ENVIRONMENTAL STANCES AND LIFESTYLE PREFERENCES IN CZECHIA: GENERATIONAL ASPECTS AND SOCIO-DEMOGRAPHIC IMPLICATIONS

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Abstract

The struggle toward an environmentally sustainable economy brings forward many difficult decisions and actions. Governments may confront substantial resistance from the general public as they try to promote or enforce policies that will be necessary to secure a stable natural environment and sustainable economic performance for generations to come. Understanding the current stances of the population towards environmental issues is a prerequisite for any successful implementation of environmentally concerned policies. The goal of this paper is to provide (based on primary data) structured information on generational and other socio-demographic differences in individual environmental stances and related lifestyle preferences. Given the Likert-scale based data collected from the questionnaires, we use ordered multinomial logistic regression as our main tool for quantitative analysis. Major differences in stances are identified between genders and among different age and education groups. Women and younger individuals exhibit higher levels of environmental awareness. Lifestyle preferences segmentation provides additional context for our analysis and the basis for incentivising and targeting environmental policies. Overall, our contribution brings forward fundamental and actionable information that can facilitate many of the complicated decisions and policy actions leading toward environmental sustainability.

Implications for Central European audience: Environmental protection and sustainability plans are thoroughly implemented into most of EU policies, programs, and subsidies. However, for Central European economies, the transition towards sustainable and environmentally neutral economies may be more complicated as compared to “old” member states. Weaker GDP per capita, a historically strong coal-based energy sector and prevailing energy-intensive production segments imply a slower and more costly transition. Our analysis can be used to ease some of the impediments and complications lying ahead.

Keywords: environmental stances; generational aspects; ordered multinomial logistic regression

JEL Classification: D10, M38, Q58

Introduction

Addressing environmental issues and staying on course towards economic sustainability and carbon neutrality is a task faced by all governments, economic sectors and all citizens (consumers). Besides changes being implemented by the energy industry, technological changes will be made across all sectors, services and a whole range of non-economic activities. However, the immediate positive reception of the necessary changes – and the additional costs involved – is far from guaranteed. In fact, climate change mitigation programs and environmental protection activities are already facing significant pushbacks from various corporate and/or political sources and from certain socio-demographic groups.

The goal of this paper is to analyse the attitudes of the Czech population on environmental issues (based on primary data) and to recommend a suitable method of target segmentation, in which demographic and lifestyle variables are reflected.

To facilitate a positive reception and successful implementation of the technological and behavioural changes ahead, substantial sociological and consumer-oriented (i.e. marketing-like) research must be carried out. Central authorities would certainly prefer motivating and incentivising environmentally responsible behaviour over "forced" and unpopular implementation through administrative and/or economic regulations and sanctions. Clearly, the positive approach requires detailed prior research: segmenting the population into relevant socio-demographic and socio-economic groups, describing these groups, and understanding their preferences. Besides using socio-demographic criteria, it is informative to segment the population by lifestyle preferences, which have pronounced effects on individual stances towards environmental issues. Once this information is available, policymakers can develop tailored strategies for different population (consumer) segments and efficiently motivate individuals to adopt new technologies, accept patterns of sustainable consumer behaviour and embrace the changes tied with all the forthcoming environmentally responsible technological trends.

Clean energy production from renewable sources and clean individual transportation (e.g. using electric vehicles) rank among the most important and most discussed themes of environmental sustainability and its technological and economic feasibility. No doubt, developing economies would face relatively higher economic and social costs in terms of their overall prosperity – as compared to highly developed economies such as Germany, the UK, etc. However, if environmental issues and challenges are addressed successfully, developing economies may achieve substantial competitive advantages (Saleem et al., 2021).

Today, individuals, governments and corporate entities are increasingly involved in activities that are designed as environmentally neutral and/or aiming in a sustainable direction (Appiah et al., 2020). However, eliminating negative environmental externalities may incur additional costs, and both central authorities and enterprises seek ways of positioning and presenting their environmental and ecological activities (products & services) in a market-acceptable way.

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This contribution uses primary data surveyed in Czechia in 2021 (February – April) for a structured analysis of individual stances towards a complex range of environmental topics and lifestyle preferences of the Czech population (aged 18 years and older). Our findings provide essential information for policymakers, corporate and academic economists as well as marketers.

EU's climate and energy policies are aimed at preventing the effects of climate change by significantly cutting carbon dioxide and other greenhouse gas (GHG) emissions by the year 2030. Reaching any material reduction in GHG emissions or even reaching carbon neutrality will not be easy. Energy production must shift from coal and gas to renewable sources (here, uranium-based nuclear fission is a somewhat controversial energy source – both non-renewable and without significant GHG emissions). Individual transportation must shift from internal combustion engine (ICE) cars towards electric vehicles (EV), etc. To reach such goals, we must start with a detailed analysis of population attitudes and use such information to take every possible step to ensure that environmental strategies are implemented as seamlessly as possible.

Based on the above discussion, we have defined two main research goals for our analysis:

Research questions (RQs):

RQ1 Focusing on climate change issues and the corresponding challenges lying ahead, we aim to identify any prominent differences in individual environmental stances that would be determined by age/generation and by general socio-demographic categorisation.

RQ2 This RQ is essentially a two-step topic: we want to identify any age-based and socio-demographically determined differences in lifestyle choices and preferences and – more importantly –focus on relationships among such choices and individual stances toward climate & sustainability issues.

1 Literature review

Both large international enterprises and smaller companies have been facing environmental concerns for several decades. Decision-makers are increasingly involved in complex choices concerning investments and economic activities where both economic performance and environmental aspects need to be considered. Economic decisions are often prominently shaped by both administrative regulations and public concerns – often verbalised and actively promoted by non-government organisations and influential individuals – public figures (Earl & Clift, 1999). This situation is not local but affects companies worldwide, which is also reflected in a substantial amount of research activities focused on environmental management (Karagozoglu & Lindell, 2000). The complexity of environmentally oriented innovations is discussed by (di Paola & Russo Spena, 2021), who also provide references to additional literature.

