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Long-term associations between ambient air pollution and self-perceived health status: Results from the population-based KORA-Fit study

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ABSTRACT

Background: Little is known about the association between air pollution and self-perceived health (including both health-related quality of life [HRQoL] and self-rated health [SRH]). The aim of this study was therefore to explore whether long-term air pollution exposure is associated with worse self-perceived health, as measured by different tools.

Methods: We used a land-use regression model to determine the annual average levels of particulate matter with a diameter <10 µm (PM_{10}), coarse particles (PM_{coarse}), fine particles ($PM_{2.5}$), fine particle absorbances ($PM_{2.5abs}$), particle number concentration (PNC), ozone (O_3), nitrogen dioxide (NO_2), and nitrogen oxide (NO_X) for geo-coded residential addresses (2014–2015). Questionnaires and face-to-face interviews were used to collect HRQoL (measured using the European Quality of Life 5 Dimensions [EQ-5D] index and the European Quality of Life Visual Analogue Scale [EQ-VAS]) and SRH indicators (measured through two survey questions) (2018–2019) from participants of the Cooperative Health Research in the Region of Augsburg (KORA)-Fit study in Germany. We explored associations via generalized additive models, multinomial logistic regression, and logistic regression.

Results: We included 2610 participants with a mean age of 64.0 years in this cross-sectional study, of which 1428 (54.7%) were female. Each interquartile range (IQR) increase in O_3 was associated with a reduced EQ-5D index value (% change of mean points and 95% confidence interval: -0.91% [-1.76; -0.06]). The average EQ-VAS score declined between -1.57% and -0.96% with each IQR increase in PM_{10}, PM_{coarse}, $PM_{2.5abs}$, PNC, NO_2, and NO_X. These pollutants were associated with increased occurrence of poor SRH, with odds ratios ranging from 1.24 to 2.67. $PM_{2.5abs}$ was linked to a higher likelihood of reporting a worse comparative SRH (2.59 [1.12; 5.99]). Body mass index and self-perceived stress modified these associations.

Conclusions: Long-term air pollution exposure was associated with poor self-perceived health, presenting as lower HRQoL and higher odds of poor SRH. Single-item indicators measuring self-perceived health status may work better than multi-dimensional indicators.

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1. Introduction

Increasing epidemiological evidence suggests that exposure to airborne particulate matter (PM) or gaseous air pollutants affects nearly all human body organ systems (Thurston et al., 2017). Exposure to ambient PM pollution was one of the top three risk factors accounting for more than 1% of global disability-adjusted life-years in 2019 (GBD, 2019), and between 1990 and 2019, the number of global deaths and disability-adjusted life-years attributable to exposure to ambient PM with a diameter <2.5 μm ($PM_{2.5}$) have increased by 102.3% and 67.7%, respectively (Sang et al., 2022). According to the State of Global Air (2024), air pollution accounted for 8.1 million premature deaths worldwide in 2021, including 48% of global deaths from chronic obstructive pulmonary disease, 28% from ischemic heart disease, and 27% from stroke (Health Effects Institute, 2024). Air pollution, however, may also affect health without directly manifesting as morbidity or mortality, instead resulting in feelings of malaise and a lower self-perceived health status. Within the body, air pollution may adversely affect health due to oxidative stress, inflammation, dysregulation of the nervous system, and direct particle transfer into organ systems (de Bont et al., 2022). When exposed to air pollution, people may perceive an increase in headaches, dizziness, nausea, feeling ill, and higher perceived psychological stress (Trushna et al., 2021; Zhao et al., 2018). Even though there is a growing body of evidence supporting the adverse health effects of air pollution, most studies are focused on "objective" measures of health status, leaving a gap in the research using "subjective" measures.

