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Examining Individual Tax Morale in Europe with Machine-Learning Methods

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ABSTRACT

Purpose: This research examines and contributes to the behavioural literature on voluntary tax compliance. It focuses on the use and potential of machine-learning (ML) methods and models to predict individual tax morale across Europe, and it identifies the factors that influence predictive accuracy.

Design/Methodology/Approach: Using data from the fifth wave (2017–2020) of the European Values Survey (EVS), a data-driven, systematic approach employing six ML methods is applied to predict individual tax morale across Europe. The importance of formal, informal and socio-demographic factors is assessed, and the study tests whether incorporating the Corruption Perception Index (CPI) improves predictive accuracy.

Findings: The results indicate that ML methods and models can enhance understanding and prediction of individual tax morale in Europe. Among the deployed models, artificial neural networks (ANNs) achieved the highest accuracy. Accuracy increased across all ML methods when the CPI was included. Attitudes towards bribery, perceptions of immigrants' impact on the national welfare system, and gender emerged as significant formal, informal and socio-demographic factors.

Academic contribution to the field: The study offers a novel application of data-driven ML methods to the prediction of individual tax morale. Given the scarcity of empirical ML research in the social sciences, the findings provide valuable insights in a European context and may serve as a basis for further global research.

Practical Implications: The conclusions are particularly relevant for governments and tax administrations seeking to improve tax compliance and revenue collection. In the European context, the results confirm the virtuous circle linking effective government performance, high tax morale and voluntary tax compliance—insights that are crucial for decision-makers, regulators, European institutions and tax-policy makers.

Originality/Value: The findings confirm that, when ML methods are applied, individual tax morale can be viewed as an outcome of interactions between formal and informal institutions. They also show that predictive accuracy is higher in countries with lower corruption, as indicated by a higher CPI.

Keywords: *corruption, EVS, individual tax morale, machine learning*

Preučevanje individualne davčne morale v Evropi z metodami strojnega učenja

POVZETEK

Namen: Raziskava proučuje in nadgrajuje vedenjsko literaturo o prostovoljnem izpolnjevanju davčnih obveznosti. Osredotoča se na uporabo in potencial metod ter modelov strojnega učenja za napoved individualne davčne morale po Evropi ter opredeljuje dejavnike, ki vplivajo na napovedno natančnost.

Zasnova/metodologija/pristop: Na podlagi podatkov petega vala (2017–2020) Evropske raziskave vrednot (EVS) je bil uporabljen podatkovno voden, sistematičen pristop, ki vključuje šest metod strojnega učenja za napovedovanje individualne davčne morale v Evropi. Ocenjena je bila pomembnost formalnih, neformalnih in soci-demografskih dejavnikov, hkrati pa je študija preverila, ali vključitev Indeksa zaznave korupcije (*Corruption Perception Index* – CPI) poveča napovedno natančnost.

Ugotovitve: Rezultati kažejo, da lahko metode in modeli strojnega učenja izboljšajo razumevanje ter napovedovanje individualne davčne morale v Evropi. Med uporabljenimi modeli so umetne nevronske mreže dosegle najvišjo natančnost. Pri vseh metodah strojnega učenja se je natančnost povečala, ko je bil v model vključen CPI. Odnos do podkupovanja, zaznave vpliva priseljencev na nacionalni socialni sistem in spol so se izkazali za pomembne formalne, neformalne in soci-demografske dejavnike.

Akademski prispevek k področju: Študija je nov, podatkovno usmerjen pristop uporabe metod strojnega učenja za napovedovanje individualne davčne morale. Zaradi redkosti empiričnih raziskav strojnega učenja v družboslovju ugotovitve ponujajo dragocene vpoglede v evropskem kontekstu in so lahko temelj za nadaljnje globalne raziskave.

Praktična uporabnost: Sklepi so posebej pomembni za vlade in davčne uprave, ki želijo izboljšati davčno skladnost in stopnjo pobiranja prihodkov. V evropskem kontekstu rezultati potrjujejo krog pozitivnih povratnih zank, ki povezuje učinkovito delovanje vlade, visoko davčno moralo in prostovoljno izpolnjevanje davčnih obveznosti. Gre za spoznanja, ki so ključna za odločevalce, regulatorje, evropske institucije in oblikovalce davčne politike.

Izvirnost/vrednost: Ugotovitve potrjujejo, da lahko pri uporabi metod strojnega učenja individualno davčno moralo obravnavamo kot rezultat interakcij med formalnimi in neformalnimi institucijami. Prav tako kažejo, da je napovedna natančnost večja v državah z nižjo stopnjo korupcije, kar se kaže v višjem CPI.

Ključne besede: *korupcija, EVS, individualna davčna morala, strojno učenje*

JEL: H26

1 Introduction

In recent years there has been a growing academic interest into investigation of values, attitudes and social norms as possible explanations to human and economic behaviour, particularly within the extensive body of tax compliance literature (Alm and Torgler, 2007, p. 1). Even though some research into tax morale has been conducted in the late 1960s by Strümpel (1969) and Schmölders (1970; Alm and Torgler, 2007, p. 4), the empirical investigation of the tax morale concept began with the World Values Survey and the European Values Survey (WVS and EVS respectively) in the 1980s. Hence, the article wishes to contribute towards the understanding of human and economic behaviour in the investigation of individual tax morale across Europe by applying ML methods and models for the first time.

In academic literature and empirical research, several terms are closely associated with the concept of tax morale, including tax evasion and tax compliance. In theory, the social psychology has set the question about the relationship between tax evasion and tax morale (Lewis, 1982, p. 165), while empirical studies have provided strong evidence of a negative correlation between tax morale and both – tax evasion and – the size of the shadow economy (Torgler, 2005, p. 135; Sá et al, 2013, p. 1). Empirical studies have mostly relied on either WVS or EVS datasets. Furthermore, authors have investigated the concepts of tax morale and tax evasion separately, whereby tax evasion has been the subject of more than 40 years of academic research, including studies on tax evasion games (Alm and Malézieux, 2021, p. 699). In the context of the European Union (EU) and its member states, research on tax evasion has been growing, especially in relation to the size of the shadow economy (Schneider, Raczkowski and Mróz, 2015, p. 34) and an estimation of substantial loss of tax revenues due to Value Added Tax (VAT) frauds (Dobrovič, Rajnoha, and Šuleř, 2021, p. 705). In addition, significant differences exist among EU member states, with newer members (those that joined post-2004) experiencing higher levels of tax evasion compared to older member states (Yamen et al., 2018, p. 26; Dobrovič, Rajnoha, and Šuleř, 2021, p. 705). For example, in 2019, the EU average share of tax evasion expressed as a share of total tax liability amounted to 20 percent, with great differences among the EU member states (e.g. tax evasion in Sweden as an old EU member amounted to only 2% and Romania as a new EU member to 49% (Dobrovič, Rajnoha and Šuleř, 2021, p. 722)). Due to the negative consequences of tax evasion on public revenues and the tax system equity (Sá et al, 2013, p. 1), the EU institutions are actively engaged in researching and prevention of tax evasion, but also on methods and ways to increase tax morale. For instance, the EU Tax Observatory publishes global tax evasion reports, or organizations such as OECD have most recently reported on tax morale (OECD, 2019, p. 4).

