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The Impact of Air Quality on Well-Being: A Cross-European Analysis of Happiness and Life Satisfaction

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Abstract:	Introduction Air pollution is a well-established risk factor for overall quality of life, affecting both, physical and mental health. The aim of this study is to examine the association between air pollution exposure and subjective well-being – measured through life satisfaction and happiness – across 27 European countries and investigate whether key socio-demographic and socio-economic characteristics moderate those associations. Material and Methods Current study uses data from waves 10 (2020–2022) and 11 (2023–2024) of the European Social Survey, combined with national and regional fine particulate matter (PM2.5) measures. The analysis applies multilevel linear regression models with country-level random intercepts to account for the hierarchical data structure. Models control for sociodemographic, socio-economic, health-related and psychosocial factors. Interaction terms are used to assess whether the association between PM2.5 and subjective well-being varies by gender, years of education, unemployment, being retired and feeling about household income. Model fit and country-level clustering were assessed using standard diagnostic criteria. Conclusion Across model specifications, higher PM2.5 exposure is decreasing life satisfaction, while association with happiness is less consistent. The negative association is more pronounced among individuals in more vulnerable life-course and socio-economic positions, including unemployed, difficult to cope with the income, retirees and being male. ICC values suggest some country-level variation, but most variation is at the individual level. Overall, the findings suggest that while air quality play an important role in shaping subjective well-being; however, its effects are context-dependent and should be interpreted alongside broader social and individual determinants.

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The Impact of Air Quality on Well-Being: A Cross-European Analysis of Happiness and Life Satisfaction

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Declarations

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this study.

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Abstract

Introduction

Air pollution is a well-established risk factor for overall quality of life, affecting both, physical and mental health. The aim of this study is to examine the association between air pollution exposure and subjective well-being – measured through life satisfaction and happiness – across 27 European countries and investigate whether key socio-demographic and socio-economic characteristics moderate those associations.

Material and Methods

Current study uses data from waves 10 (2020–2022) and 11 (2023–2024) of the European Social Survey, combined with national and regional fine particulate matter ($PM_{2.5}$) measures. The analysis applies multilevel linear regression models with country-level random intercepts to account for the hierarchical data structure. Models control for sociodemographic, socio-economic, health-related and psychosocial factors. Interaction terms are used to assess whether the association between $PM_{2.5}$ and subjective well-being varies by gender, years of education, unemployment, being retired and feeling about household income. Model fit and country-level clustering were assessed using standard diagnostic criteria.

Conclusion

Across model specifications, higher $PM_{2.5}$ exposure is decreasing life satisfaction, while association with happiness is less consistent. The negative association is more pronounced among individuals in more vulnerable life-course and socio-economic positions, including unemployed, difficult to cope with the income, retirees and being male. ICC values suggest some country-level variation, but most variation is at the individual level. Overall, the findings suggest that while air quality play an important role in shaping subjective well-being; however, its effects are context-dependent and should be interpreted alongside broader social and individual determinants.

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1. Introduction

In recent years, growing attention has been directed toward understanding how environmental conditions, including air quality, shape not only physical health, but also broader aspects of human well-being. It has been suggested that exposure to air pollution may adversely affect subjective well-being, particularly life satisfaction and happiness (Cuñado & de Gracia, 2013; Fleury-Bahi et al., 2015; Goetzke & Rave, 2015; Montanari et al., 2025; Orru et al., 2016; Tian et al., 2022; Xia et al., 2022). Poor air quality can diminish satisfaction with daily life, reduce opportunities for outdoor activities and social interaction, increase psychological stress and heighten concerns about long-term environmental risks (Bruni, 2020; Lin et al., 2019; Orru et al., 2016). As subjective well-being plays a central role in individual functioning and societal development, understanding environmental impacts has become an important public health priority.

Well-being is a multidimensional concept reflecting overall life satisfaction and individual's capacity to live meaningful, fulfilling lives. According to the World Health Organization (WHO) well-being encompasses not only physical and mental health, but also social and economic security and the ability to cope with everyday challenges (WHO, 2021). Well-being is shaped by various factors, including health, social relationships, economic status and living environment. In recent years, environmental influences – particularly air quality – have received increasing attention due to its potential to significantly modify well-being (Bruni, 2020; Lin et al., 2019; Montanari et al., 2025; Orru et al., 2016). Air quality, especially fine particulate matter ($PM_{2.5}$) level, represents a serious global environmental and public health problem. Evidence indicates that elevated concentrations of $PM_{2.5}$ are associated with both adverse physical and mental health outcomes (Gao et al., 2025; Ku et al., 2025; Rackow et al., 2025). Poor air quality may increase the risk of cardiovascular and respiratory diseases, worsen mental health conditions and reduce overall life satisfaction (Bereziartua et al., 2026; Brown et al., 2025).

Empirical research conducted in Estonia (Orru et al., 2016), Germany (Petrowski et al., 2021), China (Xu et al., 2022), Ireland (Lyons et al., 2024) consistently documents a negative association between particulate pollution and subjective well-being. Nonetheless, much of the existing literature remains limited to single-country analyses, focuses on one specific well-being indicator or lack of harmonized socio-demographic information that would enable researchers to investigate population-level heterogeneity in pollution effects. Although Montanari et al. (2025) recently took an important step toward European-wide analysis, comprehensive comparative studies that integrate objective pollution measures with harmonized micro-level survey data remain still scarce.

The aim of this work is to analyse the relationship between air quality and subjective well-being and to improve understanding of how environmental conditions intersect with socio-demographic factors. Such knowledge can support more effective public health and environmental policy decisions.

2. Measures of Well-being

Different studies have shown that it is important to pay attention to the environment when studying quality of life as the surrounding physical environment affect human well-being and happiness (Dratva et al., 2010; Liu et al., 2022; Wu et al., 2010). Petrowski et al. (2021) and Orru et al. (2016) have pointed out in their research that among risk factors in physical environment, air pollution has a serious impact on life satisfaction. It has been shown that people who live in areas with good air quality have greater life satisfaction than those who live in areas with poor air quality (Luechinger, 2010; Orru et al., 2016; Petrowski et al., 2021).

