Predicting the Attitudes Towards Universal Basic Income In Europe

1. EXECUTIVE SUMMARY

This study seeks to explore the factors that influence citizens' attitudes towards Universal Basic Income (UBI) – a social welfare policy that provides a fixed, unconditional income to all citizens regardless of their employment status or income level (Parijs & Vanderborght, 2017). Drawing on data from the European Social Survey (ESS) round 8, Choi (2021) investigates the impact of socio-demographic characteristics, self-interest, values or beliefs, specific attitudes, and socioeconomic structures on people's attitudes towards UBI. In particular, Choi (2021) tests the hypothesis that human basic values serve as the most determinant predictor among all factors in developed welfare states.

The present study aims to examine the robustness of Choi's (2021) conclusions regarding the primary determinants of attitudes towards UBI by employing logistic regression, propensity score matching, and random forest techniques. Through this comprehensive analysis, we seek to validate and extend the findings of Choi (2021) and contribute to a deeper understanding of the factors shaping public opinion on UBI in developed welfare states.

2. BACKGROUND

Universal Basic Income (UBI) proposals can be traced back to Thomas Paine, who in 1797 advocated for government compensation to citizens due to land privatization limiting subsistence opportunities (Wright, 2021a). Economists such as Hayek and Friedman also considered UBI-like policies as a more efficient way to support society's poorest while simplifying the complex welfare system (Rallo, 2019; Bidadanure, 2019) and promising significant administrative savings (Chaudry et al., 2016).

However, critics argue that UBI could solidify poverty and class structures (Rivers, 2019) and advocate for more targeted approaches instead (Krugman in Malter & Sprague, 2019). UBI experiments in developing countries have been limited by small, non-representative samples (Banerjee et al., 2019). Furthermore, its universality could render UBI fiscally unsustainable (Lee & Lee, 2021) and potentially create stigma or resentment among both net recipients (Parsell & Clarke, 2020) and net donors (Reese, 2005).

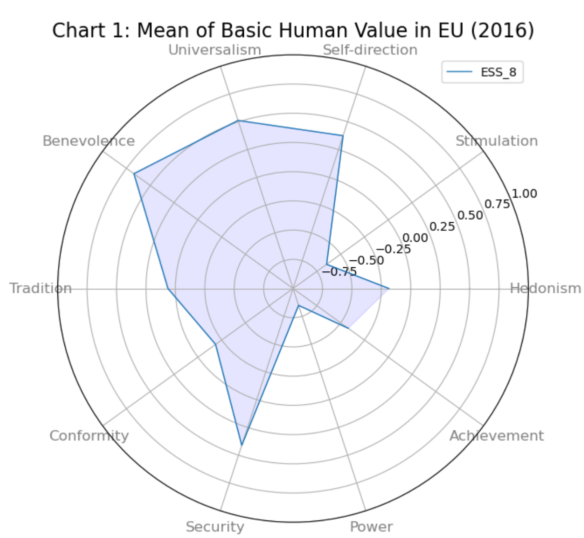
Recent advancements in AI and other automation technologies, such as ChatGPT, have led to renewed concerns about future unemployment. According to estimates from McKinsey, PricewaterhouseCoopers, and Skynet Today cited in Przegalinska and Wright (2021), AI will displace one-third of existing jobs worldwide within a decade, with the United States (up to 40%) and Japan (50%) being particularly affected. Scholars like Acemoglu and Restrepo (2017) indicate the necessity of wide adaptation of UBI, and technocrats such as Sam Altman, Elon Musk, and Andrew Yang are enthusiastic about UBI as a solution to the predicted mass unemployment in the future, regarding it as a renewal of the social contract. However, one major fallacy with this argument is that wage and transaction are seen as a result of gaming between rational agents, a proof of value creation, and a dispute resolution mechanism for distributing limited resources. Therefore, UBI as an unconditional transfer would essentially create a power imbalance between recipient and sender.

This paper aims to conduct further investigation into people's attitudes towards UBI under external shocks to understand the contextual factors and socioeconomic variables that moderate the correlation between basic human values and support for UBI. Assuming basic human values are the major predictor of preference, this paper would expect similar output results before and after pandemics, which, according to Our World in Data (2022), caused major damage to European economies and employment markets, and led 71% of Europeans to believe that the state should provide all citizens with a basic income (Europe's Stories, 2021). These results have policy significance since, if external shocks result in a large shift in citizens' attitudes, the argument that support for UBI is rooted in human basic values becomes questionable, and whether UBI could be a long-term solution to massive unemployment needs further investigation.

3. DATA

Following Choi (2021), the main data source for this paper includes proxies of human basic values and preference for social justice indicators from the European Social Survey (ESS) round 8, covering the period from August 2016 to December 2017. This dataset includes 44,387 observations at the individual level and 23 observations at the national level.

The dependent variable is an ordinal variable representing support for UBI, as indicated by survey questions asking candidates whether they are against or in favor of a basic income scheme, where '1' represents strongly against and '4' represents strongly in favor. To conduct logistic regression, this study constructs a binary indicator of support for UBI, where a response of 'strongly in favor' or 'in favor' is classified as 1 and a response of 'strongly against' or 'against' is classified as 0.



