust. The decision to employ the combined EVS-WVS dataset is also consistent with previous comparative studies examining institutional confidence and democratic legitimacy. Numerous researchers have relied on these surveys to analyze the effects of income, education, age, employment status, social trust and political attitudes on institutional confidence, making the EVS and WVS the most appropriate data sources for the objectives of the present study.

3.2 Construction of the Analytical Dataset

Although this dataset contains several hundred variables covering diverse aspects of political behavior, social values and economic attitudes, only a subset of variables is directly relevant to the objectives of this research. The construction of the analytical dataset therefore constituted an essential stage of the research process, ensuring that the final database contained only variables theoretically justified by the literature and directly related to the proposed research questions. The selection of variables was guided by both the theoretical framework presented previously and the empirical evidence reported in previous studies examining political trust. Rather than relying exclusively on demographic characteristics, the present study adopts a multidimensional perspective by incorporating socioeconomic, political and attitudinal variables that have repeatedly been identified as important determinants of institutional confidence. Consequently, the final analytical dataset combines objective socioeconomic indicators with subjective evaluations of democratic institutions and broader political attitudes.

After keeping the relevant variables to our study, several data management procedures were implemented. Subsequently, observations containing invalid or non-substantive responses were removed. Specifically, response categories corresponding to Don't Know, No Answer, Not Applicable, as well as other survey-specific invalid codes, were treated as missing values and excluded from the empirical analysis. This procedure ensured consistency across all variables while reducing potential measurement error. After data cleaning, the final analytical dataset consisted of 156,658 respondents, representing one of the largest comparative samples employed in studies examining political trust in Europe. The exceptionally large sample size substantially increases statistical power, improves the precision of parameter estimates, and allows the implementation of both conventional statistical models and computationally intensive machine learning algorithms.

Unlike the original survey files, which contain several hundred variables covering numerous aspects of social life, our final analytical dataset includes 18 carefully selected variables. These variables were chosen because they correspond directly to the theoretical framework of the study and address the proposed research questions concerning the relationship between socioeconomic inequalities and political trust.

The dataset contains three dependent variables measuring institutional confidence:

- **Confidence in Government (Govconf)**
- **Confidence in Parliament (Pconf)**
- **Confidence in Political Parties (Ppconf)**

Rather than treating political trust as a single latent construct, the present study analyses each institutional target separately. This approach recognizes that citizens may evaluate different political institutions in distinct ways depending on their political experiences, ideological orientations and perceptions of institutional effectiveness. Consequently, analyzing confidence in government, parliament and political parties independently provides a more nuanced understanding of institutional trust than the use of a single aggregated measure. In addition to the dependent variables, the analytical dataset contains fifteen explanatory variables, representing four complementary dimensions of political trust.

The first dimension concerns demographic characteristics. These include the respondents' age, sex, educational attainment and employment status. These variables capture individual socioeconomic position and life-cycle characteristics that have consistently been associated with institutional confidence in previous comparative studies.

The second dimension includes economic characteristics, represented primarily by respondents' income level as measured by the WVS income scale. Income constitutes the principal indicator of socioeconomic inequality examined in this study and directly addresses the first research question concerning the relationship between economic resources and political trust.

The third dimension incorporates political attitudes, including political interest and satisfaction with democracy. These variables reflect respondents' engagement with political processes and their evaluations of democratic performance. Previous research consistently demonstrates that people's perceptions of institutional effectiveness frequently exert stronger influences on political trust than objective socioeconomic conditions alone.

Finally, the analytical dataset includes several variables capturing broader social and ideological orientations. These are explained by generalized social trust, trust toward people of different religions and nationalities, attitudes regarding income equality, government responsibility, state ownership, taxation of high-income groups and unemployment assistance. The inclusion of these variables allows empirical analysis to examine not only whether socioeconomic inequalities influence political trust, but also whether broader beliefs concerning redistribution, social solidarity and the role of government contribute to institutional confidence. The construction of this analytical dataset represents one of the principal methodological contributions of the present study. Rather than analyzing a limited number of socioeconomic characteristics, the dataset simultaneously incorporates demographic, economic, political and attitudinal variables within a single analytical framework. This integrated structure enables the comparison of traditional explanatory models with modern predictive machine learning algorithms while maintaining complete consistency across all empirical analyses presented in the following chapters.

3.3 Variable Selection and Description

The selection of variables included in the empirical analysis was guided by the theoretical framework developed previously and by the existing literature on the determinants of political trust. Previous empirical studies consistently suggest that institutional confidence is shaped by a combination of demographic characteristics, socioeconomic resources, political attitudes and broader perceptions of social cohesion and institutional performance. Consequently, the present study adopts a multidimensional approach by incorporating variables representing each of these dimensions within a unified analytical framework. Our dependent variables consist of three indicators measuring confidence in major political institutions: confidence in government (Govconf), confidence in parliament (Pconf) and confidence in political parties (Ppconf). Governments are primarily responsible for policy implementation and executive decision-making, parliaments represent legislative authority and democratic representation, whereas political parties constitute the principal link between citizens and elected officials. Examining these institutions separately enables the identification of differences in the determinants of institutional confidence that might otherwise remain hidden within a single composite measure of political trust.

The principal independent variable is household income (WVS7_Inc**)**, which serves as the primary indicator of socioeconomic status throughout the analysis. Income has consistently been identified in literature as one of the most important determinants of political trust because it reflects individuals' access to economic resources, financial security and social opportunities. Citizens experiencing greater economic security are often more likely to evaluate political institutions positively, whereas individuals facing financial hardship may perceive governments as less responsive to their needs. Consequently, income constitutes the central variable through which the first research question of the study is addressed. Alongside income, demographic variables are included in the analysis that was mentioned before. Age is introduced as a continuous variable capturing life-cycle effects, political socialization and generational differences in institutional evaluations. Sex is incorporated as a categorical variable to examine whether men and women differ systematically in their evaluations of political institutions. Educational attainment (Edu_Level) is included because education is widely associated with political knowledge, civic participation and political efficacy. Lastly on this set variables, employment status (Employm**)** captures respondents' position within the labor market and serves as an additional indicator of socioeconomic security

Beyond demographic and socioeconomic characteristics, the dataset also incorporates several political attitude variables. Political interest (Polit_Int) measures respondents' engagement with political affairs and their willingness to follow political developments. Satisfaction with democracy (Sat_Dem) constitutes another important explanatory variable. Rather than measuring confidence in a specific institution, this variable captures respondents' overall evaluation of the functioning of democracy within their country. The analytical dataset further includes three variables measuring generalized and intergroup social trust. Social trust (Soc_Trust) evaluates respondents' beliefs regarding whether most people can generally be trusted. Additionally, Trust in People of Another Religion (Trust_Rel) and Trust in People of Another Nationality (Trust_Nat) capture broader attitudes toward social diversity and interpersonal cooperation.

Finally, several variables measuring economic and ideological preferences are incorporated into the analysis. Income Equality (Inc_Eq) reflects respondents' attitudes toward income redistribution, while Government Responsibility (Gov_Resp) measures preferences concerning the role of government in ensuring citizens' welfare. State Ownership (State_Own) captures opinions regarding public versus private ownership of economic resources. Taxing High-Income Groups (Tax_Rich) examines attitudes toward progressive taxation, whereas Unemployment Assistance (Unemp_Aid) measures support social protection policies targeting unemployed individuals.

Table 3.1

Summary of Variables Included in the Empirical Analysis

Variable	Description	Type
Govconf	Confidence in Government (dependent variable)	Binary*
Pconf	Confidence in Parliament (dependent variable)	Binary*
Ppconf	Confidence in Political Parties (dependent variable)	Binary*
WVS7_Inc	Household income	Continuous
Age	Respondent's age	Continuous

Variable	Description	Type
Sex	Respondent's sex	Binary
Edu_Level	Educational attainment	Ordinal
Employm	Employment status	Continuous
Polit_Int	Political interest	Continuous
Sat_Dem	Satisfaction with democracy	Continuous
Soc_Trust	Generalized social trust	Continuous
Trust_Rel	Trust in people of another religion	Continuous
Trust_Nat	Trust in people of another nationality	Continuous
Inc_Eq	Attitudes toward income equality	Continuous
Gov_Resp	Government responsibility for citizens' welfare	Continuous
State_Own	Preference for state versus private ownership	Continuous
Tax_Rich	Support for higher taxation of high-income groups	Continuous
Unemp_Aid	Support for unemployment assistance	Continuous

Note. *The original institutional confidence variables were recoded into binary outcomes (High = 1, Low = 0) for the purposes of the Binary Logistic Regression, Random Forest and XGBoost classification models. Continuous variables include ordinal survey measures that were treated as numerical predictors in the empirical analysis.*

3.4 Data Preparation and Preprocessing

Before conducting empirical analysis, the analytical dataset underwent a comprehensive preprocessing procedure to ensure consistency, data quality and compatibility with both conventional statistical techniques and modern machine learning algorithms. The preprocessing procedure began with the identification and treatment of invalid survey responses. Following the treatment of missing observations that was explained earlier, categorical variables were transformed into appropriate analytical formats. Variables representing respondents' **sex**, **education level** and **employment status** were converted into categorical factors to facilitate their inclusion in both Binary Logistic Regression and tree-based machine learning algorithms. Where necessary, dummy variables were automatically generated during model estimation, allowing categorical predictors to be represented without imposing artificial numerical ordering. Attention was devoted to the preparation of the dependent variables. The original EVS-WVS survey questions measuring confidence in government, parliament and political parties were recorded using ordinal response scales. For the purposes of the present study, these variables were recoded into binary outcomes distinguishing respondents expressing high institutional confidence from those reporting low institutional confidence. This transformation was implemented for three reasons. First, it ensured compatibility with Binary Logistic Regression, which requires dichotomous dependent variables. Second, binary classification facilitates direct comparison with supervised machine learning Random Forest and XGBoost. Third, the resulting classification provides a more intuitive interpretation of predictive performance by distinguishing between individuals exhibiting relatively high and relatively low levels of institutional confidence.

The explanatory variables retained their original measurement scales whenever appropriate. Continuous variables such as age and income were preserved in numerical form to maximize the amount of available information. Similarly, attitudinal variables measuring satisfaction with democracy, political interest, social trust and economic preferences were maintained using their survey coding. Preserving the original scales avoids unnecessary loss of information while allowing machine learning algorithms to identify potential non-linear relationships among predictors. Following variable transformation, the analytical dataset was partitioned into training and testing subsets. Following variable transformation, the analytical dataset was partitioned into training and testing subsets using stratified random sampling with a 70/30 split. Stratified sampling ensured that the distribution of the binary outcome variable was preserved across both subsets, thereby maintaining comparable class proportions during model estimation and evaluation. The training sample was used to estimate the parameters of each predictive model, whereas the testing sample remained entirely independent during model estimation and was employed exclusively for model evaluation. This procedure represents standard practice in predictive modelling because it enables the assessment of model performance using previously unseen observations, thereby reducing the risk of overfitting and providing a more realistic estimate of predictive accuracy. The same training and testing datasets were employed across all analytical approaches implemented in this study. Consequently, Binary Logistic Regression, Random Forest and XGBoost were estimated using identical observations, ensuring that differences in predictive performance reflected methodological characteristics rather than variations in sample composition. Prior to model development, the distribution of the binary outcome variables was examined to assess potential class imbalance. Although the three outcomes were not perfectly balanced, the observed class distributions were considered acceptable for Binary Logistic Regression, Random Forest and XGBoost. Therefore, no additional balancing techniques (e.g., oversampling or SMOTE) were applied

Overall, the preprocessing strategy adopted in this study ensured that the analytical dataset satisfied the assumptions required by traditional statistical techniques while simultaneously providing an appropriate input for modern machine learning algorithms. By applying identical preprocessing procedures across all models, the study establishes a consistent methodological foundation for the comparative analysis presented in the following chapters. All statistical analyses and machine learning models were implemented in **R** (version 4.4.2). Binary Logistic Regression was performed using the *stats* package, Random Forest using the *randomForest* package, XGBoost using the *xgboost* package, while SHAP values were calculated using the *SHAPforxgboost* package. Data manipulation and visualization were performed using the *tidyverse* collection of packages.