Subjective well-being is not a homogeneous construct, and several different approaches, scales and indexes have been developed to measure it. Contemporary empirical research usually distinguishes at least two main components of subjective well-being: life satisfaction, which reflects an individual's cognitive and reflective assessment of their life, and happiness as an affective experience related to emotional state and the balance of positive and negative feelings (Diener, 1984; Veenhoven, 1984). Distinguishing between this dimension is important because they encompass different aspects of well-being and may respond differently to social, economic and environmental conditions. One of the most common ways to measure subjective well-being is to assess life satisfaction using a single general question, which reflects the respondent's overall assessment of their life and does not require the application of complex cognitive functions (Lindert et al., 2015). Topp et al. (2015) brought out that the five item World Health Organization Well-Being Index (WHO-5) is very actively applied across a wide range of study fields, because the scale has adequate validity. A personal well-being index includes seven separate but interrelated components – these reflect satisfaction with living standards, health, life achievements, personal relationships, security, community involvement and confidence in the future, and each makes a unique contribution to the overall assessment of life satisfaction (Lindert et al., 2015).

Usually all individual-level well-being indicators are based on the subjective assessments of respondents, not on objective measures. Previous studies have shown that subjective well-being scales are valid and reliable measurement tools that cover both personal and broader societal living conditions (Diener et al., 2018). As Montanari et al. (2025) emphasize, the use of their index made it possible to measure individuals' self-esteem of their lives, distinguishing it from objective economic and health indicators, which may not fully reflect subjective well-being. Importantly, because life satisfaction and happiness measure different dimensions of subjective well-being, they can yield different or even contradictory results in relation to the same external factors. While life satisfaction reflects a more deliberate and long-term assessment of life situations, happiness is more closely related to immediate emotional experience and context (Diener, 1984; Veenhoven, 1984). Therefore, distinguishing between these dimensions is central to analysing the relationship between environmental factors, including air pollution, and subjective well-being.

To understand exactly how air quality affects life satisfaction and happiness across Europe, it is important to consider different background characteristics, in particular socio-demographic and contextual indicators. These differences are not only evident between countries, but often also within countries. For example, Mitchell & Dorling (2003) found that the most polluted areas in English counties are often also the poorest economically, meaning that people with lower socio-economic status bear a disproportionate burden of environmental pollution resulting from the lifestyles of others. A similar conclusion was reached by Montanari et al. (2025), who showed that the association between particulate matter (PM_{10}) and subjective well-being decreases with worsening air quality in rural areas compared to small cities, while in larger cities, higher pollution levels may paradoxically be associated with higher subjective well-being. This suggest that people's expectations, coping mechanisms and environmental context play a vital role in shaping perceived well-being. In addition to environmental and spatial factors, previous studies have highlighted that people's happiness and life satisfaction are strongly associated with several individual factors, including social, cultural and economic characteristics (Brulé & Veenhoven, 2017).

Therefore, when studying the relationship between well-being and air quality, it is important to include different sociodemographic indicators to distinguish environmental influences from other factors shaping well-being and to gain a more detailed overview of which factors have a stronger impact on subjective well-being and for which population groups the impact of air quality is most pronounced.

This study contributes to the literature on air quality and subjective well-being, comparing life satisfaction and happiness by examining how this association varies across European countries, considering NUTS levels and other individual-level characteristics that may confound the association of interest (e.g., subjective general health, feeling about household income, gender and years of education). Also, we aim to improve understanding of how environmental conditions intersect with socio-demographic factors.

3. Data and methods

3.1. Data

3.1.1. European Social Survey

European Social Survey is a biennial, cross-sectional, multi-country survey covering over 30, mostly European, countries. It collects detailed information on public attitudes, beliefs, and behavioural patterns, including indicators of life satisfaction, political participation, social trust, and other cultural, economic, and social aspects of everyday life (ESS ERIC, 2025a, 2025b). The survey employs face-to-face interviews with newly selected, representative cross-sectional samples, ensuring high-quality and comparable data across participating countries (ESS ERIC, 2025a, 2025b). Although, due to the impact of the COVID-19 pandemic at Round 10, a total of 9 countries switched to a self-completion (web and paper) approach, while 22 countries used ESS's usual face-to-face approach. In addition, countries opting for the usual face-to-face approach, could use video interviews as a back-up for the in-person interviews (ESS ERIC, 2025b). In this study, we used survey data from the ESS wave 10 (2020–2022) and wave 11 (2023–2024).

The survey involved individuals aged 15 years and older, living in private households, regardless of nationality, citizenship, language, or legal status in the respective countries (ESS ERIC, 2025a, 2025b). Prior to analysis, the collected data has been cleaned, and variable names harmonized to enable merging across countries and waves.

The final analytical sample comprised 27 European countries (Fig. 1) and 69,767 respondents (32,191 respondents from wave 10 and 37,576 from wave 11), after data cleaning, during which 16.7% of the rows were removed. Responses coded as "refusal", "don't know", "not applicable", or "no answer" were treated as missing values (NA) and excluded from the analyses, as they do not reflect the respondent's actual opinions or attitudes and could bias the results. Additionally, Montenegro, Cyprus and United Kingdom were excluded, due to missing air quality data in Eurostat.

Regional identifiers were available for both ESS waves in some countries, while in other they were available only in one wave. Consequently, regional coverage varies across countries and waves. All countries included the Nomenclature of Territorial Units for Statistics (NUTS), which is established by Eurostat (ESS ERIC, 2025b). The territory of the EU is subdivided at 3 different geographical levels (Eurostat, s.a.):

- NUTS 1: major socio-economic regions with a population ranging from 3 to 7 million.
- NUTS 2: basic regions generally used for the application of regional policies with a population ranging from 800,000 to 3 million.
- NUTS 3: small regions for specific diagnoses with a population ranging from 150,000 to 800,000.

NUTS is used for collecting, developing and harmonising European regional statistics, carrying out socio-economic analyses of the regions and framing of EU regional policies (Eurostat, s.a.). Since the ESS dataset can be used to determine which NUTS level an individual belongs to, and by linking this to air pollution data from the European Environmental Agency, we were able to calculate the air pollution value corresponding to each individual.

