Ghanem, S., Cabelkova, I., Smutka, L., Fandi, G., & Krepl, V. (2025). The role of personal values in predicting energy-saving behaviors for climate mitigation. *Journal of International Studies, 18*(4), 285-307. doi:10.14254/2071-8330.2025/18-4/14

Journal of International Studies

Centre of Sociological Research

Scientific Papers

The role of personal values in predicting energy-saving behaviors for climate mitigation

Safwan Ghanem*
Faculty of Economics and Management,
Czech University of Life Sciences Prague,
Prague, Czech Republic
safwanghanem@gmail.com
ORCID 0000-0002-9748-1503
** Corresponding author*

Inna Cabelkova
Faculty of Economics and Management,
Czech University of Life Sciences Prague,
Prague, Czech Republic
cabelkova@pef.czu.cz
ORCID 0000-0002-8302-1004

Lubos Smutka
Faculty of Economics,
University of South Bohemia in České Budějovice,
České Budějovice, Czech Republic
lsmutka@ef.jcu.cz
ORCID 0000-0001-5385-1333

Ghaeth Fandi
Faculty of Economics and Management,
Czech University of Life Sciences Prague,
Prague, Czech Republic
fandigha@fel.cvut.cz
ORCID 0000-0002-5488-6965

Vladimír Krepl
Faculty of Economics and Management,
Czech University of Life Sciences in Prague,
Prague, Czech Republic
krepl@ftz.czu.cz
ORCID 0000-0001-7490-422X

Abstract. Addressing climate change requires widespread individual action, particularly in reducing energy consumption. This study examines how personal values influence energy-saving behaviors by using the Portrait Values Questionnaire (PVQ) to assess motivational goals that shape climate-related attitudes and actions. Analyzing responses from a diverse sample, the study evaluates participants' perceived responsibility, concern about climate change, and beliefs in collective and governmental efforts to reduce energy use. The results indicate that emotional attachment to Europe, a sense of personal responsibility, and higher levels of climate concern significantly impact engagement in energy-saving behaviors. Conversely, individuals who prioritize tradition and customs or who believe that governments will take sufficient action are less likely to adopt proactive measures. These findings highlight the role of value-driven motivations in shaping sustainable behaviors, emphasizing the need for tailored policy interventions aligned with individuals' core values to promote energy conservation.

Received: January, 2025
1st Revision: October, 2025
Accepted: December, 2025

DOI: 10.14254/2071-8330.2025/18-4/14

Keywords: climate change, energy-saving behaviors, personal values, pro-environmental behavior, policy interventions

JEL Classification: Q54, Q41, Q48, D64, D91

1. INTRODUCTION

Climate change represents one of the most urgent and complex challenges, demanding immediate and sustained action at both the collective and individual levels. As global temperatures rise and extreme weather events become more frequent, the need for effective strategies to reduce energy consumption—a major contributor to greenhouse gas emissions—has never been greater. While systemic changes and policy interventions are essential, individual behavior plays a pivotal role in achieving meaningful reductions in energy use. Understanding the psychological drivers behind energy-saving behaviors, particularly the influence of personal values, is critical for designing targeted and effective interventions to promote sustainability.

Recent advancements in environmental psychology and behavioral science have underscored the significance of personal values as predictors of pro-environmental actions. Values such as concern for nature, social responsibility, and adherence to traditions shape attitudes and behaviors toward energy conservation (Bouman et al., 2021; Czyżewska et al., 2025). However, the relative importance of these values and their interactions remains understudied, particularly in diverse cultural contexts. Traditional statistical approaches have provided foundational insights, but emerging methodologies, such as machine learning, offer unprecedented opportunities to uncover complex, non-linear relationships between values and behaviors (Stern et al., 2023).

The climate crisis has brought renewed attention to the forecasting of energy security (Kharazishvili et al., 2025; Vasylieva et al., 2025), energy consumption (Kontautienė et al., 2024; Sutthichaimethee et al., 2024; Tomczyk et al., 2025), and the psychological drivers of sustainable behaviors, particularly in the domain of energy conservation. Building on Schwartz's refined theory of basic human values (Primc et al., 2021), current research demonstrates that self-transcendence values - particularly biospheric and altruistic concerns - consistently emerge as the strongest predictors of energy conservation behaviors. A meta-analysis by Bouman and colleagues (2021) found that biospheric values had medium-to-large effect sizes ($\beta = 0.38$–0.42) in predicting both intentions and actual energy-saving behaviors across 27 countries. However, the relationship between values and behavior is moderated by contextual factors. For instance, urban residents with strong biospheric values show greater energy conservation than their rural counterparts, likely due to differences in infrastructure and social norms (Ding et al., 2017).

The role of social identity and cultural values has gained increasing attention in recent literature. Studies employing cross-cultural designs reveal that collectivist values in Asian societies can either inhibit or promote energy conservation depending on whether sustainability behaviors are framed as individual or collective responsibilities (Chan et al., 2022; Fung et al., 2024; Piwowarski, 2024). In European contexts, research demonstrates that emotional attachment to regional identity (e.g., European identity) significantly predicts engagement in energy-saving behaviors, particularly when mediated by perceptions of collective efficacy (Czibere et al., 2020). This aligns with broader findings that group identification processes can amplify the impact of personal values on environmental actions (Hornung, 2022). Recent methodological innovations have advanced the understanding of value-behavior relationships. Machine learning approaches have revealed non-linear interactions between values that traditional regression analyses typically miss (Xu et al., 2024; Avcı et al., 2023). Emerging research directions suggest promising avenues for future investigation. Experimental studies testing value-based framing interventions show particular potential (Karimi et al., 2025). As the field moves forward, researchers emphasize the need for greater collaboration between psychologists, policymakers, and technology developers to translate theoretical insights into practical solutions (Bouman et al., 2023).

This study builds on contemporary research by employing the Portrait Values Questionnaire (PVQ) and advanced machine learning techniques, Random Forest (RF) and Support Vector Machine (SVM), to analyze how personal values influence energy-saving behaviors. By leveraging large-scale survey data, we quantify the predictive power of values such as emotional attachment to cultural identity, personal responsibility for climate mitigation, and trust in governmental action. Our approach not only identifies key drivers of sustainable behavior but also highlights potential barriers, such as strong traditionalism or over-reliance on systemic solutions. The findings of this study contribute to a growing body of literature that integrates psychological theory with data-driven methodologies to address climate change.

In the following sections, we detail our methodology, present the results of our machine learning analyses, and discuss the implications for theory and practice.

2. DATA DESCRIPTION

This study investigates the influence of personal values on energy-saving behaviors, utilizing the Portrait Values Questionnaire (PVQ) to assess the motivational goals that guide individuals' attitudes and actions towards climate change mitigation. PVQ is a psychometric instrument developed by Shalom Schwartz to operationalize his theory of basic human values. The PVQ is a well-validated and widely used tool designed to assess individuals' value priorities by capturing their endorsement of various motivational goals, including but not limited to creativity, achievement, security, and conformity. Respondents evaluate their level of identification with value-laden descriptive statements, typically using a Likert-type scale to indicate the perceived importance of each dimension. This methodological approach ensures systematic and quantifiable measurement of personal values, facilitating cross-cultural and comparative analyses in social psychology and related disciplines.

Providing demographic information about respondents is essential for describing the characteristics of the sample in social and behavioral research. Table 1 presents the gender-wise distribution of respondents, while Table 2 shows the distribution according to age.

Table 1

Gender-wise distribution of respondents

Gender	N	%
Male	10271	46.3%
Female	11919	53.7%

Source: own calculation

Table 2

Age-wise distribution of respondents

N	Minimum	Maximum	Mean	Std. Deviation
22039	15	90	51.88	18.728

Source: own calculation

Table 3 provides a detailed description of the variables employed in the study. This table includes variable codes, descriptions, ranges of possible values, and the semantic interpretation of each variable. The variables incorporated in the research represent key factors contributing to the explanation of variance in the "Perceived efficacy of large-scale energy reduction, (PLE), the target variable, reflecting individuals' beliefs that large-scale energy consumption reduction can mitigate climate change. The concern for nature and the environment (CNE) variable measures the degree of individuals' concerns for ecological preservation, which is positively associated with their valuation of energy reduction as a critical response to climate change. The importance of following traditions and customs (FTC) variable reflects the extent to which individuals adhere to established customs. This factor may influence their receptiveness to modern environmental solutions and willingness to modify energy-intensive lifestyles. The humanitarian and well-being orientation (HWB) assesses the importance individuals place on assisting others and prioritizing collective welfare, which may foster environmentally responsible behaviors as an extension of societal responsibility. Conversely, preference for autonomous decision-making (MDF) captures individuals' inclinations toward independent decision-making, potentially shaping their adoption of voluntary environmental practices without reliance on regulatory policies or social pressure.