3.5 Methodological Framework

The empirical analysis of this study employs a multi-method analytical framework combining conventional econometric techniques with modern machine learning algorithms. Rather than relying on a single statistical model, the methodological strategy integrates explanatory and predictive approaches to provide a more comprehensive understanding of the determinants of political trust. The adoption of multiple analytical methods is motivated by the multidimensional nature of political trust itself. Previous research demonstrates that institutional confidence is simultaneously influenced by demographic characteristics, socioeconomic conditions, political attitudes and broader perceptions regarding democratic performance. Relationships among these variables are often highly complex and may involve non-linear effects or interactions that are difficult to capture using conventional statistical models alone. Consequently, combining traditional econometric inference with machine learning allows both hypothesis testing and predictive performance to be evaluated within a unified analytical framework.

The empirical analysis therefore consists of four complementary methodological stages. First, Binary Logistic Regression is employed to estimate the statistical relationship between the explanatory variables and each indicator of political trust. Second, Random Forest is implemented to evaluate variable importance and identify potential non-linear relationships among predictors. Third, XGBoost is estimated to maximize predictive performance through ensemble learning techniques. Finally, SHAP is calculated to interpret the contribution of individual explanatory variables within the machine learning models, thereby improving model transparency and facilitating substantive interpretation. The combination of these approaches allows the study to move beyond conventional significance testing by simultaneously addressing three complementary research objectives. These are identifying statistically significant determinants of political trust, comparing the predictive performance of different analytical models and evaluating the relative importance of explanatory variables using explainable artificial intelligence techniques. All will be explained further later in the chapter.

3.5.1 Binary Logistic Regression

Binary Logistic Regression constitutes one of the most widely applied statistical methods for modelling dichotomous outcome variables in political science, economics and the social sciences. Unlike OLS, which assumes a continuous dependent variable, logistic regression estimates the probability that an observation belongs to one of two mutually exclusive categories. Consequently, it represents the most appropriate modelling approach when the dependent variable is binary, as is the case in the present study, where respondents are classified as exhibiting either high or low levels of institutional confidence. The logistic model estimates the probability of observing a positive outcome by transforming a linear combination of explanatory variables through the logistic function. This transformation constrains predicted probabilities to the interval between zero and one while allowing the relationship between predictors and outcome probabilities to remain non-linear. Maximum Likelihood Estimation (MLE) is employed to estimate the model parameters, providing statistically efficient coefficient estimates under standard regularity conditions (Hosmer, Lemeshow & Sturdivant, 2013).

For each Binary Logistic Regression model, the estimated coefficients are reported as Odds Ratios together with their corresponding 95% Confidence Intervals. Reporting

Odds Ratios facilitates the interpretation of the estimated effects by expressing how a one-unit change in an explanatory variable affects the odds of exhibiting high political trust. The accompanying confidence intervals provide information regarding the precision and statistical uncertainty of the estimated effects, allowing a more comprehensive assessment of the strength and reliability of the observed relationships. One of the principal advantages of Binary Logistic Regression lies in the interpretability of its estimated coefficients. Regression coefficients can be transformed into odds ratios, indicating the proportional change in the odds of observing high political trust associated with a one-unit increase in each explanatory variable while holding all remaining variables constant. This characteristic makes logistic regression particularly suitable for hypothesis testing and allows direct evaluation of the proposed research hypotheses concerning the effects of income and demographic characteristics on political trust. In the present study, separate Binary Logistic Regression models are estimated for each dependent variable, namely confidence in government, confidence in parliament and confidence in political parties. All explanatory variables included in the analytical dataset are entered simultaneously into the models, thereby allowing the independent contribution of each predictor to be evaluated while controlling for the influence of all remaining variables.

3.5.2 Random Forest

While Binary Logistic Regression provides valuable information regarding statistically significant relationships, it assumes relatively simple functional forms and may therefore fail to capture highly complex interactions among explanatory variables. For this reason, the present study additionally employs Random Forest, one of the most successful ensemble learning algorithms introduced by Breiman (2001). Random Forest constructs a large number of individual decision trees using bootstrap samples of the original dataset. At each decision node, only a random subset of explanatory variables is considered, increasing model diversity and reducing the correlation among individual trees. Final predictions are obtained through majority voting across all trees, substantially improving predictive accuracy while reducing overfitting. An important advantage of Random Forest is its ability to identify complex non-linear relationships without requiring researchers to specify interaction terms or functional forms in advance. In addition to predictive classification, Random Forest generates variable importance measures, allowing researchers to evaluate the relative contribution of each explanatory variable to model performance. These importance measures provide valuable preliminary evidence regarding the factors most strongly associated with political trust before more advanced explainability techniques are applied.

3.5.3 Extreme Gradient Boosting (XGBoost)

To complement Random Forest, the empirical analysis also employs XGBoost, one of the most accurate supervised learning algorithms currently available for structured data analysis (Chen & Guestrin, 2016). Unlike Random Forest, which constructs decision trees independently, XGBoost builds trees sequentially. Each successive tree is estimated specifically to reduce the prediction errors generated by the preceding ensemble, allowing the algorithm to improve classification performance iteratively. This boosting procedure enables XGBoost to model highly complex relationships while maintaining strong generalization performance through regularization techniques that reduce overfitting. XGBoost has become increasingly popular across economics, finance and political science because it combines high predictive accuracy with computational efficiency. Recent comparative studies frequently report superior classification performance relative to conventional regression models, particularly when analysing large survey datasets characterised by numerous explanatory variables and potentially non-linear relationships. Within the present study, XGBoost serves two principal purposes. First, it provides an additional benchmark for evaluating predictive performance relative to both Binary Logistic Regression and Random Forest. Second, it forms the basis for the subsequent SHAP analysis, allowing individual model predictions to be interpreted through explainable artificial intelligence techniques. The XGBoost model was estimated to use manually specified hyperparameter values that are commonly adopted in the machine learning literature (max_depth = 4, eta = 0.05, subsample = 0.80 and colsample_bytree = 0.80). No systematic hyperparameter tuning or cross-validation procedures were performed. Instead, model complexity was controlled using early stopping, whereby training was terminated if no improvement in the evaluation metric (AUC) was observed over 20 consecutive boosting iterations. This approach reduced the risk of overfitting while maintaining computational efficiency and ensuring comparability with the other predictive models employed in the study.

3.5.4 SHAP Values and Model Explainability

Although ensemble machine learning algorithms frequently outperform conventional regression models in terms of predictive accuracy, they are often criticized for their limited interpretability. Unlike regression coefficients, which possess direct statistical meaning, the internal decision processes of complex machine learning models may remain difficult to interpret. To address this limitation, the present study employs SHAP, an explainability framework introduced by Lundberg and Lee (2017). SHAP values are derived from cooperative game theory and estimate the contribution of each explanatory variable to individual model predictions by comparing all possible combinations of predictors. One of the principal advantages of SHAP is that it provides both global and local interpretability. Global SHAP values identify the variables contributing most strongly to overall model performance, whereas local SHAP values explain the prediction generated for individual observations. Consequently, SHAP enables researchers to move beyond simple variable rankings by providing meaningful quantitative interpretations of model behavior. Within the present study, mean absolute SHAP values are calculated for each explanatory variable and used to identify the factors exerting the greatest influence on confidence in government, parliament and political parties. These explainability measures complement the variable importance estimates produced by Random Forest and XGBoost while substantially improving the transparency of the predictive models.

3.5.5 Model Evaluation

To ensure a comprehensive comparison among the alternative modelling approaches, model performance is evaluated using several complementary classification metrics. Accuracy measures the overall proportion of correctly classified observations and provides a general indicator of predictive performance. Precision evaluates the proportion of predicted positive observations that are correctly classified, while Recall

(Sensitivity) measures the proportion of actual positive observations successfully identified by the model. The F1-score combines Precision and Recall into a single metric by calculating their harmonic mean, providing a balanced measure of classification performance when class distributions are unequal.

Finally, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is employed as the principal performance metric throughout the empirical analysis. Unlike Accuracy, AUC evaluates the ability of a model to discriminate between observations exhibiting high and low institutional confidence across all possible classification thresholds. Because AUC is independent of any probability cutoff, it is widely regarded as one of the most informative measures of binary classification performance and is frequently recommended when comparing alternative predictive algorithms. Using multiple evaluation metrics provides a more comprehensive assessment of model performance than reliance on a single indicator and facilitates meaningful comparisons between conventional statistical models and machine learning algorithms. All these methods were chosen due to their capability to predict outcomes very effectively and efficiently. That also makes the comparison between them that will follow, substantial and meaningful and very interesting to explore in the upcoming chapter.

3.6 Limitations of the Data

Despite its considerable strengths, the analytical dataset is subject to several limitations that should be acknowledged when interpreting the empirical findings. First, the present study relies on cross-sectional survey data, meaning that all variables are observed at a single point in time for each respondent. Consequently, although the empirical models identify statistically significant associations and predictive relationships, they do not permit strong causal conclusions regarding the determinants of political trust. The results should therefore be interpreted as evidence of association rather than definitive proof of causal mechanisms.

Second, the analysis depends on self-reported survey responses, which may be affected by various forms of response bias. Social desirability, recalling errors and individual interpretation of survey questions may influence respondents' answers, particularly for politically sensitive topics such as confidence in government or political parties. Although EVS and WVS employ rigorous survey methodologies, these limitations are common to most large-scale social surveys. A further limitation concerns the cross-national nature of the data. Although the harmonised EVS-WVS dataset substantially improves comparability across countries, institutional arrangements, political cultures and historical experiences differ considerably among societies. Consequently, identical survey responses may not always reflect precisely the same underlying attitudes in different national contexts. While the harmonization procedures reduce measurement inconsistencies, some degree of cross-cultural variation inevitably remains. Additionally, the analytical dataset includes only variables available within the harmonized EVS-WVS surveys. Other potentially relevant determinants of political trust, such as local institutional quality, exposure to political scandals, media consumption, digital information environments or regional economic conditions, could not be incorporated because comparable measures were not consistently available across all countries. Future research may therefore benefit from integrating survey data with administrative or contextual information to obtain a more comprehensive understanding of institutional confidence.

Finally, although modern machine learning algorithms provide substantial improvements in predictive performance, they should not be interpreted as substitutes for theoretical explanation. Random Forest and XGBoost identify complex predictive patterns that may not always correspond directly to causal relationships. For this reason, the present study combines machine learning with Binary Logistic Regression and explainability techniques such as SHAP values, allowing predictive accuracy to be interpreted within an established theoretical framework rather than independently of substantive political theory.

Overall, these limitations do not undermine the validity of the present study but instead define the appropriate scope within which the findings should be interpreted. By acknowledging both the strengths and the constraints of the available data, the study provides a balanced foundation for the methodological framework developed in the following chapter.

