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# Air Pollution Reduces the Individuals' Life Satisfaction Through Health Impairment

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## Abstract

The impact of air pollution on individuals' happiness and life satisfaction (LS), and its relationship to other factors became the focus of recent research. Though, the underlying mechanism of how air pollution impacts LS remains unclear. In this study, we examined the direct and indirect effect of air pollution on individuals' LS through health mediation. We used longitudinal individual-level data from "Understanding-Society: the UK Household-Longitudinal Study" on 59,492 individuals with 347,377 repeated responses across 11 years (2009–2019) that was linked to yearly concentrations of $NO_2$, $SO_2$, and particulate-matter (PM10, PM2.5) pollution. Generalized structural equation models with multilevel ordered-logistic regression were used to examine the direct effect of air pollution on LS and the indirect effect from health impairment. Higher concentrations of $NO_2$ (coefficient = 0.009, 95%CI = 0.007,0.012, $p < 0.001$), $SO_2$ (coefficient = 0.025, 95%CI = 0.017,0.034, $p < 0.001$), PM10 (coefficient = 0.019, 95%CI = 0.013,0.025, $p < 0.001$), and PM2.5 (coefficient = 0.025, 95%CI = 0.017,0.033, $p < 0.001$) pollutants were associated with poorer health, while poorer health was associated with reduced LS (coefficient = -0.605, 95%CI = -0.614,-0.595, $p < 0.001$). Mediation path analysis showed that air pollution impacted individuals' LS directly and indirectly. The percent of total effect mediated through health was 44.03% for $NO_2$, 73.95% for $SO_{2,}$ 49.88% for PM10, and 45.42% for PM2.5 and the ratio of indirect to direct effect was 0.79 for $NO_2$, 2.84 for $SO_{2,}$ 0.99 for PM10, and 0.83 for PM2.5. Health plays a major mediating role in the relationship between air pollution and LS. To alleviate the impact of air pollution on LS, future strategies should focus on health promotion besides reducing air pollution emissions.


**Keywords** Air pollution · Life satisfaction · Health · Mediating role · Longitudinal

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## Introduction

Life satisfaction (LS) is an important measure of peoples' well-being, which is studied extensively by researchers in the fields of environmental health, economics, and impact assessments (Du et al., 2018; Liu et al., 2021; Shi et al., 2022). LS is affected by several factors related to the individuals' age, gender, income, education, ethnicity, marital status, socioeconomic position, type of occupation, general health, lifestyle arrangements, and the quality of the surrounding physical environment (Dolan et al., 2008; Enkvist et al., 2012; Joshanloo & Jovanović, 2020; Orru et al., 2016; Proctor et al., 2018). Recently, more emphasis is being placed on the effects of the physical environment (e.g., air quality and pollution, climatic factors, noise, green spaces, and neighbourhood and housing conditions) on well-being related factors such as LS, happiness, subjective well-being, and self-reported mental health (Abed Al Ahad et al., 2022a; Ambrey & Fleming, 2013; Fernández-Portero et al., 2017; He et al., 2022; Li & Zhou, 2020; Liu et al., 2021; Orru et al., 2016; Urban & Máca, 2013; Zhang et al., 2022). In the context of well-being and LS, air pollution is one of the most studied environmental topics due to the fast industrial progress and urbanisation, which makes air pollution an increasingly severe problem in recent years (Abed Al Ahad et al., 2020; Wang, 2018). Based on a report by the European Environment Agency in 2020, approximately 90% of the European cities showed relatively high concentrations of air pollution, with life expectancy being reduced by more than eight months due to increased exposure to PM2.5 (particulate matter with diameter of 2.5 µm or less) pollution (European-Environment-Agency, 2020).

Air pollution has been found by empirical literature to negatively affect the individuals' LS (Ferreira et al., 2013; Orru et al., 2016; Schmitt, 2013; Shi et al., 2022; Silva et al., 2012; Yuan et al., 2018). For example, increasing concentrations of $NO_2$ (nitrogen dioxide), $SO_2$ (sulphur dioxide), PM10 (particulate matter with diameter between 2.5 and 10 µm), and PM2.5 pollutants impacted negatively LS in China (Du et al., 2018). In Europe, a significant reduction in LS of 0.017 points on the European Social Survey LS 10-points scale was observed per 1 µg/m$^3$ increase in PM10 annual concentrations (Orru et al., 2016). In London, both perceived and measured air pollution levels were negatively associated with LS and a 10 µg/m$^3$ increase in annual $NO_2$ concentrations resulted in 0.5 points reduction on the LS 11-points rating scale (MacKerron & Mourato, 2009). Moreover, a recent comprehensive examination of 178 published articles revealed that air pollution significantly diminishes levels of happiness and life satisfaction, while also leading to heightened anxiety, irritation, mental health issues, and thoughts of suicide (Lu, 2020).

The effect of air pollution on LS is three folds. First, air pollution exerts a direct negative effect on the human physical health, which might result in lower rates of LS (Abed Al Ahad, 2023; Abed Al Ahad et al., 2020, 2022a, b, 2023b; Orru et al., 2016). There is well-documented epidemiologic evidence on the short- and long-term effects of air pollution on morbidity and mortality, mostly related to cardiovascular, respiratory and cancer diseases (Ab Manan et al., 2018;

Abed Al Ahad et al., 2020, 2023a; Fischer et al., 2015; Hvidtfeldt et al., 2019; Manisalidis et al., 2020). Moreover, research has shown the negative effect of air pollution on birth outcomes including low birth weight, preterm birth, and childhood respiratory diseases (Esposito et al., 2014; Shah & Balkhair, 2011).

Second, exposure to air pollution affects the human brain and the autonomous nervous system, reflecting changes in physiology and emotions (Abed Al Ahad et al., 2022a; Dzhambov et al., 2018; Orru et al., 2016; Ventriglio et al., 2021). Exposure to fine particulate air pollution, such as PM2.5, has the potential to induce oxidative stress and trigger the production of inflammatory cytokines that travel across the blood–brain barrier, leading to neurodegeneration and neuroinflammation (Calderón-Garcidueñas et al., 2015). Consequently, this heightened susceptibility is associated with an elevated likelihood of experiencing mental health issues, including schizophrenia, autism spectrum disorders, psychotic episodes, cognitive impairments, anxiety, and depression (Abed Al Ahad et al., 2022a; Bakolis et al., 2020; Pedersen et al., 2004; Roberts et al., 2019; Volk et al., 2013), leading to poor LS scoring.

Third, air pollution negatively affects the LS judgements due to the psychological stress and anxiety associated with the coping behaviours that individuals have to follow in response to elevated levels of air pollution (Abed Al Ahad et al., 2022a; Orru et al., 2016). For example, a coping strategy can include opting to stay indoors rather than engaging in outdoor activities when air pollution is elevated, particularly when it exhibits visible indications (e.g., colour) or olfactory cues (e.g., bad smell) (von Lindern et al., 2016).

Despite the well-documented negative effect of air pollution on LS, it is often unclear whether this effect is more physiological or psychological. This calls for further research to disentangle the direct psychological impact of air pollution on LS from the indirect physiological effect through individual's health impairment. In this regard, some studies controlled for the individual's health status when assessing the association between air pollution and LS (Ferreira et al., 2013; Orru et al., 2016). However, this was done in simple regression models by performing models with and without control for health measures, rather than performing mediation path analysis. To our knowledge, only one recent cross-sectional study from China applied mediation analysis to show that $SO_2$ air pollution reduces individuals' happiness through impairment of their general health (Liu et al., 2021).