The worry about climate change (WCC) indicator quantifies the concern regarding climate change, as heightened environmental anxiety is often correlated with a stronger belief in energy conservation as a mechanism to mitigate climatic shifts. Furthermore, perceived personal responsibility for climate mitigation (PRC) measures individuals' sense of personal obligation to mitigate climate change, a factor that shapes their propensity to engage in energy conservation efforts. Perceived likelihood of population-wide energy reduction (LPE) reflects individuals' belief that large population segments will adopt energy-saving practices, serving as an indicator of their perceived feasibility of societal-level change. Government action confidence (GAC) assesses trust in the government's capacity to implement effective climate policies, which may influence individuals' reliance on public regulations as mechanisms for reducing energy consumption. Lastly, affiliation with European identity (AUE) gauges emotional or ideological ties to Europe, a factor that may moderate attitudes toward European environmental policies and their alignment with energy reduction objectives.

Table 3

Variables and descriptions

Variable Code	Description	Scale (Values)	Encoding Meaning
PLE	Likelihood that large-scale energy reduction will reduce climate change	0 (Very Unlikely) - 9 (Very Likely)	Higher values indicate stronger belief in energy reduction’s impact on climate change
CNE	Importance of caring for nature and the environment	0 (Not Important) - 9 (Very Important)	Higher values indicate stronger environmental concern
FTC	Importance of following traditions and customs	0 (Not Important) - 9 (Very Important)	Higher values indicate stronger attachment to traditions
HWB	Importance of helping people and caring for their well-being	0 (Not Important) - 9 (Very Important)	Higher values indicate stronger social concern
MDF	Importance of making own decisions and being free	0 (Not Important) - 9 (Very Important)	Higher values indicate stronger preference for independence
WCC	Level of worry about climate change	0 (Not Worried) - 9 (Extremely Worried)	Higher values indicate greater concern about climate change
PRC	Extent to which one feels personal responsibility to reduce climate change	0 (Not at all) - 9 (Completely)	Higher values indicate a stronger sense of personal responsibility
LPE	Likelihood that large groups of people will reduce energy use	0 (Very Unlikely) - 9 (Very Likely)	Higher values indicate greater belief in collective energy reduction
GAC	Likelihood that governments in enough countries will take action	0 (Very Unlikely) - 9 (Very Likely)	Higher values indicate greater trust in governmental action
AUE	Emotional attachment to Europe	0 (Not Attached) - 9 (Very Attached)	Higher values indicate stronger emotional connection to Europe

Source: own compilation

The descriptive indicators in Table 4 reflect the statistical characteristics of each variable, providing a deeper understanding of data distribution and variability. For PLE, the target variable measuring individuals' belief that large-scale energy reduction can mitigate climate change, the mean is 4.83 with a standard deviation of 1.88, indicating relative variation among individuals in their assessment of this effect. The value range spans from 0 to 9, with a clear concentration around mid-range values. CNE, reflecting the importance of caring for nature and the environment, has a relatively low mean of 3.62 and a standard deviation of 1.24. For FTC, which measures the importance of following traditions and customs, the mean is 4.36 with a standard deviation of 1.44. HWB, representing concern for helping others and social well-being, has a mean of 3.63, reflecting the varying importance of this factor among individuals, with values ranging from 0 to 9. MDF, measuring the importance of personal freedom and autonomy in decision-making, follows a similar pattern with a mean of 3.51 and a standard deviation of 1.92, indicating variation in individual attitudes toward this factor. WCC, expressing the level of concern about climate change, has a mean of 3.27 with a relatively low standard deviation of 1.01, suggesting data clustering around mid-range values, reflecting a general trend of moderate climate concern. On the other hand, PRC, measuring individuals' sense of responsibility toward reducing climate change, has a relatively high mean of 7.59 with a standard deviation of 1.87, reflecting a wide spread of values, where a large group of individuals feel a strong environmental responsibility. LPE, assessing individuals' belief that large groups will reduce energy consumption, has a mean of 5.18 with a standard deviation of 1.37, indicating a relatively homogeneous distribution around the mid-range value. Similarly, GAC, measuring trust in governments' ability to take environmental action, follows a comparable statistical pattern with a mean of 5.15 and a standard deviation of 1.42, suggesting limited variation in opinions on this aspect. Finally, AUE, reflecting emotional attachment to Europe, has a mean of 7.04 and a standard deviation of 8.62, indicating a wide distribution of values that points to significant cultural differences in emotional ties to Europe among participants.

Table 4

Statistical summary of data

Variable	Count	Mean	Std Dev	Min	25%	Median (50%)	75%	Max
PLE	22190.00	4.83	1.88	0.00	3.00	6.00	6.00	9.00
CNE	22190.00	3.62	1.24	1.00	1.00	2.00	3.00	9.00
FTC	22190.00	4.36	1.44	1.00	2.00	3.00	4.00	9.00
HWB	22190.00	3.63	1.19	1.00	1.00	2.00	3.00	9.00
MDF	22190.00	3.51	1.92	1.00	1.00	2.00	3.00	9.00
WCC	22190.00	3.27	1.01	1.00	3.00	3.00	4.00	9.00
PRC	22190.00	7.59	1.87	0.00	5.00	7.00	8.00	9.00
LPE	22190.00	5.18	1.37	1.00	4.00	6.00	6.00	9.00
GAC	22190.00	5.15	1.42	1.00	4.00	6.00	6.00	9.00
AUE	22190.00	7.04	8.62	0.00	5.00	7.00	8.00	9.00

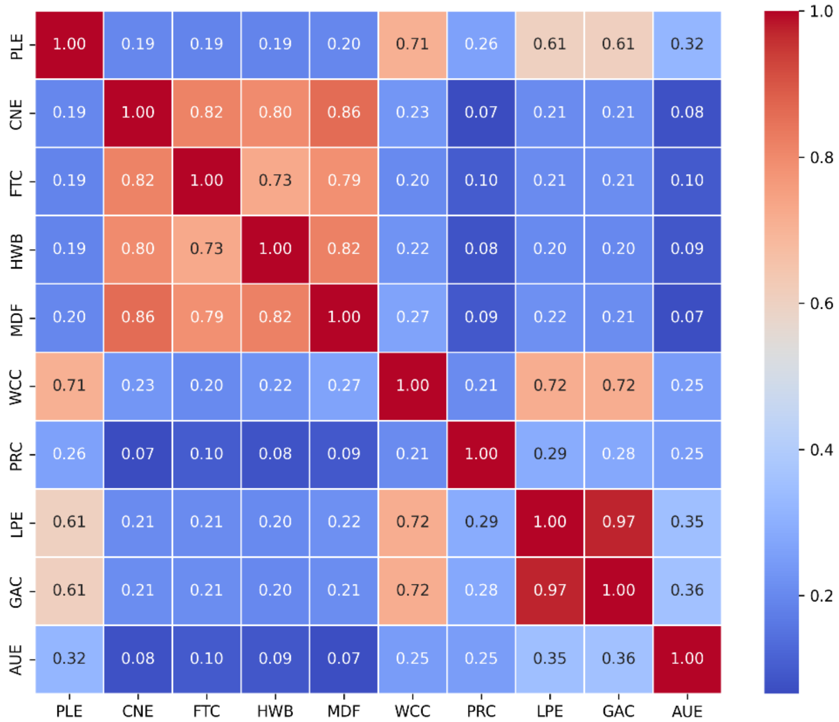
Source: own calculation

3. METHODOLOGY

The heatmap correlation matrix is employed in this study to reflect the strength and direction of relationships between variables in the study, with correlation coefficients ranging between -1 and 1, indicating the degree of linear association between each pair of variables. Thereafter, two powerful statistical models, random forest and support vector machine, are trained, and their performances are compared to find the most appropriate model to describe the relationship. The importance score of each feature in the best model is then calculated and ranked. That leads to measuring the impact of personal values on energy-saving behaviors.

Figure 1 depicts the correlation matrix of predictors and target variables. It is shown from this figure that the target variable, PLE, has a strong positive correlation with WCC (0.71), suggesting that higher levels of concern about climate change are associated with a greater belief that reducing energy consumption can mitigate climate change. Additionally, PLE exhibits moderate correlations with both LPE and GAC (0.61), indicating that individuals who believe that large groups of people will reduce energy consumption or that governments will act are more likely to endorse the idea that lowering energy use impacts climate change. On the other hand, the variables CNE, FTC, HWB, and MDF show strong intercorrelations (ranging from 0.73 to 0.86), suggesting that these personal values tend to overlap. Specifically, environmental concern (CNE) is linked with social well-being (HWB), adherence to traditions (FTC), and personal autonomy (MDF). However, their correlations with PLE are relatively weak (0.19 to 0.20), implying that while personal values may play a role in shaping beliefs about energy reduction, their influence is non-linear, likely due to variations in respondents' survey answers.