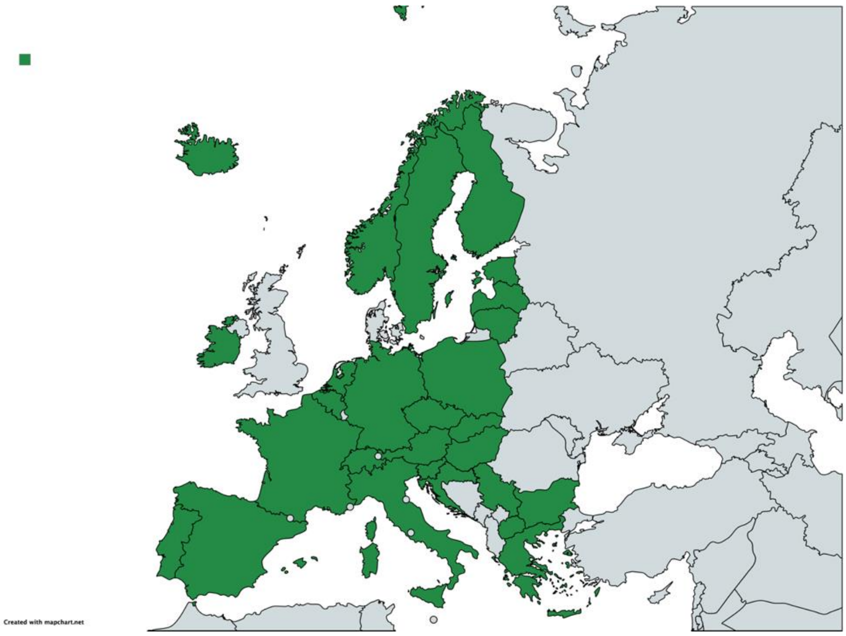

Fig. 1 Countries included in the analysis

3.1.2. Data on life satisfaction and happiness

Subjective well-being in this research was assessed using two distinct indicators: life satisfaction and happiness. Life satisfaction was measured in ESS by the question: “All things considered, how satisfied are you with your life as a whole nowadays?”. Respondents selected an answer on a scale ranging from 0 (extremely dissatisfied) to 10 (extremely satisfied). Happiness was assessed in ESS with the question: “Taking all things together, how happy would you say you are?”. Respondents provided an answer on a scale ranging from 0 (extremely unhappy) to 10 (extremely happy).

3.1.3. Background variables

A range of individual-level variables were included in the statistical analysis to account for potential confounding factors related to socio-demographic, socio-economic, health, and behavioural characteristics. All were chosen due to their relevance in previous studies (Apergis, 2018; Cuñado & de Gracia, 2013; Ferreira et al., 2013; Montanari et al., 2025; Orru et al., 2016). Variables were categorized as either numeric or categorical, with all necessary recoding performed to ensure consistency across ESS waves 10 and 11.

Socio-demographic variables comprised age, gender, years of full-time education, employment status (unemployed or retired), income difficulties, and living with a partner. Behavioural and psychological variables included religiosity and the frequency of social contact with friends, relatives, or colleagues.

The full wording of the European Social Survey questions and their response scales is presented in Online Resource 1.

Continuous variables included:

- Age (in years),
- Years of full-time education (years),
- Subjective general health (from '1 = very good' to '5 = very bad'),
- Feeling about household income (from '1 = living comfortably' to '4 = finding it very difficult'),
- Frequency of social contact (from '1 = never' to '7 = daily'),
- Interpersonal trust (0–10 scale),
- Satisfaction with democracy (0–10 scale),
- Satisfaction with government (0–10 scale),

Categorical variables included:

- Gender (male, female),
- Retired (yes, no),
- Unemployed (yes, no),
- Lives with husband/wife/partner (yes, no, based on original response categories 1-6 coded as "Yes", all others as "No").
- Religiousness (yes, no),
- Born in country (yes, no).

All categorical variables were recoded as factors, and numeric variables were explicitly converted to numeric type to ensure compatibility for statistical analyses. Before merging ESS waves 10 and 11, all variables were harmonized in terms of coding and labels, ensuring a consistent dataset for combined analysis.

3.1.4. Data on air quality

The respondent's exposure to air pollution were based on European Environmental Agency data for 2022 (EEA, 2024). We have used population weighted annual average concentration of $PM_{2.5}$ in NUTS3 level (if NUTS3 level data not available in some ESS study countries, then in NUTS2 or NUTS1 level). The detailed methodology on air pollution exposure assessment has been described by Horálek Jan et al., (2024). The method is called the Regression – Interpolation – Merging Mapping (RIMM). The linear regression model first uses air quality monitoring data followed by kriging of the residuals produced from that model (residual kriging). For different pollutants and area types (rural, urban background, and in the case of $PM_{2.5}$, also urban traffic), different supplementary data are used, depending on their improvement to the fit of the regression. $PM_{2.5}$ concentration map layers are created for rural, urban background and urban traffic areas on a grid at resolution of 1 km. Population weighted exposure is calculated from the air quality maps and population density data, both at 1 km resolution. The exposure in NUTS1–3 areas is expressed also as the population-weighted concentration, i.e. the average concentration weighted according to the population in a 1 km x 1 km grid cell in NUTS1–3 area. These values in NUTS areas were geographically linked to the ESS respondents' address at NUTS1–3 level, enabling the assessment of the association between air pollution and subjective well-being (life satisfaction and happiness). The integration of air pollution data at multiple geographical levels also allows for later analyses of cross-country differences in the relationship between environmental quality and subjective well-being.

3.2. Methods

A quantitative data analysis approach was applied to examine the relationship between subjective well-being (life satisfaction and happiness) and air quality ($PM_{2.5}$ annual average concentrations in NUTS1, NUTS2 or NUTS 3 level). The analysis was conducted in two main stages: descriptive statistics and multilevel regression modelling. All data processing and statistical analyses were performed using R software.

First, descriptive statistics were used to calculate mean values and distributions of subjective well-being and background variables across countries and socio-demographic groups. These summaries provide an initial overview of variation in well-being and contextual factors prior to multi-level modelling.

Second, we estimated mixed-effects linear regression models with random intercepts for countries to account for the hierarchical structure of the data, where individuals are nested within national contexts. Such multilevel modelling is recommended when observations are clustered, as it allows for more accurate estimation of standard errors and avoids biased inferences that may arise when ignoring group-level variability (Leyland & Groenewegen, 2020; University of Bristol, s.a.). Separate models were estimated for life satisfaction and happiness with random intercepts capturing country-level heterogeneity that may reflect institutional, environmental or cultural differences in well-being. The models included demographic and socio-psychosocial variables to assess how the associations between air quality and each well-being outcome differed.

Multicollinearity can make coefficient estimates unstable and overly sensitive to model specification, as highly correlated predictors inflate standard errors and reduce interpretability. Variance inflation factors (VIFs) are commonly used diagnostic tool, where values close to 1 indicate no multicollinearity and values of 10 or higher suggest serios concerns (Taşkaya, 2018). In our models, several individual-level predictors showed VIF values above conventional thresholds, indicating the presence of multicollinearity and suggesting that individual coefficient estimates should be interpreted with caution. VIF values are presented in Supplementary information Table S1.

However, because several predictors are conceptually and empirically related – such as age and retirement status, or age and self-rated health – the interpretation of individual coefficients is less informative than understanding overall model structure and the direction of effects. For this reason, we focus on broader patterns: the sign and magnitude of the $PM_{2.5}$ effect across specifications, shifts in the $PM_{2.5}$ estimate when additional variables of interaction terms.