Environmental stances and corresponding individual behaviour can substantially differ depending on socioeconomic profiles, connectivity to nature and underlying beliefs (Gkargkavouzi et al., 2018). Multiple studies emphasise the importance of knowing the attitudes of different demographic segments of the population to environmental and renewable energy issues. Age and gender are among the most important segmentation characteristics for consumer behaviour (Funches et al., 2017). In their study, (Coşkun & Yetkin Özbük, 2019) focus on Turkey's young millennials and their environmental behaviour – the authors use socio-demographic segmentation and provide identification and description of "green" consumer & lifestyle segments. While geographically focused segmentation studies are indispensable for the smooth implementation of environmentally responsible policies at the state level, global warming and climate change must be addressed globally (Misra & Panda, 2017). Some authors emphasise how the changing technological environment is affecting lifestyle preferences and increasing awareness of ecological threats and that new & more environmentally responsible segments of consumers emerge (Słupik et al., 2021).

Trivedi et al. (2015) focus on links between environmental attitudes and marketing. The authors concentrate on consumers' willingness to pay for purchasing environmentally responsible products. Besides threatening the future habitability of our planet, environmental problems have significant immediate business consequences. Consumer attitudes and preferences change rapidly and failing to understand such dynamics can be costly to businesses across many different sectors (Yilmazsoy et al., 2015). Consumers are becoming increasingly involved and concerned about environmental protection, and this is reflected in many contemporary marketing policies and concepts – the ongoing changes in personal preferences and motivations affect multiple behavioural and consumption attitudes (Barber et al., 2009). Understanding the so-called "green marketing mix" is only a part of the solution. To successfully operate in the "green marketplace", companies need to address changing behavioural patterns of consumers – since consumers' immediate advantages from sustainable consumption are mostly psychological (Abdulrazak & Quoquab, 2018). Among individuals who claim that they care about the environment (80% of the population), only a small fraction (about 20%) is willing to make additional efforts and change their daily habits in order to reduce environmental footprint and/or become environmentally neutral (Chwialkowska, 2019). Therefore, it is essential to understand the actual nature, attributes and comprehensive profiles of "green consumers" (Mehta & Chahal, 2021). Innovation strategies must be developed to help promote greener product alternatives and build a sustainable economy (Bowonder et al., 2010).

The implementation of EU energy and climate policies (ECP) isn't just a technical & environmental issue: it is a political agenda as well, deserving all the thorough discussion it receives from "mainstream" politicians. At the same time, environmental protection is exploited by both right-leaning and left-wing populists throughout the world. Huber et al. (2021) analyse actions of populist parties from 6 EU members (including Czechia) and discuss the differences in parties' positions and ambitions towards ECP. According to their findings, right-wing populist tend to dispute climate change and the necessity of undertaking protective actions. In contrast, left-wing populists are willing to push environmental policies far beyond EU-backed ECP programmes. An informative and detailed study on the relationship between right-wing populism and climate change agenda is provided by Lockwood (2018).

2 Methodology and data

Survey data used to address our main research topics (i.e. individual questions in the survey and corresponding answers) are primarily based on Likert scale metrics. This generates naturally ordered data series – as responses to questions are ordered multinomial variables – and implies the use of specialised quantitative estimation approaches that utilise such ordered variables. Therefore, we use polychoric correlations (Revelle, 2021) and ordered multinomial logistic regression for data analysis.

2.1 Ordered multinomial logistic regression: estimation, testing and interpretation

Ordered multinomial logistic regression (MLR) is a specialised quantitative method applicable to analyses based on Likert-scale variables. In this contribution, we use MLR models to evaluate generational and other socio-demographic effects on individual stances towards environmental and lifestyle issues. Derivation and estimation of ordered MLR models can be briefly introduced through a latent variable model (index model) of the form:

$$y_i^* = x_i'\beta + u_i, \tag{1}$$

where y_i^* is the unobserved (latent) form of the actual observed ordered categorical (qualitative) variable y for some *i*th respondent, x_i' is a row-transposed vector of regressors (exogenous factors with effects on the outcome) excluding the intercept, β is a vector of regression coefficients and u_i is the error term. As y^* crosses a series of increasing thresholds α, the observed variable y moves along the qualitative ordering. Observations of y and relations between latent and observed y can be described as:

$$y_i = \begin{cases} 0 \text{ for} & y_i^* \leq \alpha_1 \,, \\ 1 \text{ for} & \alpha_1 < y_i^* \leq \alpha_2 \\ & \vdots \\ J \text{ for} & y_i^* > \alpha_J \,' \end{cases} , \tag{2}$$

where the observed categorical variable y belongs to a level $j \in \{0,1,2,\dots,J\}$. Hence, y has $J+1$ ordered alternatives covering the whole range of mutually exclusive possible outcomes so that the probability of observing one of the outcomes is one: $P(y=0|x) + P(y=1|x) + \dots + P(y=J|x) = 1$. We assume thresholds α are ordered such that $\alpha_1 < \alpha_2 < \dots < \alpha_J$. These threshold values are respondent-specific and unobserved (we do not know the value necessary to "push" some *i*th individual from one level of y to the next. Hence, ordered logistic regression is used to estimate both the marginal effects obtained from β coefficients in equation (1) and the average α-thresholds.

To describe ordered MLR and to discuss the interpretation of estimated coefficients and marginal effects, we start with $P(y \leq j|x)$, the cumulative probability of observation y being less than or equal to some level j. The odds ratio:

$$\frac{P(y \leq j|x)}{P(y > j|x)}, \tag{3}$$

is a commonly used indicator, describing the relative chance of outcome $y \leq j$ against the relative chance of alternative outcome (i.e. $y > j$). Expression (3) is defined for $j = 0,1, \dots,$ $J-1$ only, as $P(y > J|\boldsymbol{x}) = 0$. Importantly, expression (3) can be log-transformed and denoted as "logit": $L(P(y \leq j))$. After combining and re-arranging expressions (1) to (3), the ordered MLR model may be cast as:

$$L(P(y \leq j) = \alpha_j - x_i'\beta - \varepsilon_{\boldsymbol{i}}, \tag{4}$$

where $\varepsilon_{\boldsymbol{i}}$ is an error term, intercepts (cut points) α_j are specific for each category j and β-coefficients are assumed identical across categories. This so-called proportional odds assumption is testable by the method developed by (Brant, 1990), and model (4) can be generalised to category-specific coefficients if this assumption does not hold. Both α_j and β coefficients are estimated by the maximum likelihood (ML) approach (Fox & Weisberg, 2018). In model (4), β-coefficients have an interpretation on the scale of log odds ratios (logit values), which may not be very convenient. As an example, consider some continuous regressor x_k and its corresponding coefficient $\beta_k = 1.05$. Now, if x_k changes by a unit (assuming this a "small change"), we would expect $L(P(y \leq j)$ to increase by 1.05. However, changes on the log odds scale are somewhat difficult to interpret.