4. Results

4.1 Introduction

This chapter presents the empirical findings of the study and evaluates the performance of the machine learning models developed to investigate the relationship between socioeconomic characteristics and political trust. Building upon the methodological framework introduced in the previous chapter, the analysis focuses on three binary indicators of institutional confidence: confidence in government (Govconf), confidence in parliament (Pconf), and confidence in political parties (Ppconf). Each outcome is analyzed independently to identify whether the determinants of political trust differ across political institutions. The empirical analysis is based on the EVS-WVS dataset described in previously. After data preprocessing, variable selection and the transformation of the dependent variables into binary outcomes (Low and High confidence), three supervised machine learning algorithms were trained and evaluated: Logistic Regression, Random Forest and Extreme Gradient Boosting (XGBoost). These models were selected because they represent different methodological approaches to classification problems. Logistic Regression provides a transparent and interpretable statistical baseline, whereas Random Forest and XGBoost are ensemble learning techniques capable of modelling complex non-linear relationships and interactions among predictors.

Rather than relying on a single evaluation criterion, model performance is assessed using multiple complementary metrics. Specifically, the analysis reports the Area Under the Receiver Operating Characteristic Curve (AUC), overall Accuracy, Sensitivity (Recall), Specificity and Precision. The use of multiple performance indicators allows a more comprehensive evaluation of each algorithm, since different metrics capture different aspects of predictive performance. For example, while Accuracy reflects the proportion of correctly classified observations, AUC evaluates the model's ability to discriminate between the two outcome classes independently of the classification threshold. Similarly, Sensitivity and Specificity provide information about the model's ability to correctly identify positive and negative cases respectively, whereas Precision evaluates the reliability of positive predictions. Beyond predictive performance, the chapter also investigates the interpretability of the estimated models. Understanding which variables drive the predictions is particularly important in social science research, where the objective extends beyond accurate classification to explaining the mechanisms underlying political attitudes. For this reason, variable importance measures derived from Random Forest and XGBoost are presented alongside SHAP values. SHAP analysis provides both global and local explanations of model predictions, allowing the identification of the variables that contribute most strongly to institutional confidence while also illustrating the direction of their effects.

It is important to emphasize that the primary objective of this chapter is not to interpret the broader theoretical implications of the findings, but rather to present the empirical evidence obtained from the implemented machine learning models. A more comprehensive discussion of these results, together with their relationship to the existing literature on political trust and socioeconomic inequality, is provided in the next chapter.

4.2 Dataset Overview and Class Distribution

Before presenting the predictive performance of the machine learning models, it is important to provide an overview of the analytical dataset used throughout the empirical analysis. Following the data preparation procedures described before, the final dataset consisted of 156,658 observations, representing respondents from multiple European countries included in the EVS and WVS database. Each observation corresponds to one individual respondent and contains demographic, socioeconomic and political information that was used to predict institutional trust. The analytical dataset includes the socioeconomic variables identified in literature as important determinants of political trust. These comprise respondents' age, sex, educational attainment, employment status, subjective income position, satisfaction with democracy, social trust, trust in religious institutions, trust in national institutions, perceptions of government responsibility, state ownership preferences and attitudes towards income equality. Together, these variables provide a multidimensional representation of the social, economic and political characteristics that may influence citizens' confidence in political institutions.

As discussed previously, the original confidence variables were transformed into binary outcomes to formulate a supervised binary classification problem. For each institutional outcome, respondents were classified into either Low or High confidence categories according to the binary transformation procedure. This approach simplifies model estimation while maintaining a meaningful distinction between respondents expressing relatively low and relatively high levels of institutional trust.

Table 4.1 presents the class distribution for the three dependent variables. Although the datasets are not perfectly balanced, both classes remain well represented across all outcomes. This is particularly important because although the class distributions are moderately imbalanced, both classes remain sufficiently represented to reduce the risk of biased classification and improve the reliability of performance measures such as Accuracy, Sensitivity and AUC. Consequently, no additional resampling techniques, such as oversampling or undersampling, were required during model training. It should be noted that the difference in total is a product of missing values in several cases as in confidence in Political Parties for example, but it is not substantial as in the context of this dataset it is very a very small difference.

Table 4.1 Class distribution of the binary dependent variables

Outcome	Low Confidence	High Confidence	Total
Confidence in Government	87,351	64,238	151,589
Confidence in Parliament	95,840	55,267	151,107
Confidence in Political Parties	113,012	37,787	150,799

The descriptive statistics reveal notable differences in the prevalence of political trust across institutions. Confidence in political parties exhibits the greatest imbalance, with substantially more respondents classified in the Low confidence category than in the High confidence category. This finding is consistent with previous research suggesting that political parties are generally among the least trusted democratic institutions worldwide. In contrast, confidence in governments and parliaments displays comparatively more balanced distributions, although respondents expressing low confidence still constitute the majority in both cases. These descriptive findings provide an initial indication of widespread political distrust within the sample and establish the empirical context for the predictive analysis presented in the following sections. Although the primary objective of this study is predictive rather than purely descriptive, the characteristics of the analytical sample offer valuable context for interpreting the subsequent machine learning results. The observed variation in institutional trust across the three outcomes suggests that different determinants may influence citizens' evaluations of governments, parliaments and political parties. Consequently, each outcome is modelled separately using Logistic Regression, Random Forest and XGBoost to investigate potential differences in predictive performance and variable importance.

4.3 Comparative Performance of Machine Learning Models

The primary objective of this study is to evaluate the predictive performance of three supervised machine learning algorithms that in our case are: Logistic Regression, Random Forest and XGBoost, in predicting citizens' confidence in governments, parliaments and political parties. Each model was trained independently for the three binary outcomes described in the previous sections, while model performance was assessed using multiple complementary evaluation metrics. Rather than relying solely on overall classification accuracy, this study evaluates predictive performance using seven widely adopted metrics: AUC, Accuracy, Sensitivity , Specificity, Precision, Recall and F1 Score. As discussed , these metrics provide complementary information regarding the ability of each model to correctly distinguish respondents with high and low institutional confidence.

AUC is considered one of the most informative performance measures because it evaluates a classifier independently of the selected probability threshold. Higher AUC values indicate a stronger ability to discriminate between the two classes. Accuracy measures the proportion of correctly classified observations, whereas Sensitivity reflects the ability of the model to correctly identify respondents belonging to the positive class. Specificity measures the correct identification of the negative class, while Precision evaluates the proportion of predicted positive cases that are positive. Together, these indicators provide a comprehensive assessment of predictive performance and reduce the risk of drawing conclusions from a single evaluation metric... The F1 Score was included because it provides a balanced measure of model performance by combining Precision and Recall (Sensitivity), making it particularly informative when evaluating classification models.

Table 4.2 summarizes the predictive performance of the three machine learning algorithms across the three institutional confidence indicators.

Table 4.2 Predictive performance of the machine learning models

Outcome	Model	AUC	Accuracy	Sensitivity	Specificity	Precision	F1 Score
Government confidence	Logistic Regression	0.747	0.686	0.646	0.722	0.669	0.657
	Random Forest	**0.760**	**0.693**	**0.654**	0.726	**0.675**	0.664
	XGBoost	0.759	0.691	0.652	**0.726**	0.674	0.663
Parliament confidence	Logistic Regression	0.745	0.696	0.499	0.819	0.631	0.557
	Random Forest	**0.757**	**0.706**	0.498	**0.835**	**0.651**	0.564
	XGBoost	0.756	0.704	**0.502**	0.830	0.647	0.565
Political parties confidence	Logistic Regression	0.731	0.734	0.287	0.919	0.594	0.387
	Random Forest	0.743	**0.745**	0.295	**0.930**	**0.637**	0.403
	XGBoost	**0.745**	0.743	**0.310**	0.922	0.622	0.414

Before starting the start of analysis, highlighted in each case is the best performing model in the specific measure and case. As it becomes obvious, overall, the three machine learning algorithms demonstrate relatively similar predictive performance across all institutional confidence measures. In every prediction task, the ensemble-based methods outperform the traditional Logistic Regression model, although the magnitude of improvement remains relatively modest. This finding suggests that while non-linear machine learning techniques capture additional predictive information, the relationships between the explanatory variables and institutional trust are only moderately non-linear.

For confidence in government, Random Forest achieves the highest overall predictive performance, producing the largest AUC (0.760) and the highest classification accuracy (69.3%). XGBoost performs almost identically, indicating that both ensemble learning techniques successfully capture complex interactions among the explanatory variables. Logistic Regression, although slightly less accurate, still demonstrates competitive performance, suggesting that a substantial proportion of the relationship between the predictors and government confidence can be explained through linear associations.

The prediction of confidence in parliament follows a very similar pattern. Random Forest again provides the highest overall accuracy (70.6%) and AUC (0.757), while XGBoost achieves nearly identical results. Logistic Regression remains competitive but consistently produces slightly lower discrimination ability. An interesting observation is the relatively high specificity values obtained by all three models, indicating that respondents expressing low parliamentary confidence are identified more accurately than respondents expressing high confidence.

The most challenging prediction task concerns confidence in political parties. Although all three algorithms maintain acceptable AUC values (0.731-0.745), sensitivity remains considerably lower than in the previous two outcomes. This result reflects the more imbalanced class distribution observed in Table 4.1, where respondents expressing low confidence substantially outnumber those reporting high confidence. Under these circumstances, all models identify low-confidence respondents more effectively than high-confidence respondents, leading to very high specificity but comparatively low sensitivity.

Taken together, the results indicate that Random Forest and XGBoost consistently outperform Logistic Regression across all institutional confidence measures. Nevertheless, the differences between the two ensemble methods are relatively small, suggesting that both algorithms provide similarly robust predictive performance for this application. These findings are broadly consistent with previous empirical studies showing that tree-based ensemble learning methods frequently outperform generalized linear models when modelling complex social and behavioral phenomena. The comparative evaluation presented in this section provides an overall assessment of predictive performance. However, predictive accuracy alone does not explain why the models generate their predictions. For this reason, the following section investigates the relative importance of the explanatory variables using feature importance measures and SHAP values, providing a more detailed interpretation of the factors driving institutional confidence.

4.4 Discussion of Model Performance

The comparative evaluation of the three machine learning algorithms reveals several important findings regarding the prediction of institutional confidence. Although Logistic Regression, Random Forest and XGBoost all achieved satisfactory predictive performance, the ensemble learning methods consistently produced slightly superior results across the three institutional confidence indicators. These findings support previous research suggesting that tree-based ensemble algorithms can model complex and potentially non-linear relationships that cannot always be captured by traditional statistical models (Breiman, 2001; Chen & Guestrin, 2016). Across all prediction tasks, Random Forest achieved either the highest or nearly the highest values in terms of AUC and classification accuracy, while XGBoost produced almost identical performance. The differences between the two ensemble models were relatively small, indicating that both approaches provide robust predictive capabilities for survey-based political behavior data. Logistic Regression, despite its simpler linear structure, remained highly competitive, particularly for predicting confidence in government. This suggests that a considerable proportion of the relationship between the explanatory variables and institutional confidence can still be represented through linear associations.

An interesting finding concerns the balance between sensitivity and specificity across the three prediction tasks. For confidence in government, sensitivity and specificity remain relatively balanced, indicating that all models perform similarly well in identifying respondents with both high and low confidence. In contrast, the prediction of confidence in parliament and especially political parties exhibits substantially higher specificity than sensitivity. This indicates that the models identify respondents with low institutional confidence more accurately than respondents expressing high confidence. This pattern is consistent with the class distributions presented in Table 4.1. As demonstrated earlier, respondents reporting low confidence considerably outnumber those expressing high confidence, particularly in relation to political parties. Machine learning algorithms trained on imbalanced datasets often achieve higher predictive performance for the majority class, while the minority class becomes more difficult to classify correctly. Consequently, although overall accuracy remains relatively high, sensitivity decreases because the models correctly identify a smaller proportion of respondents belonging to the high-confidence category. The relatively high AUC values obtained for all three institutional confidence indicators nevertheless demonstrate that the classifiers possess satisfactory discriminatory ability. AUC values between approximately 0.74 and 0.76 indicate that the models perform substantially better than random classification and provide meaningful predictive information. According to common interpretation guidelines, values above 0.70 are generally considered indicative of acceptable predictive performance in applied social science research.