The investigation in concepts related to tax morale as a component of tax compliance (Luttmer and Sighal, 2014, p. 150) has its roots in the Allingham and Sandmo (1972, pp. 323–324) benchmark model of tax evasion. So, the academic interest and related research to why people pay taxes (or do not) has been examined throughout decades, and yet still the understanding remains limited (Dulleck et al., 2016, p. 9). Authors deal with this issue from different perspectives all grounded in the traditional economics-of-crime approach (Becker, 1968, p. 173; Dulleck et al., 2016, pp. 9–10) which is elaborated through tax compliance. Tax compliance could be viewed from three perspectives: general deterrence theory, economic deterrence models and fiscal psychology (Riahi-Belkaoui, 2004, p. 137). Tax compliance or non-compliance (as investigated through the concept of tax evasion) have been evaluated in all three concepts and their economic and political impact in the society have also been measured (Riahi-Belkaoui, 2004; Barone and Mocetti, 2011, p. 5). However, the social psychology question to why people pay or evade taxes (Lewis, 1982, p. 165), still remains open, so, in order to solve a puzzle, researchers have introduced a concept of 'tax morale' as an 'individual intrinsic motivation to pay taxes' (Feld and Frey, 2002, p. 88; Riahi-Belkaoui, 2004, p. 137; Barone and Mocetti, 2011, p. 5). Due to the negative correlation between tax morale and tax evasion, the literature dealing with tax evasion is as comprehensive as the literature on tax morale and it has been investigated and empirically researched through the concept of 'tax evasion games' using different methods and models for more than 40 years now (Alm and Malézieux, 2021, p. 700). In this article, the focus is on applying new methods and models in the prediction of individual tax morale which contributes towards tax compliance literature.

Tax morale, as an important and popular concept that increases voluntary tax compliance (Luttmer and Singhal, 2014, p. 151) has been gaining prominence in the empirical research over the past three decades. Different aspects of tax morale have been investigated so far – from five possible tax morale mechanisms (intrinsic motivation, reciprocity, peer effects and social influences, cultural factors and information imperfections and deviations from utility maximization) defined in the works of Luttmer and Singhal (2014, pp. 155–163), to more specific investigation of determinants of tax morale (Hofmann et al., 2017, pp. 64–65). In terms of factors that influence tax morale, three main categories have been recognized (formal and informal institutions and socio-demographic characteristics, Horodnic, 2018, p. 870).

The OECD highlights the significance of the virtuous circle between effective government performance and high tax morale/high tax compliance (OECD, 2018; 2019) indicating the significance of formal institutions as defined by Horodnic (2018, p. 871) or reciprocity as a tax morale mechanism defined by Luttmer and Singhal (2014, p. 157). The inevitable party of interest is the tax administration as the executive power of the state that keeps records and collects tax revenues. Understanding concepts and determinants are of a crucial importance to governments, tax administration officials and tax policy makers, all aiming to improve tax compliance and revenue collection.

The research uses ML methods in the prediction of individual tax morales since ML methods have not yet been used. The results of the research ought to help tax administration officials and tax policy makers in improved prediction accuracy regarding individual tax morale as well as the identification of key determinants of individual tax morale primarily across Europe. Furthermore, results may be replicated to other countries as well. The significance of such interdisciplinary research being conducted for the first time has been highlighted in the works of Athey (2018, p. 507). So, for the first time, present research wishes to contribute to current theoretical and empirical literature gap related to the application of ML methods and models in the prediction of individual tax morale. After the introduction section, the paper is divided into four parts: a brief literature review, research design and methodology, results and discussion and conclusion sections.

2 Literature Review

The investigation of tax morale takes an interdisciplinary approach, drawing from multiple scientific fields all trying to explain human and economic behaviour. Following the arising questions in the traditional economics-of-crime approach (Becker, 1968, p. 173; Allingham and Sandmo, 1972; Dulleck et al., 2016, pp. 9–10) related to why people pay (or not) taxes, the concept of tax compliance has been gaining academic prominence over last few decades (Luttmer and Singhal, 2014, p. 166). However, the basic economics-of-crime approach cannot fully capture the vibrant nature of decisions and motivations to comply or evade taxes as explained in tax compliance theory and practice (Dulleck et al., 2016). Dulleck et al. (2016, pp. 13–16) argue that other factors, social norms, individual, social, and cognitive dissonance affect tax compliance. Even though Luttmer and Singhal (2014, p. 151) consider enforcement as the primary driver of tax compliance, authors also argue that concept of tax morale is an important component of voluntary tax compliance.

The concepts of tax morale and tax evasion have been theoretically introduced and investigated in the social psychology in the early works of Lewis (1982, p. 165). The empirical investigation and possible connection between attitudes and behaviour have been exhaustively investigated with the WVS and the EVS surveys introduced in the 1980s, and several questions thereof that might explain and measure the level of tax morale, or the size of tax evasion (Torgler, 2005, p. 136; Sá et al., 2013, p. 1).

The tax compliance concept in economic theory is closely examined through concepts of tax avoidance and tax evasion as explained in seminal works of Allingham and Sandmo (1972, p. 323) and Yitzhaki (1974, p. 201). Over more than 50 years of study, researchers have tried to disentangle individual determinants of tax compliance. Alm et al. (1995, p. 6), have used experimental methods to explore the major factors – economic and noneconomic – that affect tax compliance: detection and punishment, the burden of taxation, public good provision, overweighting of low probabilities, and social norms. Authors such as García et al. (2018, p. 8) argue that the causes of tax evasion acceptance may be divided into three categories: *internal or individual* that depends on values, *contextual, social or institutional* that focuses on differences across countries and regions (Lago-Peñas and Lago-Peñas, 2010, p. 441) and a third category introduced by Alm (2014) that combines *group motivations such as altruism and fairness* (Alm, 2014, pp. 261–267; García et al., 2018, p. 8). Most recently, Horodnic (2018, p. 878) in the systematic literature review argues that tax morale could be perceived as an outcome of interaction between formal and informal institutions, whereby socio-demographic variables are mostly used as control variables.