DATA SCIENCE 2 FINAL PROJECT

As suggested by Choi (2021), regarding basic human values, individual universalism as a self-transcendence value is positively and significantly associated with support for UBI, while benevolence as another self-transcendence value has negative impacts. In contrast, power and achievement as self-enhancement values are positively linked to support for UBI. This paper follows Schwartz's (n.d.) methodology to construct 10 scores of human basic values using 21 variables in the ESS 8 survey. To obtain an overview of the mean of 10 basic values across individuals, this paper creates a radar graph (graph 1), visualizing the average of all value variables.

Yeung (2022) suggests that by using an equalizing-opportunity frame, emphasizing UBI's ability to promote fairness and personal responsibility, or a limiting government frame, highlighting UBI as a way of reducing bureaucracy, conservatives in the United States would continue to oppose UBI. This rigidity in reasoning and difficulty in changing attitudes are partially due to an echo chamber created by biased party propaganda and easily polarizing content spread by the media. This study constructs variables indicating left-wing and right-wing positions on the political spectrum using a survey question asking respondents about their 'placement on the left-right scale,' where 0 indicates left and 10 indicates right. Additionally, to observe respondents' reception of political information, this study converts the variable - 'how many minutes do you spend every day watching political news' to hours of watching political news, assuming that the length of time would negatively correlate with support for UBI.

Roosma (2022) suggests that individuals with lower socio-economic status, left-leaning ideology, a preference for an equalized society, and belief in providing assistance to the poor are more likely to support UBI. Choi (2021) also analyzes how economic beliefs, preferences, and attitudes towards welfare impact individual attitudes towards UBI. This paper selects three variables related to economic individualism, economic fairness, and preference for redistribution to explore the relationship between economic beliefs and attitudes towards UBI. To investigate the impact of an individual's welfare attitudes, this paper uses five variables, including the perception of welfare's influence on preventing poverty, promoting equality, increasing laziness (negative), burden on businesses (negative), and strain on the economy (negative), to construct a synthesized score as an approximation of individual evaluation of welfare effectiveness. Additionally, welfare chauvinism is indicated by the question of when immigrants should obtain rights to social benefits/services, with '1' representing immediately after arrival and '5' representing never.

Chart 2: Country-level Associations between Support for UBI Underpinnings Principles of Basic Human Values

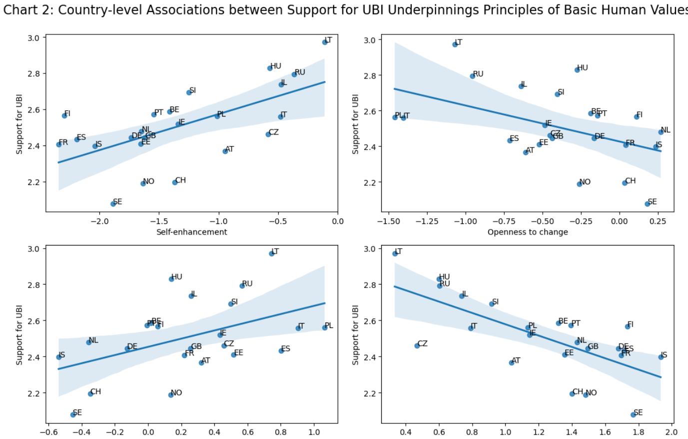
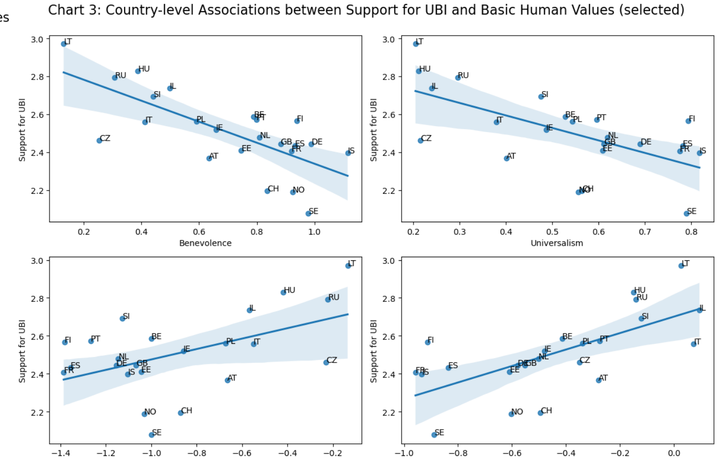


Chart 3: Country-level Associations between Support for UBI and Basic Human Values (selected)