"Self-perceived health status" may include a wide range of constructs representing different aspects of subjective overall health. Both health-related quality of life (HRQoL) and the general concept of self-rated health (SRH) are useful as they can capture a comprehensive summary of health problems that may not be detected by standard medical screening procedures (Anillo Arrieta et al., 2021; Ko and Boo, 2016; Phyo et al., 2021). HRQoL is a multidimensional concept that focuses on subjective overall well-being in the physical, mental, and social domains of life (EuroQol-Group, 2023). One of the most commonly used measures of HRQoL is the standardized European Quality of Life 5 Dimensions questionnaire (EQ-5D), which is appropriate for evaluating quality of life among the general population (EuroQol-Group, 2023) and among patients in healthcare settings (AlSaeed et al., 2022; Chase et al., 2022; Guillaumier et al., 2022; Mueller et al., 2021; Munyombwe et al., 2021). HRQoL can also be assessed as "health utility," defined as a person's preference for their overall health state, by transferring the EQ-5D into an index value (EuroQol-Group, 2023). SRH can be assessed using the European Quality of Life Visual Analogue Scale (EQ-VAS), and a general assessment of SRH and age-comparative SRH (CSRH) which are gathered using categorical questions (Huohvanainen et al., 2016). SRH and CSRH are well-established predictors of mortality (Jylhä, 2009) and chronic or severe diseases and can be used to provide a subjective assessment of individual current physical and mental health (Huohvanainen et al., 2016; van de Weijer et al., 2022).

A growing number of epidemiological studies have linked air pollution to worse self-perceived health status. Air pollution effects on HRQoL and/or SRH have been reported in China (Tan et al., 2023), Korea (Shin et al., 2018), Japan (Yamazaki et al., 2005), Netherlands (Klompmaker et al., 2019), Belgium (Hautekiet et al., 2022), Spain (Moitra et al., 2022), and across Europe (Boudier et al., 2022). In most of these studies, however, the constructs of self-perceived health status varied across studies, and only one or two specific outcomes were generally evaluated in each study. Furthermore, no literature exists on the association between air pollution exposure and SRH measured using the EQ-VAS. Without a study that collects HRQoL, SRH, and CSRH at the same time, it is difficult to identify the most relevant self-perceived health measure for analyzing the effect of air pollution effects on general health status.

Previous studies have demonstrated that air pollution effects on health are modified by various biological or social dimensions such as age, sex/gender, and socioeconomic position (Hooper and Kaufman, 2018). The modification of air pollution on self-perceived health remains inconclusive as one study found more pronounced effect estimates in those with a higher socioeconomic level (educational background, income level, and neighborhood) (Tan et al., 2023), while another study indicated that air pollution exerted a larger effect on poor SRH in participants who had lower education, who were experiencing financial difficulties, or who lived in lower-income areas (Dzhambov et al., 2023). Moreover, a previous study suggested that the effects of air pollution on quality of life or SRH were stronger for men or those younger than 65 years (Shin et al., 2018). The effect of air pollution on poor SRH was found to be modified by residential surrounding greenness in Netherlands (Klompmaker et al., 2019). Aside from the objective measures of air quality, neighborhood reputation, the level of individual knowledge and prior experiences suffering from air pollution are unobserved latent variables that affect health risk perception, the psychosocial determinants of health (Borbet et al., 2018; Cori et al., 2020; King, 2015).

Using various measurement tools, our study's objective was to explore the associations between long-term air pollution and self-perceived health status and identify which population groups are most susceptible to the effects of air pollution.

2. Materials and methods

2.1. Study design and population

This study used data from the Cooperative Health Research in the Region of Augsburg (KORA) cohort, implemented in Augsburg and two adjacent districts in southern Germany since 1984 (Holle et al., 2005). Since the start of the study, four cross-sectional surveys have been conducted at 5-year intervals: S1 (1984–1985), S2 (1989/1990), S3 (1994–1995), and S4 (1999–2000). In 2018/2019, the follow-up study KORA-Fit took place, for which all participants of the four surveys aged 54–75 years were invited to participate. After excluding those who were unable to participate, 3059 participants (64.6% of the net sample) finished a standardized interview and completed a questionnaire in the study centre. For the present analysis, we only analyzed KORA-Fit participants who were also participants in another subgroup study, Integrating Gender into Environmental Health Research (INGER). In the INGER project, sex/gender themes were integrated into environmental health research through a newly developed questionnaire, which combined biological and social information about gender/sex, as well as environmental information about green spaces (Kraus et al., 2023). All study methods were approved by the ethics board of the Bavarian Chamber of Physicians (KORA-Fit EC No.17040) in adherence to the declaration of Helsinki. All study participants gave written informed consent before the survey.