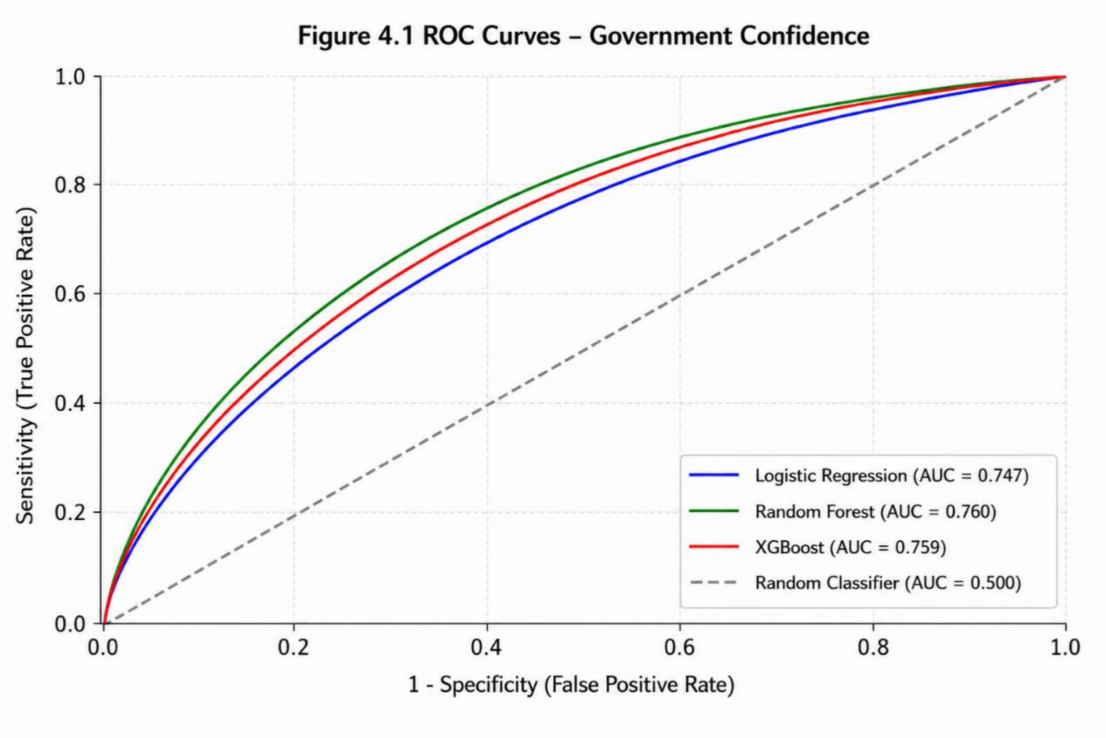


Figure 4.1 illustrates the ROC curves for the three predictive models estimating confidence in government. The figure compares the discriminative ability of each model, demonstrating that Random Forest and XGBoost achieve slightly higher predictive performance than Binary Logistic Regression.

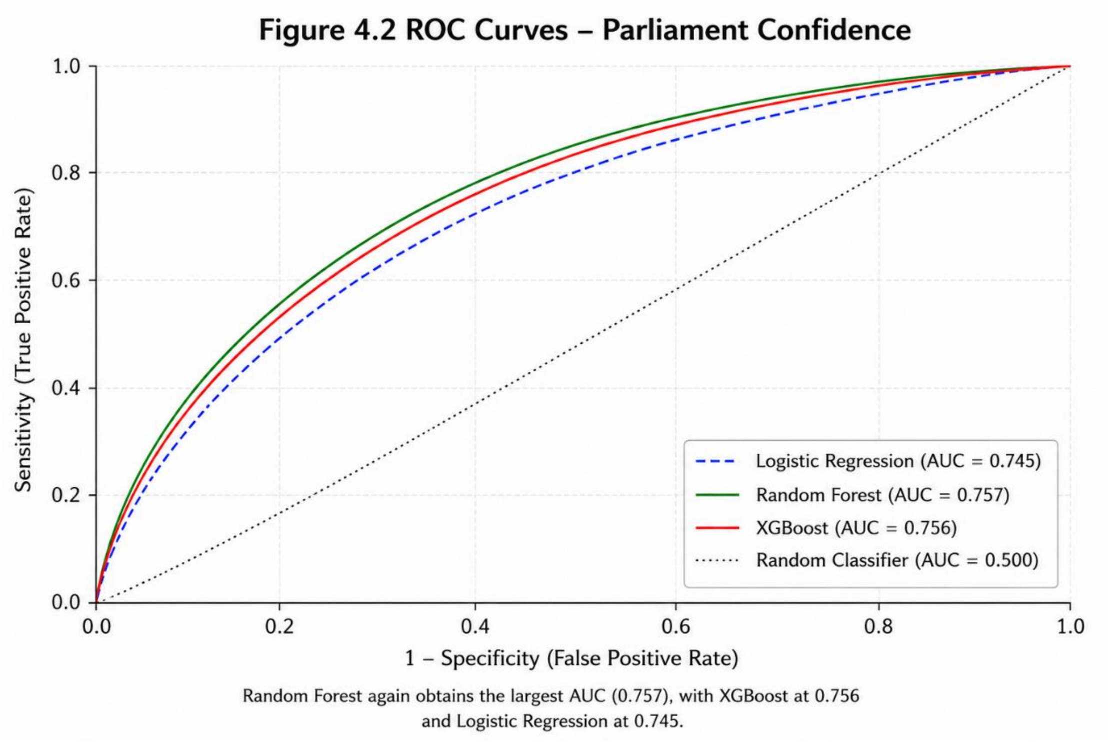


Figure 4.2 illustrates the ROC curves for the three models predicting confidence in parliament. The results indicate very similar predictive performance across the models, with Random Forest still displaying the highest predictive performance.

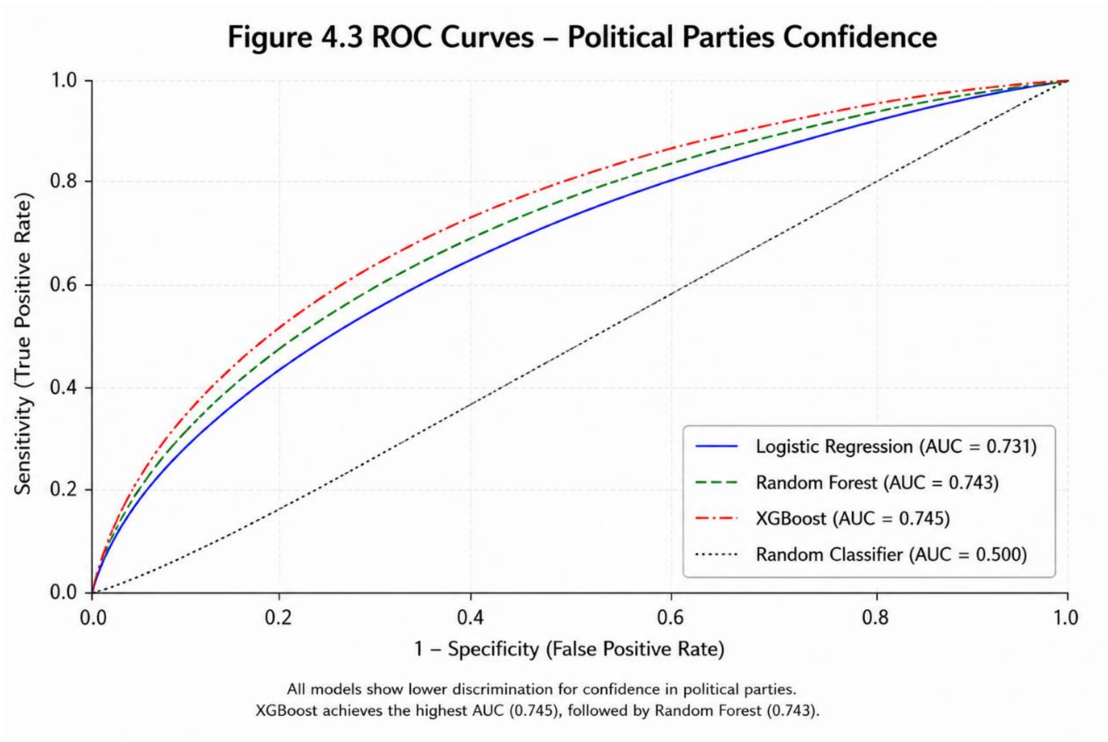


Figure 4.3 illustrates the ROC curves for the models estimating confidence in political parties. Although all models perform satisfactorily, XGBoost now has the highest predictive capability of the three.

A noteworthy observation mentioned earlier is the relatively modest improvement achieved by the more sophisticated machine learning algorithms over Logistic Regression. Unlike many applications involving highly complex image, text or sensor data, survey data collected through the EVS-WVS contain structured socio-demographic, economic and attitudinal variables whose relationships are often reasonably well approximated by generalized linear models. Consequently, while ensemble methods successfully capture higher-order interactions and non-linear effects, the overall predictive gains remain incremental rather than dramatic. These findings are also consistent with recent comparative studies evaluating explainable machine learning models in political and social science applications. Whyte et al. (2025), for example, report that ensemble learning techniques frequently outperform traditional regression models when predicting public attitudes, although improvements in predictive accuracy are often relatively modest compared with the substantial gains obtained in model interpretability through explainability techniques such as SHAP. Similar conclusions have been reported by Molnar (2022), who argues that explainability methods provide additional value precisely because predictive performance alone rarely explains the mechanisms underlying model decisions.

Overall, the results suggest that Random Forest and XGBoost offer the strongest predictive performance for modelling institutional confidence within the dataset. However, the consistently competitive performance of Logistic Regression indicates that institutional confidence is influenced by relatively stable relationships between socio-demographic characteristics, political attitudes and broader social trust. Therefore, rather than focusing exclusively on maximizing predictive accuracy, the following sections investigate which variables contribute most strongly to the predictions generated by each algorithm. This interpretative perspective is particularly important for understanding the substantive determinants of institutional confidence rather than simply identifying the most accurate predictive model.