Mediation path analysis is a statistical method commonly used to assess the direct and indirect path associations between independent and dependent variables through an intermediate variable called the mediator (Gunzler et al., 2013). As indicated before, the effect of air pollution on lower scores of LS might be largely due to the negative effect of air pollution on individuals' physical and mental health (Abed Al Ahad et al., 2020, 2022a, b, 2023b; Manisalidis et al., 2020). For example, in Montreal-Canada, poor self-reported health has been associated with increased exposure to PM2.5 pollution (Goldberg et al., 2015). Thus, health might act as a potential mediator for the association between air pollution and individuals' LS.

Moreover, many of the studies on air pollution and LS rely on datasets that do not allow for air pollution assessments at a high spatial resolution and/or do not cover long periods of time (Dolan & Laffan, 2016; Ferreira et al., 2013; Orru et al., 2016).

This calls for further research that can look at the effects of air pollution on LS at finer spatial and temporal scales.

Additionally, despite the consensus of the harmful impact of air pollution on LS in the literature, there is significant variation in the size of effect estimates. Not to mention that the majority of existing studies focus on only one pollutant. For example, Orru et al. (2016) identified an inverse correlation between heightened exposure to PM10 pollution and diminished life satisfaction, and Ferreira et al. (2013) found a negative association between increased exposure to $SO_2$ pollution and reduced LS. Analysing the impact of several pollutants on LS within the same study would help in understanding the mechanisms by which certain pollutants influence LS, whether more directly or indirectly through health impairment. This is important because pollutants differ in size, shape, colour, odour, and physiological effects, which would impact LS differently. For example, small pollutants like PM2.5 can have a more tremendous impact on health, especially respiratory health, compared to other pollutants (Abed Al Ahad et al., 2020, 2023a; Manisalidis et al., 2020).

To sum up, there is lack of research on the mediating effect of general health on the association between long-term exposure to air pollution and LS using longitudinal individual-level data linked to fine spatial resolution air pollution data for multiple pollutants. Accordingly, this study uses 11 years of longitudinal individual-level data from the United-Kingdom (UK) linked to air pollution data at a fine spatial resolution to assess the direct effect of $NO_{2,}$ $SO_{2,}$ PM10, and PM2.5 air pollutants on individuals' self-reported LS and the indirect effect of the four pollutants on LS mediated through the individuals' general health. The mediation path analysis will control for the individuals' socio-demographic and lifestyle factors.

## Methods

### Study Design, Data, and Sample

In this research, we employed longitudinal individual-level data obtained from the "*Understanding Society: The UK Household Longitudinal Study (UKHLS)*" (UniversityofEssex, 2020). This extensive dataset comprises 10 waves of data collection spanning from 2009 to 2020, involving approximately 40,000 households recruited in the first wave from the four nations of the UK: England, Wales, Scotland, and Northern Ireland.

The UKHLS dataset consists of two main surveys: the youth survey which is filled by young people (aged 10 to 15) and the adult survey which is filled by individuals aged 16 + (UniversityofEssex, 2020). The dataset encompasses details on individuals' socio-demographic attributes like gender, age, marital status, education, occupation, socioeconomic classification, perceived financial situation, ethnicity, and country of birth (Abed Al Ahad, 2023; Abed Al Ahad et al., 2022a, 2023b). Additionally, it includes self-reported information on general health, well-being, life satisfaction, smoking status, and the specific local authority and census lower super output areas (LSOAs) of residence. Further information on the UKHLS dataset is described elsewhere (Abed Al Ahad, 2023; Abed Al Ahad et al., 2022a, 2023b; Lynn et al., 2018).

In this study, we utilized individual-level data from the adult survey of the UK Household Longitudinal Study (UKHLS), focusing on 59,492 adults aged 16 and above who contributed a total of 347,377 responses spanning 11 years (2009–2019) across the ten data collection waves. It's important to highlight that the initial adult survey for waves 1 to 10 encompassed 87,045 individuals with 444,181 surveys, and 96,804 surveys were excluded based on the criteria outlined in Fig. 1.

## Study Variables

### Life Satisfaction Dependent Variable

*Life satisfaction (LS)* was measured as an ordered variable by asking individuals to rate their overall life satisfaction on a 7-points Likert scale as follows: 1 = completely dissatisfied, 2 = mostly dissatisfied, 3 = somewhat dissatisfied, 4 = neither satisfied nor dissatisfied, 5 = somewhat satisfied, 6 = mostly satisfied, and 7 = completely satisfied.

### Air Pollution Independent Variable

Annual air pollution data, encompassing various sources like road traffic and industrial/combustion processes for $NO_2$, $SO_2$, PM10, and PM2.5 pollutants, were extracted from the database of the "Department for Environment Food and Rural Affairs" (Department-for-Environment-Food-and-Rural-Affairs, 2020). These data are in raster format, representing mean annual concentrations of pollutants measured in μg/m$^3$ up to the year 2019. The estimations were derived using air dispersion

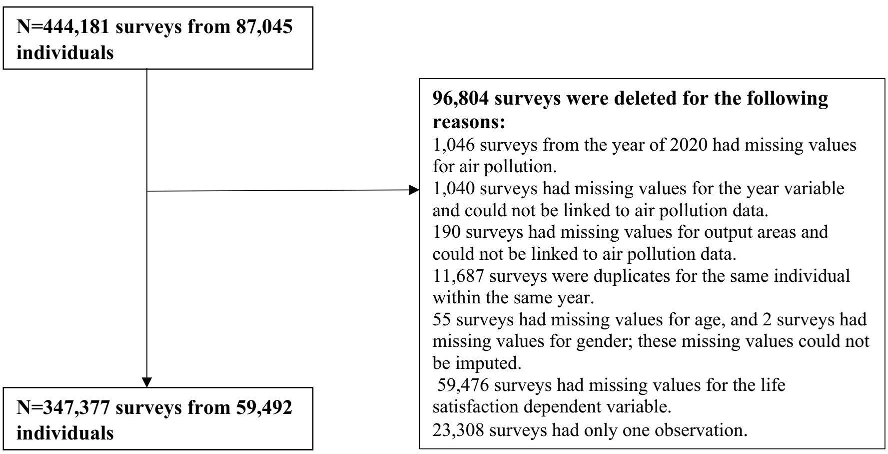


**Fig. 1** The reasons for deleting survey responses from the UKHLS data

modelling with a spatial resolution of 1 $km^2$ and were projected using the UK National Grid (Department-for-Environment-Food-and-Rural-Affairs, 2020).

This raster air pollution data at 1 $km^2$ resolution was connected to the UK Household Longitudinal Study (UKHLS) data by utilizing the census Lower Super Output Areas (LSOAs; data zones for Scotland and Super Output Areas for Northern Ireland) of residence for each individual in each year from 2009 to 2019. LSOAs, serving as the smallest geographical unit in the UKHLS dataset, help decompose England and Wales based on population size into areas with a minimum population of 1000 people. Some LSOAs, particularly those in urbanized regions, have an area smaller than 1 $km^2$, providing a high spatial resolution for assessing the impact of air pollution on life satisfaction (LS) and health. LSOAs in England and Wales are equivalent to data zones in Scotland and Super Output Areas in Northern Ireland, collectively referred to as LSOAs for simplicity (Abed Al Ahad, 2023; Abed Al Ahad et al., 2022a, 2023b).

The linkage process involved computing an area-weighted average air pollution concentration for each LSOA in each year, considering the proportion of area intersection between the 1 $km^2$ raster squares and the corresponding LSOA. For instance, if a LSOA intersected with three 1 $km^2$ squares, with one intersection covering half of the LSOA's area and the other two covering proportions of 0.3 and 0.2, respectively, the air pollution concentration for that LSOA would be calculated as 0.5 × the air pollution concentration of the first intersected square + 0.3 × the air pollution concentration of the second intersected square + 0.2 × the air pollution concentration of the third intersected square (Abed Al Ahad, 2023; Abed Al Ahad et al., 2022a, 2023b).