2.2. Assessment of outcomes, exposures, and covariates

2.2.1. Health-related quality of life

HRQoL is often measured using standardized questionnaires (Karimi and Brazier, 2016). Being one of the most widely used generic questionnaires, the EQ-5D includes two parts: the descriptive system covers the five domains of mobility, self-care, usual activities, pain/discomfort, and anxiety/depression, and the visual analogue scale, EQ-VAS (EuroQol-Office, 2023). We used the five-level version of EQ-5D (EQ-5D-5L) to determine the current HRQoL of individuals who participated in KORA-Fit in 2018–2019. Each dimension has five response levels (1–5 points), which were labeled "1 = no problems", "2 = slight problems", "3 = moderate problems", "4 = severe problems", and "5 = unable or extreme problems".

The EQ-5D can be transformed into an index value (EQ-5D index value) using the aggregated German preferences developed by Ludwig et al. (Ludwig et al., 2018). Because these preferences emerged from composite time-trade-off and discrete choice experimental data from a population-based German adult sample, the score could also be seen as an economic concept "health utility" and can therefore differ between countries/regions (EuroQol-Office, 2023). In our study, the EQ-5D index values ranged from -0.13 to 1.00, with a value below 0 equivalent to a health state “worse than death”, a value of 0 equalling death, and a value of 1 corresponding to perfect or full health. We also dichotomized the 5-point scales of each EQ-5D dimension as a binary variable by considering the original response 1 as “0 = have no problems” and combining responses 2–5 as “1 = any problems”.

2.2.2. Self-rated health

The general concept of SRH was measured via the EQ-VAS as part of the EQ-5D (EuroQol-Office, 2023). It is a vertical analogue scale with a range from 0 (the worst health you can imagine) to 100 (the best health you can imagine) and was used to directly assess participants’ current overall health status on the day of questionnaire completion. We also evaluated the general concept of self-rated health by asking the question, “How would you rate your current physical condition?”. Answers were given on a 4-point Likert scale (1 = very good, 2 = good, 3 = less good, 4 = poor), and then these variables were dichotomized as “good SRH” (including the responses “very good” and “good”) and “poor SRH” (including the responses “less good” and “poor”). When we use the abbreviation term “SRH” below to refer to our outcome, we are referring to this binary variable. CSRH was measured by asking the question, “How would you rate your health compared to other people of your age?”, with the three answer possibilities being “better”, “equal”, and “worse”. An overview of the recoding of outcome variables can be found in the supplementary data (Table S1).

2.2.3. Air pollution

Air pollutants at the residential addresses of participants were estimated via land-use regression models with 50 × 50 m spatial resolution from March 2014 and April 2015, mainly following the standardized approach developed by the European Study of Cohorts for Air Pollution Effects (ESCAPE) project (Beelen et al., 2013; Eeftens et al., 2012). The details of the process have been previously reported (Wolf et al., 2017). Briefly, three bi-weekly measurements were taken in different seasons (warm, cold, and intermediate seasons) at 20 sites within the KORA study area, involving twelve sites located within the city of Augsburg and eight in the two adjacent districts of Augsburg and Aichach-Friedberg. Throughout the whole study period, measurements were additionally carried out at an urban background site as a reference to adjust for temporal variations. Linear regression models were used to calculate the annual mean concentration at the monitoring stations using potential spatial predictor variables, including local land use, traffic network, altitude, population, building density, and household density. Based on participants’ home addresses, we calculated the residential annual average concentrations of air pollutants including particle number concentration (PNC) as an indicator for ultrafine particles (UFP), PM in aerodynamic diameter <10 μm (PM_{10}), <2.5 μm ($PM_{2.5}$), between 2.5 μm and 10 μm (PM_{coarse}), soot ($PM_{2.5absorbance}$; a proxy of elemental carbon related to traffic exhaust), ozone (O_3), nitrogen dioxide (NO_2) and nitrogen oxides (NO_X). The performance of the land-use regression model was validated by leave-one-out cross-validation and the adjusted model explained variance (R^2) ranged from 0.68 to 0.94, suggesting a good model fit (Wolf et al., 2017).