To compare models, we rely on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which provide an established way to evaluate relative model fit and penalise unnecessary model complexity. Prior literature likewise uses AIC and BIC to assess whether linear or categorical specifications of $PM_{2.5}$ offer a better fit and to test the robustness of pollution-well-being associations (Goetzke & Rave, 2015; Lyons et al., 2024). In addition, we report the intraclass correlation coefficient (ICC), which quantifies the proportion of variance attributable to between-country differences and is a standard diagnostic for assessing the degree of clustering in multilevel models (Bottoni & Addeo, 2024). Consistent with this approach, we use AIC, BIC, marginal and conditional R^2 and the ICC to evaluate model fit across specifications rather than to draw strong substantive conclusions about individual-level coefficients.

In the third stage of the analysis, we examined whether key sociodemographic factors – years of full-time education, unemployment, retirement, perceived household income difficulty and gender – moderate the association between air quality and subjective well-being, measured through life satisfaction and happiness. These socio-demographic factors were chosen due to their relevance in earlier studies (Cuñado & de Gracia, 2013; Ferreira et al., 2013; Orru et al., 2016). To do so, we estimated a series of linear multilevel regression models with random intercepts for countries, each including an interaction term between air quality and one of these sociodemographic variables. All models controlled for the same set of additional sociodemographic and contextual covariates used in earlier stages.

4. Results

4.1. Descriptive Statistics for Countries and Background Variables

The highest levels of life satisfaction were observed in Finland (8.1) and Iceland (8.0), whereas the lowest levels were reported in Bulgaria (6.1) and Slovakia (6.3) (Table 1). Happiness was highest assessed in Finland and Switzerland (both 8.1) and lowest in Bulgaria (6.4), and Slovakia (6.6) (Table 1). $PM_{2.5}$ annual average concentration were highest in North Macedonia (22.1 μg/m^3) and lowest in Iceland (3.6 μg/m^3) (Table 1). The mean life satisfaction score across the sample was 7.2 (SD = 2.04), and the mean happiness score was 7.4 (SD = 1.85) (Table 1).

Table 1 Overview of countries statistics

Country	Average life satisfaction	Average happiness	Annual average $PM_{2.5}$ concentration (μg/m^3)	NUTS level	n
Austria	7.8	7.8	10.0	2	2210
Belgium	7.6	7.8	10.2	2	2832
Bulgaria	6.1	6.4	15.1	3	4639

Croatia	7.3	7.5	14.3	3	2901
Czech Republic	7.1	6.9	13.2	3	2151
Estonia	7.4	7.5	5.6	3	1499
Finland	8.1	8.1	4.4	3	2928
France	6.9	7.5	9.4	2	3458
Germany	7.7	7.8	9.2	1	2332
Greece	6.4	6.7	15.8	2	5245
Hungary	6.7	7.1	14.0	3	3585
Iceland	8.0	8.1	3.6	3	1608
Ireland	7.4	7.7	7.0	3	3424
Italy	6.9	7.0	14.8	1	4700
Latvia	6.5	6.8	8.5	2	1041
Lithuania	6.9	7.3	9.8	3	2591
Netherlands	7.9	7.9	9.3	2	2985
North Macedonia	6.4	6.7	22.1	3	1299
Norway	7.8	7.9	5.4	2	2647
Poland	7.5	7.6	16.1	2	1196
Portugal	6.7	7.1	9.2	2	2910
Serbia	6.8	7.3	19.2	2	1275
Slovakia	6.3	6.6	13.8	3	2543
Slovenia	7.6	7.8	13.5	3	2263
Spain	7.5	7.9	10.7	2	1637
Sweden	7.9	7.8	5.2	2	1170
Switzerland	8.2	8.1	8.5	2	2698
Dependent variables	**Average**	**Std.Dev**			
Life satisfaction	7.2	2.04			
Happiness	7.4	1.85			

The respondents' ages ranged from 15 to 90 years, and mean years of the full-time education was 13.3 years (SD = 4.04) (Table 2). Subjective general health was measured on a scale from 1 to 5, the mean score was 2.1 (SD = 0.90) (Table 2). Feelings about household with higher values reflecting greater difficulty in managing household income (M = 1.9, SD = 0.83) (Table 2). Frequency of social contacts, with higher scores indicating more frequent social interaction (M = 4.7, SD = 1.59) (Table 2). Interpersonal trust where higher scores denote greater trust in other people (M = 4.7, SD =1.59) (Table 2). The mean score for satisfaction with democracy was 5.2 (SD = 2.58) and for satisfaction with the government 4.4 (SD = 2.56) (Table 2).

Table 2 Continuous variables descriptive statistics

Variables	Min	Max	Mean	Std.Dev
Age	15	90	51.4	18.36
Years of full-time education	0	69	13.3	4.04
Subjective general health	1	5	2.1	0.90
Feeling about household income	1	4	1.9	0.83
Frequency of social contact	1	7	4.7	1.59
Interpersonal trust	0	10	5.1	2.46

Satisfaction with democracy	0	10	5.2	2.58
Satisfaction with government	0	10	4.4	2.56

In terms of gender distribution, 53.2% of respondents were males (n = 37,116). A total of 27.9% were retired (n = 19,437) and 3.2% were unemployed (n = 2,252). More than half of the sample (58.7%) reported living with a spouse or partner (n = 40,932). Regarding religious affiliation, 62.3% of respondents identified as religious (n = 43,445). Additionally, 91% of the sample were born in the country in which they currently reside (n = 63,983).

4.2. Multilevel regression models of life satisfaction and happiness

The first two models on life satisfaction and happiness were a multilevel regression to predict life satisfaction and happiness which included all individual background variables and a country-level random intercept. The estimates and standard errors are shown in table 4.

The individual-level residual variance for life satisfaction is 3.594 and for happiness it is 3.019, indicating how much unexplained variation in life satisfaction and happiness remains between individuals after accounting for all predictors in the model. The country-level variance for life satisfaction is 0.618 and for happiness 0.297. The intraclass correlation coefficient (ICC) value for life satisfaction is 0.147, which means that about 14.7% of the variability in life satisfaction is between countries. And for the happiness the ICC value is 0.089, which means that about 8.9% of the variability in happiness is between countries. The ICC, marginal and conditional R^2, AIC and BIC values for the life satisfaction and happiness models are presented in Supplementary Information Table S2.