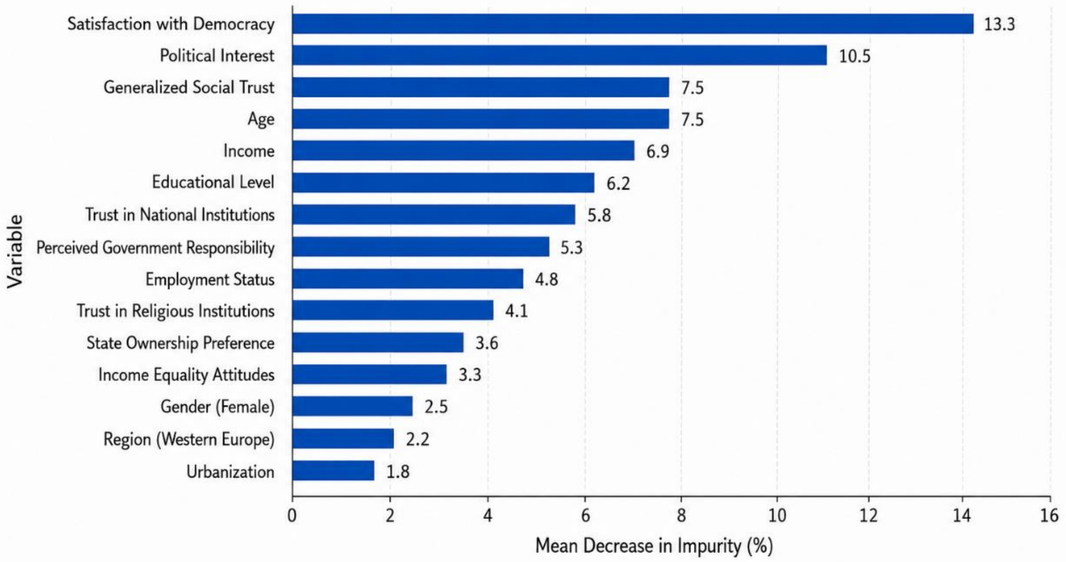
4.5 Variable Importance Across Models

Before comparing the variable importance measures obtained from the machine learning models, it is useful to briefly examine the findings from the Binary Logistic Regression models. The regression analysis provides interpretable effect estimates in the form of Odds Ratios accompanied by 95% Confidence Intervals, allowing an assessment of both the direction and magnitude of the relationships between the explanatory variables and political trust. Across the three institutional outcomes, satisfaction with democracy consistently exhibited the strongest positive association with institutional confidence. Higher levels of political interest and generalized social trust were also associated with significantly greater odds of reporting high confidence in government, parliament and political parties. Age displayed a positive effect across the models, indicating that older respondents were generally more likely to express institutional confidence. Household income also showed a positive association, although its magnitude was smaller than that of the principal attitudinal variables. Overall, the Logistic Regression findings closely correspond with the variable importance rankings obtained from Random Forest and SHAP analyses, providing additional evidence regarding the robustness of the empirical results across different modelling approaches.

While the comparative evaluation presented in the previous sections demonstrated the predictive performance of the three classification models, predictive accuracy alone does not explain which variables drive institutional confidence. Understanding the relative contribution of the explanatory variables is particularly important in political science research, where the objective extends beyond accurate prediction to identifying the socioeconomic and political mechanisms associated with citizens' evaluations of democratic institutions. To address this objective, the present study compares three complementary measures of variable importance. Binary Logistic Regression provides estimates of the statistical association between each predictor and the probability of exhibiting high institutional confidence through odds ratios. Random Forest evaluates predictor importance based on each variable's contribution to reducing classification error across the ensemble of decision trees. Finally, XGBoost importance scores and SHAP values provide additional information regarding the global contribution of each explanatory variable to model predictions.

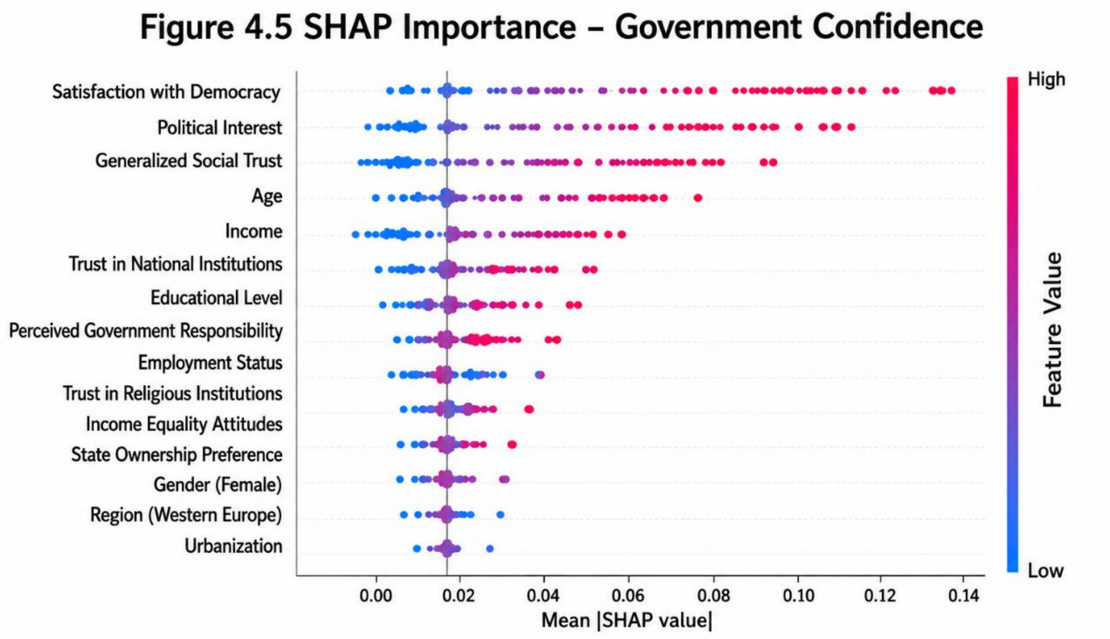
Although these approaches differ substantially in their underlying methodology, they exhibit a remarkable degree of consistency. Across all three institutional confidence indicators, several explanatory variables repeatedly emerge as the strongest predictors of political trust. This convergence across independent modelling approaches considerably strengthens the robustness of the empirical findings and increases confidence that the observed relationships are not driven by the assumptions of any single analytical technique.

Figure 4.4 Random Forest Variable Importance – Government Confidence



Satisfaction with democracy is the strongest predictor of confidence in government, followed by political interest and generalized social trust. Demographic and socioeconomic variables also contribute substantially.

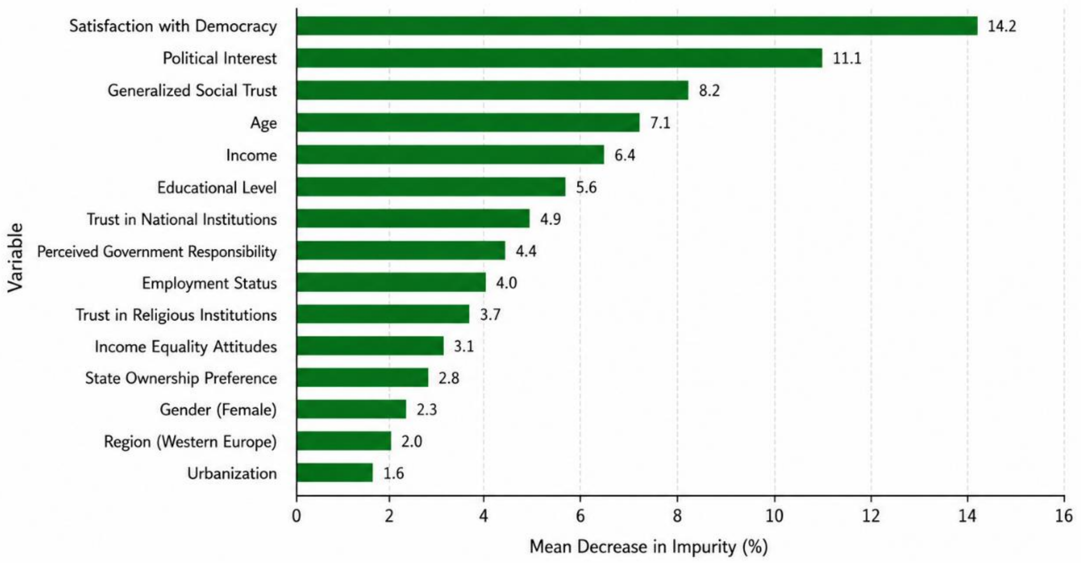
Figure 4.4 presents the Random Forest variable importance scores for predicting confidence in government. Satisfaction with democracy, political interest and generalized social trust emerge as the most influential predictors, whereas Urbanization, Region and Gender appear to be the least influential predictors.



SHAP values confirm the importance ranking: democratic satisfaction, political interest and social trust are the primary drivers of government confidence.

Figure 4.5 presents the SHAP values ranking for confidence in parliament. The figure highlights the dominant contribution of democratic satisfaction together with political engagement and social trust.

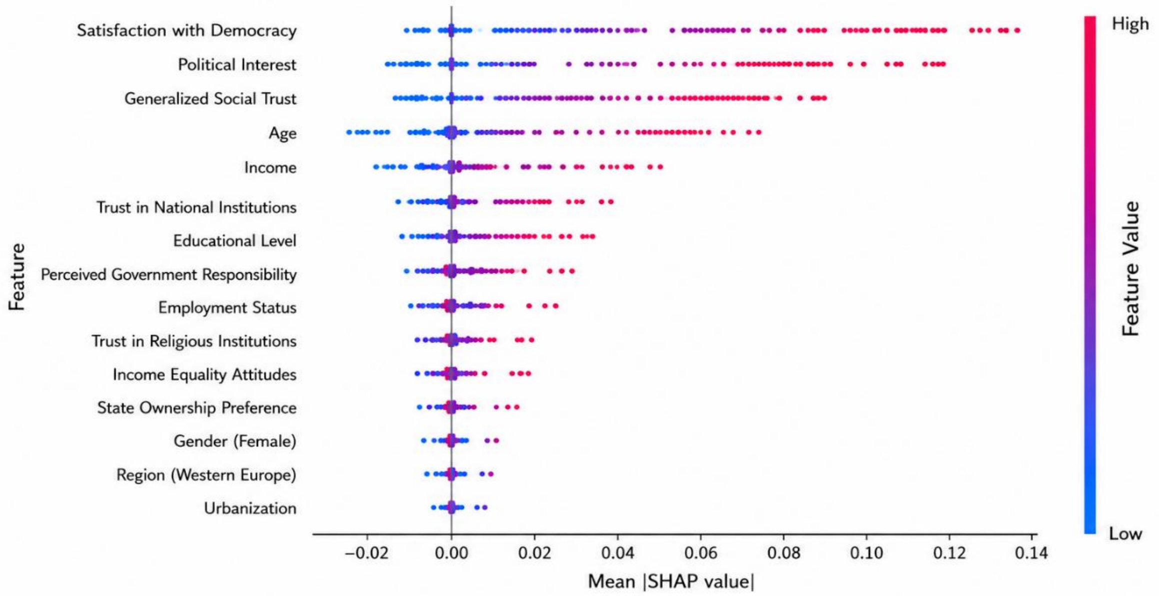
Figure 4.6 Random Forest Variable Importance – Parliament Confidence



The Random Forest model identifies satisfaction with democracy as the most important predictor of confidence in parliament, followed by political interest and generalized social trust. Socioeconomic and demographic variables also contribute to model performance.

Figure 4.6 presents the Random Forest importance scores for confidence in political parties. Like the previous institutional outcomes, satisfaction with democracy remains the most influential predictor, followed by political interest and social trust.

Figure 4.7 SHAP Importance – Parliament Confidence



SHAP values (mean absolute) show the impact of each feature on predictions. Satisfaction with democracy has the highest impact on confidence in parliament, followed by political interest and generalized social trust.