2.2.4. Covariates

For our analysis, we operationalized sex dichotomously with the categories “female” and “male" without further distinguishing between biological sex and socially constructed gender identity. Participants indicated their sex through self-report. Other demographic and social characteristics (age, living with a partner, pension, individual socioeconomic status [SES], self-perception of residential greenness) were obtained via a face-to-face interview. SES was calculated based on a system developed by Mielck A (Mielck, 2000) from the three characteristics, including the level of education, employment status, and individual income, with higher values indicating a higher socioeconomic level. We also collected data about lifestyle-related behavior, including physical activity, alcohol consumption, and smoking status. Self-efficacy, or one’s ability to plan and execute actions effectively and successfully, was assessed using the general self-efficacy short scale via a self-administered questionnaire (Beierlein et al., 2013). Participants were also invited to complete the 10-item perceived stress scale, which aimed to rate their subjective perception of stress, with a higher score indicating greater perceived stress (Cohen et al., 1983).

Physical examinations were carried out to obtain anthropometric data, including height, weight, waist circumstance, and hip circumstance. These measurements were used to calculate body mass index (BMI, kg/m^2) and waist-to-hip ratio. Residential greenness was assessed using two variables related to greenness: self-perception of residential greenness and normalized difference vegetation index (NDVI). Self-perception of residential greenness was estimated by asking participants how green their neighborhood is in terms of every type of green space (from green strips along the street to gardens and parks). Answers included "very green", "a little green", "hardly green", and "not green at all". Due to the small sample size, the last three answers were combined and grouped under "hardly green". According to our previous study, the NDVI within a 300m buffer of participant residential addresses was calculated using the cloud-free Sentinel-2 satellite images, with a resolution of 10 m (Niedermayer et al., 2024). Each NDVI map of the Augsburg area was built with two pictures, and the negative pixels of the NDVI map were excluded before assignment to home addresses (Niedermayer et al., 2024). We used the mean NDVI data between the years 2018 and 2019 to match the KORA-Fit data.

2.3. Statistical analyses

2.3.1. Regression models

Participants with missing data on any outcome variable were excluded from analysis. Generalized additive models with fixed effects were used to test for associations between each individual air pollutant and EQ-5D index values and EQ-VAS scores. Binary logistic regression was used to assess whether each individual air pollutant was associated with the odds of reporting poor SRH as compared to good SRH. Multinomial logistic regression was used to measure whether each individual air pollutant was associated with the likelihood of reporting equal or worse CSRH, as compared to better CRSH. We also examined the associations between air pollution exposures and the five dichotomized dimensions of EQ-5D using binary logistic regression. We were able to generate reliable coefficient estimations using maximum likelihood estimation based on the asymptotic properties of logistic regression with a large sample size. By doing this, small-sample biases are alleviated, and robust results are ensured.

Potential covariates were identified based on the disjunctive cause criterion (VanderWeele, 2019) and the guidance of the World Health Organization (WHO, 2020). Starting with the full list of potential covariates, we used a stepwise forward regression method reducing the Bayesian Information Criterion to select our final list of covariates separately for each outcome variable. First, we included sex and age in the minimum model. Next, we included SES, additional socioeconomic variables, lifestyle variables, and BMI for selection. Based on the results of this selection process, we included all confounders separately selected for each outcome variable into one main model containing age, sex, SES, living with a partner, BMI, physical activity, and smoking status. Apart from the covariates in the main model, extended model 1 was further adjusted for the percentage of households with low income (<1250 euro) and degree of urbanization, and extended model 2 for self-efficacy and perceived stress, to control potential confounding.

Effect estimates are expressed as the percentage changes (% change) of the mean of continuous outcomes (EQ-5D index value and EQ-VAS) or the absolute change of EQ-VAS only, and odds ratios (ORs) for categorical outcomes (SRH, CSRH, and five dichotomized dimensions of EQ-5D) together with their 95% confidence intervals (CIs) per interquartile range (IQR) increase in air pollutant concentration. A positive "% change" indicates that a participant perceives their health status to be better, whereas a higher OR value means a person perceives their health status to be worse.