### Health Mediating Variable

*Health* was measured as an ordered variable by asking individuals to rate their general health condition on a 5-points Likert scale as follows: 1 = excellent, 2 = very good, 3 = good, 4 = fair, and 5 = poor.

### Socio-Demographic and Lifestyle Control Variables

Based on the factors considered by the literature to affect individuals' life satisfaction and health (Abed Al Ahad et al., 2020; Enkvist et al., 2012; Joshanloo & Jovanović, 2020; Orru et al., 2016; Papi & Cheraghi, 2021; Proctor et al., 2018; Wang & Geng, 2019), we selected a number of socio-demographic and lifestyle control variables as follows: gender (1 = male; 2 = female); age (coded as 16–18 and then in 5 years increments as 19–23; 24–28; 29–33; 34–38; 39–43; 44–48; 49–53; 54–58; 59–63; 59–63; 64–68; 69–73; 74–78; > 78); ethnicity (1 = British-white; 2 = Other-white; 3 = Indian; 4 = Pakistani/Bangladeshi; 5 = Black/African/Caribbean; 6 = mixed ethnicities; 7 = Other ethnicities); country of birth (1 = born in UK; 2 = not born in UK; 3 = No answer); marital status (1 = married; 2 = living as a couple; 3 = widowed; 4 = divorced/separated; 5 = single never married; 6 = no answer); education (1 = university degree; 2 = high school degree; 3 = lower educational levels; 4 = other qualifications; 5 = still a student); occupation (1 = managers/professionals/employers;

2 = non-manual workers; 3 = manual workers; 4 = not applicable: Student/retired/not working; 5 = no answer); perceived financial situation (1 = living comfortably/doing alright; 2 = living difficultly; 3 = no answer); smoking status (0 = non-smoker; 1 = smoker; 2 = no answer); rural–urban indicator (1 = urban; 2 = rural); and year dummies (calendar years: 2009–2019) (Abed Al Ahad, 2023; Abed Al Ahad et al., 2022a, 2023b).

### Data Analysis and Modelling Specifications

Percentages were computed to describe the individuals' LS, general health, socio-demographic, and lifestyle factors for each wave (waves 1–10) of the UKHLS sample. We also described the average concentrations of $NO_2$, $SO_2$, PM10, and PM2.5 pollutants across the LSOAs for each year (2009–2019) and examined the correlation between the four pollutants by constructing a Pearson's correlation matrix. Due to the substantial correlations noted between the pollutants (Pearson's coefficient $\geq 0.7$ (Schober et al., 2018)), separate models were employed to analyse the associations of $NO_2$, $SO_2$, PM10, and PM2.5 pollutants with life satisfaction (LS) and general health.

To examine both the direct impact of air pollution on LS and its indirect influence mediated through individuals' health, we employed generalized structural equation modelling (GSEM) path analysis incorporating multilevel ordered-logistic regression. Ordered logistic regression is a suitable analysis method for ordinal dependent variables such as life satisfaction and general health (Williams, 2016) and GSEM is a well-established method for mediation path analysis (Danner et al., 2015; Gunzler et al., 2013; Wang & Geng, 2019). GSEM possesses numerous advantages over the standard mediation analysis proposed by Baron and Kenny (Baron & Kenny, 1986), which involves a series of regression equations. The first advantage of GSEM is that it allows for ease of interpretation and estimation by testing complicated mediation models that may involve multiple independent, dependent, or mediator variables in a single analysis (Gunzler et al., 2013). This is not available in standard regression analysis whereby informal methods of combining the results of two or more equations to derive the asymptotic variance are used for inference about indirect and total effects (Gunzler et al., 2013). Second, GSEM can be extended easily to fit longitudinal data within a single conceptual framework, which is not the case for standard regression approaches (Gunzler et al., 2013). Finally, GSEM "implies a functional relationship expressed via a conceptual model, path diagram, and mathematical equations which account for the causal relationships in a hypothesized mediation process, the simultaneous nature of the indirect and direct effects, and the dual role the mediator plays as both a cause for the outcome and an effect of the intervention" (Gunzler et al., 2013).

Based on the hypothesised conceptual framework of our study (Fig. 2), we fitted a two-levels (standard errors for yearly observations clustered within individual IDs) ordered logistic generalised structural equation model which consists of two sub-models. Model 1 estimates the association between the independent air pollution variable and the dependent LS variable controlling for the general health

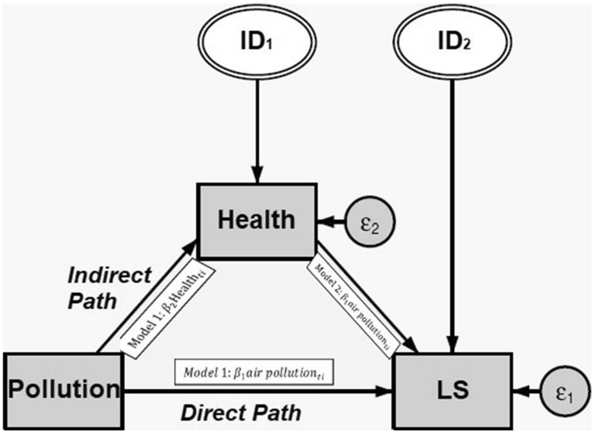


**Fig. 2** Conceptual framework for the mediating effect of health on the association between air pollution and LS. $\varepsilon_1$ is the error term for model 1 and $\varepsilon_2$ is the error term for model 2; ID1 is level 2 random intercept of individuals for model 1; ID2 is level 2 random intercept of individuals for model 2. Therefore, we included in the structural equation modelling a random intercept in each of the two models at the individual level, and we specified a covariance matrix that allows for an interaction between ID1 and ID2 random intercepts

mediator. Model 2 estimates the association between air pollution (independent variable) and general health (mediator that is considered as dependent variable in model 2). Both models 1 and 2 control for the same set of individuals' socio-demographic and lifestyle covariates described in the previous section of this article. Those socio-demographic and lifestyle covariates affect both the indirect and direct paths of the association between air pollution and LS through health.

$$\text{Model 1}: \log\left(\frac{Life\ satisfaction_{ti}^{(j)}}{1-Life\ satisfaction_{ti}^{(j)}}\right) = \beta_0^{(j)} + ID_{1i} + \beta_1\text{air pollution}_{ti} + \beta_2\text{Health}_{ti} + \beta_n\text{Control covariates}_{ti} + \varepsilon_1$$

$$\text{Model 2}: \log\left(\frac{Health_{ti}^{(s)}}{1-Health_{ti}^{(s)}}\right) = \beta_0^{(s)} + ID_{2i} + \beta_1\text{air pollution}_{ti} + \beta_n\text{Control covariates}_{ti} + \varepsilon_2$$

where $Life\ satisfaction_{ti}$ is the dependent variable for individual $i$ at year $t$; $j$ is the level of an ordered category with j levels for the life satisfaction ordinal variable; $s$ is the level of an ordered category with s levels for the health ordinal variable; air $\text{pollution}_{ti}$ is the air pollution exposure independent variable for individual $i$ at year $t$; $Health_{ti}$ is the health mediating variable for individual $i$ at year $t$; $\text{Control covariates}_{ti}$ are the socio-demographic and lifestyle control covariates including gender, age, ethnicity, country of birth, marital status, education, occupation, perceived financial situation, smoking status, rural–urban indicator, and year dummies (2009–2019); $\varepsilon_1$ is the error term for model 1 and $\varepsilon_2$ is the error term for model 2; $\beta_1$, $\beta_2$ …. $\beta_\text{n}$ are the slopes of fixed effects; $\beta_0$ is the fixed intercept; $ID_{1\text{i}}$ is level 2 random intercept of yearly observations nested within individual's IDs for model 1; $ID_{2\text{i}}$ is level 2 random intercept of yearly observations nested within individual's IDs for model 2; covariance matrix that allows for an interaction between $ID_{1\text{i}}$ and $ID_{2\text{i}}$ random intercepts was specified during the model fitting.