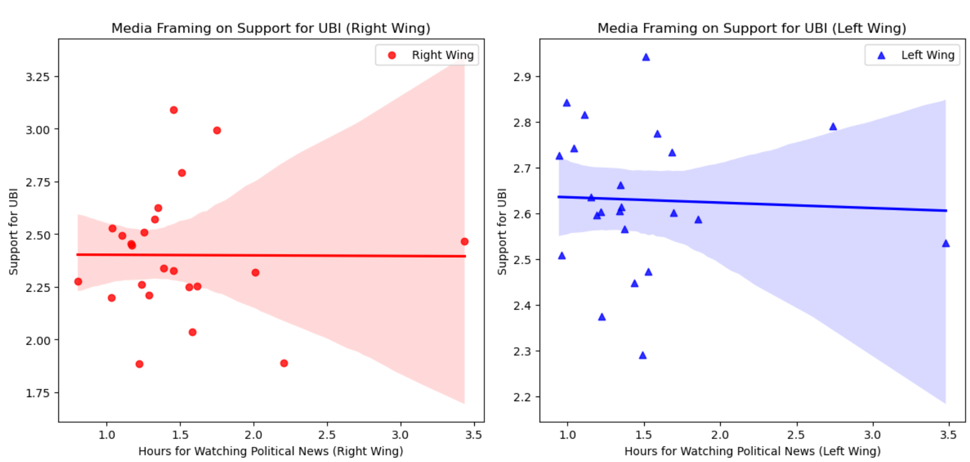


Control variables concerning individual characteristic predictors include age, gender, employment status, education, citizenship, level of happiness, level of health, and presence of children in the household. This study specifically investigates individuals who have a history of employment for at least three months, are currently unemployed, or are anxious about unemployment within 12 months.

First, this paper plots the marginal effect of four underlying principles behind basic values on attitudes towards UBI (see graph 2), indicating a positive relationship between support for UBI with self-enhancement and conservation, and a negative relationship with openness and self-transcendence. According to Schwartz (2016), this pattern suggests that UBI positively correlates with anxiety-based values, prevention of loss goals, and self-protection against threats, while negatively correlating with anxiety-free values, promotion of gain goals, and self-expansion and growth. This is consistent with the demand-driven prediction due to massive unemployment under automation. To further explore the elements of basic value correlation with support for UBI, this paper follows Choi (2021) to observe the pattern of correlation in 'benevolence,' 'universalism,' 'power,' and 'achievement.' Results show that support for UBI negatively correlates with the former two value variables and positively correlates with the latter two variables, which can be explained by the poor perception of welfare scheme effectiveness, generally regarded as a reason for increasing laziness and decreasing caring between social agents. Moreover, people eager to gain socioeconomic status and demonstrate their competence are more likely to support UBI.

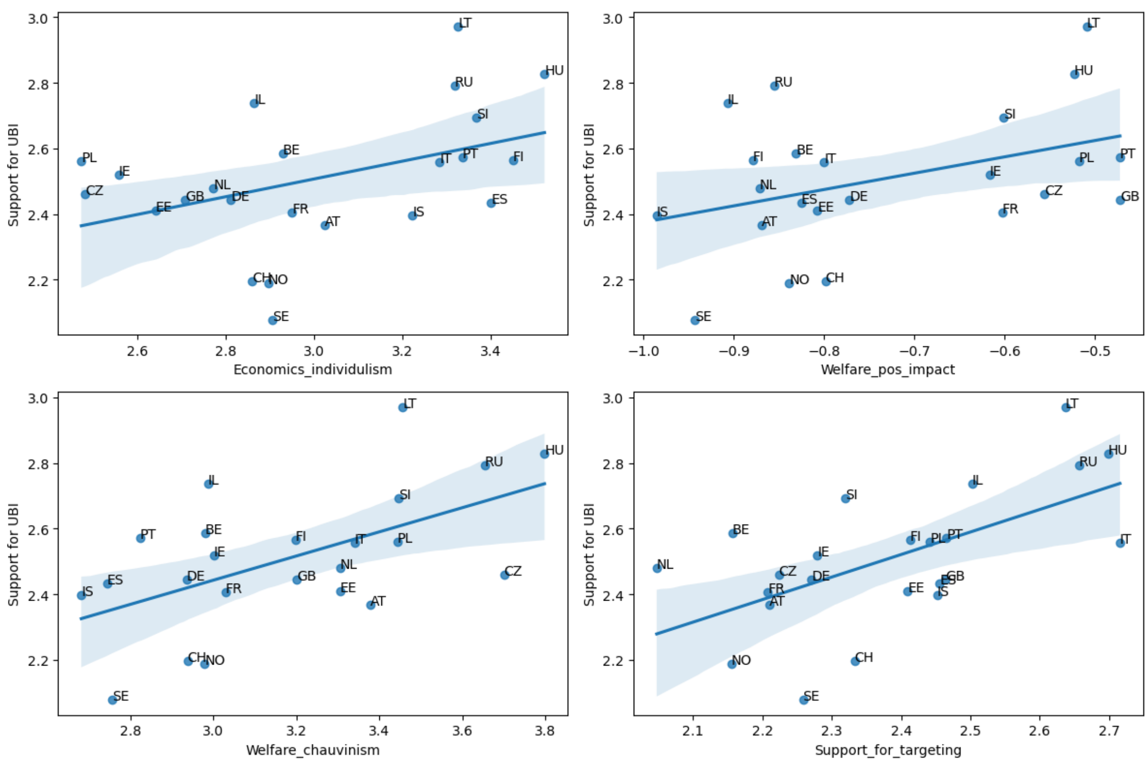
Regarding media framing for UBI (see graph 5), using a score of 1-10 to indicate the distance on the value spectrum to the left, this paper classifies 1-3 as left-wing and 7-10 as right-wing, separating them into two different datasets before analyzing the marginal effects of time spent on political news on support for UBI. Only a slight negative relationship is identified, which may not be significant after removing outliers.