Fortunately, β-coefficients can be transformed back to the odds ratio scale (3) by exponentiating. Continuing with our simple example, $exp(\beta_k) = exp(1.05) = 2.85$ and thus the odds ratio (3) becomes 2.85 times bigger following a unit increase in x_k and holding all other factors constant (Revelle, 2021). Similarly, if β_k is negative, then $0 < exp(\beta_k) < 1$ and the odds ratio decreases after a unit increase in x_k. Combining the estimated parameters with observed data, we may retrieve predicted probabilities for each category *j* being observed for every *i*th individual. Subsequently, this information may be conveniently summarised into average partial effects (APEs), visualised, and easily interpreted (Fox & Weisberg, 2018).

Statistical significances of β_k and $exp(\beta_k)$ may require a short discussion as well. The situation is relatively easy with β_k from equation (4): ML-based estimators provide the usual statistical inference and standard errors can be used to evaluate the null hypothesis stating that β_k is not different from zero, i.e. that changing x_k has no effect on the expected outcome of dependent variable (in terms of odds or log-odds ratios). While obtaining $exp(\beta_k)$ is rather trivial, one cannot simply exponentiate standard errors. Instead, we must either use the delta method based on Taylor series or the simulation approach (Fox & Weisberg, 2018).

2.2 Data

For our analysis, we use surveyed primary data for the Czech Republic. Data collection was performed from February to April 2021. Given the COVID19 pandemic and related restrictions, personal interviewing was replaced by computer assisted web interviewing (CAWI). Stratified quota sampling was used to obtain a representative dataset, considering gender, age, education, and location. The survey was conducted by a team of trained researchers to minimise the effect of non-probability sampling, which is often associated with quota sampling techniques. In total, we have collected a sample of 414 complete questionnaires from individuals representing the Czech population aged 18 or more. Tab. 1

shows both the true demographic structure & the match between sample and population frequencies. Overall, the dataset collected provides adequate match to the population and can be used for statistical analysis and interpretation with respect to the Czech population aged 18 and above.

Table 1 | Czech population structure and the quota sampling used

Category	Strata	Population Quota (%)	Sample Respondents (%)
Gender	Male	49 %	47%
	Female	51%	53%
Age group	1: 18 – 26 years	11 %	22.2%
	2: 27 – 45 years	35 %	31.9%
	3: 46 – 64 years	30 %	23.2%
	4: 65+ years	25 %	22.7%
Education	Basic and secondary without state exam	46 %	45.2%
	Secondary with state exam	34 %	34.3%
	University degree	19 %	20.5%
Location	Prague	12 %	14.3%
	Bohemia	54 %	60.4%
	Moravia	34 %	25.3%

Source: authors

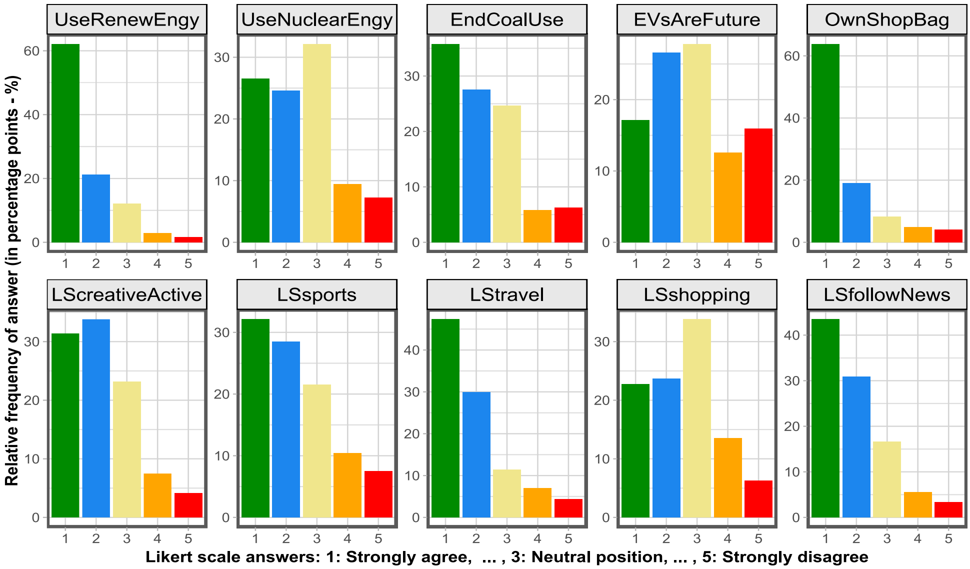
Organisation, preparation and realisation of the survey was executed by academic researchers, graduate and undergraduate students at Prague University of Economics and Business. The questionnaires and the topics addressed were carefully designed with major focus on interpretability of the results. Most of the data collection was performed by a team of students of marketing, under the guidance and supervision of experienced university teachers (associate professors). Various data-validation methods and statistical tests (e.g. the “Runs” test) were used to check for potential data mistreatment (Gibbons & Chakraborti, 2003). This study is part of a long-term research project focusing on socio-demographic aspects of individual stances and consumer behaviour and the influences introduced by recent technological advancements and environmental concerns (Formánek & Tahal, 2020; Tahal et al., 2017).

The CAWI method was used to gather different types of data: socio-demographic classification of respondents, multiple work, leisure and lifestyle preferences and stances/attitudes towards key questions concerning environmental and technology-related topics. All data were anonymised before analysis. Different question types were used to assemble the questionnaire (and thus the dataset): Yes/No (binary), Likert scale qualitative inquiries and interval-based quantitative questions. In total, 37 different variables were selected from the surveyed data and used for subsequent analysis.