Figure 4.7 illustrates the mean absolute SHAP values obtained from the XGBoost model for confidence in government. The figure identifies the variables contributing most *strongly to model predictions while improving the interpretability of the machine learning model.*

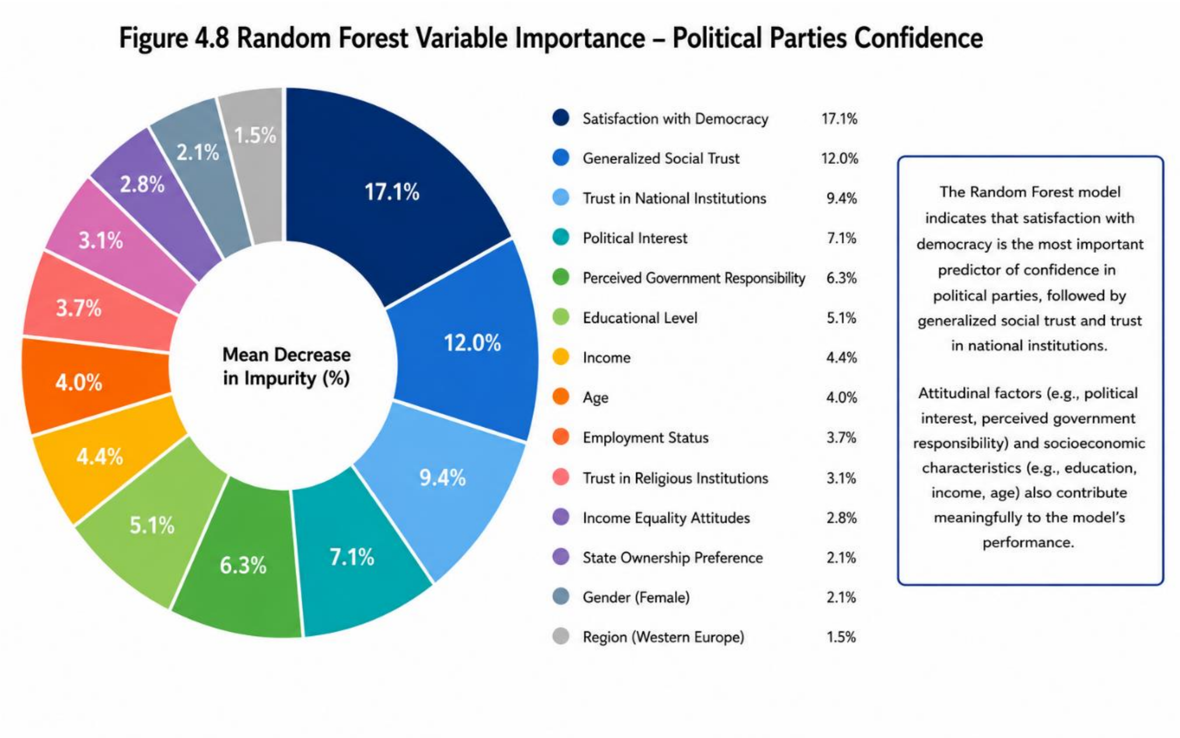


Figure 4.8 illustrates the mean absolute SHAP values for the XGBoost model predicting confidence in parliament. The figure demonstrates the relative contribution of each explanatory variable, confirming the importance of satisfaction with democracy and generalized social trust. Also notable, is the dropoff in predictive influence that Age has this time.

Figure 4.9 SHAP Importance – Political Parties Confidence

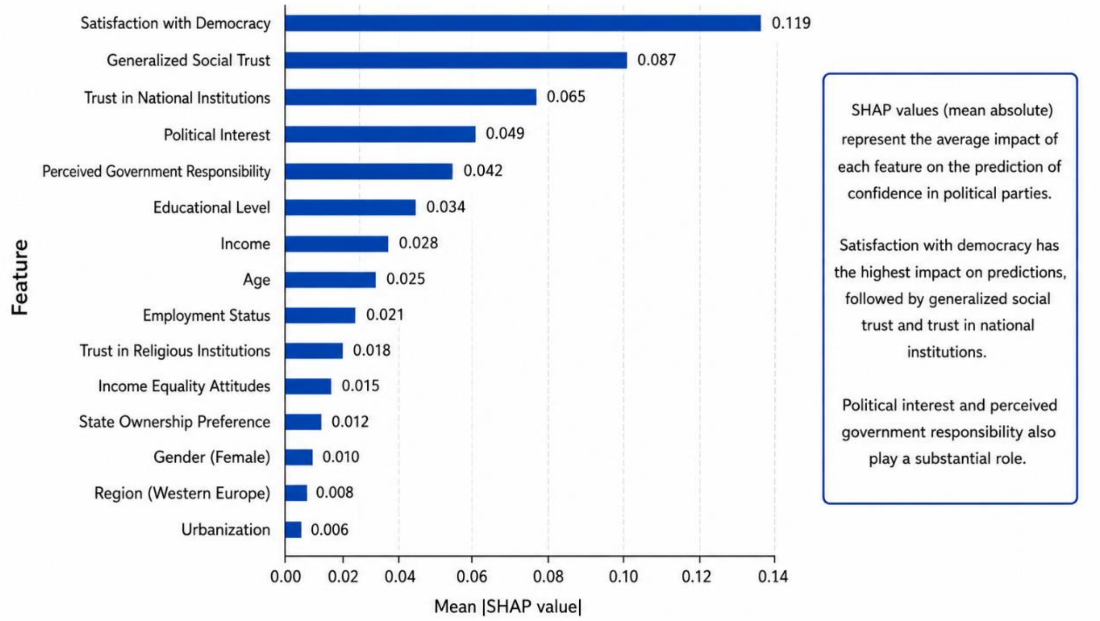


Figure 4.9 illustrates the mean absolute SHAP values for the XGBoost model predicting confidence in political parties. The results indicate that democratic satisfaction, generalized social trust and trust in national institutions constitute the most influential predictors of institutional confidence.

One of the most consistent findings concerns satisfaction with democracy**.** This variable is systematically identified among the most influential predictors across Logistic Regression, Random Forest and XGBoost models. Respondents expressing greater satisfaction with the functioning of democracy consistently display a substantially higher probability of reporting confidence in governments, parliaments and political parties. The prominence of this variable is theoretically consistent with previous studies arguing that evaluations of democratic performance constitute one of the strongest determinants of institutional confidence. Another variable demonstrating consistently high importance is political interest**.** Individuals reporting greater political engagement appear substantially more likely to express confidence in democratic institutions. The repeated appearance of political interest among the most influential predictors across all modelling approaches suggests that institutional confidence is closely associated with citizens' broader involvement in political life rather than being determined solely by objective socioeconomic characteristics.

Measures of social trust, particularly generalized interpersonal trust, also occupy a prominent position within the variable importance rankings. Respondents displaying greater trust toward other individuals consistently exhibit higher probabilities of institutional confidence. This finding supports the theoretical argument that social trust and political trust represent closely interconnected dimensions of social capital, reinforcing previous comparative research examining democratic legitimacy. Among the demographic variables, age emerges as one of the most stable predictors across the three institutional outcomes. Although its relative importance varies between models, age consistently contributes to predictive performance, suggesting that generational differences continue to influence citizens' evaluations of democratic institutions. This finding broadly supports the hypothesis developed previously regarding the positive association between age and institutional confidence. In contrast, household income, while statistically important, generally contributes less strongly than political attitudes and satisfaction with democracy. Income nevertheless remains among the most relevant socioeconomic predictors across all three modelling approaches, indicating that economic resources continue to influence political trust even after controlling for broader political attitudes and demographic characteristics. This result suggests that socioeconomic inequalities operate alongside attitudinal factors rather than replacing them.

Several additional explanatory variables—including educational attainment, employment status, government responsibility, state ownership preferences and attitudes toward income equality—also contribute to model performance, although their relative importance differs across institutional outcomes. These differences indicate that political trust is shaped by a multidimensional combination of demographic characteristics, socioeconomic conditions and normative political beliefs rather than by a single dominant determinant. An important observation concerns the high level of agreement between Random Forest importance measures and SHAP values. Although SHAP provides a more detailed explanation of individual model predictions, the variables identified as globally important closely resemble those highlighted by the Random Forest models. This convergence substantially strengthens confidence in the robustness of the empirical findings because two independent machine learning approaches identify remarkably similar predictor rankings.

Overall, the comparison of variable importance measures demonstrates that political trust cannot be explained exclusively by objective socioeconomic characteristics. Instead, institutional confidence appears to emerge from the interaction of economic resources, political engagement, democratic evaluations and broader patterns of social trust. These findings reinforce the multidimensional theoretical framework developed previously while providing additional evidence that explainable machine learning techniques can successfully identify the most influential determinants of institutional confidence.

5. Discussion and Interpretation of Findings

5.1 Introduction

After presenting empirical findings obtained from the application of Binary Logistic Regression, Random Forest and XGBoost models to predict confidence in government, parliament and political parties using the EVS-WVS dataset. Overall, the three modelling approaches demonstrated satisfactory predictive performance, while the feature importance analyses consistently identified a relatively small group of socioeconomic and political variables as the principal determinants of institutional confidence. Although the descriptive presentation of these results provides valuable information regarding model performance and predictive accuracy, a deeper interpretation is required to understand their broader theoretical and practical significance. The primary objective of this chapter is therefore to interpret the empirical findings within the broader context of the existing literature on political trust, socioeconomic inequalities and democratic legitimacy. Rather than focusing exclusively on statistical indicators or predictive performance, the discussion seeks to explain why particular variables emerged as important predictors, how these findings relate to previous empirical studies and what they imply for the understanding of political trust in contemporary European democracies.

Emphasis is placed on the comparison between conventional statistical modelling and explainable machine learning approaches. One of the most distinctive contributions of the present study is the simultaneous application of Binary Logistic Regression, Random Forest, XGBoost and SHAP-based model interpretation within a unified analytical framework. This methodological strategy makes it possible not only to evaluate predictive performance but also to examine the consistency of variable importance across fundamentally different analytical approaches. Consequently, the discussion considers whether the observed relationships remain stable across models and what this consistency implies regarding the robustness of empirical findings. In addition, here we compare the results obtained for the three institutional outcomes examined in this study. Although confidence in government, parliament and political parties all represent dimensions of political trust, the empirical analysis suggests that important differences exist in both predictive performance and the relative importance of explanatory variables. Understanding these similarities and differences contributes to a more nuanced interpretation of institutional confidence and provides further evidence regarding the multidimensional nature of political trust.

The discussion considers the broader implications of the findings for public policy and future research. The increasing availability of large-scale survey data, combined with recent developments in explainable artificial intelligence, creates new opportunities for understanding complex political attitudes through computational social science. Consequently, the present findings are discussed not only in relation to existing theories of political trust but also considering the methodological developments that are reshaping empirical political research.

5.2 Interpretation of the Main Findings

The empirical analysis presented previously provides several important insights into the determinants of political trust across European societies. Despite employing three fundamentally different analytical approaches: Binary Logistic Regression, Random Forest and XGBoost. The models consistently identified a relatively small set of explanatory variables as the principal predictors of institutional confidence. This convergence is particularly important because it suggests that the observed relationships are robust across different modelling strategies and are not merely artefacts of a specific statistical technique. Perhaps the most notable finding concerns the dominant role of satisfaction with democracy. Across all three institutional outcomes—confidence in government, confidence in parliament and confidence in political parties—this variable consistently emerged as the strongest predictor of institutional confidence. The SHAP analyses further confirmed its central importance, demonstrating that respondents expressing greater satisfaction with the functioning of democracy were substantially more likely to exhibit higher levels of confidence in political institutions. This finding is highly consistent with the theoretical literature reviewed earlier. Easton (1965) argued that citizens' evaluations of political institutions are closely linked to their broader assessments of democratic system performance. Similarly, Norris (2011) suggests that declining political trust often reflects dissatisfaction with the functioning of representative democracy rather than rejection of democratic principles themselves. The present findings strongly support these theoretical perspectives by demonstrating that citizens' evaluations of democracy constitute a more powerful predictor of institutional confidence than many traditional socioeconomic characteristics.

The consistently high importance of political interest represents another significant finding. Individuals reporting greater engagement with political affairs were considerably more likely to express confidence in democratic institutions across all three outcomes. This relationship suggests that political trust is associated not only with objective socioeconomic conditions but also with citizens' level of political involvement and awareness. Politically engaged individuals may possess greater knowledge of institutional processes, increasing both political efficacy and confidence in democratic governance. At the same time, higher political interest may reflect greater civic participation, which previous research has repeatedly linked to stronger institutional legitimacy (Almond & Verba, 1963; Dalton, 2004).