The variable PRC shows a weak correlation with PLE (0.26), indicating that personal responsibility toward climate change is not strongly linearly associated with belief in the effectiveness of energy reduction. This may suggest a need for clearer policies to bridge the gap between individual responsibility and actual climate impact. Interestingly, LPE and GAC exhibit an exceptionally high correlation (0.97), meaning that individuals who believe in society's ability to reduce energy consumption also have strong trust in governments' ability to implement environmental policies, reflecting a general trend of confidence in systemic change. Finally, AUE shows weak linear correlations with most variables, likely due to significant variation in attitudes toward climate change and energy reduction among survey respondents. However, it has moderate correlations with LPE and GAC (0.35 and 0.36, respectively), which may indicate a minor influence of cultural and geographical factors on individuals' perceptions of environmental policies.



	PLE	CNE	FTC	HWB	MDF	WCC	PRC	LPE	GAC	AUE
PLE	1.00	0.19	0.19	0.19	0.20	0.71	0.26	0.61	0.61	0.32
CNE	0.19	1.00	0.82	0.80	0.86	0.23	0.07	0.21	0.21	0.08
FTC	0.19	0.82	1.00	0.73	0.79	0.20	0.10	0.21	0.21	0.10
HWB	0.19	0.80	0.73	1.00	0.82	0.22	0.08	0.20	0.20	0.09
MDF	0.20	0.86	0.79	0.82	1.00	0.27	0.09	0.22	0.21	0.07
WCC	0.71	0.23	0.20	0.22	0.27	1.00	0.21	0.72	0.72	0.25
PRC	0.26	0.07	0.10	0.08	0.09	0.21	1.00	0.29	0.28	0.25
LPE	0.61	0.21	0.21	0.20	0.22	0.72	0.29	1.00	0.97	0.35
GAC	0.61	0.21	0.21	0.20	0.21	0.72	0.28	0.97	1.00	0.36
AUE	0.32	0.08	0.10	0.09	0.07	0.25	0.25	0.35	0.36	1.00

Figure 1. Correlation matrix of predictor and target variables

Source: own calculation

3.1. Random forest

The Random Forest (RF) is an effective machine learning technique for classification and regression. RF aggregates multiple independent decision trees to enhance prediction accuracy and reduce model variance. The core concept of this technique involves creating numerous weak learners (decision trees) and then combining their outputs to produce more stable and accurate predictions. Each tree is trained on a random subset of data through bootstrap sampling, while a random subset of features is selected at each node split. This approach enhances model diversity and mitigates overfitting issues.

The RF model is chosen in this study because it excels at handling high-dimensional data and can evaluate feature importance by assessing each variable's impact on model decisions, thereby improving interpretability. Additionally, RF effectively processes data with nonlinear relationships between variables, making it particularly suitable for analyzing complex trends that traditional linear models cannot easily represent.

The RF model is employed in this research to analyze the relationship between personal values and energy-saving behaviors. The model is trained on a comprehensive dataset, divided into training and testing subsets to ensure objective performance evaluation.

The RF regression model is calculated using a Python script and the "RandomForestRegressor" algorithm with 100 decision trees. After training the model on the training dataset through the "fit" function, its predictive performance is quantitatively assessed by computing the R^2 score for both training and testing datasets. Feature importance analysis is conducted by calculating the "feature_importances" function which provides a ranked list of variables based on their relative influence on the model's predictions. Furthermore, five-fold cross-validation is employed, via the "cross_val_score" function, to rigorously evaluate the model's stability and generalization capability. This validation approach systematically partitioned the dataset into five distinct subsets, enabling comprehensive testing of the model's performance across different data segments and ensuring robust assessment of its predictive reliability on unseen data. Table 3 details the model setup and its outcomes.

Table 5

Model training and evaluation summary

Step	Details
Data Splitting	
Independent Variables (X)	df[features]
Dependent Variable (y)	df['PLE']
Test Size	20% (test_size=0.2)
Random State	42
Training Set Size	17,752 samples
Test Set Size	4,438 samples
Model Training	
Model Type	RandomForestRegressor
Number of Estimators	100
Random State	42
Model Evaluation	
Training R^2 Score	0.9277
Test R^2 Score	0.*9186*
Cross-Validation	
Number of Folds (cv)	5
Cross-Validation R^2 Scores	[0.7657, 0.8475, 1.0000, 0.9999, 0.9999]

Source: own calculation

Table 5 presents a detailed summary of the training and evaluation of the RF model used in the study. The data are split into two sets: the training set comprising 80% of the data (17,752 samples) and the test set containing 20% (4,438 samples), with a random state value of 42 to ensure reproducibility. The RF model with 100 decision trees demonstrated strong performance on the training set, achieving an R^2 score of 0.9277, indicating that the model explains approximately 92.77% of the variance in the training data. On the test set, the R^2 value recorded 0.9186, showing that the model has good generalization capability on new data, with only a slight decrease in accuracy compared to the training set.

Five-fold cross-validation was also applied, yielding R^2 scores ranging between 0.7657 and 1, with three folds approaching perfect accuracy (1 and 0.9999). These results reflect the model's high stability and strong generalization ability across different data subsets, confirming its robustness in interpreting complex relationships between the independent variables and the dependent variable (PLE), even with the lowest fold that achieved an R^2 value of 0.7657.

These findings indicate that the EF model possesses high explanatory power and good stability, making it an effective tool for analyzing complex, multidimensional data in this research. The evaluation is conducted using a confusion matrix, and results are shown in Fig. 2.

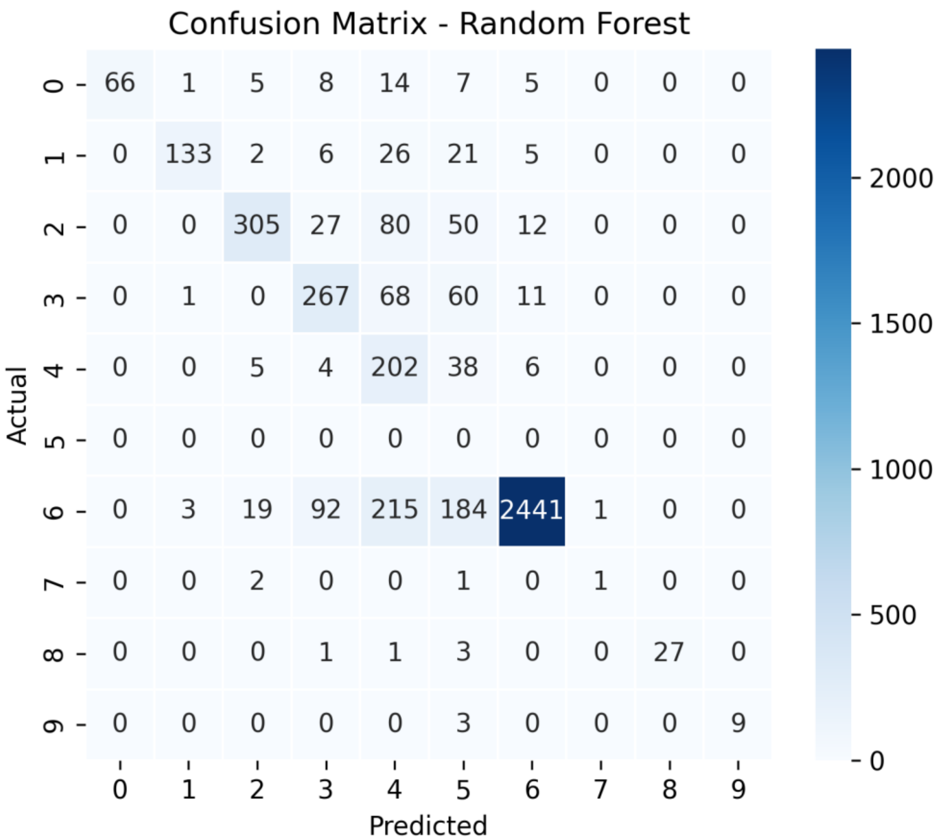


Figure 2. Confusion matrix of the random forest model
Source: own calculation

The confusion matrix of the RF model demonstrates its strong classification performance, with most diagonal values being substantially higher than off-diagonal entries. This pattern indicates that the model correctly classifies most instances across different categories. It is shown from that matrix that Class 6, which achieves 2,441 correct classifications, reflects the model's exceptional ability to distinguish this specific category. Similarly, Classes 2, 3, and 4 exhibited consistently high accuracy rates, further confirming the model's robustness in processing diverse data patterns.