Following the GSEM and to obtain the direct, indirect, and total estimates for the health mediated association of air pollution with LS, we ran nonlinear combinations of parameter calculations, which are based on the "delta method", an approximation suitable for large samples (Raykov & Marcoulides, 2004) such as our UKHLS sample as follows (Fig. 2):

$$\begin{aligned}&\text{Indirect effect} = \text{Model 1}: \ \beta_2\text{Health}_{ti} \times \text{Model 2}: \ \beta_1\text{air pollution}_{ti};\\&\text{Direct effect} = \text{Model 1}: \ \beta_1\text{air pollution}_{ti}; \text{Total effect} = \text{indirect effect} + \text{direct effect};\\&\text{Percent of total effect that is mediated} = (\text{indirect} \div \text{total effect}) * 100;\\&\text{Ratio of indirect to direct} = \text{indirect} \div \text{direct effect}\end{aligned}$$

In addition to investigating the direct and indirect effects of air pollution on LS, we performed heterogeneity analysis by assessing the association between air pollution, general health, and LS by the type of occupation and area of residence, comparing living in rural areas to living in urban areas.

Statistical analysis was conducted in STATA version 15 software and the GSEM package was used to perform the path mixed-effects multilevel mediation analysis. Spatial pre-processing for air pollution linkages was carried out using ArcGIS Pro software. Findings are presented in the form of coefficients and 95% confidence intervals (CIs) per 1 μg/m$^3$ increase in air pollutants. Statistical significance is determined at a *P*-value below 0.05.

Given that GSEM in STATA does not allow for the calculation of model goodness of fit statistics such as standardized root mean squared residual (SRMR) and coefficient of determination (CD), we repeated the same models in a sensitivity analysis using structural equation models (SEM) instead of GSEM. It should be noted, however, that unlike GSEM, SEM does not allow for mixed-effects multilevel structural equation modelling that is required when analysing longitudinal data. However, we adjusted the standard errors in SEM for the clustering of repeated observations within each individual ID.

We also ran sensitivity analysis to investigate the association between air pollution and LS without and with controlling for general health using three-levels mixed effects ordered logistic regression with a random intercept for the individual ID (level 2) and the LSOA of residence (level 3).

## Results

### Description of Life Satisfaction, General Health and Individuals' Socio-Demographic and Lifestyle Factors

In all the ten waves, the majority of individuals were mostly satisfied with their life (Fig. 3), had very good or good general health (Fig. 4), were females, aged between 34 and 58 years old, had British-white ethnicity, were born in the UK, were married, had a university or high school or other educational qualifications, were non-manual workers (if working), had a comfortable/alright financial situation, were non-smokers, and lived in urban areas (Table 1).

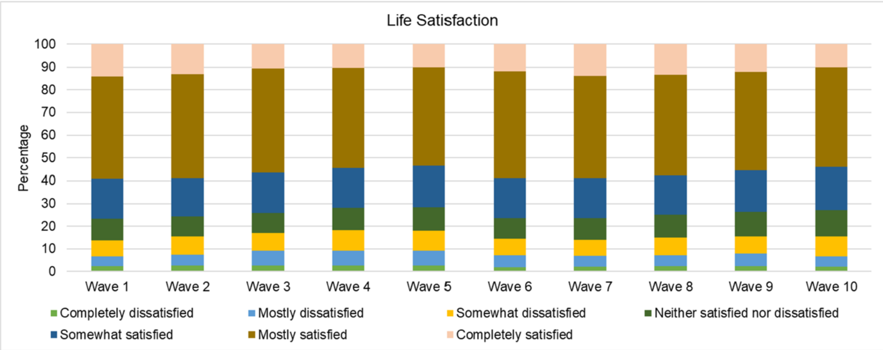


**Fig. 3** Description of individual's life satisfaction for each wave of the UKHLS sample ($N=347{,}377$ surveys from 59,492 individuals)

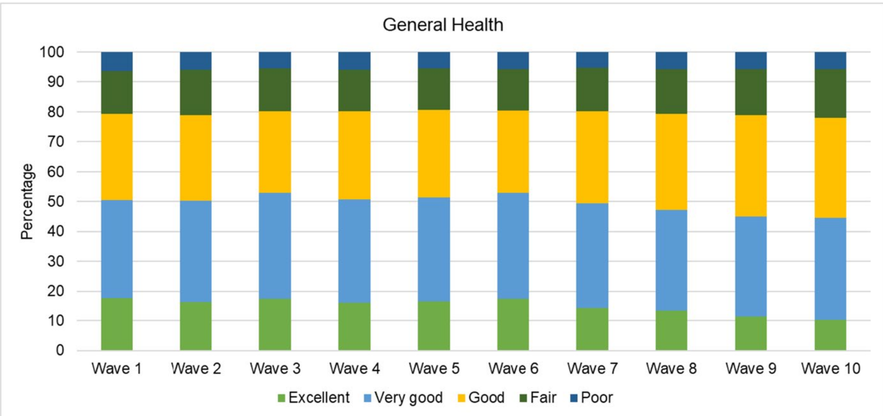


**Fig. 4** Description of individual's general health for each wave of the UKHLS sample ($N=347{,}377$ surveys from 59,492 individuals)

## Description of Air Pollution

Across the 11 years of follow-up (2009–2019), air pollution decreased from 17.7 μg/m$^3$ in 2009 to 13.6 μg/m$^3$ in 2019 for $NO_2$, from 15.5 μg/m$^3$ in 2009 to 13.6 μg/m$^3$ in 2019 for PM10, from 10.4 μg/m$^3$ in 2009 to 8.6 μg/m$^3$ in 2019 for PM2.5, and from 2.7 μg/m$^3$ in 2009 to 1.4 μg/m$^3$ in 2019 for $SO_2$ (Fig. 5). This presents a successful story for the efforts put by policymaking in the UK to reduce air pollution emissions.

Overall, the 11 years (2009–2019) mean of $NO_2$, $SO_2$, PM10, and PM2.5 pollutants was 15.80 μg/m$^3$ (SD = 7.47), 1.89 μg/m$^3$ (SD = 1.26), 14.38 μg/m$^3$ (SD = 3.18), and 9.76 μg/m$^3$ (SD = 2.40), respectively (Table 2).