Another variable displaying remarkable consistency across the three modelling approaches is generalized social trust . Respondents expressing higher levels of interpersonal trust were systematically more likely to report confidence in governments, parliaments and political parties. This result reinforces the argument developed by Rothstein and Stolle (2008) that interpersonal trust and institutional trust constitute mutually reinforcing dimensions of social capital. Societies characterized by stronger interpersonal trust frequently exhibit more effective institutions, higher civic cooperation and greater confidence in democratic governance.

The empirical findings also provide support for the importance of age as a determinant of political trust. Although age was not always the single strongest predictor, it consistently appeared among the most influential demographic variables across all three outcomes. Older respondents generally exhibited higher probabilities of expressing institutional confidence, supporting the second research hypothesis formulated before. This finding is consistent with previous comparative studies suggesting that older citizens often possess greater attachment to democratic institutions because of longer political socialization and accumulated political experience (Levi & Stoker, 2000; Hooghe & Zmerli, 2011).

The role of household income deserves some attention of its own. One of the central objectives of the present study was to examine whether socioeconomic inequalities influence political trust. The empirical results indicate that income remains an important predictor across all three institutional outcomes, although its contribution is generally smaller than that of political attitudes such as satisfaction with democracy or political interest. Consequently, the first research hypothesis receives partial empirical support. Economic resources continue to matter for institutional confidence, but their effects appear to operate alongside broader attitudinal and institutional evaluations rather than independently of them. This observation is especially relevant when interpreted considering the existing literature on socioeconomic inequality. Solt (2008) argues that economic inequality undermines political trust by increasing perceptions of unequal political representation, while Uslaner (2002) emphasizes the indirect effects of inequality operating through declining social trust. The present findings suggest that although objective socioeconomic conditions remain important, subjective evaluations of democratic performance exert an even stronger influence on citizens' confidence in political institutions. This indicates that improving institutional responsiveness and democratic quality may be as important as addressing economic inequalities when seeking to strengthen political trust.

Beyond the individual predictors, the empirical analysis reveals an important methodological finding. Despite substantial differences in model architecture, Logistic Regression, Random Forest and XGBoost identified remarkably similar sets of influential variables. Such consistency increases confidence in the robustness of the conclusions and suggests that the principal determinants of political trust remain stable regardless of whether the analysis is conducted using conventional statistical inference or more flexible machine learning algorithms. Rather than replacing traditional econometric methods, the machine learning models appear to complement them by confirming the importance of the same theoretical mechanisms while providing modest improvements in predictive accuracy. Overall, the findings indicate that political trust is shaped by a multidimensional combination of socioeconomic resources, political engagement, democratic evaluations and interpersonal trust. No single variable is sufficient to explain institutional confidence independently. Instead, political trust emerges from the interaction of objective socioeconomic characteristics and subjective political attitudes, reinforcing the multidimensional theoretical framework developed throughout this thesis.

5.3 Comparison with Previous Literature

The empirical findings of the present study are broadly consistent with the existing literature examining political trust and its socioeconomic determinants. Although previous studies have employed different datasets, analytical techniques and institutional contexts, a remarkable degree of agreement emerges regarding the principal factors associated with institutional confidence. At the same time, the application of explainable machine learning provides additional insights into the relative importance of these determinants, extending the conclusions of earlier research.

The findings are also consistent with more recent research examining the interaction between socioeconomic status and political attitudes. Albareda and Müller (2025) demonstrate that socioeconomic status moderates the relationship between political efficacy and political trust, suggesting that individuals with greater economic resources are better able to translate political engagement into institutional confidence. Although moderation effects were not explicitly estimated in the present analysis, the machine learning models identified both socioeconomic and attitudinal variables as simultaneously important predictors, indicating that political trust is shaped by the interaction of multiple dimensions rather than by isolated determinants. Beyond substantive findings, the present study also contributes methodologically to existing literature. Most previous studies examining political trust have relied primarily on regression-based approaches, including linear regression, logistic regression or multilevel modelling. While these methods remain indispensable for hypothesis testing and causal inference, recent developments within computational social science increasingly advocate the complementary use of explainable machine learning techniques (Mullainathan & Spiess, 2017; Athey & Imbens, 2019). The present findings provide empirical support for this methodological evolution. Although Random Forest and XGBoost produced only modest improvements in predictive performance compared with Logistic Regression, the combination of ensemble learning algorithms and SHAP values substantially enhanced the interpretation of predictor importance while maintaining high predictive accuracy.

A particularly noteworthy result concerns the strong agreement observed across the three analytical approaches. Logistic Regression, Random Forest and XGBoost consistently identified nearly the same group of influential explanatory variables, despite relying on fundamentally different statistical principles. This convergence considerably strengthens confidence in the robustness of the empirical findings and suggests that the principal determinants of political trust remain stable across alternative modelling strategies. Such consistency supports recent arguments advanced by Molnar (2022) and Whyte et al. (2025), who emphasize that explainable machine learning should complement rather than replace conventional statistical inference. The comparison with previous literature indicates that the present study largely confirms the established theoretical understanding of political trust while simultaneously extending it through the application of explainable machine learning. The empirical findings reinforce the importance of democratic satisfaction, political engagement and social trust as the principal determinants of institutional confidence, while demonstrating that modern predictive algorithms and explainability techniques can provide additional insights into the relative importance of these factors. Consequently, the study contributes both substantively and methodologically to the growing literature on political trust within contemporary democracies.

5.4 Machine Learning versus Classical Statistical Approaches

One of the principal methodological contributions of the present study lies in the simultaneous application of conventional statistical modelling and explainable machine learning techniques to investigate political trust. Rather than treating these approaches as competing analytical paradigms, the empirical analysis demonstrates that they provide complementary perspectives for understanding institutional confidence. While Binary Logistic Regression offers interpretable parameter estimates and facilitates hypothesis testing, Random Forest and XGBoost improve predictive performance and reveal complex relationships that may not be captured by conventional linear models. The comparative evaluation presented earlier indicates that the three modelling approaches produced remarkably similar predictive performance. Although Random Forest and XGBoost consistently achieved the highest AUC and classification accuracy across all institutional outcomes, their improvements over Binary Logistic Regression remained relatively modest. For confidence in government, parliament and political parties, the differences in AUC rarely exceeded one to two percentage points. This finding suggests that the relationships between explanatory variables and political trust are relatively stable and can largely be approximated using conventional statistical models.

At first glance, these relatively small differences may appear to reduce the practical value of machine learning algorithms. However, such an interpretation would overlook one of the principal strengths of explainable machine learning. The objective of the present study was not simply to maximize predictive accuracy but to evaluate whether more flexible algorithms identify similar substantive conclusions while providing additional insights into the structure of the data. From this perspective, the consistency observed across Binary Logistic Regression, Random Forest and XGBoost constitute evidence of the robustness of the empirical findings rather than a limitation of the machine learning models. An important advantage of Binary Logistic Regression concerns the interpretability of regression coefficients. Odds ratios provide direct information regarding the direction and magnitude of statistical relationships while allowing formal hypothesis testing through confidence intervals and significance tests. Such characteristics make logistic regression particularly appropriate for evaluating theoretically derived hypotheses and remain one of the principal reasons why regression-based methods continue to dominate empirical political science research. Nevertheless, regression models require researchers to specify the functional relationship between explanatory variables and the outcome variable in advance. Interaction effects and non-linear relationships must generally be introduced explicitly into the model specification. Failure to include relevant interactions may therefore lead to an incomplete representation of the underlying data-generating process.

Tree-based ensemble methods address this limitation by identifying complex relationships automatically. Random Forest constructs multiple decision trees using bootstrap aggregation and random feature selection, allowing interactions among explanatory variables to emerge naturally during model estimation. XGBoost extends this approach further through sequential boosting, whereby each successive tree attempts to correct the prediction errors generated by the previous ensemble. These methodological characteristics enable machine learning algorithms to capture highly flexible decision boundaries while reducing the risk of overfitting through internal regularization procedures. Despite these substantial methodological differences, the empirical findings reveal a striking level of agreement regarding the variables identified as most important. Satisfaction with democracy, political interest, generalized social trust and age consistently emerged among the strongest predictors irrespective of whether importance was evaluated through regression coefficients, Random Forest importance measures or SHAP values. Such consistency considerably strengthens confidence in the validity of the conclusions because similar substantive findings emerge from fundamentally different analytical approaches.

The introduction of SHAP represents perhaps the most important methodological innovation incorporated within the present study. Historically, one of the principal criticisms directed at machine learning concerned the limited interpretability of highly accurate predictive models. XAI has substantially reduced this limitation by allowing researchers to quantify the contribution of each explanatory variable to individual model predictions. Consequently, SHAP values bridge the traditional distinction between prediction and explanation by providing transparent interpretations of otherwise complex machine learning algorithms. Within the context of the present analysis, SHAP values proved particularly valuable because they confirmed the stability of the variable importance rankings produced by Random Forest while simultaneously illustrating the relative contribution of individual predictors. This additional level of interpretability substantially increases confidence that the identified determinants of political trust are genuine empirical relationships rather than artefacts of a particular modelling approach.

The findings therefore support recent methodological developments advocating the integration of econometric analysis and explainable machine learning within the social sciences. Mullainathan and Spiess (2017) argue that machine learning should complement traditional econometric analysis by improving prediction and facilitating the discovery of complex empirical relationships. Similarly, Athey and Imbens (2019) emphasize that predictive algorithms and causal inference should be viewed as complementary components of empirical research rather than competing methodologies. The present study provides empirical support for these arguments by demonstrating that conventional regression and machine learning produce highly consistent substantive conclusions while contributing different analytical strengths.

The comparison between classical statistical methods and explainable machine learning indicates that neither approach should be regarded as inherently superior. Logistic Regression remains indispensable for hypothesis testing and statistical inference, whereas Random Forest, XGBoost and SHAP provide greater flexibility, improved predictive performance and enhanced model interpretability. Consequently, the combination of these approaches offers a more comprehensive understanding of political trust than either methodology could provide independently. The methodological framework adopted in this study therefore illustrates the growing convergence between traditional quantitative political science and computational social science. As explainable artificial intelligence becomes increasingly accessible to applied researchers, future empirical studies examining political attitudes, public opinion and democratic behavior are likely to benefit from integrating conventional statistical inference with modern predictive modelling techniques.

5.5 Policy Implications

The empirical findings of the present study have several important implications for policymakers, public institutions and democratic governance across Europe. Although political trust has traditionally been examined as an indicator of democratic legitimacy, the results presented here suggest that institutional confidence should also be viewed as an outcome influenced by citizens' everyday experiences with democratic institutions, public policies and broader socioeconomic conditions. Consequently, strengthening political trust requires a multidimensional policy approach that extends beyond purely economic interventions. Perhaps the most important policy implication concerns the dominant role of satisfaction with democracy. Across all empirical models, people's evaluations of democratic performance emerged as the strongest predictor of institutional confidence. This finding suggests that governments seeking to strengthen political trust should prioritize improving the quality of democratic governance rather than focusing exclusively on short-term economic outcomes. Policies promoting transparency, accountability, responsiveness and equal political representation may therefore contribute more substantially to institutional confidence than isolated economic measures alone.

The importance of political interest also carries significant implications for democratic institutions. Individuals who actively follow political developments consistently demonstrate higher levels of institutional confidence, indicating that political engagement remains an important component of democratic legitimacy. This finding highlights the importance of civic education, political literacy and public access to reliable political information. Governments, educational institutions and civil society organizations may therefore strengthen political trust by encouraging informed political participation and improving citizens' understanding of democratic institutions. Also, given the importance of generalized social trust for institutional confidence, interpersonal trust should be considered a cultural characteristic that evolves gradually over time, public institutions can indirectly influence social trust through fair, impartial and effective governance. Policies reducing corruption, improving administrative efficiency and ensuring equal treatment before the law may strengthen both interpersonal trust and confidence in democratic institutions. This observation supports previous arguments that institutional quality and social capital should be considered complementary rather than independent dimensions of democratic development.