Chart 5: Country-level Associations between Support for UBI and media framing



To investigate the potential influence of economic preferences and beliefs on support for UBI, this paper examines the relationship between economic individualism, which can be indicated by the acceptance of large differences in income to reward talents and efforts. The variable 'welfare_pos_impacts' is the synthesized score of five variables, aiming to approximate the average perception of welfare's positive effect on society among individuals. The variable 'welfare_chauvinism' primarily aims to represent the differences between local communities and immigrants, while 'supporting_for_targeting' represents the extent to which a welfare program should specifically target the poor. The positive relationship between support for UBI and all variables mentioned above indicates their potential explanatory power towards support for UBI.

Chart 6: Country-level Associations between Support for UBI and Attitudes towards Welfare



4. METHODOLOGY

4.1 Fixed Effect Logistic Regression

Fixed effect logistic regression is an appropriate method to analyze panel data, as it accounts for unobserved time-invariant individual-specific factors that may influence the outcome variable (Allison, 2009). In the context of this study, the panel data consists of multiple observations on individuals over time, encompassing a variety of individual-level characteristics, employment status, values, trust, media framing, preferences, beliefs of justice, and welfare attitudes. Utilizing fixed effects logistic regression allows the model to control for unobserved heterogeneity, yielding more accurate estimates of the relationships between the independent variables and the binary outcome variable, "support for ubi dummy" (Wooldridge, 2010).

Furthermore, the inclusion of country-level fixed effects in the model helps to control for unobserved time-invariant country-specific factors that may also impact the outcome (Greene, 2012). By incorporating these fixed effects, the model is able to isolate within-country variation in support for universal basic income and provide a more accurate assessment of the relationships between the independent variables and the dependent variable. The fixed effect logistic regression approach, therefore, allows for a robust estimation of the relationships while accounting for both individual-level and country-level unobserved factors (Cameron & Trivedi, 2005).

In a comprehensive study by Giuliano and Spilimbergo (2014), the researchers utilized country-level fixed effects logistic regression to investigate the relationship between the level of democracy and the probability of supporting democratic values in European countries. Drawing upon data from the European Social Survey (ESS), the analysis focused on individual-level characteristics, such as age, gender, education, and income, as well as country-level factors, such as the quality of democratic institutions and historical legacies. By employing fixed effects logistic regression, the authors were able to account for unobserved country-level heterogeneity, isolating the effects of individual and contextual factors on the likelihood of endorsing democratic principles. The results of the study revealed a strong positive association between the quality of democratic institutions and the support for democratic values among European citizens, while controlling for individual socio-demographic characteristics. This research highlights the importance of understanding the role of contextual factors in shaping public opinion and the value of employing fixed effects logistic regression to analyze multilevel data in a cross-national setting.

4.2. Decision Tree

Parametric modeling provides a framework for estimating the parameters of a distribution and making predictions about future observations; however, it is subject to several significant limitations. These limitations include reliance on the underlying distribution of the data, inflexibility in capturing complex relationships, and susceptibility to the influence of outliers (Hastie et al., 2009). Consequently, this study employs non-parametric modeling as an alternative approach, which offers numerous advantages over its parametric counterpart.

Non-parametric models do not require a priori assumptions about the distribution of the data, making them more robust to deviations from assumed distributions (Wasserman, 2006). Additionally, they are more resistant to the effects of outliers and can capture non-linear relationships between variables, resulting in more accurate predictions (James et al., 2013). Overall, non-parametric models provide a versatile and robust alternative to parametric models, addressing their inherent limitations and offering a more flexible approach to data analysis (Hastie et al., 2009).

Utilizing a decision tree model, such as the DecisionTreeClassifier with a max depth of 7 in this case, offers several advantages when analyzing the relationship between a set of independent variables and a dependent variable. Firstly, decision trees are non-parametric models, which means that they do not assume a specific distribution for the data, making them more flexible and robust against violations of parametric assumptions (Breiman et al., 1984). This flexibility allows decision trees to capture complex, non-linear relationships between variables, which can lead to more accurate predictions (James et al., 2013).

Another advantage of decision trees is their ability to handle a mix of continuous and categorical variables, as well as missing values, without the need for extensive preprocessing (Hastie et al., 2009). Moreover, the interpretability of decision tree models is particularly appealing, as the resulting tree structure can be easily visualized and understood. By calculating variable importance, researchers can identify the most influential variables in the model, aiding in the interpretation of results (Breiman, 2001). In addition to the decision tree model, ensemble methods, such as random forest and AdaBoost classifiers, can be employed to improve model performance by aggregating predictions from multiple base models (Liaw & Wiener, 2002; Freund & Schapire, 1997). Ensemble methods typically demonstrate higher accuracy and are more robust against overfitting compared to single decision trees (James et al., 2013).