While the overall performance is impressive, the matrix reveals some classification errors worth examining. Certain instances of Class 6 are misclassified as either Class 4 or 5, suggesting potential areas for improvement. These inaccuracies likely occur due to overlapping features between categories, where samples share similar characteristics that challenge clear differentiation. Additionally, some less influential features may not have been optimally weighted during model training, contributing to these occasional misclassifications.

Despite these minor limitations, the confusion matrix results strongly support the effectiveness of the RF model for this study. The high overall accuracy rates across multiple categories validate the model's reliability and suggest it is well-suited for applications requiring precise and consistent classification performance.

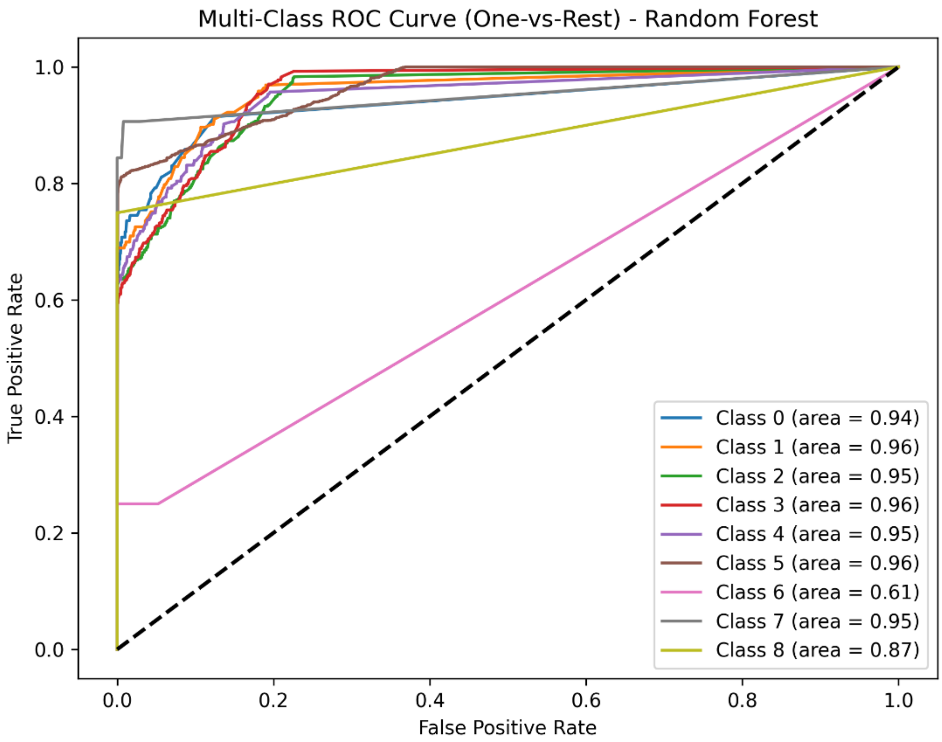


Figure 3. Multi-Class ROC Curve (One-vs-Rest) - Random Forest

Source: own compilation

Figure 3 presents the multi-class receiver operating characteristic curve (ROC) for the RF model, generated using the One-vs-Rest (OvR) approach. The ROC curve is a statistical measure used to evaluate the performance of a classification model by illustrating the relationship between the true positive rate (TPR) and the false positive rate (FPR) across different classification thresholds. The area under the curve (AUC) quantifies the model's ability to distinguish between classes, with higher values indicating better performance.

It is observed from Fig. 4 that most classes (Class 0 to Class 5 and Class 7) exhibit very high AUC values, ranging between 0.94 and 0.96. This indicates that the model excels at discriminating these classes from others. For instance, Class 1 achieves an AUC of 0.96, demonstrating the model's high precision in classifying this category with a low error rate. However, Class 6 shows a relatively lower AUC of 0.61, though still above the minimum acceptable threshold of 0.5. This suggests greater variability among the members in this class, likely due to overlapping features with other categories. Additionally, Class 8 has an AUC of 0.87, which is good but lower than other classes, reflecting more pronounced variability in the characteristics of this group.

Table 6

Model parameters and tree details

Category	Parameter	Value
General Parameters		
Bootstrap	bootstrap	True
CCP Alpha	ccp_alpha	0.0
Class Weight	class_weight	None
Criterion	criterion	gini
Random State	random_state	42
Verbose	verbose	0
Warm Start	warm_start	False
Tree Structure		
Max Depth	max_depth	None (Unlimited)
Max Features	max_features	sqrt
Max Leaf Nodes	max_leaf_nodes	None
Max Samples	max_samples	None
Min Impurity Decrease	min_impurity_decrease	0.0
Min Samples Split	min_samples_split	2
Min Samples Leaf	min_samples_leaf	1
Min Weight Fraction Leaf	min_weight_fraction_leaf	0.0
Monotonic Constraints	monotonic_cst	None
Forest Details		
Number of Trees	n_estimators	100
Number of Jobs	n_jobs	None
Out-of-Bag Score	oob_score	False
Tree Statistics		
Average Tree Depth		28.34
Max Tree Depth		34
Min Tree Depth		23
Feature Importance		
Feature Importance		True

Source: own calculation

The key parameters of the RF model implemented in this study are outlined in Table 6. The model employs bootstrap sampling (Bootstrap=True) with Gini impurity (criterion="Gini") as the splitting criterion, ensuring robust tree construction while maintaining equal class weighting (class_weight=None). It is also stated in this table that trees grow without depth restrictions (max_depth=None) and can split nodes down to single-sample leaves (min_samples_split=2, min_samples_leaf=1), allowing for maximum granularity in decision-making. Feature consideration at each split is optimized through the square root method (max_features="sqrt"), effectively reducing inter-tree correlation. The forest comprises 100 decision trees (n_estimators=100), striking a balance between predictive accuracy and computational efficiency. While out-of-bag scoring was disabled (oob_score=False) in favor of manual data splitting, the model tracks feature importance to assess variable contributions. Tree statistics reveal a mean depth of 28.34 (range: 23-34), indicating moderately complex yet varied decision structures within the ensemble.

3.2. Support vector machine

The support vector machine (SVM) is one of the most powerful machine learning algorithms used for classification and regression. It relies on margin maximization between classes to achieve high classification accuracy. The principle of this model is to find the optimal hyperplane that best separates different classes, making it particularly effective for handling high-dimensional data and non-linear patterns. To address the issue of non-linear separability, the SVM model employs kernel functions, which transform the data into a higher-dimensional space where classes become more separable. This study uses the radial basis function (RBF) kernel due to its ability to handle complex data and improve model performance. The SVM parameters are tuned to ensure optimal performance.

The regularization parameter (C) is set to balance margin maximization and error reduction. The gamma (γ) parameter is automatically determined based on the data scale. The One-vs-Rest (OVR) strategy is employed in this study for multi-class classification. The key parameters used in training and evaluating the model are summarized in Table 5.

Table 7

SVM model parameters and details

Category	Parameter	Value
General Parameters		
Regularization (C)	C	1.0
Kernel Type	kernel	rbf
Gamma	gamma	scale
Degree (Polynomial)	degree	3
Coef0	coef0	0.0
Decision Function Shape	decision_function_shape	ovr
Max Iterations	max_iter	-1 (No limit)
Tolerance	tol	0.001
Random State	random_state	42
Cache Size	cache_size	200
Shrinking	shrinking	True
Probability	probability	True
Verbose	verbose	False
Support Vectors		
Number of Support Vectors		4797
Support Vectors per Class		[236, 336, 730, 903, 624, 1842, 46, 50, 30]
Sample Support Vectors		
First 5 Support Vectors	[[2., 4., 3., 2., 4., 7., 6., 6., 7.], [2., 3., 2., 1., 4., 8., 6., 6., 5.], [2., 4., 1., 1., 4., 8., 6., 6., 2.], [3., 4., 3., 1., 2., 8., 6., 6., 5.], [3., 2., 2., 1., 1., 0., 6., 6., 2.]]	