$PM_{2.5}$ shows a statistically significant negative association with life satisfaction. The coefficient (-0.113 per 1 $\mu g/m^3$ of $PM_{2.5}$) indicates that, holding socio-demographic and psychosocial factors constant, higher levels of $PM_{2.5}$ are linked to slightly lower life satisfaction (Table 4). This suggest that air quality is associated with life satisfaction beyond individual variables. Several covariates display expected patterns: being retired, living with partner, more frequent social contact, higher interpersonal trust, belonging to a particular religion or denomination and greater satisfaction with democracy and government are associated with higher life satisfaction. Although higher age, having more years of education, poorer subjective health, lower feeling about household income, being unemployed, born in the same country show negative associations with life satisfaction. These relationships are interpreted at the level of tendencies rather than as causal mechanisms.

In contrast, in the model predicting happiness, $PM_{2.5}$ has a statistically significant positive association (0.043 per 1 $\mu g/m^3$ of $PM_{2.5}$) (Table 4). However, it is important to note that $PM_{2.5}$ is a country-level variable. Country-level analyses based on aggregated data show a strong negative association between $PM_{2.5}$ and both happiness ($r = -0.63$) and life satisfaction ($r = -0.63$). This indicates that countries with higher air pollution tend to have substantially lower average well-being. Therefore, the positive coefficient observed in the multilevel model likely reflects within-country associations rather than between-country differences and should not be interpreted as evidence that higher air pollution improves happiness. Other variables show broadly similar associations as in the life satisfaction model: higher age, living with partner, more frequent social contact, higher interpersonal trust, belonging to a particular religion or denomination and greater satisfaction with democracy and government are positively associated with happiness. Having more years of education, poorer self-reported health, lower feeling about household income, being retired, being unemployed, born in the same country are negatively associated with happiness. As with life satisfaction, these associations describe general patterns rather than isolated causal effects on each variable.

The marginal R^2 shows that fixed effects explain approximately 38.6% of the variance in life satisfaction, whereas the conditional R^2, which includes both fixed and random effects, accounts for 47.6% of the variance (Table S2). The model demonstrates good fit, with an Akaike Information Criterion (AIC) of 298906.6 and a Bayesian Information Criterion (BIC) of 299071.3, both calculated for the final multilevel regression model (Table S2). The marginal R^2 indicates that fixed effects explain around 34.9% of the variance in happiness and the conditional R^2 captures 40.7% of the variance (Table S2). This model also demonstrates acceptable fit, with AIC = 286719.7 and BIC = 286884.4 (Table S2).

Table 4 Multilevel linear regression models on life satisfaction and happiness

	Life satisfaction		Happiness	
	Estimate	Std.errors	Estimate	Std.errors
Intercept	6.868***	.166	6.801***	.122
Air quality (1 µg/m³ $PM_{2.5}$)	-.113***	.003	.043***	.003
Age	-.025***	.001	.010***	.000
Male (ref female)	-.166***	.013	-.084***	.012
Years of full-time education	-.011***	.002	-.004*	.002
Subjective general health	-.133***	.007	-.679***	.006
Feeling about household income	-.559***	.008	-.343***	.007
Retired (ref no) Yes	.778***	.017	-.346***	.016
Unemployed (ref no) Yes	-.377***	.040	-.268***	.036
Lives with husband/wife/partner (ref no) Yes	1.054***	.012	.751***	.011
Born in country (ref no) Yes	-.583***	.017	-1.512***	.015
Frequency of social contact	.341***	.004	.192***	.004
Interpersonal trust	.183***	.002	.103***	.002
Belonging to a particular religion or denomination (ref no) Yes	.916***	.014	.585***	.012
Satisfaction with democracy	.155***	.003	.144***	.003
Satisfaction with government	.033***	.003	.075***	.003
Signif. codes: * (<0,05), **(<0,01), ***(<0,001)				

4.3. The role of socioeconomic factors in explaining the relationship between air quality and subjective well-being

Next models on life satisfaction and happiness include interactions between gender, being unemployed, being retired, feeling about household income difficulty and years of education. Also, all individual background variables and a country-level random intercept were included. The estimates and standard errors are shown in Table 5.

4.3.1. Education years

In the life satisfaction model, where years of education was included as an interaction term, the main effect of $PM_{2.5}$ as well as effect of years of education was negative ($\beta = -0.165$, $\beta = -0.056$, respectively; $p < 0.001$) (Table 5). However, the interaction between $PM_{2.5}$ and education was positive ($\beta = 0.004$, $p < 0.001$), suggesting that the negative association of air quality with life satisfaction is somewhat weaker for individuals with higher levels of education.

In the happiness model, the main effect of $PM_{2.5}$ was positive ($\beta = 0.023$, $p < 0.001$), while the main effect of years of education was negative ($\beta = -0.021$, $p < 0.001$) (Table 5). The interaction between $PM_{2.5}$ and education was positive ($\beta = 0.002$, $p < 0.001$), indicating that education moderates the effect of air quality. Specifically, the positive interaction indicates that the association between air pollution and happiness becomes more positive at higher levels of education.

4.3.2. Unemployment

In the life satisfaction model, where unemployment was included as an interaction term, the main effect of $PM_{2.5}$ was negative ($\beta = -0.112$, $p < 0.001$), whereas the main effect of unemployment status was positive ($\beta = 0.244$, $p < 0.05$) (table 5). The interaction between $PM_{2.5}$ and unemployment was negative ($\beta = -0.052$, $p < 0.001$), suggesting that unemployed individuals have a stronger negative impact of air quality on life satisfaction compared to employed individuals.

In the happiness model, the main effect of $PM_{2.5}$ as well as effect of unemployment was positive and statistically significant ($\beta = 0.044$, $\beta = 0.545$, respectively; $p < 0.001$) (Table 5). The interaction between $PM_{2.5}$ and unemployment was negative ($\beta = -0.067$, $p < 0.001$), indicating that the negative association between air quality and happiness is stronger for unemployed individuals compared to employed individuals.

4.3.3. Retired

In the life satisfaction model, where retirement was included as an interaction term, the main effect of $PM_{2.5}$ was negative ($\beta = -0.052$, $p < 0.001$) and the main effect of retirement positive ($\beta = 1.473$, $p < 0.05$) (Table 5). The interaction between air quality and retirement was negative ($\beta = -0.067$, $p < 0.001$), suggesting that retired individuals have a stronger negative impact of air pollution on life satisfaction.

In the happiness model, the main effect of $PM_{2.5}$ was positive and statistically significant ($\beta = 0.006$, $p < 0.1$), while retirement was negatively associated with happiness ($\beta = –0.777$, $p < 0.001$) (Table 5). The interaction between air quality and retired was positive ($\beta = 0.042$, $p < 0.001$), indicating that the positive association between air quality and happiness is stronger for retired individuals compared to not retired individuals.