**Table 1** Description of individual's socio-demographic and lifestyle factors for each wave of the UKHLS sample ($N=347{,}377$ surveys from 59,492 individuals)

| | | Wave1 (2009–2011) $N=31{,}179$ Percent | Wave2 (2010–2012) $N=39{,}835$ Percent | Wave3 (2011–2013) $N=38{,}658$ Percent | Wave4 (2012–2014) $N=37{,}363$ Percent | Wave5 (2013–2015) $N=35{,}214$ Percent | Wave6 (2014–2016) $N=34{,}001$ Percent | Wave7 (2015–2017) $N=35{,}255$ Percent | Wave8 (2016–2018) $N=34{,}346$ Percent | Wave9 (2017–2019) $N=31{,}867$ Percent | Wave10 (2018–2019) $N=29{,}659$ Percent |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Gender | Male | 43.0 | 43.6 | 43.8 | 44.0 | 44.3 | 44.4 | 44.4 | 44.4 | 44.3 | 44.0 |
| | Female | 57.0 | 56.4 | 56.2 | 56.0 | 55.7 | 55.7 | 55.7 | 55.6 | 55.7 | 56.0 |
| Age | Young (<34) | 26.3 | 25.5 | 25.8 | 25.2 | 25.1 | 23.6 | 23.8 | 23.3 | 22.5 | 20.9 |
| | Middle age (34–58) | 46.1 | 44.9 | 45.3 | 44.6 | 44.5 | 44.3 | 44.3 | 43.7 | 43.3 | 43.5 |
| | Old (>58) | 27.6 | 29.6 | 28.9 | 30.2 | 30.4 | 32.2 | 31.9 | 33.1 | 34.2 | 35.6 |
| Ethnicity | British-white | 81.4 | 82.5 | 81.8 | 81.8 | 82.0 | 81.6 | 77.3 | 77.1 | 78.2 | 79.0 |
| | Other-white | 4.1 | 4.8 | 4.7 | 4.7 | 4.5 | 4.7 | 5.3 | 5.4 | 5.3 | 5.1 |
| | Indian | 3.1 | 2.5 | 2.6 | 2.6 | 2.6 | 2.8 | 3.8 | 3.9 | 3.8 | 3.6 |
| | Pakistani/Bangla-deshi | 3.5 | 2.7 | 3.0 | 3.0 | 3.1 | 3.4 | 4.6 | 4.7 | 4.6 | 4.6 |
| | Black/African/Caribbean | 3.9 | 3.0 | 3.4 | 3.4 | 3.3 | 3.1 | 4.2 | 4.0 | 3.6 | 3.3 |
| | Mixed ethnicities | 1.7 | 1.3 | 1.5 | 1.5 | 1.6 | 1.6 | 1.8 | 1.8 | 1.8 | 1.7 |
| | Other ethnicities | 2.4 | 3.2 | 3.1 | 3.1 | 3.0 | 2.9 | 3.1 | 3.1 | 2.8 | 2.8 |
| Country of birth | Born in the UK | 86.3 | 67.7 | 67.0 | 68.0 | 68.6 | 68.6 | 67.1 | 67.3 | 68.2 | 68.4 |
| | Not born in the UK | 13.7 | 10.5 | 10.6 | 10.6 | 10.3 | 10.5 | 13.7 | 13.7 | 12.6 | 12.0 |
| | No answer | 0.0 | 21.9 | 22.4 | 21.5 | 21.1 | 20.9 | 19.2 | 19.1 | 19.2 | 19.6 |

**Table 1** (continued)

| | | Wave1 (2009–2011) $N=31{,}179$ | Wave2 (2010–2012) $N=39{,}835$ | Wave3 (2011–2013) $N=38{,}658$ | Wave4 (2012–2014) $N=37{,}363$ | Wave5 (2013–2015) $N=35{,}214$ | Wave6 (2014–2016) $N=34{,}001$ | Wave7 (2015–2017) $N=35{,}255$ | Wave8 (2016–2018) $N=34{,}346$ | Wave9 (2017–2019) $N=31{,}867$ | Wave10 (2018–2019) $N=29{,}659$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Percent | Percent | Percent | Percent | Percent | Percent | Percent | Percent | Percent | Percent |
| Marital status | Married | 53.2 | 53.6 | 52.7 | 52.1 | 51.7 | 52.9 | 52.8 | 53.2 | 53.7 | 55.2 |
| | Living as a couple | 11.8 | 11.6 | 11.5 | 11.8 | 11.6 | 11.1 | 10.8 | 10.5 | 10.0 | 9.6 |
| | Widowed | 5.5 | 5.8 | 5.7 | 5.9 | 5.8 | 6.0 | 5.8 | 5.8 | 5.9 | 5.9 |
| | Divorced/separated | 9.0 | 8.4 | 8.5 | 8.6 | 8.5 | 8.2 | 8.0 | 7.8 | 8.0 | 8.1 |
| | Single never married | 20.4 | 20.6 | 21.7 | 21.5 | 22.2 | 21.4 | 22.4 | 22.6 | 22.1 | 20.9 |
| | No answer | 0.1 | 0.0 | 0.0 | 0.1 | 0.2 | 0.4 | 0.2 | 0.2 | 0.3 | 0.4 |
| Education | University degree | 32.1 | 25.6 | 27.2 | 28.1 | 29.3 | 29.9 | 30.7 | 31.6 | 32.8 | 34.2 |
| | High school degree | 33.1 | 25.8 | 26.2 | 26.5 | 26.7 | 26.9 | 26.5 | 26.7 | 27.0 | 26.9 |
| | Lower educational levels | 1.4 | 1.1 | 1.1 | 1.1 | 1.1 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| | Other qualifications | 27.1 | 40.6 | 38.8 | 37.7 | 36.4 | 36.2 | 35.4 | 34.7 | 33.5 | 33.3 |
| | Still a student | 6.4 | 7.0 | 6.8 | 6.7 | 6.6 | 6.0 | 6.4 | 6.0 | 5.7 | 4.7 |

**Table 1** (continued)

| | | Wave1 (2009–2011) $N=31,179$ Percent | Wave2 (2010–2012) $N=39,835$ Percent | Wave3 (2011–2013) $N=38,658$ Percent | Wave4 (2012–2014) $N=37,363$ Percent | Wave5 (2013–2015) $N=35,214$ Percent | Wave6 (2014–2016) $N=34,001$ Percent | Wave7 (2015–2017) $N=35,255$ Percent | Wave8 (2016–2018) $N=34,346$ Percent | Wave9 (2017–2019) $N=31,867$ Percent | Wave10 (2018–2019) $N=29,659$ Percent |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Occupation | Managers/Professionals/employers | 12.4 | 12.1 | 12.0 | 12.2 | 12.4 | 12.2 | 12.1 | 12.2 | 12.1 | 11.8 |
| | Non-manual workers | 27.6 | 27.2 | 27.5 | 27.3 | 28.0 | 27.6 | 27.7 | 27.1 | 26.7 | 26.4 |
| | Manual workers | 17.9 | 18.0 | 18.2 | 17.9 | 18.3 | 18.1 | 18.2 | 17.8 | 17.1 | 16.3 |
| | Not applicable: Student/retired/Not working | 41.9 | 42.5 | 41.6 | 42.1 | 41.0 | 41.6 | 41.4 | 42.0 | 41.9 | 42.6 |
| | No answer | 0.2 | 0.2 | 0.7 | 0.4 | 0.3 | 0.6 | 0.6 | 1.0 | 2.2 | 2.8 |
| Perceived financial situation | living comfortably/doing alright | 60.1 | 62.4 | 62.0 | 64.5 | 66.3 | 71.7 | 72.4 | 73.1 | 71.6 | 71.6 |
| | living difficultly | 39.8 | 37.5 | 37.9 | 35.4 | 33.6 | 28.1 | 27.5 | 26.7 | 28.2 | 28.2 |
| | no answer | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.2 | 0.2 | 0.3 | 0.2 |
| Smoking status | non-smoker | 74.0 | 79.2 | 73.4 | 72.4 | 82.1 | 83.1 | 84.4 | 85.3 | 86.6 | 87.1 |
| | smoker | 19.5 | 20.7 | 19.7 | 19.4 | 17.9 | 16.8 | 15.5 | 14.5 | 13.3 | 12.8 |
| | no answer | 6.6 | 0.1 | 6.9 | 8.2 | 0.0 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 |
| Rural–Urban indicator | Urban area | 76.8 | 74.1 | 74.6 | 74.2 | 74.4 | 74.4 | 75.9 | 75.7 | 75.2 | 74.8 |
| | Rural area | 23.2 | 25.9 | 25.4 | 25.8 | 25.6 | 25.6 | 24.1 | 24.3 | 24.8 | 25.2 |