Source: own calculation

Table 7 presents the parameters of the SVM model employed in the analysis. The regularization parameter C is set to 1.0 to balance margin maximization and classification error minimization, controlling the model's tolerance for misclassified points. The gamma parameter is configured to "scale," automatically calculated based on the number of features to determine the influence range of each data point on classification decisions. For multiclass classification, the OVR method is implemented, training individual models for each class against all others to ensure accurate classification. Training is permitted to continue indefinitely (maximum iterations = -1) until convergence, with a tolerance threshold of 0.001 to guarantee solution stability. A 200 MB cache size is allocated to optimize training speed, while the shrinking heuristic is enabled to enhance computational efficiency by eliminating inactive support vectors during the optimization process. Probability estimates are activated (probability = True) to facilitate detailed performance evaluation. The final model incorporated 4,797 support vectors distributed unevenly across classes [236, 336, 730, 903, 624, 1,842, 46, 50, 30], reflecting the dataset's inherent class imbalance. Analysis reveals that the model's decision boundaries are primarily defined by these support vectors, enabling precise classification of new data instances, particularly in scenarios involving complex data patterns. Examination of the first five support vectors demonstrates their diverse characteristics, indicating the model's capacity to process varied data structures.

A detailed summary of the SVM model training and evaluation process is presented in Table 8. The data splits into a training set (80% of samples, 17,752 instances) and a test set (20%, 4,438 instances). Features (X) are selected from the data frame using df[features], while df['PLE'] represents the dependent variable - the target classification output. A random state of 42 ensures reproducible results. The model trains using SVC with probability=True to calculate predictive probabilities, enabling detailed analysis of classification confidence. The model achieves a training accuracy of 0.8734, demonstrating strong performance on training data with low error rates. When tested on the test data, it maintains a comparable accuracy of 0.8724, indicating good generalization with minimal gap between training and test performance, suggesting no overfitting issues. Five-fold cross-validation further evaluates model performance across different data partitions, yielding accuracy scores ranging from 0.6489 to 0.9977. While performance varies across folds, the model shows overall stability with a mean cross-validation accuracy of 0.8724, matching the test accuracy and confirming reliability.

Table 8

SVM model training and evaluation summary

Step	Details
Data Splitting	
Independent Variables (X)	df[features]
Dependent Variable (y)	df['PLE']
Test Size	20% (test_size=0.2)
Random State	42
Training Set Size	17,752 samples
Test Set Size	4,438 samples
Model Training	
Model Type	SVC
Kernel	rbf
Probability	True
Random State	42
Model Evaluation	
Training Accuracy	0.8734
Test Accuracy	0.8724
Cross-Validation	
Number of Folds (cv)	5
Cross-Validation Scores	[0.6489, 0.7215, 0.9959, 0.9977, 0.9977]
Mean Accuracy	0.8724

Source: own calculation

Figure 4 displays the confusion matrix for the SVM model used to classify data into nine distinct categories, where rows represent actual class values and columns indicate model predictions. A color gradient illustrates frequency counts in each cell, with darker shades denoting higher numbers of correct classifications. Diagonal value analysis reveals the model's classification accuracy per category, showing the performance for class 5 (cell 5,5) with 2,940 correct classifications. Whereas classes 0, 1, 2, and 3 demonstrate reasonable accuracy, they exhibit some misclassifications, notably class 2, which scores 298 correct identifications but sees 176 instances erroneously classified as class 4, suggesting feature similarity between these two categories. Inter-class errors are more obvious in underrepresented categories (classes 6, 7, and 8), where limited sample sizes and potential pattern similarities lead to classification challenges, evidenced by misclassifications between classes 7 and 8. Overall, the matrix reflects good SVM performance with particularly accurate classification of dominant categories, while highlighting difficulties with minority classes due to either data scarcity or feature overlap.

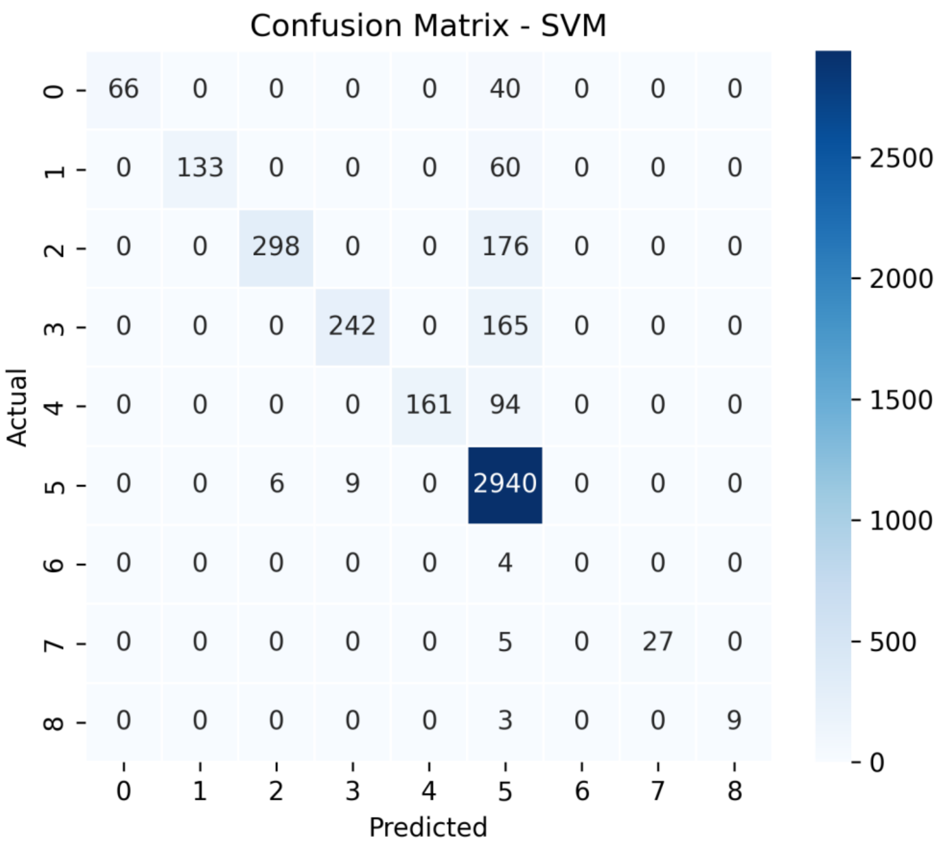


Figure 4. Confusion Matrix of the SVM Model

Source: own calculation

Figure 5 shows the multi-class ROC curves for the SVM model. The horizontal axis shows the false positive rate (FPR), while the vertical axis displays the true positive rate (TPR). Each curve represents the model's performance in distinguishing one class from other classes, with the area under the curve (AUC) reflecting the model's classification capability for that class. Higher AUC values indicate better classification performance, with classes 2, 3, and 5 demonstrating strong results (AUC = 0.93, 0.92, and 0.91, respectively), showing effective separation from other classes. Classes 0, 1, 7, and 8 also show good performance (AUC between 0.88-0.91), indicating acceptable discrimination capability.

However, class 6 shows low performance (AUC = 0.20), suggesting significant difficulty in distinguishing it from other classes, likely due to limited samples and feature similarity with neighboring classes. Class 4 shows relatively lower performance (AUC = 0.78), possibly indicating partial overlap with other classes. The mean AUC across all classes is 0.82, reflecting the model's overall classification effectiveness while highlighting specific challenges with certain categories.

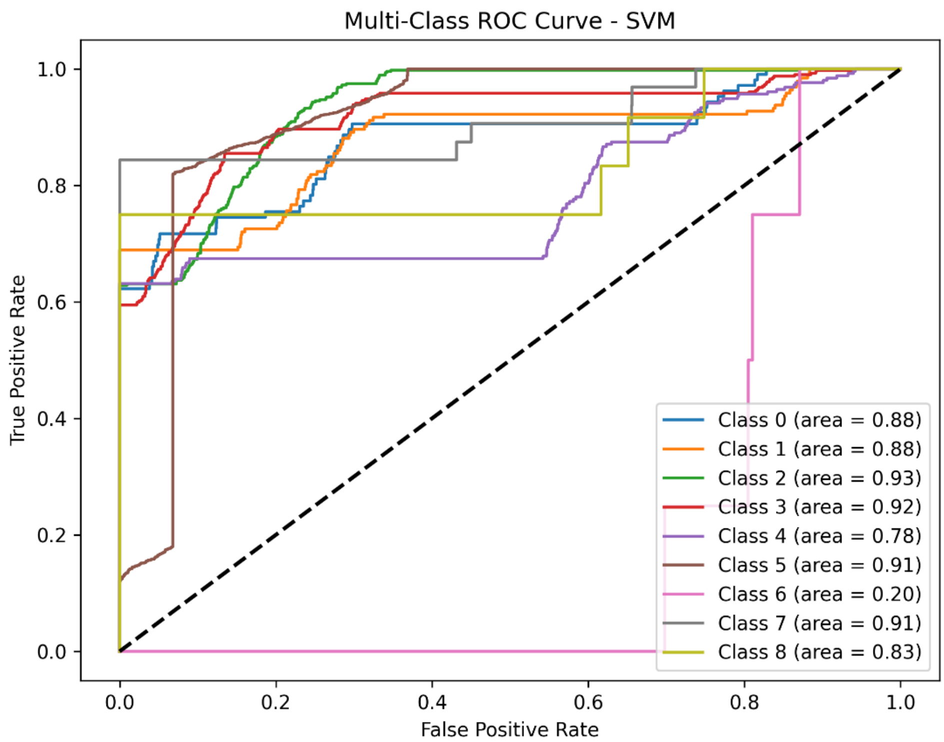


Figure 5. Multi-Class ROC Curve – SVM

Source: own compilation

3.3. Decision to choose the better model

A comprehensive comparison is conducted between RF and SVM models to determine the most effective approach for interpreting the relationship between personal values and energy-saving behaviors. The evaluation is based on rigorous statistical metrics, including the coefficient of determination (R^2), classification accuracy, cross-validation, confusion matrices, and ROC curves with AUC values.