Following the identification of five classes of tax morale mechanisms (intrinsic motivation, reciprocity, peer effects and social influences, cultural factors and information imperfections and deviations from utility maximization) defined in the works of Luttmer and Singhal (2014, pp. 155–163), the first mechanism of intrinsic motivation measures tax morale as a feeling of guilt or shame (Andreoni et al., 1998, pp. 850–852). With the EVS cross-country surveys in several waves, the academic research in the measurement of tax morale and its determinants through EVS questionnaire within and across countries has been exhaustive (Hofmann et al., 2017, p. 65). In all research, the dependent variable taken as a representative of the level of tax morale has been the statement from the EVS survey responded at the scale from 1 (never) to 10 (always): Please tell me for each of the following statements whether you think it can always be justified, never be justified, or something in between: "*Cheating on tax if you have the chance*". García et al. (2018, p. 8) have identified that previous studies included two groups of research related to the EVS's statement on cheating on taxes. The first group included research where higher scores involved higher intrinsic willingness to pay taxes (Torgler, 2003, p. 286; Torgler, 2012, p. 23; Lago-Peñas and Lago-Peñas, 2010, p. 441). In the second group authors examined 'unwillingness to cheat' (Alm et al., 2006, p. 861; Frey and Torgler, 2007, pp. 140–142). Academic research also acknowledges the measurement of individual tax morale through various survey questions. According to social psychology theory (Lewis, 1982, p. 144), when individuals observe widespread tax evasion or the behavior of their peers, their willingness to pay taxes may decline, diminishing intrinsic motivation and encouraging opportunistic behavior (Torgler, 2005, p. 136). Hence, authors such as Torgler (2005, p. 136), Sá et al. (2013, p. 4) and Doerrenberg et al. (2014, p. 39) have analysed responses to the level of tax morale by including the statement of '*avoidance of the payment of public transport fare*', or '*manage to avoid paying all his tax*' in the Latinobarómetro (Torgler, 2005, p. 136) together with cheating on tax statement.

The research therefore involves two sets of modelling organized around two EVS statements: *cheating on tax* and *avoidance of the payment of public transport fare*. Since the full list of all articles where EVS has been previously academically used is available on GESIS Leibniz Institute for the Social Sciences (Gesis, 2023), Appendix 1 provides an overview of the relevant findings. Appendix 1 indicates measurement of individual tax morale through cheating on taxes statement (Tax morale represented as a dependent variable in Appendix 1), its determinants, methods used and obtained results. Appendix 1 clearly indicates statistical and econometric methods and models that have exhaustively dealt with causality detection and identification of key factors of predicting individual tax morale in different circumstances – individual countries, cross-country analyses, etc. Appendix 1 also indicates that determinants of individual tax morale are multifaceted, encompassing trust in institutions, perceived fairness, social capital, cultural background, socio-demographic factors, economic context, and psychological considerations. Horodnic (2018, p. 870) provides systematic review of tax morale arguing that all factors could be grouped into three categories: formal institutions, informal institutions and socio-demographic characteristics and personal values. Under such circumstances, tax morale is argued to be a result of the interaction between the formal and informal institutions.

The possibility of ML's application in social sciences and public policies has been recognized by Athey (2018, p. 509) and Lee (2020, p. 14), but not sufficiently applied. As the results from both Web of Science and Scopus topic research by two keywords of *tax morale* and *machine learning* generate only one result that examine the effects of religiosity and religion on individual tax morale (Davidescu et al., 2022, p. 2), ML application in social sciences is scarce. Most recently, Weber et al. (2018, p. 577) used ANN in the application regarding voter turnout and Chen et al. (2022, p. 1) used ANN together with Ordinal Logistic Regression method in predicting happiness levels of European immigrants and natives.

With further research, it has been determined that ML methods and models have demonstrated substantial potential in enhancing various tax-related processes, but not prediction of individual tax morale. Most recent academic research indicates that by leveraging advanced algorithms and feature transformation techniques, ML models can significantly improve the accuracy of tax default predictions (Abedin et al., 2020, p. 19879), tax burden forecasts of agricultural enterprises (Kharitonova, 2023, p. 28), the detection of tax avoidance (Rahman et al., 2019, p. 536; Rahman et al., 2020, p. 722) and fraud (Murorunkwere et al., 2023, p. 731). These advancements not only help tax administrators and policymakers but also contribute to more efficient and informed financial decision-making. However, the ethical implications and potential biases of ML applications in these fields warrant careful consideration and ongoing research.

Based upon current literature, a combination of formal and informal institutions together with socio-demographic and personal characteristics to predict individual tax morale has been used by deploying ML methods. The motive for this investigation arose from the fact that respondents across Europe in the EVS usually state that they would never cheat on taxes, but indicators in the economy such as tax evasion (e.g. VAT gap report) or corruption index tell a different story. Bearing in mind the significance of corruption as a vertical trust or a formal institution parameter (Horodnic, 2018, p. 873) or mechanism of reciprocity in tax morale as defined by Luttmer and Singhal (2014, p. 157), a further investigation on the significance of perceived levels of corruption on predicting individual tax morale has been conducted. Corruption in relation to tax morale has been somewhat investigated but mostly in Latin America, whereby Torgler (2005, p. 153) highlights that tax morale in Latin America is significantly affected by the shadow economy, corruption, and trust in officials. Gerstenblüth et al. (2009, p. 2) and Gerstenblüth et al. (2012, pp. 129–131) discuss how GDP per capita, income distribution, and corruption perception shape tax morale in Latin America and the Caribbean while Jahnke and Weisser (2019, pp. 5–7) analyse how does petty corruption affect tax morale in Sub-Saharan Africa. Alm et al. (2016, p. 147) find that corruption among tax officials leads to higher levels of tax evasion of firms, with bribes reducing reported sales for taxes. Cung (2019, p. 189) shows that in Vietnam, economic freedom and corruption perceptions positively impact corporate income tax revenue, while inflation negatively impacts it. Most recently, Hsu (2023, p. 4) finds that when individuals perceive more government corruption, fiscal transparency is associated with lower tax morale. However, no research has yet integrated corruption perception index in assessing individual tax morale across Europe, as most European countries are among those with the lowest levels of perceived corruption worldwide.