Market segmentation strategies can differ substantially, based on marketers' knowledge (of the customers) and the goals sought (Hosseini & Shabani, 2015). Traditional methods of customer segmentation are evaluated in terms of their economic efficiency in the traditional and the newly establishing on-line environment (Jarratt & Fayed, 2012). To address this problem, Jansen et al. (2021) develop a framework that allows for reducing the number of customer segments as much as possible – without losing key information on the underlying population. In our analysis, segmentation observes the challenges and rules for social marketing segmentation put forward by (Dibb, 2017). Age intervals are chosen to reflect the human life cycle. Namely: student age, younger family, older family, senior age. To assess the prominence and significance of generational and other socio-demographic factors influencing individual stances towards the ever-more important climate change issues, we select five survey questions/variables, covering a relatively broad spectrum of key topics related to GHG emissions and sustainability considerations in general. All those variables and the relative frequencies of answers are shown in the top line of Figure 1.

The variables can be described as follows: The first variable on the left is $UseRenewEngy$ and it records individual stances towards the statement "I am in favour of using renewable energy". This is a Likert scale variable, with "1" (green colour in Figure 1) representing strong agreement, "3" (light yellow) is used for a neutral position and "5" (red) stands for strong disagreement. The second variable $UseNuclearEngy$ records answers to the statement "I am in favour of using nuclear energy" and the same Likert scale and colour coding are used – this holds for all variables shown in Figure 1. Next variable $EndCoalUse$ depicts stances toward the statement "Coal-based electricity should be abandoned". The next two questions are more focused on personal attitudes (rather than a general concept): variable $EVsAreFuture$ describes responses to statement "The future of mobility lies in electric vehicles" and $OwnShopBag$ is used for "When shopping, I bring my own shopping bag" (i.e. instead of using single-use plastic/paper bags).

Figure 1 | Relative frequencies of answers (individual stances) towards selected questions



Source: authors

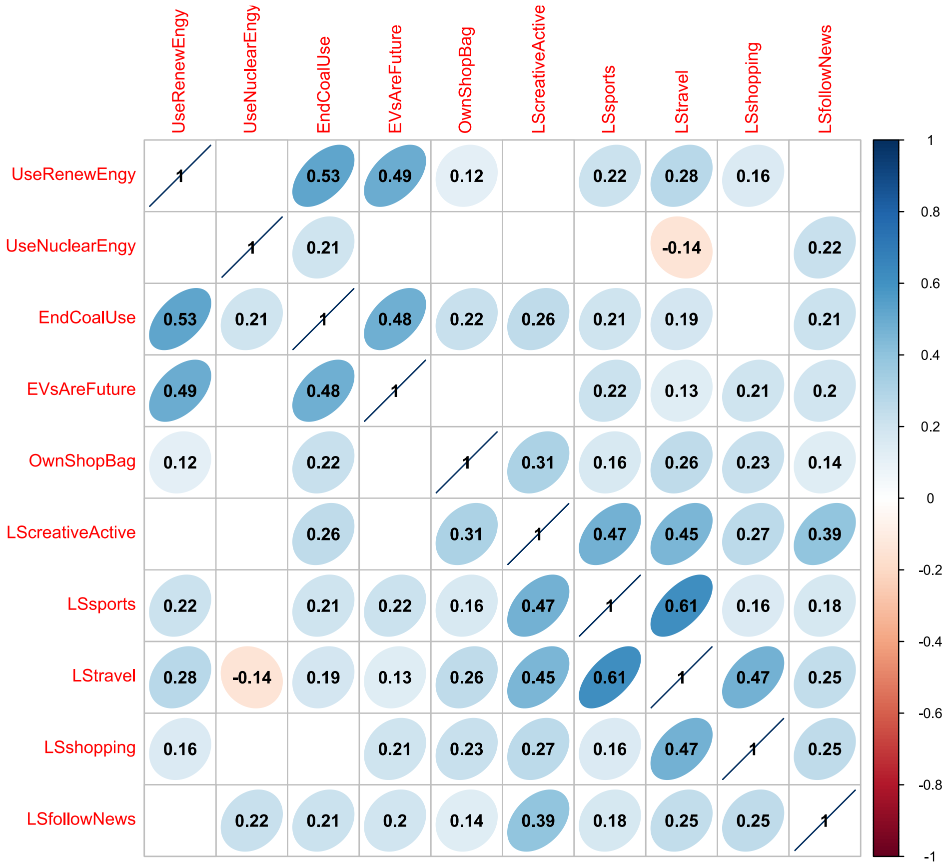
The second line of charts in Figure 1 describes lifestyle variables and individual preferences that relate to our RQ2. The first variable from the left is $LScreativeActive$, and this relates to the statement "I am a creative and active person". Next variable, $LSsports$, records responses to "I like to exercise/do sports", followed by variable $LStravel$ that is used for the statement "I like to travel" and $LSshopping$ that which identifies personal stances towards the statement "I like shopping". Finally, $LSfollowNews$ records how individuals perceive themselves with respect to the statement "I follow the news". Please note that all the lifestyle variables and questions surveyed should be interpreted in terms of self-positioning (and aspirations). This is clearly stated in the questionnaire, and we do not impose quantitative measures to evaluate attitudes – say, money spent on shopping, the extent of time devoted to sports or news, etc.

Figure 1 can only describe overall preferences and stances, along with their relative proportions. The next section uses polychoric correlation and MLR models to provide detailed & structured analysis and to identify relevant and significant socio-demographic and lifestyle factors affecting individual positions.