The RF model has a superior performance in terms of R^2 values, achieving 92.77% for training data and 91.86% for test data. These results indicate good generalization capabilities to new data, with consistent performance between training and test sets. During five-fold cross-validation, R^2 values ranged from 0.7657 to 1.0000, demonstrating the model's stability and strong generalization ability. In comparison, the SVM model showed relatively high classification accuracy with 87.34% training accuracy and 87.24% test accuracy, indicating good consistency between training and testing phases. However, the SVM exhibited greater variability in cross-validation results (ranging from 0.6489 to 0.9977), suggesting higher sensitivity to data variations.

For deeper performance evaluation, confusion matrices are analyzed to assess each model's correct and incorrect classification patterns across different categories. The RF model demonstrates high accuracy for most categories, for instance, class 6, where 2.441 samples are correctly classified. Some relatively minor classification errors are observed, such as a few samples from class 6 being misclassified into classes 4 and 5, indicating limited overlap between these categories due to similar characteristics. The confusion matrix reveals that most values are concentrated along the diagonal (correct classifications), confirming the model's effective ability to distinguish between categories with high accuracy, reaching approximately 92.77%. On the other hand, the SVM model successfully classifies most categories with acceptable accuracy, yet it has difficulties with certain classes. In this model, class 2 achieves 298 correct classifications, and 176 instances are misclassified as class 4, indicating significant challenges in distinguishing between categories with similar characteristics. One more observation occurs with class 6, which has a sharp decline in performance with an AUC value of just 0.2, revealing substantial limitations in the model's ability to properly identify this class, representing a critical weakness in the classification system.

ROC curve analysis shows that the RF model achieves consistently high AUC values ranging between 0.94 and 0.96 for most classes, demonstrating its superior discriminative ability. In contrast, while the SVM model performs well overall, it shows a sharp decline in performance for class 6, with an AUC of only 0.20, highlighting a significant classification weakness.

Based on this comprehensive and detailed comparison of the two models, the RF model proves to be the most efficient and accurate. Given these findings, the RF model is selected as the primary model for this study, owing to its clear superiority in accuracy, stability, and interpretability. This makes it the optimal choice for analyzing the relationship between personal values and energy-saving behaviors in addressing the challenges of climate change.

3. RESULTS

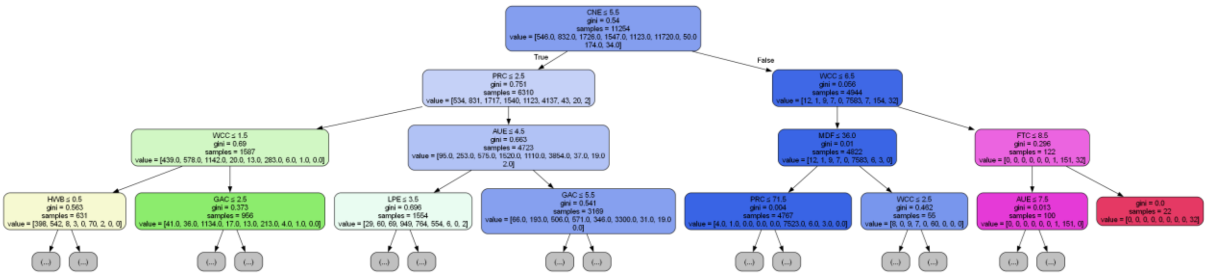


Figure 6 Simplified decision tree from the RF model

Source: own compilation

A simplified decision tree extracted from the RF model is presented in Fig. 6. It clearly illustrates the model's decision-making mechanism based on specific conditions related to independent variables. The tree begins with the root node representing the variable (CNE), where the data splits at the threshold value (5.5), with a Gini impurity index of 0.54. This initial split covers 100% of the samples, subsequently dividing them into two paths: the first (True path) containing 56.1% of samples, and the second (False path) with 43.9%.

At the second level of partitioning, the variable (PRC) is used with a threshold of 2.5, showing a higher Gini index (0.751), indicating greater sample heterogeneity within this node. The splitting continues with variables like (WCC) at threshold 1.5 (Gini=0.69, 14.1% samples) and (AUE) at threshold 4.5 (Gini=0.663, 42% samples). Meanwhile, in the second main branch (CNE > 5.5), the model uses (WCC) at threshold

(6.5) with a very low Gini index (0.056) covering 43.9% of samples, suggesting high homogeneity in this group.

Additional splits are performed using variables (MDF) at threshold 36 (Gini=0.01, 42.8% samples) and (FTC) at threshold 8.5 (Gini=0.296, 1.1% samples), with the latter showing relatively higher impurity. The tree ultimately terminates at leaf nodes representing precise final classification decisions for each sample group based on the sequential splitting process.

These results demonstrate the RF model's capability to effectively utilize relationships between variables, while highlighting quantitative criteria such as variable thresholds, impurity indices, and sample distributions.

Feature importance scores are calculated from the RF model and listed in Table 9. These results reveal significant variations in each variable's contribution to explaining energy-saving behaviors within the context of climate change. The emotional connection to Europe (AUE) emerges as the most influential variable, accounting for 18.16% of importance. This indicates that this cultural and emotional factor plays a pivotal role in shaping individuals' energy conservation attitudes, likely tied to feelings of belonging and positive engagement with European environmental policies.

Table 9

Feature Importance Scores

Rank	**Feature**	**Importance Score**
1	AUE	0.1816
2	PRC	0.1756
3	WCC	0.1113
4	MDF	0.1050
5	HWB	0.1047
6	LPE	0.0933
7	CNE	0.0800
8	FTC	0.0747
9	GAC	0.0738

Source: own compilation

Closely following is personal responsibility toward mitigating climate change (PRC) at 17.56%, highlighting the strong motivational power of individual accountability in environmental behavior. Climate change concern (WCC) ranked third (11.13%), confirming environmental anxiety as a significant driver of energy reduction commitments. In contrast, personal autonomy in decision-making (MDF) showed relatively lower influence (10.50%), suggesting that independently minded individuals exhibit moderately different environmental behaviors compared to the aforementioned factors. Similarly, concern for others and societal wellbeing (HWB) accounted for 10.47%, underscoring the relevance of social considerations in environmental decision-making, particularly when linked to collective welfare.

Belief in large groups' capacity to reduce energy consumption (LPE) and the importance of nature care (CNE) demonstrated more modest impacts at 9.33% and 8.00% respectively, functioning as secondary influences. Adherence to traditions (FTC) ranked penultimate (7.47%), reflecting its limited role in shaping environmental behavior, possibly due to potential conflicts between traditional practices and modern ecological practices. Finally, confidence in government actions (GAC) registered the lowest impact (7.38%), indicating that trust in policy measures alone proves insufficient as an independent motivator for environmental behavior compared to personal, cultural, and social factors.

These findings emphasize the critical role of personal, cultural, and social considerations in shaping energy conservation behaviors. This should be considered when future environmental policy and program design are aimed at achieving broader societal engagement in energy and climate change initiatives. The variables' relative importance is also visualized in Fig. 7.

4. COMPARISON WITH RELATED RESULTS IN THE LITERATURE

This study provides a comprehensive statistical analysis that distinguishes it from previous studies. The analysis is conducted by deploying two machine learning models, random forest and support vector machines. The current methodology has a qualitative leap forward compared to the study by Ling & Xu (2020), which relies on basic descriptive correlation analysis between personal values and environmental behaviors. While the approach used in this study employs predictive statistical models evaluated through metrics like the coefficient of determination (R^2), confusion matrices, and ROC curves with AUC measurements. Therefore, a deeper and more precise interpretation of complex relationships and non-linear interactions is achieved compared to traditional statistical methods used by Ling & Xu (2020). The findings in this study provide a statistically refined analysis of the relative importance of personal variables influencing energy-saving behaviors, enabling objective comparison with prior studies. In this context, the current study aligns with Ling & Xu (2020) in confirming personal values as determinants of environmental behavior. Both studies demonstrate that environmentally-conscious values (CNE) significantly guide ecological behaviors. However, our analysis reveals a statistical difference because CNE showed moderate importance (8%) compared to emotional connection to Europe (AUE) which emerged as most influential (18.16%), followed closely by personal responsibility (PRC) at 17.56%. This nuanced quantification of variable impacts represents a methodological advancement beyond the level of statistical precision achieved in Ling & Xu's earlier work.