3 Methods and Research Design

3.1 Machine Learning Methods and Models in The Individual Tax Morale Context

Academic research across various disciplines suggests that the machine learning (ML) methods and models presented in this subsection have a broad applicability. After providing an overview of the six universal ML methods and models, their role in assessing individual tax morale will be contextualized and explored in the following subsections. The explanation will include the necessary research steps required, which will be presented in the results section.

In the literature review section, the identified problem of predicting tax morale has been investigated through regression analysis (measurement on a scale with values from a continuous set, Appendix 1) or classification analysis (respondents are grouped into categories, Appendix 1). The article contributes to the latter. In terms of assessment of the level of individual tax morale, two target variables were selected: 'Cheating on taxes' (CoT) and 'Avoiding fare of public transport' (AFoPT). Respondents are classified into three groups based on their answers which reflect the degree of their agreement to those statements: 'Never justifiable', 'Somewhat justifiable', 'Almost always justifiable'. So, a multiclass classification problem is defined. Thus, the aim is to predict the respondent's group using available formal, informal, and socio-demographic data, framing the problem as a multiclass classification task in six ML methods and models.

For the ML methods, contrary to binary classification problems, multiclass classifiers can distinguish between more than two classes. In order to solve the classification problem, a wide range of classical ML algorithms and methods that are available in Scikit-Learn, an open-source ML library for Python, such as Logistic Regression, Random forests, k-Nearest Neighbors, etc. Also, deep learning frameworks in Python are used to build artificial neural network model using Keras and TensorFlow.

It is important to note that before briefly explaining methods and models, some of the classical binomial classifiers can be easily adapted to multiclass classifiers (such as Decision trees and Random forests), while some others are based on multiple applications of binary classifiers when solving multiclass classification problems (such as logistic regression and Support vector classifiers). When binary classification is used to solve multiclass classification problem, two strategies are available (Géron, 2022): the first strategy is called one-versus-the-rest (OvR) which uses one binary classifier for each class in the dataset, and the second strategy is called one-versus-one (OvO) which uses a binary classifier per each pair of classes in the dataset. Also, it is possible to use the cross-entropy loss if the 'multi_class' option is set to 'multinomial'. Under Scikit-Learn, different strategies can be selected depending on applied algorithm (Yu et al., 2011).

For a multiclass classification problem, six types of models were created and tested: the logistic regression (LR), the decision tree (DT), random forest (RF), k-Nearest Neighbors (kNN), Support vector classifier (SVC) and an artificial neural network (ANN) model providing explanation for each selected model.

The logistic regression (LR) model is based on the estimation of the probability that an instance belongs to a particular class using a logistic function. When using logistic regression for the multiclass classification problem different solvers are available. A 'newton-cg' as a solver has been used, based on Newtons method, and parameter 'multi_class' is defined as 'multinomial' (Yu et al., 2011).

The decision tree (DT) model is based on a tree (constructed from nodes and edges), as a hierarchical data structure. Each node in the constructed tree represents a decision based on a feature, while each leaf node represents a class.

The prediction is made by traversing through the model tree from the root to the leaf using input data.

Random forest (RF) is a typical example of an ensemble model, i.e., it uses several models and aggregates their result. Precisely, the RF model uses many decision trees on random subsets of the features of the problem, then produces a result by averaging out their predictions.

k-Nearest Neighbors (kNN) model for classification estimates the class that an instance belongs to, using majority voting among the k-nearest neighbors of the given instance. The model assumes that the distance between the given instance and all the data in the training set is precalculated and that the hyperparameter k is selected, thus k-nearest neighbors can be identified.

Support vector classifier (SVC) is a model for solving multiclass classification problems based on maximizing the margin between the decision boundary and the closest samples from the different classes in the feature space of the data set. It applies OvO strategy by default.

An artificial neural network (ANN) is a machine learning model inspired by the networks of biological neurons, hence it is based on the neural network. The basic idea of ANN is to learn complex relationships between features and outputs by simulating the behaviour of neurons in the human brain. Neural network consists of layers of adequately connected nodes (neurons) where the initial layer corresponds to the features, while the final layer contains information about the classes of the problem. Internal layers are usually called hidden layers. Each neuron in a hidden layer receives inputs from the previous layer, performs some computations, and passes outputs to the next layer (Géron, 2022). The research in social sciences applies ANN for improving prediction accuracy (Schmidhuber, 2015; Weber et al., 2018, p. 580; Chen et al., 2022, p. 2).

3.2 Research Design and Data

The statement about cheating on taxes if one would have the chance measured on a scale from 1 to 10 within the EVS has been exhaustively applied as a measurement of individual tax morale across European countries (Appendix 1). The statement regarding avoidance of the payment of public transport fare has also been previously used in the academic research in an additional measurement of the level of individual tax morale (Torgler, 2005, p. 136; Sá et al., 2013, p. 4; Doerrenberg et al., 2014, p. 39). However, the statement about the avoidance of paying a public transport fare might be seen as either a representation of 'civic attitudes' or might even represent dissatisfaction of transport service (Doerrenberg et al., 2014, p. 40) with a possibility of paying a small penalty. The cheating on taxes statement in its formulation might be used to predict that a decline in tax attitudes or tax morale will lead to an increase in tax evasion (Lewis, 1982, p. 177; Torgler, 2005, p. 135), indicating a potentially stronger representation of a decline in tax morale than the avoidance of public transport fare statement. Both statements have previously been used in the assessment and measurement of individual tax morale. The academic research shows that determinants that explain the level of tax morale across countries are groups of socio-demographic variables together with groups of subjective economic, institutional, and social variables (Lago-Peñas and Lago-Peñas, 2010, p. 441; Hofmann et al., 2017, p. 65). Alternatively, factors that influence tax morale may be grouped as formal institutions, informal institutions and socio-demographic factors (Horodnic, 2018, p. 870) whereby tax morale is a result of interaction between formal and informal institutions, highlighting the significance of reciprocity as defined by Luttmer and Singhal (2014, p. 157).