In a study conducted by Chen et al. (2019) titled "Predicting the risk of heart failure with EHR sequential data modeling," the authors used decision tree models to identify the most important features for predicting heart failure risk in patients. The researchers utilized electronic health record (EHR) data, including demographics, diagnoses, lab results, and medication records, to create a comprehensive dataset for their analysis. By employing a decision tree model, they were able to determine the key variables that significantly contributed to heart failure risk. The decision tree's interpretable structure provided valuable insights into the relationships between the variables, allowing medical professionals to better understand the factors driving the risk of heart failure and make more informed decisions regarding patient care.

5. ANALYSIS

5.1 Logistic Regression

Following the Choi (2021), this paper uses fixed effect logistic regression, and the results provide valuable insights into the relationships between various predictor variables and the outcome of interest. In the first panel, this paper concentrates on studying the relationship between individual characteristics and support towards UBI, and observe the strong relationship between age groups and the dependent variable. The coefficients for each age group (20.0, 30.0, 40.0, 50.0, 60.0, and 70.0) are consistently negative and statistically significant across different models, indicating that older age groups generally exhibit lower values for the outcome variable compared to the reference group. The magnitude of the coefficients increases with age, suggesting a stronger effect for older age groups. For example, the coefficient for the age group 40.0 in Model 3 is -0.377 ($p<0.01$), demonstrating a stronger effect compared to the coefficient for the age group 20.0, which is -0.169 ($p<0.01$).

In the second panel, we focus on the importance of basic human value predictors such as ‘achievement’, ‘benevolence’, ‘difficult_on_present_income’, and ‘economics_fairness’. These variables display statistically significant coefficients across different models, suggesting that they have a substantial impact on the dependent variable. For instance, an increase in achievement and difficult_on_present_income is associated with higher values of the outcome variable, while an increase in benevolence and economics_fairness corresponds to lower values. These variables display statistically significant coefficients across different models ($p<0.01$), suggesting that they have a substantial impact on the dependent variable. For instance, an increase in achievement in Model 5 is associated with higher values of the outcome variable, with a coefficient of 0.126 ($p<0.01$). Likewise, an increase in difficult_on_present_income in Model 5 corresponds to a coefficient of 0.225 ($p<0.01$). Conversely, an increase in benevolence and economics_fairness in Model 5 is associated with lower values of the outcome variable, with coefficients of -0.122 ($p<0.01$) and -0.233 ($p<0.01$), respectively.

The third panel highlights the importance of the media framing and social trust by adding the predictor of time spent on political news, position on political spectrum, social trust to indicate the cynical tendencies, and interaction terms such as political_news_hour and left_on_scale. These interaction terms capture the joint effect of two predictor variables on the dependent variable. In this case, the interaction between political_news_hour and left_on_scale is consistently negative and statistically significant, indicating that the combined effect of these two variables results in a decrease in the dependent variable. These interaction terms capture the joint effect of two predictor variables on the dependent variable. In this case, the interaction between political_news_hour and left_on_scale in Model 5 is consistently negative and statistically significant, with a coefficient of -0.006 ($p<0.01$), indicating that the combined effect of these two variables results in a decrease in the dependent variable.

The fourth panel examines the relationship between support for Universal Basic Income (UBI) and preference and belief regarding social justice. The results suggest that support for UBI is positively correlated with economic individualism and negatively correlated with economic fairness. This implies that those who place more value on individual economic freedom and less on equality of economic outcomes are more likely to support UBI.

The fifth panel explores attitudes towards welfare and their relationship with support for UBI. The results show that support for UBI is negatively correlated with welfare chauvinism, which is the belief that welfare benefits should only be given to those who are seen as deserving or deserving based on national identity. On the other hand, support for UBI is positively correlated with promoting equality and strain on the economy, which refers to the belief that welfare programs should be targeted to those who need them the most. As in the previous panel, the model includes control variables such as age, gender, education, political views, and social traits such as social trust and political news exposure.

Logistic regression, as used in this study, has several advantages of being able to model the relationship between a dichotomous outcome variable and multiple predictor variables, which may be continuous, categorical, or a combination of both. Additionally, logistic regression provides easily interpretable results in the form of odds ratios, which can be used to quantify the effect of each predictor variable on the outcome.

However, there are also some limitations of logistic regression. One disadvantage is that logistic regression assumes a linear relationship between the logit of the outcome variable and the predictor variables. This assumption may not hold true for the study, leading to biased estimates. Moreover, logistic regression is sensitive to multicollinearity, which occurs when predictor variables are highly correlated, which is highly likely in this study. Therefore, this paper also adopts non-parametric modeling.

5.2 Decision Tree

The Decision Tree Classifier was implemented using scikit-learn library. This model was trained using a dataset partitioned into training and testing sets, and subsequently evaluated for its predictive performance on the test set, as indicated by the score method (`tree.score(Xtest, ytest)`). This score, approximately 57.6%, signifies the accuracy of the model, demonstrating that the target variable was correctly predicted for about 57.6% of the cases in the test set.