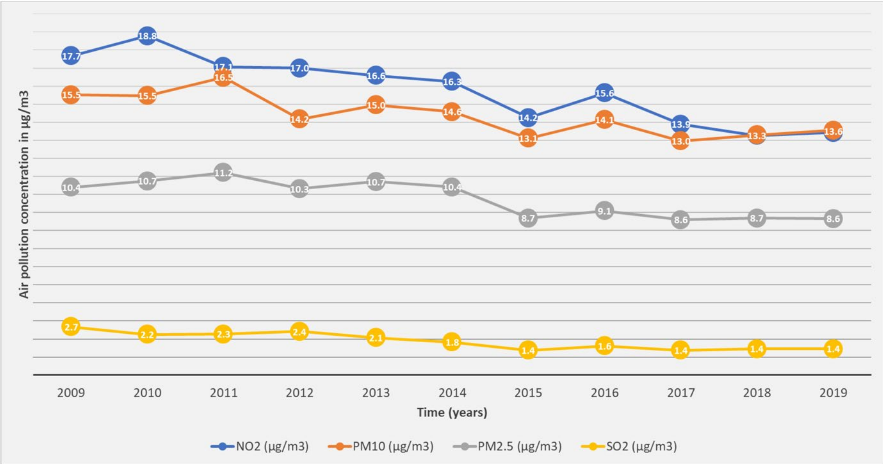


**Fig. 5** The annual mean of $NO_2$, $SO_2$, PM10, and PM2.5 air pollutants at the LSOAs level in the UK from the year 2009 to 2019 ($N$ = 42,619 LSOAs)

**Table 2** Exposure description and correlation matrix of air pollutants at the LSOAs level ($N$ = 42,619 LSOAs)

| | Pearson's correlation coefficient | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $NO_2$ ($\mu g/m^3$) | $SO_2$ ($\mu g/m^3$) | PM10 ($\mu g/m^3$) | PM2.5 ($\mu g/m^3$) | Mean | SD | Median | Interquartile range |
| $NO_2$ ($\mu g/m^3$) | 1.00 | | | | 15.80 | 7.47 | 14.91 | 9.69 |
| $SO_2$ ($\mu g/m^3$) | 0.36 | 1.00 | | | 1.89 | 1.26 | 1.59 | 1.06 |
| PM10 ($\mu g/m^3$) | **0.76** | 0.28 | 1.00 | | 14.38 | 3.18 | 14.53 | 4.32 |
| PM2.5 ($\mu g/m^3$) | **0.79** | 0.31 | **0.97** | 1.00 | 9.76 | 2.40 | 9.88 | 3.30 |

Strong correlations with correlation coefficient ≥ 0.70 are highlighted in bold

Moreover, a strong correlation (Pearson's coefficient ≥ 0.7) was noted between $NO_2$, PM10, and PM2.5 pollutants (Table 2), potentially attributed to chemical reactions occurring between particulate matter and $NO_2$ pollutants within the atmosphere.

## Empirical Results for the Health Mediated Association Between Air Pollution and Life Satisfaction

Results showed that lower ratings of LS (1 = completely dissatisfied to 7 = completely satisfied) are associated with higher concentrations of $NO_2$ (coefficient = -0.007, 95%CI = -0.009, -0.005, $p < 0.001$), $SO_2$ (coefficient = -0.005, 95%CI = -0.012, 0.002), PM10 (coefficient = -0.011, 95%CI = -0.016, -0.007, $p < 0.001$), and PM2.5 (coefficient = -0.018, 95%CI = -0.024, -0.012, $p < 0.001$) pollutants (Table 3). Higher concentrations of $NO_2$ (coefficient = 0.009, 95%CI = 0.006, 0.012, $p < 0.001$), $SO_2$

**Table 3** The effect of air pollution and the general health mediator on LS ($N = 347{,}377$ surveys from 59,492 individuals)

| | | Model 1: dependent variable = LS | | | Model 2: dependent variable = Health | | |
|---|---|---|---|---|---|---|---|
| | | Coefficient | 95% CI | *P*-value | Coefficient | 95% CI | *P*-value |
| Independent variable | $NO_2$ (μg/m$^3$) | -0.007 | -0.009,-0.005 | 0.000 | 0.009 | 0.006,0.012 | 0.000 |
| Mediating variable | General health | -0.604 | -0.614,-0.595 | 0.000 | | | |
| Independent variable | $SO_2$ (μg/m$^3$) | -0.005 | -0.012,0.002 | 0.129 | 0.025 | 0.017,0.034 | 0.000 |
| Mediating variable | General health | -0.605 | -0.614,-0.595 | 0.000 | | | |
| Independent variable | PM10 (μg/m$^3$) | -0.011 | -0.016,-0.007 | 0.000 | 0.019 | 0.013,0.025 | 0.000 |
| Mediating variable | General health | -0.605 | -0.614,-0.595 | 0.000 | | | |
| Independent variable | PM2.5 (μg/m$^3$) | -0.018 | -0.024,-0.012 | 0.000 | 0.025 | 0.017,0.033 | 0.000 |
| Mediating variable | General health | -0.605 | -0.614,-0.595 | 0.000 | | | |

Model 1 includes LS dependent variable, air pollution independent variable, general health mediator variable, and control variables which include gender, age, ethnicity, country of birth, marital status, education, occupation, perceived financial situation, smoking status, rural–urban indicator, and year dummies (2009–2019); Model 2 includes health mediator considered as dependent variable in model 2, air pollution independent variable, and control variables which include gender, age, ethnicity, country of birth, marital status, education, occupation, perceived financial situation, smoking status, rural–urban indicator, and year dummies (2009–2019); Full results of Models 1 and 2 including control variables coefficients, 95% CIs, and *P*-values are shown in Tab s1, Tab s2, Tab s3, and Tab s4

(coefficient = 0.025, 95%CI = 0.017, 0.034, $p < 0.001$), PM10 (coefficient = 0.019, 95%CI = 0.013, 0.025, $p < 0.001$), and PM2.5 (coefficient = 0.025, 95%CI = 0.017, 0.033, $p < 0.001$) pollutants were also associated with poorer health (1 = Excellent health to 5 = poor health), while poorer health was associated with reduced LS (coefficient = -0.605, 95%CI = -0.614, -0.595, $p < 0.001$) (Table 3).

Besides the association between air pollution, health, and LS, results also showed that lower ratings of LS are associated with being from an ethnic minority, with being single, widowed, divorced, or living as a couple compared to married marital status, with having high school or lower educational levels compared to a university level, with being non-manual worker compared to managerial or professional occupations, with having difficult financial situation, with being a smoker, and with increasing time compared to the year of 2009. On the other hand, females, old age people (64 + compared to young age of 16–18), non-UK-born individuals, manual workers (compared to managerial and professional occupations) and people who live in rural areas were more satisfied with their life (Tab s1, Tab s2, Tab s3, and Tab s4).

As for model 2 results, poorer self-reported health was associated with female gender, older age, being from an Indian, Pakistani, Bangladeshi, mixed, or other ethnicities group compared to British-White, being single, widowed, divorced, or living as a couple compared to married marital status, having high school or lower educational levels compared to a university level, being non-manual or manual workers compared to managerial or professional occupations, having difficult financial situation, and being a smoker. In contrast, better health was shown among non-UK-born individuals and people living in rural areas (Tab s1, Tab s2, Tab s3, and Tab s4).