3 Empirical analysis

Figure 1 shows the summarised proportions (relative frequencies) of attitudes towards selected topics and questions. However, there is no information about how similar/dissimilar individual responses are across different questions. For example, positive outcomes for the first two variables - $UseRenewEngy$ and $UseNuclearEngy$ could be generated from identical respondents, mutually exclusive respondent-groups, or with some degree of positive or negative overlap. To analyse the behaviour of Likert scale variables (ordered multinomial variables), we start by estimating pairwise polychoric correlations. While the calculation of the polychoric correlation coefficient ρ_{pc} is somewhat complex (Tahal & Formánek, 2020), its interpretation is in line with the standard (Pearson's) correlation, the usual correlation interval $\rho_{pc} \in \langle -1,1 \rangle$ applies, and we need to keep in mind the distinction between correlation and causation.

Figure 2 | Polychoric correlations among answers to selected questions



Source: authors

Figure 2 provides insight into the fundamental relationships among personal stances toward environmental issues and general lifestyle preferences. The correlation matrix in Figure 2 is symmetric along the main diagonal, so that $\rho_{pc}(X,Y) = \rho_{pc}(Y,X)$ for any two variables X and Y. The blue colour indicates co-movement of variables (i.e. positive polychoric correlation), and inverse relationships are shown in red. Lighter shades and more "circular" shapes indicate statistically less significant and independent outcomes. Figure 2 provides correlations for all ρ_{pc} coefficients that are statistically different from zero at the 5% significance level (insignificant correlations are removed to improve human readability). The sample-based pairwise ρ_{pc} coefficients shown in Figure 2 are calculated using underlying assumptions involving latent variables, rather similar to expression (2), and by assuming normal distributions of the latent variables. (Revelle, 2021).

Individual cells of the correlation matrix in Figure 2 show a high level of logical consistency in the answers surveyed. From the first row, we can see that individuals who support the use of renewable energy are also in favour of ending coal use (with $\rho_{pc} = 0.53$) and tend to see EVs as the future of mobility ($\rho_{pc} = 0.49$). Interestingly, there is essentially zero correlation between $UseRenewEngy$ and $UseNuclearEngy$ variables (at $\rho_{pc} = -0.06$, correlation is not statistically significant and thus omitted from Figure 2). Typically, one would expect the most active proponents of renewable energy to be against nuclear energy as well. For example, Germany is in the process of shifting towards renewables and concurrently closing nuclear power plants. However, such expectations are not reflected in the positions expressed by the general public in Czechia. One could argue that while nuclear energy is not renewable, it does not produce GHG pollution either.

Positive correlations among environmentally focused questions and lifestyle-oriented questions show that environmentally aware (engaged) individuals tend to be more active and involved in their private undertakings and hobbies – at least subjectively, i.e. as reported in the survey. Clearly, this finding also holds when lifestyle attitudes are compared among themselves: people expressing activity and involvement in one area also tend to report higher levels of activity in other queried areas of interest as well.

3.1 Ordered multinomial logistic regression model

While Figures 1 and 2 provide a general overview of the environmental and lifestyle preferences of Czechia's population, ordered MLR models derived from equations (1) – (4) can be used for identification and quantification of statistically significant socio-demographic factors affecting individual stances. We follow the ten variables shown in Figure 1 and analyse their dependencies on the effects of gender, age, education, and population size (of the place of domicile). The selection of explanatory variables for MLR models was based on a combination of stepwise selection methods and a random forest non-parametric approach (Hastie et al., 2001).

Other socio-demographic and socio-economic contrasting factors had to be removed from the model due to lack of statistical significance: once we control for population size in the city (place) of domicile, regional distinctions between Bohemia, Moravia, and the capital city Prague become insignificant. Similarly, categorisations based on economic activity did not show any significant contrasting effects on our dependent variables – this includes both activity status (i.e. respondent being a student, employed, unemployed, retired, on maternity leave, etc.) and household income categories. Overall, our structured model specification process led to the following MLR equation, which follows from the general log-odds form of the MLR model (4):

$$L(P(y \leq j) = \alpha_j + \beta_1 Female_i + \beta_2 AgeGroup2_i + \beta_3 AgeGroup3_i + \beta_4 AgeGroup4_i \tag{5}$$

$$+ \beta_5 Educ2_i + \beta_6 Educ3_i + \beta_7 Domicile2_i + \beta_8 Domicile3_i + \varepsilon_i ,$$

where $L(P(y \leq j)$ is the log-transformed odds ratio from expression (3), with values of y following from section 2.2 and Figure 1. Five levels of j are observed on the Likert scale: $j \in \{1,2,3,4,5\}$, with "1 = Strongly agree", "3 = Neutral position", and "5 = Strongly disagree". For the sake of interpretation and following the ordering of natural numbers, we assume $"1" < "2" < \ldots < "5"$. Hence, our dependent variable is ordered (in ascending sequence) from strong agreement to strong disagreement. Therefore, positive β_k (and $exp(\beta_k) > 1$) imply that the corresponding regressor "pushes" respondents towards higher logit values and odds ratios, thus – loosely speaking – towards disagreeing with a given surveyed statement.

Regressors of the model (5) – i.e. factors affecting the outcome of the dependent variable – can be described as follows: $Female_i$ is a binary variable that identifies respondents' gender (for women, $Female_i = 1$). Here, male respondents (with $Female_i = 0$) are held as a reference category, and the estimated coefficient β_1 is interpreted accordingly: how female respondents differ from the reference group in their stances towards a given subject – again, direct interpretation of the coefficient β_1 can only be conducted in terms of log odds and odds ratios.

Next, we address the effect of age. All respondents belong to one of the four categories – age groups – described in Table 1, and we can define the following four binary variables: $AgeGroup1_i$ denotes individuals aged 18 to 26, $AgeGroup2_i = 1$ for 27 to 45 years old individuals and equals zero otherwise, $AgeGroup3_i$ covers ages 46 to 64, and finally, $AgeCat4_i$ is used for individuals aged 65 and more. As a generalisation and analogy to the "male" level for the gender variable $Female_i$, $AgeGroup1$ is used as a reference and left out of the model (note that binary variables for age groups 2 to 4 are sufficient for unique identification of respondent's age). Accordingly, coefficients β_2 to β_4 describe how individual stances (log-odds) across age groups tend to differ from stances of $AgeGroup1$.

Similarly, $Educ2_i$ and $Educ3_i$ from equation (5) are based on education categories "Secondary with state exam" and "University degree" from Table 1. Again, $Educ1_i$ ("Basic and secondary without state exam") is used as a reference, providing appropriate interpretation for the β_2 & β_4 coefficients.