Based upon literature review and the absence of the application of ML methods and models in predicting individual tax morale, following research questions have been defined:

1. *Can individual tax morale across Europe be predicted more accurately by using ML methods and models?*
2. *Does corruption perception index contribute towards a more consistent and accurate ML predictions?*
3. *What are data-driven key determinants in predicting individual tax morale across Europe by using ML methods?*

The data for the analysis is compiled from the fifth wave EVS dataset of June 2022 for all participating European countries until that point in time (EVS, 2020). EVS was conducted from September 2017 until October 2021 and alike previous EVS waves included statements that are used in the measurement of the level of tax morale. The entire fifth wave EVS methodology corresponds to EVS (2020) and includes: sampling methods of respondents older than 18 years, explanation of country-by-country data collection and inclusion of 35 participating countries (excluding Latvia which was added in 2021). Participating countries and sample size per country are provided in Appendix 2.

The data-driven analysis of the two selected statements as target variables, should contribute towards the group of research where higher scores involve higher intrinsic willingness to pay tax (Torgler, 2003, p. 286; Torgler, 2012, pp. 23–24; Alm et al., 2006, pp. 858–860; Lago-Peñas and Lago-Peñas, 2010, p. 441; Garcia et al., 2018). Both statements were recorded on a ten-point scale (1= never justified, 10=always justified) and similar to previous academic research were grouped into a three-point scale: K_0 – Never justifiable (corresponds to 1 in the original scale), K_1 – Somewhat justifiable (corresponds to values 2–7 in the original scale), and K_2 – Almost always justifiable (corresponds to values 8-10 in the original scale). Even though ML methods can overcome unbalanced datasets, similar procedure of grouping variables into three categories had been applied in previous studies, such as Alm et al. (2006, p. 852) or Ryšavá and Zídková (2021, p. 391). The instances where the targeted variables were missing have been dropped from the dataset (1342 instances or 2.3% of the entire dataset). The dataset included EVS individual data of 56761 instances collected across 35 European countries from 2017 to 2020.

Based upon literature and identified variables summarized in Appendix 1, description of selected variables (including socio-demographic, formal and informal institutions or vertical and horizontal trust variables respectively, Horodnic, 2018, pp. 872–876) are presented in Table 1. In case of missing values, Multivariate Imputation by Chained Equation method as described in the pre-processing phase has been applied.

Reciprocity mechanism of tax morale and measures for changing formal institutions are necessary for building vertical trust in public authorities (Horodnic, 2018, p. 878). In line with research questions, the research includes Transparency International's Corruption Perception Index (CPI) as the most distinguished global index of corruption and a measure of a vertical trust. CPI indicates the perceived level of public sector corruption in a country, and it ranks countries on the scale from 0 to 100 (Transparency International, 2022). The lower the perceived level of corruption, the higher the CPI and vice versa. The created CPI ranks countries by using several macroeconomic variables. Sources of data and methodology are unrelated and different from the opinion statements from the EVS, so the CPI can be integrated in such research. CPI per each country was collected for the same year as the year of EVS survey. As noted by Horodnic (2018, p. 873), wider corruption is associated with lower tax morale.

The purpose and the motivation to include external country-level determinant such as CPI in the research rose from the fact that in EVS responses, individuals mostly replied that they would never cheat on taxes and would always pay a public transport fare which usually does not correspond to the estimated level of corruption within a country (individuals tend to underestimate that they would cheat on taxes). This is the case even for European countries which traditionally have lowest levels of CPI. Previous academic research determining the relationship between EVS's tax morale and perceived corruption with the application of statistical methods and models has been scarce and already discussed in the literature review section.

3.3 Pre-Processing Phase

In the pre-processing phase some classical steps have been performed, including data cleaning, feature engineering, some scaling, and encoding categorical variables. In the feature engineering step, some of the selected variables are modified and aggregated as described in Table 1. Missing values are treated very carefully in the cleaning data process (Géron, 2022). Multivariate Imputation by Chained Equation (MICE) method is used to fill in the missing data. It is a statistical method based on multiple imputations used to produce final input values aiming to preserve relationships of variables in the original dataset and to reduce the amount of the bias. Scaling of some variables and one-hot encoding for categorical variables has been performed, as required for the application of ML algorithms. The final data set consisting of 56761 instances is split randomly into training and test dataset by 60%–40% respectively. The results are similar without significant deviations even if the data is split differently.

Table 1: Description of selected variables and coding of selected variables

	Variable	Code in EVS	Modified measurement units
Country level	Country	S003	Nominal measure – Numeric code for Country
	Year of Survey	S020	Scale measure 2017–2020
Individual-level	Gender	X001	**0** – male, **1** – female
	Age	X003	**0** – original scale 18–29 **1** – original scale 30 and more
	Education	X025_01	**0** – low education level corresponds to original scale 0, 1, 2, 3 **1** – medium level education (original scale 4, 5, 6) **2** – high level education (original scale 7, 8)
	Marital status	X007	**1** – married (original scale 1) **0** – not married (original scale 2–8)
	Religiosity	F028	**1** – once a week or more (original scale 1, 2) **0** – less than once a week (original scale 3–8)
	Public vs. Private sector employment	X052	**1** – public institution (original scale 1) **0** – not public institution (original scale 2, 3, 4)
	No. of children	X011	**0** – no child (original scale 0) **1** – one or more children (original scale 1–5)
	Employment status	X028	**2** – employed (original scale 1, 2) **1** – self-employed (original scale 3) **0** – other (original scale 4–10)
	Confidence in Government	E069_11	Scale 1 to 4: **1** – A great deal, **4** – None at all
	Confidence in Parliament	E069_07	Scale 1 to 4: **1** – A great deal, **4** – None at all
	Confidence in Justice System/Courts	E069_17	Scale 1 to 4: **1** – A great deal, **4** – None at all
	Bribery	F117	Scale 1 to 10: **1** – Never justifiable, **10** – Always justifiable
	Government responsibility	E037	Scale 1 to 10: **1** – Individuals should take more responsibility for providing for themselves, **10** – The state should take more responsibility to ensure that everyone is provided for
	Immigrants strain	G041	Scale 1 to 10: **1** – Immigrants are a strain on a country's welfare system, **10** – Immigrants are not a strain on a country's welfare system

Source: authors.

4 Results

Separate analyses have been performed for each of the two target variables as measures of individual tax morale. They have been analysed through the two scenarios named "*Country*" and "*CPI*". Initially, in the Country scenario, selected variables have been used, while in CPI scenario the 'country' variable has been replaced with the 'CPI'.