4.3.4. Income difficulty

In the life satisfaction model, where feeling about household income was included as an interaction term, the main effect of $PM_{2.5}$ as well as feeling about household was positive ($\beta = 0.031$, $\beta = 0.114$, respectively; $p < 0.001$) (Table 5). The interaction between air quality and feeling about household income was negative ($\beta = –0.053$, $p < 0.001$), indicating that the negative effect of air quality on life satisfaction is stronger for individuals who feels that it is very difficult to cope on present income.

In the happiness model, the $PM_{2.5}$ did not have an effect ($\beta = –0.007$, $p > 0.05$), while feeling about household income was negative associated ($\beta = –0.278$, $p < 0.001$) (Table 5). The interaction between air quality and feeling about household income was positive ($\beta = 0.018$, $p < 0.001$), indicating that the positive association between air quality and happiness is stronger for unemployed individuals compared to not retired individuals.

4.3.5. Gender

In the life satisfaction model, where gender was included as an interaction term, the main effect of $PM_{2.5}$ was negative ($\beta = –0.099$, $p < 0.001$), while the main effect of gender was positive ($\beta = 0.199$, $p < 0.001$) (Table 5). The interaction between air quality and gender was negative ($\beta = –0.033$, $p < 0.001$), suggesting that the negative effect of air quality on life satisfaction is stronger among men.

In the happiness model, the main effect of $PM_{2.5}$ was positive ($\beta = 0.067$, $p < 0.001$) and the main effect of gender was also positive ($\beta = 0.562$, $p < 0.001$) (Table 5). The interaction between air quality and gender was negative ($\beta = –0.058$, $p < 0.001$), indicating that the positive association between $PM_{2.5}$ and happiness is weaker for male, meaning that men experience a less favourable effect of air quality on happiness compared to female.

4.3.6. Other variables

In the life satisfaction models (Model A1–A5), poorer subjective general health and being born in the country were associated with lower life satisfaction (Table 5). In contrast, living with husband/wife/partner, more frequent social contact, higher interpersonal trust, belonging to particular denomination and greater satisfaction with democracy and government were associated with higher life satisfaction (Table 5).

A similar pattern was observed in the happiness models (Model B1–B5), subjective general health and being born in the country were consistently negatively associated with happiness, whereas living with husband/wife/partner, frequency of social contact, interpersonal trust, belonging to particular denomination, satisfaction with democracy and government were positively associated with happiness (Table 5).

Table 5 Multilevel linear regression models examining interactions between air quality and socio-demographic characteristics for life satisfaction (Models A1–A5) and happiness (Models B1–B5)

Dependent variable	Life satisfaction										Happiness									
Models	Model A1[1]		Model A2[2]		Model A3[3]		Model A4[4]		Model A5[5]		Model B1[1]		Model B2[2]		Model B3[3]		Model B4[4]		Model B5[5]	
	Estimate	Std. errors	Estimate	Std. errors	Estimate	Std. errors	Estimate	Std. errors	Estimate	Std. errors	Estimate	Std. errors	Estimate	Std. errors	Estimate	Std. errors	Estimate	Std. errors	Estimate	Std. errors
Intercept	6.680***	.163	6.852***	.166	6.425***	.151	5.463***	.156	7.393***	.174	6.469***	.118	6.781***	.121	7.071***	.119	7.288***	.124	7.004***	.132
Air quality ($PM_{2.5}$, $\mu g/m^3$)	-.099***	.004	-.112***	.003	-.052***	.004	.031***	.005	-.165***	.006	.067***	.003	.044***	.003	.006.	.004	-.007	.005	.023***	.006
Age	-.248***	.001	-.025***	.002	-.021***	.001	-.020***	.001	-.024***	.001	.010***	.000	.102***	.000	.008***	.000	.009***	.000	.010***	.000
Male (ref female)	.199***	.035	-.166***	.013	-.090***	.013	-.078***	.013	-.164***	.013	.562***	.032	-.084***	.012	-.131***	.012	-.114***	.012	-.083***	.012
Years of full-time education	-.11***	.002	-.011	.002	-.005*	.002	-.005**	.002	-.056***	.005	-.005**	.002	-.0049*	.002	-.008***	.002	-.006***	.002	-.021***	.005
Subjective general health	-.124***	.007	-.133***	.007	-.16***	.007	-.231***	.007	-.133***	.007	-.664***	.006	-.679***	.006	-.661***	.006	-.644***	.007	-.769***	.006
Feeling about household income	-.557***	.008	-.558***	.008	-.531***	.008	.114***	.020	-.553***	.008	-.341***	.007	-.342***	.007	-.360***	.007	-.577***	.018	-.341***	.007
Retired (ref no) Yes	.777***	.017	.776***	.017	1.473***	.028	.785***	.017	.774***	.017	-.348***	.016	-.35***	.016	-.777***	.026	-.349***	.016	-.348***	.016
Unemployed (ref no) Yes	-.374***	.039	.244*	.109	-.412***	.039	-.349***	.039	-.376***	.039	-.262***	.036	.545***	.996	-.246***	.036	-.278***	.036	-.268***	.036
Lives with husband/wife/partner (ref no) Yes	1.058***	.012	1.056***	.012	.954***	.012	1.018***	.012	1.058***	.012	.759***	.011	.755***	.011	.813***	.011	.764***	.011	.753***	.011
Born in country (ref no) Yes	-.575***	.017	-.582***	.017	-.693***	.017	-.673***	.017	-.575***	.017	-1.498***	.014	-1.51***	.015	-1.444***	.016	-1.481***	.015	-1.509***	.015
Frequency of social contact	.345***	.004	.342***	.004	.273***	.005	.282***	.004	.342***	.004	.2***	.004	.193***	.004	.234***	.004	.213***	.004	.192***	.004
Interpersonal trust	.18***	.002	.183***	.002	.198***	.002	.194***	.002	.183***	.002	.098***	.002	.103***	.002	.094***	.002	.099***	.002	.103***	.002

Belonging to a particular religion or denomination (ref no) Yes	.921***	.014	.916***	.014	.876***	.014	.877***	.013	.909***	.014	.592***	.012	.584***	.012	.61***	.012	.598***	.012	.582***	.012
Satisfaction with democracy	.158***	.003	.155***	.003	.148***	.003	.129***	.003	.157***	.003	.15***	.003	.144***	.003	.149***	.003	.153***	.003	.145***	.003
Satisfaction with government	.033***	.003	.032***	.003	.028***	.003	.047***	.003	.032***	.003	.075***	.003	.074***	.003	.078***	.003	.070***	.003	.074***	.003
Signif. codes: * (<0,05), **(<0,01), ***(<0,001)																				

[1]Models A1 and B1 examine the interaction between air quality and gender;

[2]Models A2 and B2 examine the interaction between air quality and unemployment status;

[3]Models A3 and B3 examine the interaction between air quality and retirement status;

[4]Models A4 and B4 examine the interaction between air quality and feeling about income difficulty;

[5]Models A5 and B5 examine the interaction between air quality and years of education.