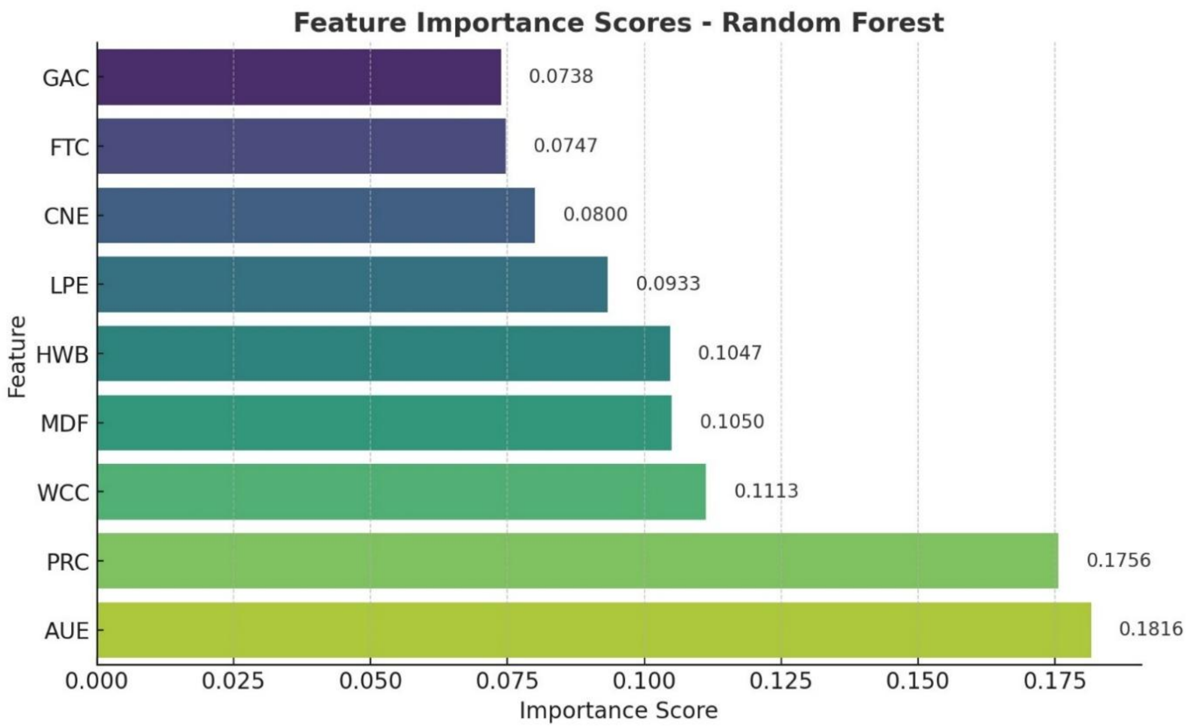


Figure 7. Feature importance scores - random forest

Source: own compilation

Furthermore, when compared to the study by Dias et al. (2020), which primarily focuses on assessing linear correlations between climate change anxiety and personal values using conventional correlation analyses, the current study demonstrates clear statistical superiority. The F model achieves notably high coefficients of determination (R^2 = 0.9277 for training and 0.9186 for testing), while providing deeper evaluation through variable importance analysis and rigorous five-fold cross-validation that is methodologically absent in Dias et al.'s (2020) approach. Both studies examined motivational values and climate change attitudes, and both observe the significance of climate change worry (WCC). However, our study delivers a more precise quantitative assessment, demonstrating that WCC's influence is relatively strong (11.13%). This supports Dias et al.'s (2020) conclusions about environmental anxiety's central role in shaping ecological behaviors, while statistically differentiating itself through revealing WCC's relative positioning compared to higher-ranking factors like PRC (17.56%) and AUE (18.16%) that Dias et al.'s methodology could not capture.

Furthermore, the current study demonstrates significant statistical advantages over Wan Hussain et al.'s (2021) work, which employed basic questionnaires and linear correlation analysis to examine environmental behaviors. In contrast, our research provides more sophisticated quantitative measurements through a confusion matrix that reveals the RF model's classification accuracy exceeding 92%, along with ROC curve analysis showing high AUC values. This represents a substantially deeper level of statistical analysis than achieved in the earlier study. While Wan Hussain et al. could only identify general behavioral patterns through simple correlations, our machine learning approach enables precise evaluation of classification performance for specific behavioral categories. The AUC values between 0.94-0.96 for most classes demonstrate our model's superior ability to distinguish between different types of energy-saving behaviors. Similarly, when compared to Wan Hussain et al. (2021), which examined the impact of environmental values among students, the current study concurs with their emphasis on the importance of environmental and social values like HWB. However, our analysis provides statistically more precise estimates of these values' influence, revealing that HWB accounted for only 10.47% of relative importance, indicating a moderate effect compared to more influential factors such as personal responsibility (PRC at 17.56%). This discrepancy demonstrates the superior capability of our RF approach in generating more accurate assessments of relative variable importance.

Similarly, when comparing this study's findings with Gregersen et al. (2021), it is observed that both have the significance of climate change anxiety (WCC). However, our study provides statistical evidence that this factor's influence is relatively moderate (11.13%) compared to stronger impacts from personal values and individual responsibility. Our approach reveals that while climate anxiety remains important, it is statistically outweighed by personal responsibility measures (PRC at 17.56%) and cultural affiliation (AUE at 18.16%). On the other hand, Gregersen et al.'s (2021) study employs a simple linear regression model to examine the relationship between environmental anxiety and conservation behavior, while our study offers significantly greater statistical depth and sophistication.

The impact of external variables (including COVID-19) on environmental behaviors is studied by Alomari et al. (2023) using basic descriptive statistics. Nevertheless, our approach incorporates rigorous cross-validation techniques that systematically evaluate the stability of our RF model, which achieved exceptional performance with high R^2 values (exceeding 0.9186 on test data). This level of analytical sophistication and model reliability is unattainable in Alomari et al.'s more elementary statistical framework. Moreover, Alomari et al. (2023)'s study focuses on external variables like COVID-19 impacts, while the current study demonstrates the statistical dominance of personal and cultural factors (AUE at 18.16% and PRC at 17.56% importance). This key difference highlights our methodology's strength in precisely quantifying the relative influence of personal determinants, and that is a dimension absent in Alomari et al.'s analysis.

In contrast to Negi's (2024) study, which employs virtual reality technology to promote environmental behaviors and lacks advanced predictive models or in-depth quantitative statistical evaluations, the current study establishes a robust statistical framework for precise model comparisons. Our research provides clear quantitative benchmarks through comprehensive performance metrics, including AUC values and confusion matrices demonstrating classification accuracy exceeding 90%, representing a significant methodological advancement over Negi's (2024) approach. When compared to studies using only RF models, our dual-model comparison (RF and SVM) with cross-validation offers several unique advantages. While the current research aligns with Negi (2024) in emphasizing the crucial role of personal and cultural values in promoting environmental behaviors, it offers distinct statistical advantages through precise variable importance ranking. Our analysis quantitatively identifies emotional connection to Europe (AUE) as the most influential factor (18.16%), closely followed by personal responsibility (PRC) at 17.56%, and those granular insights are not provided in Negi's VR-based approach.

Other studies in the literature also employed RF models (Castronuovo et al., 2023; Iqbal et al., 2024). However, the current research demonstrates clear methodological superiority through its dual-model analytical approach (RF and SVM). This innovative framework enabled direct performance comparisons, revealing that RF exhibited greater stability in cross-validation tests (scores ranging 0.7657-1.0000) compared to SVM's more variable performance (0.6489-0.9977). The current study also demonstrates significant methodological advances over previous RF applications in environmental behavior research by providing precise quantification of relative variable importance across personal, cultural, and social values.

Similarly, this study demonstrates significant statistical superiority over previous comparative analyses of RF and SVM performance (Avcı et al., 2023; Balogun & Tella, 2022) through its implementation of more rigorous evaluation metrics. Our methodological framework incorporates superior predictive accuracy, exceeding 92% classification rates, higher coefficient of determination values, R^2 up to 0.9277, and sophisticated ROC/AUC analyses. This study differs significantly from Avcı et al. (2023)'s machine learning comparison by providing unprecedented depth in variable importance analysis.