Having in mind that the level of tax morale measured by the two target variables might not be free from biases and problems (Torgler and Valev, 2010), in the conducted ML analysis, it is necessary to include the CPI in all models as an external variable not accounted for in the EVS. The reason lies in the examination if the level of prediction of individual tax morale would improve. Since cross-cultural comparisons should be used cautiously, especially in countries with high corruption and tax evasion (Torgler, 2005), the inclusion of the CPI can be justified from the speeding up reasons (Torgler and Valev, 2010).

The six ML models and methods are applied for each target variable and for each scenario. Created models are evaluated and compared using accuracy, a commonly used metric to evaluate multiclass classification models. Results represented as accuracies are calculated for the training and test sets and are presented in Table 2.

Table 2: ML methods performance of "Country" and "CPI" scenarios for target variables 'CoT' and 'AFoPT'

	Accuracy - CoT				**Accuracy - AFoPT**			
	Training set		**Test set**		**Training set**		**Test set**	
Scenario	Country	CPI	Country	CPI	Country	CPI	Country	CPI
LR	0.72205	0.71036	0.71733	0.70641	0.64925	0.62878	0.65118	0.62532
DT	0.99471	0.71036	0.63637	0.70641	0.99413	0.99325	0.56071	0.56195
RF(10)	0.97175	0.97158	0.71975	0.71790	0.97199	0.97146	0.63400	0.63083
RF(100)	0.99471	0.99401	0.73552	0.73548	0.99410	0.99324	0.65268	0.64506
kNN(10)	0.71385	0.71036	0.66426	0.70641	0.67486	0.65953	0.61097	0.58291
kNN(25)	0.69544	0.68449	0.67236	0.66294	0.64852	0.63084	0.61845	0.59092
kNN(50)	0.68549	0.67253	0.67373	0.66118	0.63701	0.61863	0.61709	0.59560
SVC	0.71192	0.70487	0.70786	0.70099	0.63205	0.62333	0.63096	0.61973
ANN	0.74131	0.74656	0.73056	0.74104	0.70575	0.65416	0.65684	0.64643

Source: authors.

To understand and evaluate each of the universal six ML models and methods, it is necessary to contextualize and explain them in the specific assessment of the individual tax morale. In the two models – RF and kNN, the values in brackets next to RF and kNN in Table 2 indicate several hyperparameters scenarios. For RF model hyperparameter represents number of trees used to create model, while for the kNN hyperparameter k represents number of neighbors of a single instance used for the prediction. For the ANN models underlying network is created using a classical "half-rule" approach. According to this rule, the number of neurons in each successive hidden layer is approximately half the size of the previous layer. Thus, for the Country scenario, 3 hidden layers with 26, 13 and 7 neurons were used. For CPI scenario, number of initial variables is considerably smaller since categorical variables for the variable 'country' are replaced with numerical variable CPI, thus hidden layer consists of 9 and 5 neurons. In both cases half of the instances in the test sets are used as a validation set.

A significant difference in the accuracy in train and test sets for DT and RF models indicates that overfitting occurs, i.e., the model is too complex, and it captures the noise in the training data instead of the underlying patterns. Thus, other models are preferred or - in ML methodology – some pruning, i.e., limiting the depth of the tree, needs to be done. So, the two models were excluded from further analysis.

Six ML methods and models were further deployed to see if the level of prediction of the tax morale across Europe may be improved by including the country-level CPI as one of the most important vertical trust factors that shape the tax morale (Horodnic, 2018, p. 878). As the research developed in terms of interlinking vertical trust factors with the individual tax morale, a further investigation from the CPI scenario was researched by separating instances into two groups based on the country level CPI, namely the *High corruption* (CPI less or equal to 50) and the *Moderate corruption* group (CPI equal or greater than 51). The complete procedure was repeated for the two groups separately. The data set for High corruption group consisted of 21974 instances, while Moderate corruption group consisted of 34757 instances and the results are presented in Table 3.

As the results in Table 2 indicate, accuracies for all six ML methods are consistent for both variables of interest. Very small differences between accuracies on the test and training datasets indicate that overfitting is not present, and that all conducted ML models are adequate.

Table 3: Models' performance for High corruption and Moderate corruption groups for target variable 'CoT' and for target variable 'AFoPT'

	Accuracy 'CoT'				Accuracy 'AFoPT'			
	Training set		Test set		Training set		Test set	
Group	High corruption	Moderate corruption	High corruption	Moderate corruption	High corruption	Moderate corruption	High corruption	Moderate corruption
LR	0.69804	0.72303	0.68817	0.72203	0.59815	0.64670	0.60262	0.63917
kNN(10)	0.69342	0.71124	0.63823	0.67273	0.63721	0.67368	0.56473	0.59871
kNN(25)	0.66512	0.69461	0.64585	0.67632	0.61233	0.64622	0.57281	0.60374
kNN(50)	0.65276	0.68101	0.64152	0.67826	0.60133	0.63362	0.57952	0.60884
SVC	0.69023	0.71431	0.68191	0.71276	0.59603	0.64215	0.59044	0.63356
ANN	0.73128	0.76181	0.71741	0.75321	0.64886	0.68259	0.61086	0.66154

Source: authors.

5 Discussion

After applying several ML methods and models, the results and a response to the first research question indicate and confirm (Schmidhuber, 2015) that ML methods and models may be used in the assessment of the individual tax morale. Among all six ML methods and models, ANN model provides superior results compared to all other ML methods and models in predicting individual tax morale (Table 2 and Table 3).

The perception of corruption has been previously identified as one of the key factors affecting individual tax morale (e.g. Torgler, 2005, p. 139; OECD, 2019, p. 28). To assess the significance of CPI as a measurement of corruption in the data-driven evaluation of individual tax morale, another set of ML methods and models were conducted as an answer to the second research question as presented in Table 3. Previous empirical research indicated a close relationship between the level of corruption measured by the CPI (Torgler, 2005, p. 153; Torgler, 2006; Torgler and Valev, 2010; Garcia et al., 2018) or inclusion of the perceived bribery in the explanation of the two target variables. Bribery is a concept closely related to corruption (OECD, 2013) and in tax terminology related to tax evasion and tax audits, it is also considered a type of corruption. Furthermore, Vargas-Hernández (2009, p. 272) states that some examples of forms of corruption are bribery, collusion, embezzlement of public funds and theft, fraud, extortion, abuse of discretion, favouritism, clientelism, nepotism, the sale of government property by public officials, patronage, etc.