The model's feature importance was evaluated to understand which features significantly contributed to the decision tree's predictions. Among the features, `economics_fainess` was identified as the most critical, with a feature importance of approximately 0.406, indicating that the `economics_fainess` feature played a significant role in the model's decision-making process, influencing the majority of the splits in the decision tree. The second most important feature was `support_for_targeting`, with a feature importance of approximately 0.334. Also, the features `less_caring` and `welfare_pos_impact` displayed lower feature importance scores, approximately 0.092 and 0.036 respectively, indicating a lesser influence on the model's decision-making process. To decide the value of hyperparameter tuning, this paper use validation curve, and find out the training dataset do not follow the traditional convex pattern, and although this decision tree model relatively low score may related to shallow depth, this could potentially be improved in many ways such as feature engineering use other method to select the hyperparameter.

5.3 Random Tree Forest

The Random Forest model is a powerful machine learning algorithm that is known for its robustness and ability to handle complex datasets. In this study, we implemented a Random Forest classifier with a maximum depth of 3, which was trained on a dataset that was partitioned into training and testing sets. The predictive performance of the model was evaluated on the test set, which resulted in an accuracy score of approximately 0.587 or 58.7%.

The feature importance analysis of the Random Forest model provides insights into which features are most critical in predicting the target variable. The feature importance values are calculated by determining the reduction of the criterion (such as Gini impurity or entropy) brought by that feature, averaged over all trees in the forest. The most significant feature in this analysis was found to be `economics_fainess`, with an importance value of approximately 0.201, which is consistent with previous results obtained from the decision tree. This feature played a crucial role in the model's decision-making process across all the decision trees in the Random

Forest. The second most important feature was found to be `support_for_targeting` with an importance value of approximately 0.189. The feature `difficult_on_present_income` was ranked as the third most important, with an importance value of approximately 0.154.

Other features such as `increasing_laziness`, `economics_individulism`, `achievement`, `welfare_pos_impact`, `benevolence`, `less_caring`, etc. also contributed to the model's predictions to varying degrees, albeit less significantly than the top three. It is worth noting that while the accuracy of the Random Forest model was approximately 58.7%, indicating although there is improvement from the decision tree, the value is still low.

5.4 AdaBoost

As a popular ensemble learning method used for classification tasks, AdaBoost classifier with a base estimator, a Decision Tree Classifier with a maximum depth of 3, was trained on a given dataset. The model's predictive performance was evaluated on the test set, resulting in an accuracy score of approximately 0.590 or 59%.

The feature importance analysis of the AdaBoost model provides insights into which features were most critical in making predictions with the model. The feature importance scores are based on the weighted contribution of the base estimators to the final predictions. The most significant feature in this analysis was found to be `power`, with an importance value of approximately 0.126. This feature had the most substantial impact on the model's predictions across all the base estimators in the AdaBoost ensemble. The second most important feature was found to be `stimulation`, with an importance value of approximately 0.105. This means that this feature also played a crucial role in the decision-making process across all the base estimators in the AdaBoost ensemble. `Achievement` held the third position in terms of feature importance, with a value of approximately 0.096. While the AdaBoost model achieved an accuracy of 59%, there is always scope for improvement depending on the requirements of the application.

The importance features are different from those selected by decision tree and random forest algorithm, because of the way of assigning importance to features. AdaBoost assigns higher weights to training examples that are misclassified by previous weak learners, which means that features that are important for correctly classifying these examples will be given higher importance. Decision Trees evaluate the importance of features based on their ability to reduce impurity or increase information gain, while Random Forest evaluates the importance of features based on their ability to improve the performance of multiple decision trees.

The relatively low score among three models could be several reasons. Firstly, the dataset may not contain enough information or may not be representative of the modeling of people's attitudes towards UBI. This can lead to poor model performance, as the models are not able to learn the underlying patterns and relationships in the data accurately. Secondly, the features used to train the models may not be relevant or informative enough for making accurate predictions. In such cases, more extensive feature engineering may be required to identify more relevant features or create new features that can better capture the underlying patterns in the data.

Also, the models this paper chooses may not be suitable for the problem. It may be necessary to explore other models or even develop custom models that can better capture the underlying patterns in the data. Overall, to improve the performance of the models, it is necessary to carefully examine each of these factors and take appropriate actions. Improving the quality of the dataset, identifying more relevant features, optimizing the models effectively, and selecting appropriate models are all critical steps in building accurate machine learning models.

6. CONCLUSION

The logistic regression analysis reveals that several features have a significant association with the support for Universal Basic Income (UBI). The variables such as achievement, self-direction, stimulation, and universalism show a positive relationship with the support for UBI, while variables such as benevolence, economics fairness, and welfare chauvinism have a negative relationship with the support for UBI. Furthermore, age groups also have a significant negative association with support for UBI, which suggests that the support for UBI decreases with age.

The decision tree model has an accuracy score of 0.576, indicating a relatively low prediction accuracy. The feature importance analysis shows that economics fairness, support for targeting, and difficulty on present income are the top three predictors for the model, indicating that these factors have the greatest influence on the support for UBI. The random forest model has an accuracy score of 0.587, which is slightly better than the decision tree model. Additionally , the adaboost model has an accuracy score of 0.590, which is the highest among the three models. The feature importance analysis shows that power, stimulation, achievement, and self-direction are the top four predictors for the model. The results are consistent with the logistic regression However, three models' low accuracy suggests that they may not be the most effective in predicting support for UBI.