Finally, when compared to studies like Li & Yuan (2024) and Vojdani Fakhr et al. (2024), the current study stands out by providing precise quantitative analysis of variable importance and impact. While these previous studies focused primarily on direct behavioral effects, our research delves deeper into a detailed statistical examination of personal and social value variables.

5. CONCLUSION AND FUTURE WORK

This study examined the role of personal values in shaping energy-saving behaviors using advanced machine learning approaches. The analysis revealed that emotional attachment to Europe, personal responsibility for climate change mitigation, and concern about climate change were the strongest predictors of proactive energy conservation behaviors. In contrast, strong adherence to traditions and high confidence in government action were associated with lower engagement in energy-saving measures. The RF model demonstrated superior performance compared to the SVM, achieving high predictive accuracy and robust classification across most behavioral categories. The feature importance analysis provided novel insights by quantifying the relative influence of different personal values, with cultural identity and individual responsibility emerging as more significant than environmental concern alone. These findings advance our understanding of the psychological drivers behind sustainable behaviors while highlighting the limitations of approaches that rely solely on systemic or policy-based solutions. The study's methodological innovations, particularly in applying machine learning to value-behavior relationships, offer a template for future research in environmental psychology and behavioral science.

Several promising directions emerge from this research. First, expanding the study's cultural and geographic scope could test whether the observed value-behavior relationships hold across different regions and national contexts. Longitudinal designs tracking how value systems evolve and influence behavior over time would provide deeper causal insights. Incorporating objective behavioral measures, rather than relying solely on self-reports, would strengthen the validity of findings. Methodologically, future studies could enhance model interpretability through techniques like SHAP values and explore hybrid modeling approaches to capture complex value-behavior interactions better. These future directions would collectively advance both theoretical understanding and practical applications of value-based approaches to promoting sustainable behaviors.

REFERENCES

Alomari, M. M., Hania, E. K., Topal, A., & Alshdaifat, N. I. (2023). Exploring the impact of the COVID-19 pandemic on energy literacy and conservation behavior in academic buildings of Kuwait. *Heliyon, 9*(11).

Avcı, C., Budak, M., Yağmur, N., & Balçık, F. (2023). Comparison between random forest and support vector machine algorithms for LULC classification. *International Journal of Engineering and Geosciences, 8*(1), 1–10.

Balogun, A. L., & Tella, A. (2022). Modelling and investigating the impacts of climatic variables on ozone concentration in Malaysia using correlation analysis with random forest, decision tree regression, linear regression, and support vector regression. *Chemosphere, 299*, 134250.

Bouman, T., Steg, L., & Dietz, T. (2021). Values versus environmental knowledge as triggers of a process of activation of personal norms for eco-driving. *Nature Human Behaviour, 5*(8), 1058–1065.

Bouman, Thijs, Linda Steg, & Goda Perlaviciute. (2021). From values to climate action. *Current Opinion in Psychology, 42*, 102–107.

Castronuovo, G., Favia, G., Telesca, V., & Vammacigno, A. (2023). Analyzing the interactions between environmental parameters and cardiovascular diseases using random forest and SHAP algorithms. *Reviews in Cardiovascular Medicine, 24*(11), 330.

Chan, H.-W., Udall, A. M., & Tam, K.-P. (2022). Effects of perceived social norms on support for renewable energy transition: Moderation by national culture and environmental risks. *Journal of Environmental Psychology, 79*, 101750.

Czyżewska, M., Szczygieł, E., Papathanasiou, J., & Tsaples, G. (2025). Youth knowledge, attitudes, and SRI intentions: Evidence from Poland and Greece. *Journal of International Studies, 18*(3), 87–107. https://doi.org/10.14254/2071-8330.2025/18-3/5

Czibere, I., Kovách, I., & Megyesi, G. B. (2020). Environmental citizenship and energy efficiency in four European countries (Italy, The Netherlands, Switzerland and Hungary). *Sustainability, 12*(3), 1154.

Dias, N. M. O. C., Vidal, D. G., Sousa, H. F. P. E., Dinis, M. A. P., & Leite, Â. (2020). Exploring associations between attitudes towards climate change and motivational human values. *Climate, 8*(11), 135.

Ding, Z., et al. (2017). Research on differences in the factors influencing the energy-saving behavior of urban and rural residents in China – A case study of Jiangsu Province. *Energy Policy, 100*, 252–259.

Fung, K. C., Cheung, K. Y., Lai, C. Y., & Pang, L. L. L. (2024). The impacts of attitude, knowledge, and belief on carbon neutrality: Evidence from Hong Kong. *Economics and Sociology, 17*(3), 62–81. https://doi.org/10.14254/2071-789X.2024/17-3/4

Gregersen, T., Doran, R., Böhm, G., & Poortinga, W. (2021). Outcome expectancies moderate the association between worry about climate change and personal energy-saving behaviors. *PLoS One, 16*(5), e0252105.

Hornung, J. (2022). Social identities in climate action. *Climate Action, 1*(1), 1–12.

Iqbal, N., Shahzad, M. U., Sherif, E. S. M., Tariq, M. U., Rashid, J., Le, T. V., & Ghani, A. (2024). Analysis of wheat-yield prediction using machine learning models under climate change scenarios. *Sustainability, 16*(16), 6976.

Karimi-Malekabadi, F., Sachdeva, S., & Dehghani, M. (2025). A value-based topography of climate change beliefs and behaviors. *PNAS Nexus, 4*(2), pgae590.

Kharazishvili, Y., Bilan, Y., Sukhodolia, O., Grishnova, O., & Mishchuk, H. (2025). Scientific and strategic foresighting: The trajectory of sustainable development (on the example of Ukraine's energy security). *Sustainable Futures, 9*, 100580. https://doi.org/10.1016/j.sftr.2025.100580

Kontautienė, R., Stravinskas, T., & Barkauskas, V. (2024). Forecasts of sustainable consumption in small economies. *Journal of International Studies, 17*(2), 9–37. https://doi.org/10.14254/2071-8330.2024/17-2/1

Li, L., & Yuan, X. (2024). The influence of energy-saving information in online reviews on green home appliance purchase behavior based on machine learning. *Energy and Buildings, 314*, 114296.

Ling, M., & Xu, L. (2020). Relationships between personal values, micro-contextual factors and residents' pro-environmental behaviors: An explorative study. *Resources, Conservation and Recycling, 156*, 104697.

Negi, S. K. (2024). Exploring the impact of virtual reality and augmented reality technologies in sustainability education on green energy and sustainability behavioral change: A qualitative analysis. *Procedia Computer Science, 236*, 550–557.

Piwowarski, B. (2024). Increasing energy awareness through effective advertising messages – a neurophysiological approach to engagement study. *Human Technology, 20*(3), 676–700. https://doi.org/10.14254/1795-6889.2024.20-3.12

Primc, K., et al. (2021). How does Schwartz's theory of human values affect the proenvironmental behavior model? *Baltic Journal of Management, 16*(2), 276–297.

Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (2023). A value-belief-norm theory of support for social movements: The case of environmentalism. *Human Ecology Review, 29*(1), 81–97.

Sutthichaimethee, P., Mentel, G., Voloshyn, V., Mishchuk, H., & Bilan, Y. (2024). Modeling the efficiency of resource consumption management in construction under sustainability policy: Enriching the DSEM-ARIMA model. *Sustainability, 16*(24), 10945. https://doi.org/10.3390/su162410945

Tomczyk, A., Wojciechowski, W., Walczak, J., Lipiński, P., Wosiak, A., Morawski, M., & Napieralski, P. (2025). Operational HVAC energy load prediction: Edge-oriented forecasting models. *Human Technology, 21*(2), 431–447. https://doi.org/10.14254/1795-6889.2025.21-2.10

Vasylieva, T., Derkacz, A., Popp, J., & Horsch, A. (2025). From energy dependency to energy security: How the war in Ukraine accelerated renewable deployment in Europe. *Economics and Sociology, 18*(3), 229–253. https://doi.org/10.14254/2071-789X.2025/18-3/13

Vojdani Fakhr, B., Yegane, M., & Walzberg, J. (n.d.). Exploring attitudes and behavioral patterns in residential energy consumption: A machine learning approach. *Available at SSRN 4580743.*

Wan Hussain, W. N. H., Halim, L., Chan, M. Y., & Abd Rahman, N. (2021). Predicting energy-saving behaviour based on environmental values: An analysis of school children's perspectives. *Sustainability, 13*(14), 7644.

Xu, W., et al. (2024). Predicting daily heating energy consumption in residential buildings through integration of random forest model and meta-heuristic algorithms. *Energy, 301*, 131726.