Finally, the domicile-related variables are cast so that $Domicile1_i = 1$ for individuals living in locations (villages) with populations up to 5,000 (and $Domicile1_i = 0$ otherwise), $Domicile2_i$ relates to locations with 5,001 to 50,000 inhabitants and $Domicile3_i$ marks locations with population levels higher than 50 thousand. Following our model construction approach, $Domicile1_i$ is left out as the reference level (the specification used still allows for identification of population category for each respondent).

Table 2 | Estimated coefficients (exponentiated) with corresponding [standard errors] and significance levels

Variable	UseRenewEngy	UseNuclearEngy	EndCoalUse	EVsAreFuture	OwnShop Bag
Female	0.661*	3.282***	1.017	0.675*	0.338***
	[0.135]	[0.625]	[0.186]	[0.121]	[0.072]
AgeGroup2	3.620***	1.026	2.026**	2.534***	0.579*
	[1.187]	[0.257]	[0.512]	[0.637]	[0.161]
AgeGroup3	2.885**	0.815	1.440	3.276***	0.294***
	[1.026]	[0.219]	[0.399]	[0.910]	[0.094]
AgeGroup4	3.805***	0.799	1.785*	2.236**	0.419**
	[1.311]	[0.221]	[0.493]	[0.609]	[0.128]
Educ2	1.035	0.780	1.032	1.164	0.575*
	[0.245]	[0.164]	[0.216]	[0.242]	[0.138]
Educ3	0.868	0.685	0.765	1.217	0.593˚
	[0.251]	[0.171]	[0.188]	[0.295]	[0.177]
Domicile2	0.881	1.073	0.855	1.151	0.723
	[0.204]	[0.228]	[0.183]	[0.242]	[0.176]
Domicile3	0.460**	1.345	1.035	0.751	0.658
	[0.130]	[0.322]	[0.246]	[0.178]	[0.184]
Observations	414	414	414	414	414

Note: ˚p<0.1, *p<0.05, **p<0.01, ***p<0.001
Source: authors

Table 3 | Estimated coefficients (exponentiated) with corresponding [standard errors] and significance levels

Variable	LScreativeActive	LSsports	LStravel	LSshopping	LSfollowNews
Female	0.726˚	1.115	0.472***	0.339***	1.120
	[0.133]	[0.203]	[0.092]	[0.064]	[0.210]
AgeGroup2	0.422***	1.852*	0.680	0.569*	0.624˚
	[0.108]	[0.485]	[0.191]	[0.144]	[0.159]
AgeGroup3	0.340***	2.690***	1.677 ˚	1.551	0.444**
	[0.094]	[0.743]	[0.483]	[0.420]	[0.123]
AgeGroup4	0.744	3.623***	3.143***	1.709*	0.485*
	[0.202]	[1.023]	[0.928]	[0.465]	[0.137]
Educ2	0.921	0.837	0.882	0.878	0.565**
	[0.193]	[0.173]	[0.196]	[0.186]	[0.123]
Educ3	0.767	0.495**	1.256	1.426	0.879
	[0.190]	[0.123]	[0.328]	[0.349]	[0.216]
Domicile2	0.697˚	0.908	0.858	0.645*	0.978
	[0.148]	[0.188]	[0.187]	[0.137]	[0.211]
Domicile3	0.573*	0.724	0.413***	0.568*	0.641˚
	[0.136]	[0.173]	[0.110]	[0.137]	[0.157]
Observations	414	414	414	414	414

Note: ˚p<0.1, *p<0.05, **p<0.01, ***p<0.001
Source: authors

For our ten variables of interest (dependent variables describing individual stances towards environmental issues and lifestyle preferences), MLR model (5) was estimated, and the output is summarised in Tables 2 and 3. Coefficients shown in Tables 2 & 3 are exponentiated for better interpretation and presented on the scale of odds ratios. However, the interpretation of coefficients from MLR models is somewhat tedious, even if odds ratios are used. For a simpler and more intuitive output, marginal effects of gender and age are visualised in Figure 3. Besides coefficient estimates, Tables 2 & 3 provide standard errors that were obtained analytically using the delta method. The estimated α_j coefficients are left out from the output: both to conserve space and due to their small informative value. Using the likelihood ratio test, all ten models shown in Tables 2 and 3 are highly statistically significant with $p-value < 0.01$, and proportional odds assumptions hold at the 5% significance level (Brant, 1990).

Interpretation of estimated coefficients from a MLR model can be somewhat laborious, even as we use odds ratios instead of the log-odds scale. To provide additional "human readability", we also include Figure 3, which summarises age and gender effects on stances towards the ten topics analysed in our article while keeping education and domicile variables fixed at representative levels. It is possible to provide an analogy of Figure 3 showing education and domicile effects (while fixing other variables), yet the plotted differences in individual stances are not nearly as visually pronounced, and such figures would not be sufficiently informative – hence they are left out from this article to conserve space.

We can start by focusing on the comparison between female and male attitudes towards the statement "I am in favour of using nuclear energy", where the estimated effect, as shown in Table 2, amounts to $exp(\beta_1) = 3.282$, and it is highly statistically significant. Hence, odds ratios are higher for women and – roughly speaking – we would expect that women disagree with the statement considerably more than male respondents (ceteris paribus). This effect can also be observed from the corresponding graph in Figure 3. The "I am in favour of using nuclear energy" section of Figure 3 contains two plot columns: the left column is for female respondents, right column is for males (each column also features an age structure following age groups 1 to 4). It can be easily observed that the green ("1" strongly agree) and blue ("2" mostly agree) areas (describing answer probability on the y-axis of the plot) are much smaller/lower for women when compared to men. Similarly, the red ("5" strongly disagree) and orange ("4" mostly disagree) regions are more prominent for women, along with the yellow ("3" neutral position) region. As shown in the proper segment of Figure 3, this outcome holds for all four age categories considered. For the "I am in favour of using nuclear energy" statement, the age-based variability of answers is much less pronounced when compared to the gender-based difference. This, again, can be cross-checked with the significance of corresponding age-related coefficients shown in Table 2.