Each model includes air quality, one interaction term (with gender, unemployment, retirement, income difficulty or years of education), the same set of control variables (age, gender, income difficulty, belonging to particular denomination, unemployment, interpersonal trust, living with partner, being born in the country, frequency of social contact, subjective general health, satisfaction with democracy and government), with a random intercept for country. Models A predict life satisfaction; Models B predict happiness.

5. Discussion

The present study examined the association between $PM_{2.5}$ air pollution and subjective well-being in Europe using ESS wave 10 and 11 data and explored whether this relationship varies across socio-demographic variables. Although bad air quality is typically associated with worse health and lower well-being, our results indicate a more complex pattern. In the baseline models, the association between $PM_{2.5}$ and happiness were positive, whereas the relationship with life satisfaction was largely weak or negative. This initially counterintuitive finding aligns with several recent studies that highlight contextual, regional and socioeconomic mechanisms shaping the relationship between environmental conditions and well-being (Montanari et al., 2025; Tian et al., 2022). Furthermore, we extend previous work by examining whether key socio-demographic and socio-economic factors – such as gender, unemployment, retirement, years of education and perceived household income difficulties – moderate the relationship between air quality and subjective well-being. These characteristics may influence individuals' vulnerability to environmental stressors or their ability to cope with them, yet their moderating role remains insufficiently understood. This study therefore provides evidence on both direct associations between pollution and well-being and the potential heterogeneity of these associations across socio-demographic characteristics.

5.1. Urbanisation and structural confounding

The positive effect of air pollution on happiness should not be interpreted as pollution increasing well-being. Air pollution often occurs with urban modernization and therefore, the impact of air pollution on happiness can be divided into two effects: positive and negative (Montanari et al., 2025; Tian et al., 2022). Montanari et al. (2025) brought out in their analysis that association between particulate matter (PM_{10}) and their well-being index they did not find association, rather this association depends on the area of residence. They found that subjective well-being decreases, when air quality becomes worse in the countryside, but for the bigger cities, higher levels of pollution tend to increase subjective well-being (Montanari et al., 2025). However, different researchers think that this may be because in the more pollution city centres there is access to more services, amenities and jobs, which affects the perceived subjective well-being (Montanari et al., 2025; Tian et al., 2022). This interpretation is also supported by Veneri & Pontarollo (2025), who show that although air pollution is negatively associated with life satisfaction, cities with higher well-being tend to offer better amenities and opportunities and are also characterised by higher living cost. This suggest that urban advantages may offset environmental disadvantages in shaping subjective well-being. Tian et al. (2022) came to conclusion that the impact of air pollution on happiness depends on the contrast of positive and negative forces and the relationship between the two is an inverted U-shaped relationship. It is also important to note what Diener (1984) has pointed out: life satisfaction refers to an individual's cognitive and reflective assessment of their life, based on personal standards, expectations and goals. In contrast, happiness describes primarily an emotional state and reflects the balance of positive and negative emotions experienced over a certain period (Veenhoven, 1984).

In addition, we checked the effect of different characteristics on the model result, including the relationship with pollution, regardless of which characteristics we removed from the model, air pollution still gave a positive result for happiness. From this, we concluded that the analyses performed are probably collinear and that this is some kind of hidden characteristic that is not currently present in these models. Considering that no theory confirms that more air pollution should make people happier, it is still the result of the effect of some hidden characteristic. Therefore, it is important to take this knowledge into account when interpreting the results. Taking the above into account and in our analysis, all regions were combined the relationship between air pollution and happiness may appear positive. Regions with higher population density, where air pollution is higher but, for example, working and living conditions are better, might have made a stronger positive contribution to the model, while the negative impact of smaller regions is hidden in the aggregate analysis.

5.2. Moderators: years of full-time education, unemployment, retirement, feeling about household income and gender

It appeared that several interaction effects reveal substantial heterogeneity in how pollution relates to well-being. The positive interaction between $PM_{2.5}$ and years of full-time education suggests that the association between $PM_{2.5}$ and happiness became more positive at higher levels of education. This finding should not be interpreted as air pollution is increasing happiness among educated individuals: rather, higher education may be associated with greater access to economic, social and psychological resources that buffer or outweigh the negative effects of environmental stressors. More educated individuals are more likely to hold higher-status occupations and earn higher incomes (Durante & Fiske, 2017). Also, they may reside in urban or industrialised areas where air pollution levels are higher but employment opportunities, services and living conditions may also be better (Cao et al., 2023; Frey, 2008; Li et al., 2024; Samavati & Veenhoven, 2024). Interestingly, the moderating effect of years of full-time education appears to differ depending on the well-being indicator: while education years may exacerbate the negative association between air pollution and life satisfaction, it seems to mitigate the negative association with happiness. Additionally, higher education may be linked to stronger social networks, greater job satisfaction and improved coping strategies, all of which can contribute positively to subjective well-being (Durante & Fiske, 2017). Therefore, the observed interaction likely reflects contextual and compositional factors rather than a direct beneficial effect of air pollution on happiness.

The negative interaction between air quality and unemployment indicate that unemployed individuals experience negative associations between air pollution and subjective well-being compared to employed individuals. These findings should not be interpreted as air pollution increasing happiness for employed individuals or having a direct beneficial effect; rather, they likely reflect the heightened vulnerability of unemployed individuals: unemployment reduces access to materials, social and psychological resources – such as stable income, structured routines, occupational support and social networks – that buffer against environmental stressors (Brulé & Veenhoven, 2017). As a result, unemployed individuals are more sensitive to the negative effect of $PM_{2.5}$ on both life satisfaction and happiness. Therefore, the observed interaction likely reflects the combined effects of social and economic vulnerability, rather than a direct causal effect of air pollution.

The positive interaction between $PM_{2.5}$ and retirement suggest that the association between air quality and happiness becomes more positive among retired individuals. This finding should not be interpreted as air pollution increasing happiness for retirees; rather, retirement may be associated with lower exposure to work-related stressors, greater flexibility in daily routines and stronger integration into local networks, which could buffer or outweigh environmental stressors (Cao et al., 2023; Frey, 2008; Li et al., 2024; Samavati & Veenhoven, 2024). Interestingly, the moderating effect of retirement appears to differ depending on the well-being indicator: while retirement may exacerbate the negative association between air pollution and life satisfaction, it seems to mitigate the negative association with happiness. Therefore, the observed interaction likely reflects contextual and compositional factors rather than a direct beneficial effect on air pollution.