The results from Table 3 reveal several important findings. Firstly, the results are consistent for both target variables across applied ML models which can be verified by the best fitting results obtained in the ANN models. Secondly, if the results within training set or within test set for both target variables are compared, the results show an improvement of accuracy of predictions in the Moderate corruption group compared to High corruption group. Thirdly, the results remain consistently improved in the test set with reduced variability in comparison to the training set. Finally, and most importantly, the results for both target variables regardless of training and test set indicate an increase in accuracy of prediction in the Moderate corruption group where country-level CPI is higher, hence the level of perceived corruption is lower. The results are in line with previous literature as stated in Horodnic (2018, p. 878) and the response to the second research question is positive. In the broader context of the virtuous circle between effective government performance and tax morale, the application of the six ML methods and models with the inclusion of the CPI as a measurement of corruption has several important policy implications in the assessment of individual tax morale. As Torgler (2005, p. 135) and Sá et al. (2013, p. 1) found a negative correlation between tax morale and tax evasion and shadow economy, corruption has been recognized as a factor that affects the taxpayers in terms of lowering their tax morale (hence increasing tax evasion, Torgler, 2005, p. 139). Furthermore, since corruption also affects morality among the tax administration officials (Torgler, 2005, p. 139), if corruption occurs within public administration, it inevitably affects the entire tax system and therefore credibility of formal institutions (Horodnic, 2018, p. 871). It affects both efficiency of allocation in terms of possible delays in transactions and affects the fairness of the entire tax system, which in turn confirms the social psychology milestones set by Lewis (1982, p. 177) in diminishing intrinsic motivation to pay taxes and encouraging opportunistic behaviour if the avoidance occurs and therefore might lead to evasion. The presented research investigated both – the intention to avoid paying a public transport fee as a proxy to avoidance issues, and the intention to evade taxes measured through a proxy of cheating on taxes statement and the obtained results confirmed that ML methods and models may be used for such predictions.

If the obtained results are compared to the previous academic analyses of the differences between old and new EU member states in terms of the level of tax evasion (Yamen et al., 2018, p. 26; Dobrovič, Rajnoha, and Šuleř, 2021, p. 705), the data-driven results from six ML methods and models still confirm the existing differences in the level of individual tax morale among countries in their significance of a country belonging to a high versus a moderate CPI group.

The results support the fact that in countries with higher CPI and therefore lower perceived corruption, the perceived level of individual tax morale can be predicted with higher accuracy, indicating higher respondent's honesty when asked to estimate individual level of tax morale. The opposite is valid for responses in the High corruption group of countries with lower CPI and higher perceived corruption. These results further support the significance of reciprocity mechanism of tax morale (Luttmer and Singhal, 2014, p. 157). Similar conclusions, using different methods have been previously elaborated in Torgler (2006), Lago-Peñas and Lago-Peñas (2010), Garcia et al. (2018) and Horodnic (2018, p. 878).

As presented in Table 3, the results indicate higher accuracy of prediction for the 'CoT' target variable than 'AFoPT' target variable across all models. This indicates superiority of the 'CoT' variable to 'AFoPT' variable in estimating and measuring individual tax morale and/or individual tax morale. A further explanation might be that 'AFoPT' is considered a less serious aspect of tax evasion due to its relatively small penalty and the fact that the sanction for non-compliance is only financial (payment of a fine/penalty). A possible limitation of the AFoPT statement might be in a fact that respondents indicated a dissatisfaction with a transport service (Doerrenberg et al., 2014, p. 40). Therefore, the results by using ML methods and models are more accurate with the 'CoT' variable, that is considered a more fraudulent, with higher financial implications that might also have criminal implications. Both of results are in line with previous studies such as James et al. (2019).

To answer the final, third research question, the importance of the input variables for ANN models has been further analysed. The permutation importance method is performed to calculate the feature importance of constructed models for the given dataset. Feature importance as mostly applied in ANN has been obtained in a such way that it can be understood as a decrease in a score associated with the model when values for the selected feature are shuffled randomly. The effects of random shuffling values are measured using an appropriate scoring function and the 'Explained variance' metric as a scoring function has been used. Even though the list may be more exhaustive, as a response to the third research question, the results indicate three most important determinants of individual tax morale:

1. The respondents' attitudes towards accepting a bribe during their duties emerged as the most significant variable across all CPI scenarios and groups within;
2. CPI was consistently the second most crucial variable, except in the case of CPI scenario (CoT) and Moderate corruption group, where it was replaced by the gender variable;
3. Gender together with respondents' belief that immigrants impose a strain on a country's welfare system were a third most important determinant of individual tax morale.

On one side, these findings support the significance of interaction between the formal and informal institutions together with socio-demographic factors as indicated in the works of Horodnic (2018, p. 879). On the other, the results highlight the significance of reciprocity of tax morale (Luttmer and Singhal, 2014, pp. 157-160). Furthermore, in the European context, the results confirm the virtuous circle between effective government performance, high tax morale and voluntary tax compliance (OECD, 2018) which are very important to the European tax administration officials and tax policy makers. Finally, the results contribute towards academic literature in the understanding of human and economic behaviour in the investigation of individual tax morale across Europe by applying ML methods and models.

Recommendations for future research include the application of other possible variables in the present research, such as country's belonging to the European Union (or not) together with other official macroeconomic country indicators. Obtained results by using different sources of data, for example Special Eurobarometer 498 – Wave EB92.1., World Values Survey, Afrobarometer, Latinobarómetro, may also be tested using ML methods and models which ought to provide useful insights and perhaps highlight important regional differences. Further research might also use target variables on the original scale, since ML methods available in Python can handle imbalanced datasets. As a research limitation, it is important to note that the accuracy of predictions in social sciences is somewhat below the results that can be obtained with ML methods and models in natural sciences or engineering.

6 Conclusions

The primary purpose of the interdisciplinary study was in the contribution towards academic literature in the understanding of human and economic behaviour in the investigation of individual tax morale across Europe by applying data-driven ML methods and models. Research was based on the dataset that included 56761 individual data selected from 35 countries and compiled from the EVS over 2017-2020 period. The study investigated the relationship between 'CoT' (cheating on taxes) and 'AFoPT' (avoiding public transport fare), as two target variables and proxies to individual tax morale, together with factors explained by sixteen sociodemographic and subjective economic, institutional, and social variables. Three research questions have been defined with several important policy level conclusions for government and tax administration officials across European countries and beyond. The research highlights the role of ML methods and models in explaining individual tax morale, corruption levels, and broader human behaviour. The findings demonstrate that ML methods and models enhance accuracy and predictive power, particularly when the CPI is incorporated into the analysis. Among all applied ML methods and models, ANN models yielded the highest prediction accuracy. Furthermore, the results indicate that CPI is a stronger predictor than country-specific variables for the two proxy variables of individual tax morale, reinforcing the importance of corruption levels in tax morale assessments. The results again highlight the significant policy implications for the European decision makers, regulators together with the EU institutions (tax officials, tax administration and beyond, Horodnic, 2018, p. 871; OECD 2018; 2019) in their determination to research and tackle tax evasion and increase tax morale across EU.