Finally, mediation path analysis showed that air pollution impacted individuals' LS directly and indirectly through impairing their general health (Table 4). The percent of total effect mediated through health was 44.03% for $NO_2$, 73.95% for $SO_2$, 49.88% for PM10, and 45.42% for PM2.5 and the ratio of indirect to direct effect was 0.79 for $NO_2$, 2.84 for $SO_2$, 0.99 for PM10, and 0.83 for PM2.5 (Table 4).

Assessing the association between air pollution, general health, and LS by the type of occupation (Tab s5) and area of residence (Tab s6) revealed lower LS among individuals living in rural areas compared to living in urban areas with higher exposure to $NO_2$ pollution, yet no significant differences were noted with respect to the type of occupation. Moreover, non-manual and manual workers were more likely to report poorer general health with increased exposure to $NO_2$, PM10, and PM2.5 pollution than managers/professionals/employers (Tab s5).

Sensitivity analysis with SEM instead of GSEM revealed a similar pattern of associations (Tab s7 and Tab s8). The goodness of fit statistics obtained from SEM showed a good fit for all the models with SRMR being less than 0.08 (Hu & Bentler, 1999) and CD indicating that more than 25% of the variance in the dependent variable (LS) is predicted by the model.

Similar results were also shown in additional sensitivity analysis with multilevel mixed effects ordered logistic regression instead of GSEM (Tab s9). Increased exposure to all four air pollutants was significantly associated with lower ratings of LS (model 1). However, when the model was adjusted for general health (model 2), the significance of the association between increased exposure to $SO_2$ and lower ratings of LS disappeared, confirming to the GSEM analysis, and suggesting that $SO_2$ affects LS indirectly through poor general health rather than directly (Tab s9).

## Discussion

In this study, we demonstrated that the impact of air pollution on life satisfaction (LS) can manifest both directly and indirectly through health deterioration. Greater exposure to $NO_2$, $SO_2$, PM10, and PM2.5 pollutants correlated with diminished health, and poorer health was linked to a decline in life satisfaction. The connection between air pollution and reduced life satisfaction aligns with findings in pertinent literature (Du et al., 2018; MacKerron & Mourato, 2009; Schmitt, 2013; Shi et al., 2022; Silva et al., 2012; Yuan et al., 2018). Studies from Europe have found a robust negative impact of PM10 and $SO_2$ pollutants on LS (Ferreira et al., 2013; Orru et al., 2016). Similarly, the association between air pollution and poor health is

**Table 4** Mediation path analysis results including the direct and indirect effects of air pollution on LS through the general health mediator ($N = 347{,}377$ surveys from 59,492 individuals)

| | $NO_2$ (μg/m$^3$) | | | $SO_2$ (μg/m$^3$) | | |
|---|---|---|---|---|---|---|
| | Coefficient | 95% CI | *P*-value | Coefficient | 95% CI | *P*-value |
| Direct effect | -0.007 | -0.009,-0.005 | 0.000 | -0.005 | -0.012,0.002 | 0.129 |
| Indirect effect | -0.006 | -0.007,-0.004 | 0.000 | -0.015 | -0.020,-0.010 | 0.000 |
| Total effect | -0.013 | -0.015,-0.010 | 0.000 | -0.021 | -0.029,-0.012 | 0.000 |
| | Percent of total effect that is mediated = 44.03% | | | Percent of total effect that is mediated = 73.95% | | |
| | Ratio of indirect to direct effect = 0.79 | | | Ratio of indirect to direct effect = 2.84 | | |
| | PM10 (μg/m$^3$) | | | PM2.5 (μg/m$^3$) | | |
| | Coefficient | 95% CI | *P*-value | Coefficient | 95% CI | *P*-value |
| Direct effect | -0.011 | -0.016,-0.007 | 0.000 | -0.018 | -0.024,-0.012 | 0.000 |
| Indirect effect | -0.011 | -0.015,-0.008 | 0.000 | -0.015 | -0.020,-0.010 | 0.000 |
| Total effect | -0.023 | -0.029,-0.017 | 0.000 | -0.033 | -0.041,-0.025 | 0.000 |
| | Percent of total effect that is mediated = 49.88% | | | Percent of total effect that is mediated = 45.42% | | |
| | Ratio of indirect to direct effect = 0.995 | | | Ratio of indirect to direct effect = 0.83 | | |

well-documented in the literature (Abed Al Ahad et al., 2020, 2022b, 2023b; Collart et al., 2018; Fischer et al., 2015; Goldberg et al., 2015; Manisalidis et al., 2020).

Nevertheless, the link between air pollution, health, and LS is not fully studied and requires further research. Our study attempted to fill this literature gap by using 11 years of longitudinal individual-level data linked to fine spatial resolution air pollution to show that the association between multiple air pollutants and LS can be direct and indirect through poor health. Thus, our study provided new evidence for exploring the underlying mechanism for the effect of air pollution on LS through the mediating role of health. The direct negative impact of air pollution on LS can be explained by the psychological stress and anxiety associated with coping behaviours such as staying indoors rather than enjoying outdoor activities during periods of elevated air pollution (Abed Al Ahad et al., 2022a; Orru et al., 2016; von Lindern et al., 2016). The indirect effect can be explained through the harmful impact of air pollution on humans' health which affects the cardiovascular, respiratory, immune and autonomous nervous systems (Costa et al., 2014; Manisalidis et al., 2020), reflecting changes in physiology, emotions, and physical abilities (Abed Al Ahad et al., 2022a; Orru et al., 2016; Ventriglio et al., 2021) and resulting in low LS. In support to our findings, a recent cross-sectional study from China showed in a mediation analysis that $SO_2$ air pollution reduces individuals' happiness through health impairment (Liu et al., 2021).

Our study showed that almost half of the air pollution effect on LS is mediated by health. However, $SO_2$ pollutant showed a different mediation pattern than the other studied pollutants. For $SO_{2,}$ the indirect effect was stronger than the direct effect (ratio of indirect to direct effect = 2.84). In contrast, $NO_{2,}$ PM10, and PM2.5 pollutants showed stronger direct effects. This could be related to the toxicity of $SO_2$ and its source of emission. Experimental research has shown that $SO_2$ contributes to respiratory and cardiovascular symptoms such as respiratory irritation, bronchitis, mucus production, and bronchospasm by penetrating deep into the lungs and interacting with sensory receptors leading to changes in the airway physiology (Chen et al., 2007; Manisalidis et al., 2020). Chronic exposure to $SO_2$ can also disrupt the signal transmission and synaptic communications between neurons and initiate oxidative stress and the production of reactive oxygen species that can cross the blood–brain barrier resulting in neurodegeneration and neuronal dysfunction (Ku et al., 2017; Manisalidis et al., 2020). The respiratory, cardiovascular, and neuronal effects caused by $SO_2$ pollutant lead to various health complications and poor health, which exert a strong indirect negative impact on LS.

Industry and fossil fuel combustion are the main sources of $SO_2$ emissions while $NO_{2,}$ PM10, and PM2.5 pollutants are mainly liberated from traffic exhaust (Abed Al Ahad et al., 2020; Manisalidis et al., 2020). Thus, $SO_2$ is expected to affect mainly people who live in the vicinity of factories and energy production facilities. Literature has shown that people who live near industrial complexes show worse respiratory and allergic symptoms and are at a higher risk of developing lung and uterine cancers (Eom et al., 2018). Living near petrochemical industries was also shown to increase the risk of cancer morbidity and mortality (Domingo et al., 2020). Not to mention that people who live in industrial regions are exposed to the industrial-related $SO_2$ pollution as well as to the traffic-related

$NO_2$, PM10, and PM2.5 pollution, leading to worse health outcomes. This reiterates the idea that exposure to industrial $SO_2$ pollution affects health in a negative way, which reflects a strong indirect effect on low LS.