For a contrasting interpretation example, we focus on the statement, "When shopping, I bring my own shopping bag". Here, we see an opposite situation, where $exp(\beta_1) = 0.338$ (i.e. $\beta_1 < 0$). Hence, fixing other factors, women tend to have lower odds ratios and – roughly speaking – tend to disagree less (i.e. agree more) with the statement. Again, from Figure 3 (plot-element on 3rd row, left column), we can see that the difference in stances between men and women is prominent (women agree more), and this difference holds for all age groups. Also, from the plot and from the age-related coefficients shown in Table 2, we can see how older

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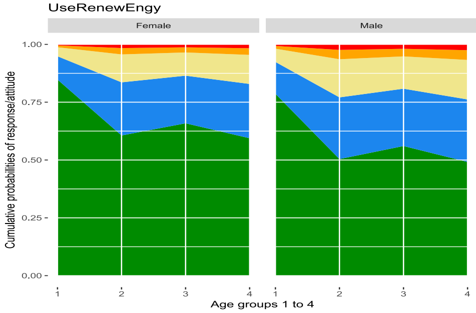
people tend to bring their own shopping bags more. This conclusion generally holds – although there is some relative drop in agreement levels for the 65+ age group compared to the previous age group, the increase over our reference category (18 – 26 years) is still statistically and materially significant.

A brief & systematic discussion of individual estimation results from our MLR model can start with the “I am in favour of using renewable energy” statement. Female and younger respondents agree with the statement more, no education-related differences in personal stances were identified, and individuals living in larger municipalities (with a population of 50,000+) are more in favour of renewable energies. For the “Coal-based electricity should be abandoned” statement, we observe no significant gender-based differences and all age groups of individuals aged 27 and older disagree with the statement significantly more than the reference (18 to 26 years old). Hence, the youngest generation is the one that is most in favour of ending coal and replacing it with renewable energy production.

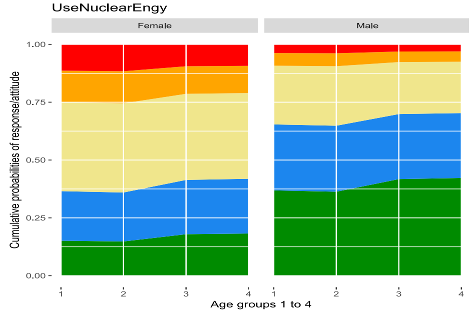
As we look at the estimated output for the “The future of mobility lies in electric vehicles” statement, we can see that the Czech population is far less convinced (agreeing with) the concept of ending ICE-based mobility in favour of EVs – say, comparing to attitudes toward using renewable energy sources. However, we can identify statistically significant differences in beliefs/stances based on gender (women being more in favour of EVs) and age: while all older age groups agree less with EVs when compared to the youngest group, individuals aged 46 to 64 are the ones to disagree the most. No education nor domicile related stratification was identified as statistically significant.

Figure 3 | Estimated probabilities of answers based on gender and age effects

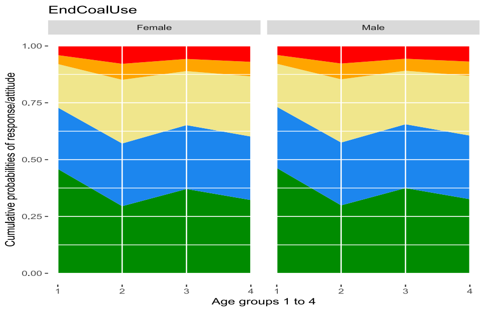
"I am in favour of using renewable energy"



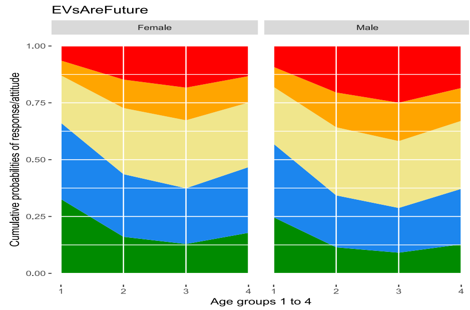
"I am in favour of using nuclear energy"



"Coal-based electricity should be abandoned"

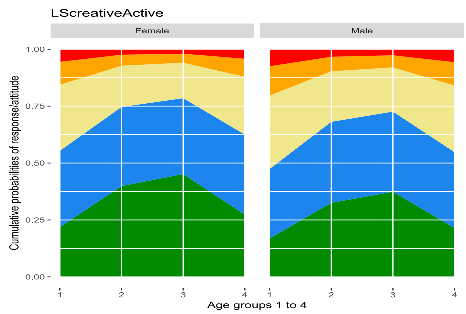


"The future of mobility lies in electric vehicles"



"When shopping, I bring my own shopping bag"

"I am a creative and active person" (LS)



"I like to exercise / do sports" (LS)

"I like to travel" (LS)

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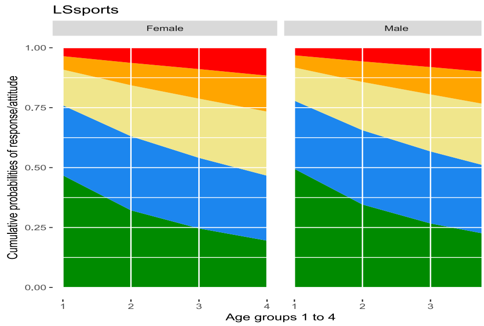
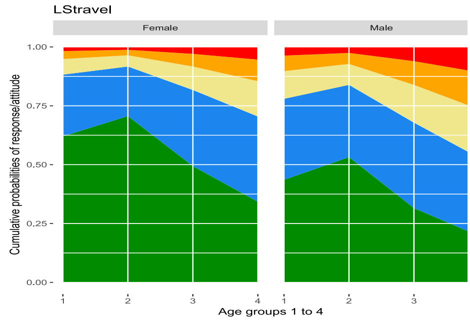
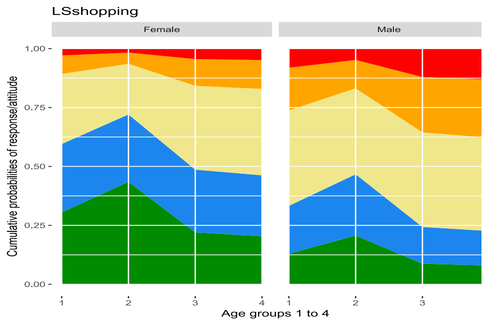
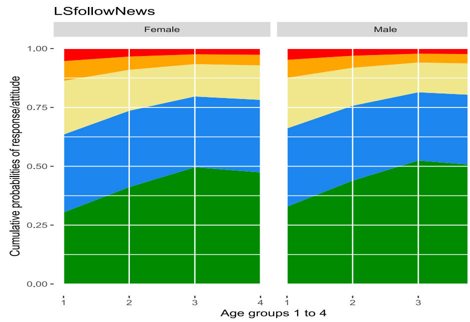