Finally, findings of this study contribute significantly to social sciences by enhancing the understanding of human behaviour measured by the key factors shaping individual tax morale across Europe. The results reveal that respondents' attitudes toward bribery, the CPI, beliefs about immigrants' impact on national welfare, and gender are the most important determinants of tax morale. These insights align with previous social science research (e.g., Lago-Peñas and Lago-Peñas, 2010; Garcia et al., 2018), highlighting the importance of these variables in shaping tax compliance behaviour. Future research should continue to incorporate ML methods and models in the assessment of the key factors influencing perceived tax morale, as they offer a deeper understanding of the social, economic, and ethical dimensions influencing individuals' willingness to comply with tax obligations.

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Appendix 1. Overview of the most relevant findings regarding measurement of individual tax morale

Author(s)	Methods/Data	Dependent Variable	Independent Variables	Results
Listhaug and Miller (1985)	Regression analysis	Tax morale	Political ideology, religious values, political dissatisfaction, self-interest, personal dissatisfaction, political interest	Strongest support for symbolic politics model; weak support for self-interest explanation
Torgler (2005)	Empirical study (Latinobarómetro and World Values Survey)	Tax morale	Size of shadow economy, tax burden, lack of honesty, corruption, trust in officials, belief in law enforcement, pro-democracy attitudes	Tax morale is influenced by the size of the shadow economy, with tax burden, lack of honesty, and corruption being key factors; trust in officials, belief in law enforcement, and pro-democracy attitudes positively impact tax morale
Torgler and Schneider (2005)	Weighted probit estimation	Tax morale	Societal institutions such as trust or pride	Decrease in tax morale between 1990 and 1999 in Austria; societal institutions are key determinants
Richardson (2006)	Cross-country investigation (OLS regression analysis)	Tax evasion - TEVA - country survey rating of tax evasion collected by the World Economic Forum	Complexity, education, income source, fairness, tax morale	Lower complexity, higher education, income source, fairness, and tax morale are associated with lower tax evasion levels across 45 countries
Torgler and Schneider (2007)	Ordered probit model	Tax morale	Cultural and institutional differences	Differences in tax morale exist between Switzerland, Belgium, and Spain
Alm and Gómez (2008)	Unique dataset (Spain's Survey of Fiscal Policy)	Tax morale	Social capital, perception of benefits from public goods and services, perceived fiscal fraud	Social capital and perception of benefits from public goods and services significantly influence tax morale in Spain, while perceived fiscal fraud negatively affects it
Lago-Peñas and Lago-Peñas (2010)	Multilevel model	Tax morale	Socio-demographic characteristics, personal financial experiences, political attitudes, regional GDP, tax arrangements, ethnic and linguistic fractionalizations	Tax morale in European countries varies with socio-demographic characteristics, personal financial experiences, political attitudes, regional GDP, tax arrangements, ethnic and linguistic fractionalizations
Torgler and Valev (2010)	Weighted probit modelling	Tax morale	Gender, public attitudes towards corruption and tax evasion	Women are less likely to justify corruption and tax evasion

Lubian and Zarri (2011)	Non-RCT observational study	Stated happiness	Fiscal honesty	Tax morale, the intrinsic motivation to pay taxes, is a new determinant of happiness, as fiscal honesty generates a higher hedonic payoff than cheating
Molero and Pujol (2012)	Empirical study (binomial logit model)	Tax morale	Grievances about taxes, public funds, underground economic activities, duty, solidarity	Tax morale is influenced by grievances about taxes, public funds, and underground economic activities, with a lesser impact from duty and solidarity
Torgler (2012)	Weighted ordered probit model	Tax morale	Socio-demographic, economic, social, political, and institutional variables	Significant decrease in tax morale in 7 out of 10 Eastern European countries between 1999 and 2008
Kountouris and Remoundou (2013)	Empirical study (European Social Survey)	Tax morale	Culture (immigrant origin country tax morale)	Culture significantly influences individual tax morale, with immigrant origin country tax morale significantly influencing morale in the destination country
Doerrenberg et al. (2014)	Ordinary Least Squares (OLS)	Tax morale	Tax rates, avoiding public transport fee (instrumental variable)	Higher tax morale groups bear a higher tax burden
Cyan et al. (2016)	Binary probit regression model	Tax morale	Education, gender, age, location (industrialized population centres)	Tax morale in Pakistan is higher among educated individuals, especially those with very low or very high education, and is highest in major industrialized population centres; females generally show higher tax morale than males
Horodnic (2018)	Systematic review	Tax morale	Trust (vertical and horizontal), formal and informal institutions	Horizontal and vertical trust are the most significant factors that positively influence tax morale
García et al. (2018)	Generalized linear model	Tax morale	Socio-demographic factors, subjective economic, social, institutional variables	Impact of spatial dependence, economies of agglomeration, income inequality, economic imbalances, and perceived corruption on the variable -rejection of tax evasion
Castañeda (2021)	Pooled cross-sectional data	Tax morale	Horizontal equity, vertical equity	Tax equity, including horizontal and vertical equity, is the most important determinant of fiscal morale

Source. Own interpretation.

Appendix 2. Participating countries and sample size per country

ISO Country code	EVS No.of respondents	ISO Country code	EVS No.of respondents	ISO Country code	EVS No.of respondents	ISO Country code	EVS No.of respondents	ISO Country code	EVS No.of respondents	ISO Country code	EVS No.of respondents	ISO Country code	EVS No.of respondents
DK	3362	DE	2170	GB-GBN	1788	UA	1612	RS	1499	PL	1352	SE	1194
CH	3174	FR	1870	BA	1724	BG	1558	HR	1487	EE	1304	NO	1122
NL	2404	RU	1825	AT	1644	BY	1548	LT	1448	PT	1215	MK	1117
IT	2277	CZ	1811	IS	1624	HU	1514	AL	1435	ES	1209	SI	1075
GE	2194	AZ	1800	RO	1613	AM	1500	SK	1432	FI	1199	ME	1003

Source: EVS, 2020.