In conclusion, this paper attempts to capture the most important features impacting people's attitudes towards UBI under the wave of automation and digitalization. While the results vary across models, it is not consistent with our original assumption that human value is the most important determinant of the attitudes. As the determinant is not the fundamental value, this means that UBI could only be a temporary measure to solve the social problem and not be viewed as a renewal of social contract or a long-term solution.

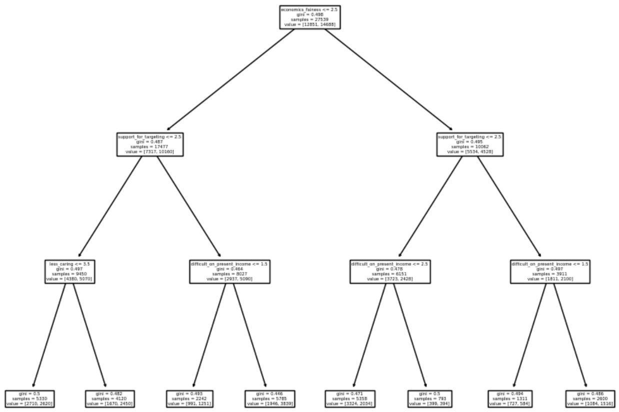
7. APPENDIX

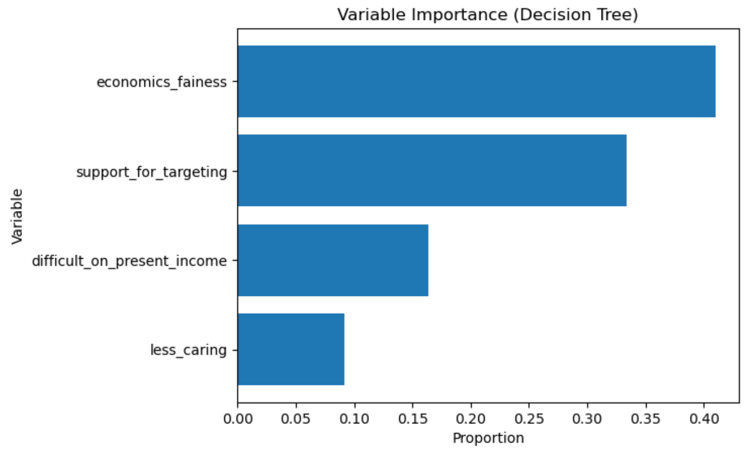
	Dependent variable:				
	(1)	(2)	(3)	(4)	(5)
age group 0 - 20		-0.211***	-0.182***	-0.169***	-0.129**
		(0.056)	(0.061)	(0.062)	(0.065)
age group 20 - 30		-0.350***	-0.282***	-0.276***	-0.209***
		(0.057)	(0.063)	(0.064)	(0.067)
age group 30 - 40		-0.447***	-0.379***	-0.377***	-0.298***
		(0.058)	(0.063)	(0.064)	(0.067)
age group 40 - 50		-0.473***	-0.413***	-0.432***	-0.368***
		(0.056)	(0.061)	(0.062)	(0.065)
age group 60 - 70		-0.468***	-0.396***	-0.411***	-0.378***
		(0.056)	(0.061)	(0.062)	(0.065)
age group 70 - 100		-0.474***	-0.403***	-0.455***	-0.433***
		(0.057)	(0.063)	(0.064)	(0.067)
Intercept	0.279***	0.057	0.241**	0.694***	0.064
	(0.014)	(0.075)	(0.098)	(0.110)	(0.136)
achievement		0.130***	0.127***	0.129***	0.126***
		(0.012)	(0.013)	(0.014)	(0.014)
benevolence		-0.142***	-0.129***	-0.129***	-0.122***
		(0.018)	(0.019)	(0.019)	(0.021)
difficult on present income		0.287***	0.287***	0.249***	0.225***
		(0.014)	(0.015)	(0.016)	(0.017)
economics fairness				-0.258***	-0.233***
				(0.012)	(0.013)
economics individualism				0.068***	0.048***
				(0.010)	(0.011)
fair in people			-0.016**	-0.015**	-0.016**
			(0.007)	(0.007)	(0.007)
healthy$_{l}evel$		0.036***	0.031**	0.032**	0.022
		(0.013)	(0.014)	(0.014)	(0.015)
helpful in people			0.020***	0.019***	0.012*
			(0.006)	(0.006)	(0.006)
increasing laziness					0.083***
					(0.014)
is bachelor		0.053**	0.048*	0.059**	0.025
		(0.025)	(0.027)	(0.027)	(0.029)
is female		0.060***	0.028	0.026	0.042*
		(0.021)	(0.022)	(0.023)	(0.024)
is unemployed		0.051	0.065	0.064	0.053
		(0.056)	(0.060)	(0.061)	(0.065)
left on scale			-0.057***	-0.042***	-0.035***
			(0.006)	(0.006)	(0.007)
less caring					0.040***
					(0.014)
live with child		0.003	0.004	0.010	0.016
		(0.025)	(0.026)	(0.027)	(0.028)
political news hour			0.028**	0.026**	0.030**
			(0.013)	(0.013)	(0.014)
political news hour:left on scale			-0.005**	-0.005**	-0.006**
			(0.002)	(0.002)	(0.002)
power	0.125***	0.066***	0.055***	0.069***	0.051***
	(0.011)	(0.014)	(0.014)	(0.015)	(0.016)
preventing poverty					-0.009
					(0.014)
promote equality					-0.065***
					(0.014)
self direction		-0.083***	-0.079***	-0.062***	-0.055***
		(0.014)	(0.015)	(0.015)	(0.016)
stimulation		0.087***	0.080***	0.084***	0.084***
		(0.011)	(0.012)	(0.012)	(0.013)
strain on the economy					0.029**
					(0.012)
support for targeting					0.240***
					(0.015)
trust in people			0.005	0.004	-0.003
			(0.006)	(0.006)	(0.006)
universalism		0.170***	0.143***	0.098***	0.073***
		(0.020)	(0.021)	(0.022)	(0.023)
was unemployed exceed 3months		0.115***	0.110***	0.090***	0.093***
		(0.024)	(0.026)	(0.027)	(0.028)
welfare chauvinism					-0.046***
					(0.012)
Observations	40,592	39,847	35,011	34,493	31,389
R^2					
Adjusted R^2					
Residual Std. Error	1.000(df = 40590)	1.000(df = 39827)	1.000(df = 34985)	1.000(df = 34465)	1.000(df = 31354)
F Statistic	(df = 1.0; 40590.0)	(df = 19.0; 39827.0)	(df = 25.0; 34985.0)	(df = 27.0; 34465.0)	(df = 34.0; 31354.0)