Another explanation for the stronger indirect effect of $SO_2$ pollution on LS is that people who live in industrial areas and perceive their areas to be industrial show less depression and anxiety and better psychological health than those living in non-industrial areas (Marques & Lima, 2011). This corresponds to the psychological health hypothesis (Taylor & Brown, 1994), whereby "if I live in an industrial place, it is actually best for my mental health that I recognize it as such" (Marques & Lima, 2011). In addition, people who live in industrial areas may be more focused on the positive aspects of industry such as economical development and regional employment rather than the negative impacts of air pollution (Boardman et al., 2008), which results in better psychological health and higher LS. Relative to our study, this reduces the direct effect of air pollution on low LS and strengthens the indirect effect through poor health.

However, it has been found in the literature that perceptions of air pollution, especially when characterised with visible (e.g., colour) or olfactive (e.g., bad smell) signs, are associated with increased psychological stress and anxiety and the necessity for coping behaviours such as replacing outdoor stress-relieving activities with indoor activities (von Lindern et al., 2016). This in turn leads to strong direct effects of air pollution on low LS. Nevertheless, this can be attributed more to the traffic-related air pollutants (e.g. $NO_2$, PM10, and PM2.5) (Abed Al Ahad et al., 2020; Manisalidis et al., 2020) characterised with odour, particles, and smoke that are sensed on a daily basis by all people whether living in an industrial or non-industrial region. This is in line with our findings whereby the direct effect of $NO_2$, PM10, and PM2.5 pollutants on LS was stronger than the indirect effect, while $SO_2$ impacted LS mostly indirectly through health impairment.

Further heterogeneity analysis also revealed that the rating of LS for individuals residing in rural areas is more sensitive to $NO_2$ pollution exposure than for individuals residing in urban areas. This could be attributed to the fact that $NO_2$ – a traffic-related pollutant is less abundant in rural areas. Thus, when individuals who live in rural areas are exposed to it, this may have a greater impact on their LS ratings compared to those living in urban areas who are exposed to this pollutant more frequently.

Our study is one of its kind in highlighting the direct effect of air pollution on LS and the indirect effect mediated through health. It exhibits methodological novelty by applying mediation path analysis on 11 years of longitudinal individual-level data (i.e., lengthy temporal scale) linked to fine spatial resolution air pollution data. In contrast to cross-sectional data, longitudinal data encompasses both the dynamics within individuals and the variations between individuals across time (Tang et al., 2013). This gives better indication of whether changes in the mediator are more likely to precede changes in the outcome; thus, allowing for precise illustrations of the temporal order of change over time and more accurate conclusions about mediation (Gunzler et al., 2013).

Still, our study has some limitations. First, the study design involved linking individual-level data from the UKHLS dataset to annual air pollution data at the LSOAs level, assuming that individuals in the same LSOA share the same air pollution concentration. While LSOAs offer high spatial resolution, it is advisable to utilize a dataset allowing air pollution linkages at the postcode level, which has the highest spatial resolution in the UK, to mitigate exposure bias. Another potential source of bias in exposure might arise from assessing individuals' exposure based on their place of residence (LSOA), which may not accurately represent their true personal exposure. In reality, exposure is more intricate, involving indoor settings, workplaces, and commuting patterns. Therefore, future studies should integrate air pollution exposure assessments for both residence and workplace, considering both ambient and indoor air pollution exposure. Second, our study explored the mediating role of self-reported health in the relationship between air pollution and life satisfaction, rather than employing a more objective mediator such as hospital admissions. This choice may introduce social desirability or reporting bias, where individuals might overestimate or underestimate their general health. Nevertheless, the literature demonstrates high correlations between self-reported health and objective health measures, including hospital admissions, enhancing the reliability of the self-reported health mediator (Ul-Haq et al., 2014; Williams et al., 2017). Finally, in this study, we performed mediation path analysis in which the independent (i.e., air pollution), mediator (i.e., health) and dependent (i.e., LS) variables were all measured within the same year per each individual-yearly observation rather than mediation analysis with latent variables whereby air pollution is lagged by one, two or several years. Analysing the effect of lagged air pollution exposure on LS through health would provide a better conceptualisation of temporal sequence by ensuring that previous yearly exposures to air pollution are affecting LS directly and indirectly through health impairment rather than same year exposures. However, the UKHLS data does not allow for mediation analysis with latent variables because data collection including the collection of individuals' places of residence are based on collection waves (waves 1 to 10) and not all individuals are present at every wave. This makes the linkage of air pollution exposures at previous years impossible without knowing the yearly history of individual's place of residence. Thus, for future research, it is recommended to use other data sources that allow for the linkage of lagged air pollution data such as administrative data that contain individuals' residential histories.

## Conclusion

This study utilised 11 years of longitudinal individual-level data linked to fine spatial resolution data on multiple pollutants to provide evidence that air pollution affects the individuals' LS directly and indirectly through health impairment. Our study revealed pollutant differences in the direct and indirect effects with $SO_2$ showing stronger indirect effect on low LS that is mediated through poorer health. The relationship between long-term exposure to air pollution and how satisfied people are with their lives overall and how this is related to their general health status can be monetized to provide the basis for air pollution abatement strategies for maintaining both health and well-being of societies. The results of this study also suggest that future policies aiming at better life satisfaction are urged to enhance the air quality and promote effective health planning.

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**Author Contribution** The author Mary Abed Al Ahad was responsible for all the aspects of this article including Conceptualization, Investigation, Methodology, Data curation, Formal Analysis, Writing-Original Draft, Writing-Review and Editing, Visualization, Project administration, and Funding acquisition.

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**Data Availability** We cannot make the data underlying our analysis publicly available due to ethical and legal restrictions.We are using the "Understanding Society: The UK Household Longitudinal Study" dataset which is an initiative funded by the Economic and Social Research Council and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by NatCen Social Research and Kantar Public. These data are protected by a copyright license and strictly distributed by the UK Data Service which is the largest digital repository for quantitative and qualitative social science and humanities research data in the UK.Therefore, data underlying our analysis can only be accessed through the UK Data Service for authorized researchers from the following https://beta.ukdataservice.ac.uk/datacatalogue/series/seriesid=2000053

## Declarations

**Ethical Approval** This paper is part of a project that was granted ethical approval on the 14th of May 2020 by the School of Geography and Sustainable Development Ethics Committee, acting on behalf of the University Teaching and Research Ethics Committee (UTREC) at the University of St Andrews, Scotland, United Kingdom. This paper uses data from the "Understanding Society: The UK Household Longitudinal Study" which was collected by the University of Essex and can be downloaded from the UK Data Archive. The University of Essex Ethics Committee has approved all data collection on Understanding Society main study and innovation panel waves, including asking consent for all data linkages except to health records. Requesting consent for health record linkage was approved at Wave 1 by the National Research Ethics Service (NRES) Oxfordshire REC A (08/H0604/124), at BHPS Wave 18 by the NRES Royal Free Hospital & Medical School (08/H0720/60) and at Wave 4 by NRES Southampton REC A (11/SC/0274). Approval for the collection of biosocial data by trained nurses in Waves 2 and 3 of the main survey was obtained from the National Research Ethics Service (Understanding Society—UK Household Longitudinal Study: A Biosocial Component, Oxfordshire A REC, Reference: 10/H0604/2).

**Competing Interests** The authors declare that they have no competing interests.

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