"I like shopping" (LS)



"I follow the news" (LS)



Source: authors

Focusing on lifestyle-related topics, we start with the "I am a creative and active person" statement. Here, female respondents have significantly lower odds ratios and thus tend to perceive themselves more as being active and creative when compared to men. Similarly, individuals belonging to Age groups 2 to 4 (i.e. aged 27 to 64) report being more active and creative when compared to the youngest (18 - 26) and oldest (65+) age groups. Education is not a significant contrasting factor for creativity. Individuals living in larger cities perceive themselves as more active when compared to the base level (locations/villages with up to 5.000 inhabitants).

For the variable "I like to exercise/do sports", there are no gender-based differences in attitudes. Both the estimates in Table 3 and colour-coded graphs in Figure 3 show that this type of activity decreases with age (it is lower for older individuals). There are no domicile-related differences. Based on education, individuals with a university degree agree more with the statement (have lower odds ratios compared to the base education group, as shown in Table 1). Female respondents and individuals living in larger cities agree more (disagree less) with the statement "I like to travel". Education level is not a significant differentiator for travelling, and the hump-shaped dependency on age can be easily observed in Figure 3.

Women and individuals aged 27 – 45 (Age group 2) are significantly more likely to agree with the statement "I like shopping" when compared to other age categories (and men). Again, education is not a contrasting factor here, and individuals in larger cities (50 thousand and more) have lower odds ratio and therefore are more likely to agree. Finally, there is no gender-based difference related to the statement "I follow the news", and individuals tend to follow the news more with increased age and higher education. This also holds for individuals living in larger cities (50 thousand and more).

As central authorities begin to prepare and implement programs for transitioning different sectors of the economy towards environmental sustainability and/or zero GHG emissions, increased attention should be paid to older individuals (mostly men), living in non-urban areas and smaller cities – this is the socio-demographic group of consumers (and voters) with the highest opposition to environmentally oriented changes. Members of this group dispute the efficiency of costs/inconveniences related to eliminating GHG emissions and similar negative externalities.

Conclusions and discussion

Climate change and its negative effects are ubiquitous. Czechia and other countries are facing many necessary yet unpopular decisions & actions aimed at conserving and restoring our natural environment, reaching climate neutrality and securing favourable living conditions for future generations. In this contribution, we provide a socio-demographic analysis of individual stances toward environmental issues and personal lifestyle preferences.

We have identified important distinctive properties of different socio-demographic groups – such as gender-based differences and a prominent generational divide in attitudes towards environmental protection. While young individuals are environmentally aware, old individuals (men in particular) are significantly less inclined to support measures and restrictions leading to sustainability.

The research revealed that the generational and gender approach to the segmentation of the Czech population in terms of attitudes to environmental issues makes sense. Considering environmental stances and lifestyle preferences together, a few general findings can be drawn from our estimates: female respondents are more environmentally conscious, support renewable and cleaner technologies, and at the same time they are more “active” in terms of creativity, travelling, shopping attitudes, etc., as compared to men. Essentially the same conclusion can be made when comparing younger individuals (more environmentally aware and generally involved) to members of older age groups. While the effects of domicile and education are less general and less pronounced, university-degree holders and individuals domiciled in larger cities show higher levels of both environmental awareness and overall “activity” in their lifestyles.

A gender-focus perspective on the Czech population shows that women tend to express significantly more interest in travelling and shopping, while other lifestyle variables do not exhibit gender-based differences in attitude. For travelling and shopping, women’s approach seems to be more pro-environmental as compared to men. This finding is supported by expressed stances in favour of using renewable energy and using one’s own bag when shopping. Finally, female respondents have prominently more negative stances toward the use of nuclear energy. This topic is worth additional research efforts, as our data do not support a conclusive explanation of this phenomenon. This situation is mostly due to the focus of the questionnaires used in our analysis, which were oriented towards answering our research questions RQ1 and RQ2.

Our data clearly show superior levels of environmental responsibility in women. Also, the age divide in environmental stances is very real, while domicile has quite a limited effect and education is barely significant. Overall, central authorities should address the discrepancy between the environmental stances of older and younger individuals (who are also consumers, voters). For an effective and stable transition towards a sustainable economy, a general consensus is necessary. Forcing unpopular changes on the general public through poorly communicated restrictions could result in political backslashes and widespread repulse, eventually inducing both pro-environmental and anti-environmental populism and perhaps destabilising or even reversing the whole ECP-based progress towards sustainability.

This paper concentrates on the analysis of lifestyle preferences and determinants of the Czech population, with a major focus on connections with personal stances towards environmental issues. For comparison and context, the readers may refer to the fork of Marquart-Pyatt (2012), focused on related issues within the Central and Eastern European (CEE) region. According to this research, respondents in CEE display greater concerns about environmental threats as compared to respondents in Western Europe. Similarly, Art (2018) deals with the issue of environmental protection and socially sustainable development in the CEE region and discusses how CEE countries implement sustainable economic strategies through their EU-integration processes.

The segmentation provided can be used by the central authorities as they shift from anecdotal evidence towards using data-driven evidence for planning, implementing, and fine-tuning a whole range of environmental policies: from raising public awareness and support to implementing policy actions (sometimes costly and less popular) leading to actual sustainability.

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