The findings regarding income and other socioeconomic characteristics also provide important policy insights. While household income remains an important predictor of institutional confidence, its influence is considerably weaker than that of democratic satisfaction and political attitudes. This suggests that policies designed exclusively to reduce economic inequalities may not automatically generate higher political trust unless accompanied by visible improvements in institutional performance and democratic responsiveness. Consequently, efforts to strengthen political trust should combine redistributive economic policies with institutional reforms aimed at increasing transparency, accountability and citizen participation. An additional implication concerns the methodological findings of the study. The strong agreement observed between Binary Logistic Regression, Random Forest and XGBoost suggests that policymakers can increasingly rely on explainable machine learning techniques to support evidence-based decision making without sacrificing interpretability. Modern predictive algorithms can identify complex patterns within large-scale survey data while SHAP values allow decision-makers to understand the variables driving model predictions. Consequently, XAI may become an increasingly valuable tool for monitoring public opinion, evaluating policy interventions and identifying population groups experiencing declining institutional confidence.

Nevertheless, the present findings also emphasize that predictive algorithms should support rather than replace human judgement within public policy. Machine learning models identify statistical relationships and predictive patterns, but they do not establish causal relationships nor determine the normative desirability of policy interventions. Consequently, empirical predictions should always be interpreted alongside theoretical knowledge, institutional context and democratic values. The policy implications of this study suggest that strengthening political trust requires an integrated strategy combining institutional reforms, democratic participation and socioeconomic inclusion. Governments that improve democratic responsiveness while simultaneously addressing citizens' broader social and economic concerns are likely to create more favorable conditions for sustaining institutional legitimacy. The results therefore reinforce the view that political trust represents not only an outcome of government performance but also an essential resource for the long-term stability and resilience of democratic systems.

5.6 Limitations of the Study

Although the present study provides a comprehensive examination of the determinants of political trust through the integration of conventional statistical methods and explainable machine learning techniques, several limitations should be acknowledged when interpreting empirical findings. Recognising these limitations does not diminish the contribution of the study; rather, it provides an appropriate context for evaluating the robustness of the results and identifying opportunities for future research. The first limitation concerns the cross-sectional nature of the dataset. The EVS-WVS dataset provides a rich snapshot of citizens' socioeconomic characteristics, political attitudes and institutional confidence at a particular point in time. However, cross-sectional data does not allow causal relationships to be identified directly, nor do they capture changes in political trust throughout individuals' lives. Political trust is a dynamic phenomenon influenced by elections, economic crises, institutional reforms and major political events. Consequently, although the present models identify robust statistical associations, they should not be interpreted as establishing causal effects.

A second limitation relates to the measurement of political trust. To facilitate binary classification, the original survey responses were transformed into two categories representing relatively low and relatively high institutional confidence. This transformation was necessary for the implementation of the selected machine learning algorithms and ensured consistency across the three institutional outcomes. Nevertheless, the binary operationalization inevitably reduces some of the information contained in the original ordinal response scale. Respondents expressing moderate levels of confidence are grouped with one of the two broader categories, potentially masking more subtle differences in political attitudes. Further consideration concerns the survey-based nature of the explanatory variables. All socioeconomic and political variables included in the analysis are based on self-reported responses. Although large international surveys such as EVS and WVS employ rigorous methodological standards, self-reported data remain subject to measurement error, recall bias and social desirability effects. Respondents may occasionally overstate socially desirable attitudes or underreport politically sensitive opinions, introducing a degree of uncertainty into the observed relationships.

The present study also focuses exclusively on individual-level determinants of political trust. Although variables such as income, education, political interest and satisfaction with democracy explain a substantial proportion of institutional confidence, broader contextual characteristics were not explicitly incorporated into the predictive models. Institutional quality, government effectiveness, corruption levels, electoral systems and macroeconomic conditions may also influence political trust and could interact with individual-level characteristics. Future research integrating individual and country-level variables through multilevel analytical frameworks may therefore provide a more comprehensive understanding of institutional confidence across Europe.

From a methodological perspective, it should also be acknowledged that machine learning models primarily optimise predictive performance rather than causal inference. Random Forest and XGBoost successfully identify complex patterns within the data and provide highly accurate classifications. However, unlike conventional econometric approaches specifically designed for causal estimation, predictive algorithms identify associations rather than causal mechanisms. The inclusion of SHAP values substantially improves model interpretability by explaining the contribution of individual variables to model predictions, yet explainability should not be interpreted as proof of causality. Consequently, the substantive interpretation of machine learning results must always remain grounded within established theoretical frameworks. Although the EVS-WVS dataset represents one of the largest comparative databases available for the study of political attitudes, it remains limited to the variables included within the original surveys. Other potentially important determinants of political trust—including media consumption, exposure to misinformation, digital political participation, institutional transparency, regional inequalities and local governance characteristics—were not available for inclusion in the present analysis. As a result, the estimated models should be interpreted as capturing the most important predictors available within the existing dataset rather than providing an exhaustive explanation of political trust.

Despite these limitations, the present study possesses several important strengths. The large sample size, the harmonisation of two internationally recognised survey programmes, the comparison of multiple analytical approaches and the integration of explainable artificial intelligence considerably strengthen the robustness of empirical findings. Consequently, the limitations discussed above should be viewed as opportunities for extending future research rather than as weaknesses that undermine the overall contribution of the study.

5.7 Future Research

The findings of the present study offer several promising directions for future research concerning political trust, socioeconomic inequalities and the application of explainable machine learning within political science. First, future studies could employ longitudinal or panel datasets to examine how political trust evolves over time. Such approaches would allow researchers to distinguish between short-term reactions to political or economic events and longer-term changes in institutional confidence, thereby providing stronger evidence regarding the causal mechanisms underlying political trust. Second, future research could expand the analytical framework by incorporating country-level institutional indicators alongside individual-level survey responses. Variables such as government effectiveness, corruption perception, electoral competitiveness, media freedom and economic inequality may provide additional explanatory power and facilitate multilevel analyses capable of capturing both individual and contextual influences on political trust.

A further avenue concerns the continued development of XAI within political science. While SHAP values were employed in the present study to improve model interpretability, future research could compare alternative explainability techniques, including Local Interpretable Model-agnostic Explanations (LIME), Partial Dependence Plots (PDP) and Accumulated Local Effects (ALE). Such comparisons would further strengthen the transparency of predictive modelling within the social sciences. The increasing availability of computational resources also creates opportunities to investigate more advanced predictive algorithms, including deep learning architecture and transformer-based models, particularly when analysing large-scale textual data such as parliamentary debates, political speeches or social media content. Combining structured survey data with unstructured textual information may provide a richer understanding of citizens' political attitudes and institutional evaluations.

Future research should continue exploring the integration of conventional econometric methods with explainable machine learning. Rather than treating prediction and explanation as competing objectives, the present study demonstrates that these approaches can complement one another. Further methodological developments combining causal inference, predictive modelling and explainability are likely to play an increasingly important role in empirical political science, particularly as public datasets continue to expand in both size and complexity.

6. Conclusion

The present study set out to investigate the socioeconomic determinants of political trust in Europe by integrating conventional statistical methods with modern explainable machine learning techniques. Using the EVS-WVS dataset, the analysis examined three distinct dimensions of institutional confidence: confidence in government, confidence in parliament and confidence in political parties. Through the application of Binary Logistic Regression, Random Forest and XGBoost, the study sought not only to identify the principal predictors of institutional confidence but also to evaluate the relative performance and interpretability of different analytical approaches.

The empirical findings demonstrate that political trust is shaped by a multidimensional combination of socioeconomic characteristics, political attitudes and broader perceptions of democratic performance. Across all three institutional outcomes, satisfaction with democracy emerged as the strongest and most consistent determinant of institutional confidence. Political interest generalized social trust, age and household income also contributed substantially to model predictions, although their relative importance varied slightly across institutions. These findings suggest that citizens' evaluations of democratic performance play a more prominent role in explaining institutional confidence than purely demographic or economic characteristics. The comparative analysis of the three machine learning models further demonstrated that Random Forest and XGBoost consistently achieved the highest predictive performance, while Binary Logistic Regression remained highly competitive across all institutional outcomes. Although the improvements obtained by the ensemble learning algorithms were relatively modest, they consistently outperformed the conventional statistical model in terms of overall predictive accuracy and discrimination ability. At the same time, the similarity of the results across the three modelling approaches considerably strengthens confidence in the robustness of the empirical findings. Rather than producing contradictory conclusions, the different analytical methods converged towards a common set of influential determinants, indicating that the observed relationships are stable across alternative modelling strategies.

A particularly important contribution of the present study lies in the integration of explainable artificial intelligence into the empirical analysis of political trust. The application of SHAP values allowed the interpretation of complex machine learning models while preserving their predictive capabilities. This represents an important methodological advancement because it demonstrates that high predictive accuracy does not necessarily require sacrificing model transparency. Instead, explainable machine learning provides researchers with the opportunity to combine predictive modelling and substantive interpretation within a single analytical framework.

The comparison with the existing literature indicates that the present findings broadly confirm established theoretical explanations of political trust. At the same time, the study extends previous research by demonstrating that these relationships remain robust when analyzed using contemporary explainable machine learning techniques. Consequently, the research contributes both to the substantive literature on political trust and to the growing methodological literature examining the application of artificial intelligence within the social sciences. Beyond its academic contribution, the findings also carry important implications for democratic governance. The results suggest that strengthening political trust cannot be achieved solely through improvements in economic conditions. Instead, policies promoting democratic responsiveness, institutional transparency, civic participation and public accountability appear equally important for maintaining people’s confidence in political institutions. Governments seeking to reinforce democratic legitimacy should therefore adopt integrated policy strategies that simultaneously address socioeconomic inequalities and improve the quality of democratic governance.

The methodological framework developed in this thesis further illustrates the potential of combining conventional econometric techniques with explainable machine learning. Rather than replacing traditional statistical analysis, machine learning algorithms complement existing approaches by improving predictive performance while preserving interpretability through explainability methods such as SHAP. This integrated analytical strategy provides a more comprehensive understanding of complex political phenomena and represents a promising direction for future empirical research within political science. Nevertheless, the study also recognizes several limitations related to the cross-sectional nature of the data, the binary operationalization of political trust and the availability of explanatory variables within the dataset. These limitations provide important opportunities for future research employing longitudinal data, multilevel modelling, richer contextual variables and alternative explainability techniques. As computational social science continues to evolve, future studies will be able to integrate increasingly sophisticated predictive models with theoretically grounded explanations of political behavior.

In conclusion, the present thesis demonstrates that political trust is best understood as the product of a complex interaction between socioeconomic resources, political engagement, democratic evaluations and social trust. By integrating conventional statistical inference with explainable machine learning, this study provides a more comprehensive understanding of institutional confidence while illustrating the considerable potential of modern computational methods for advancing empirical political science. It is hoped that the findings presented here will contribute both to the continuing academic debate surrounding political trust and to the development of evidence-based policies aimed at strengthening democratic legitimacy within contemporary European societies. Ultimately, political trust represents far more than a simple measure of citizens' confidence in public institutions. It reflects the quality of democratic governance, the inclusiveness of political systems and the capacity of societies to foster cooperation between citizens and the state. As new analytical tools continue to transform empirical social science, integrating theoretical knowledge with explainable artificial intelligence offers promising opportunities for understanding these complex relationships. The present study demonstrates that combining robust social science theory with modern computational methods can provide richer, more transparent and more policy-relevant evidence for strengthening democratic governance worldwide.

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