The interaction between $PM_{2.5}$ and individuals perceived difficulty of coping with household income suggest that socioeconomic vulnerability moderates the impact of environmental stressors on subjective well-being. In the life satisfaction model, the negative interaction indicates that air pollution reduces life satisfaction more strongly for individuals who find it very difficult to cope with their present income. In contrast, in the happiness model, the positive interaction suggests that the association between air pollution and happiness is less negative for those experiencing income difficulties, although the main effect of air pollution is not statistically significant. These patterns should not be interpreted as a direct beneficial effect of air pollution; rather, they likely reflect differences in resilience and access to protective resources: individuals with limited financial means may have fewer material, social and psychological buffers, making them more sensitive to stressors in some domains (life satisfaction), while in other domains (happiness), the same vulnerability interacts with other factors that mitigate negative effects (Brulé & Veenhoven, 2017). This highlights the importance of considering socioeconomic context when assessing environmental impacts on subjective well-being. In contrast the meta-analysis by Olstrup et al. (2025) concluded that the effect of $PM_{2.5}$ on all-cause mortality does not depend on individual education or income. This indicates that the interaction between education, income and air quality might be different for well-being compared to vital health effects.

The interactions between $PM_{2.5}$ and gender indicate that the association between air quality and subjective well-being differs for men and women, with men exhibiting greater sensitivity to air pollution across both well-being indicators. In the life satisfaction model, the negative interaction suggest that air pollution is more strongly negatively associated with life satisfaction among men than among women. In the happiness model, although the average association between air pollution and happiness is positive, the negative interaction indicates that this association is weaker for men, implying that men experience a less favourable relationship between air pollution and happiness compared to women. The observed gender differences likely reflect gendered patterns of exposure, roles and vulnerability (Diener, 1984; Frey, 2008; Mitchell & Dorling, 2003; Montanari et al., 2025; Veenhoven, 1984). Men may be more exposed to environmental stressors due to occupational characteristics, commuting patterns or time spent in polluted environments, which could amplify the negative effects of air pollution on evaluative well-being such as life satisfaction (Kraus et al., 2025; Mitchell & Dorling, 2003; Zhang et al., 2022). Additionally, gender differences in health perceptions, coping strategies and emotional processing may contribute to the divergent patterns observed between life satisfaction and a (Diener et al., 2018; Gui et al., 2025). Overall, the results suggest that gender moderates the relationship between air pollution and subjective well-being, but that this moderation operates differently across well-being dimensions. This highlights the importance of considering gender-specific contexts and mechanisms when assessing environmental impacts on well-being.

5.3. Well-being measures and conceptual considerations

Our findings also suggest that it is important to consider different characteristics when studying well-being. (VanderWeele et al., 2020) argue that relying on a single measure, such as global life satisfaction, may misrepresent an individual's well-being; people may report being satisfied with life despite severe social isolation, addiction or poor mental health. The discrepancies between happiness and life satisfaction in our models reflect this conceptual distinction: happiness appears more sensitive to contextual and immediate experiential factors (such as urban amenities), while life satisfaction in our models reflects more evaluative judgments tied to long-term conditions, including environmental quality.

The divergent patterns observed between happiness and life satisfaction further highlight the multidimensional nature of subjective well-being (Diener, 1984; Tian et al., 2022; Veenhoven, 1984). Happiness might appear more responsive to immediate and contextual features of everyday life, while life satisfaction might reflect more evaluative judgments related to long-term conditions, including environmental quality (Diener et al., 2018; Tian et al., 2022). Treating these dimensions as interchangeable risks obscuring important mechanisms through which environmental exposures affect human well-being.

5.4. Methodological considerations

Although some variables – particularly age and retirement status – show moderate correlations, the level of multicollinearity does not undermine the primary aim of the models. While multicollinearity may inflate standard errors for specific coefficients, we believe it does not bias the estimated effect on $PM_{2.5}$ itself. The consistent direction and significance of key predictors across models provide additional confidence in the robustness of the findings.

Nevertheless, several limitations should be acknowledged. First, the cross-sectional nature of the ESS data precludes strong causal interpretations, as unobserved factors may jointly influence residential location, pollution exposure and well-being. Second, air pollution exposure is measured at aggregated regional levels and may not fully capture individual-level variation in actual exposure. Third, although extensive controls were included, some relevant factors—such as long-term residential history or detailed environmental perceptions—could not be accounted for.

Although the robustness check did not indicate statistically significant differences between ESS waves 10 and 11, the timing of data collection should still be considered when interpreting the results. The data collection period overlapped with the COVID-19 pandemic and its aftermath, which may have influence respondents' assessments of subjective well-being. In addition, country coverage varies across waves: some countries are represented in only one wave, whereas others are included in both waves. This uneven country representation may affect interpretation of cross-country comparisons and results based on the pooled dataset.

It is also important to mention that the analysis performed is probably collinear and is a hidden feature that is not yet in the model. Considering that no theory confirms that more air pollution should make people happier, it is still the result of the influence of some hidden feature. Therefore, this should be considered in the future, and this relationship should be better studied. Future research could address these limitations by using longitudinal data, finer-grained exposure measures or experimental designs.

6. Conclusion

This study examined the association between air quality and subjective well-being across 27 European countries using latest European Social Survey data. The results show that $PM_{2.5}$ is related to subjective well-being, but the direction and strength of this association differ across well-being dimensions. Higher air pollution levels are consistently associated with lower life satisfaction and poorer subjective general health, while the association with happiness is weaker and on average, positive.

Importantly, the association between air quality and subjective well-being is not uniform across the population. Interaction analyses indicate that the negative relationship between $PM_{2.5}$ exposure and life satisfaction is stronger among individuals in more vulnerable socio-economic or life-course positions, including the unemployed, retirees, men, lower education years and individuals experiencing income difficulties. For happiness, negative associations with $PM_{2.5}$ emerge primarily among individuals facing economic strain or unemployment, whereas for other groups the association is weaker or positive.

Multilevel analyses further indicate that while most variation in subjective well-being is attributable to individual-level differences, a meaningful share of variation exists between countries, highlighting the relevance of broader national contexts. Overall, the findings demonstrate that air pollution is associated with subjective well-being across Europe; however, its consequences are socially patterned, affecting population groups differently depending on their socio-economic and life-course circumstances.

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Supplementary material