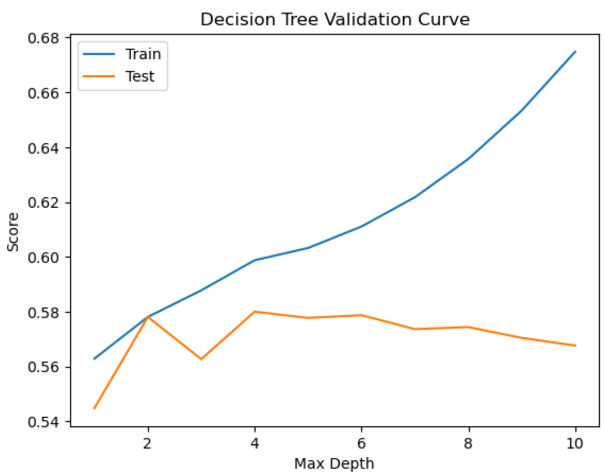
Note: *p$<$0.1; **p$<$0.05; ***p$<$0.01

DATA SCIENCE 2 FINAL PROJECT

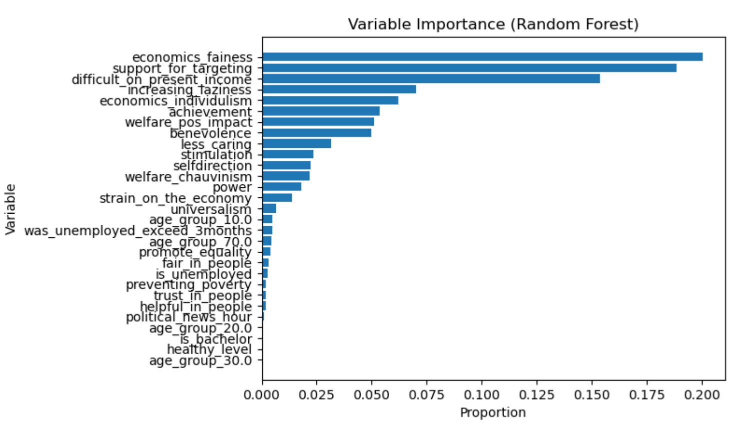
2. Decision Tree Result



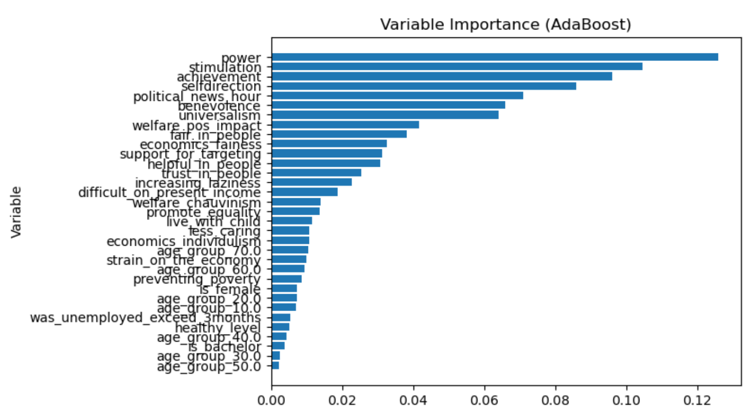




3. Random Forest Result



4. Adaboost Result



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