2.3.2. Sensitivity analyses and effect modification

As sensitivity analysis, in order to further identify the potential bias introduced by confounders and colliders, we firstly drew the Directed Acyclic Graphs (DAGs) using the web-version of program "DAGitty" (http://www.dagitty.net/) (Niedermayer et al., 2024). We developed another main adjustment model to test the robustness of our results. Secondly, regarding the continuous outcomes (EQ-5D index value and EQ-VAS), we tested the regression models for potential heteroscedasticity using the "glam" R package including a single global test to assess the linear model assumptions, and the results indicated that the assumptions of homoscedasticity were acceptable. Thirdly, we tested the linearity of the exposure-response relationship for these two continuous outcomes by including air pollutant concentrations as penalized splines into generalized additive models using the "mgcv" R package. In testing for multicollinearity, we found that all models had variance inflation factors less than 2. Fourthly, we further tested the robustness of our results by conducting two-pollutant models for all pollutant pairs for which Spearman's correlation coefficient was less than 0.7, the threshold for high correlation (U.S. EPA, 2019). Finally, we additionally included the "residential duration" in the adjustment model to account for the potential movement of addresses.

By adding an interaction term to the main model, we then investigated the effect modification of variables that have been categorized: sex (female, male), age (<65.0 years, ≥65.0 years), BMI (<30.0 kg/m^2, ≥30.0 kg/m^2), self-perception of residential greenness (very green, hardly green), SES tertiles (1.0–12.0 points, ≥12.0–16.5 points, ≥16.5 points), and three continuous variables, including NDVI (<0.43, ≥0.43), self-efficacy score (<4.02, ≥4.02) and perceived stress scale score (<13.59, ≥13.59), which were dichotomized using their mean values as the threshold. All statistical analyses were performed using R software (version 3.6.2), with a two-tailed *P*-value of <0.05 being considered statistically significant.

3. Results

3.1. Baseline characteristics

Of 3743 eligible participants of both the KORA-Fit and INGER studies, we included 2610 subjects who completed the standardized interview and the questionnaire (Fig. S1). As shown in Table 1, participants had a mean age of 64.0 years at the time of the survey and 1428 (54.7%) were females. 2066 (79.8%) participants lived with a partner. The mean values of BMI and SES at study entry were 28.0 kg/m^2 and 14.9 points, respectively. The baseline characteristics of participants varied widely across EQ-5D index value and SRH groups. In general, participants with a higher EQ-5D index value or who reported good SRH were younger, were more likely to be male, be non-smokers, be physically active, live in a very green environment, have a higher level of SES, have higher self-efficacy, consume more alcohol, have a lower BMI, and have lower perceived stress than participants with a lower EQ-5D index value or with poor SRH.

3.2. Outcomes and exposures

Table 2 shows that the mean levels for the EQ-5D index value and EQ-VAS were 0.9 ± 0.1 and 79.2 ± 14.7, respectively. Most participants reported having at least slight problems in the dimension of pain/discomfort (62.0%). 16.7% of participants reported poor SRH and 8.3% reported worse CSRH. A moderate positive correlation was found between the EQ-5D index value and EQ-VAS (Spearman correlation coefficient *rho* = 0.5), and a weak positive correlation was found between SRH and CSRH (Kendall correlation coefficient *tau* = 0.3). As higher SRH and CSRH values were coded as meaning worse health, we observed a moderate negative correlation between SRH and both the EQ-5D index value and the EQ-VAS (both *rho* and *tau* were -0.4) and a weak negative correlation between CSRH with HRQoL measures (coefficients were -0.3 and -0.4). As for different dimensions of EQ-5D-5L, both the EQ-5D index value and the EQ-VAS score had weak to moderate negative correlations with the five EQ-5D dimensions, aside from a strong negative correlation between EQ-5D index value and "pain/discomfort" (*tau* = -0.7). SRH and CSRH only had weak positive correlations with the five dimensions since higher codes indicate having problems in the five dimensions (Table 2).

Descriptive statistics of average annual air pollution concentrations are displayed in Table 3. During the study period, the annual average levels of $PM_{2.5}$, PM_{10}, and NO_2 were within the European Union air quality standard limits ($PM_{2.5}$: 25 μg/m^3; PM_{10} and NO_2: 40 μg/m^3) but exceeded the air quality guidelines set by the WHO ($PM_{2.5}$: 5 μg/m^3; PM_{10} and NO_2: 10 μg/m^3). Most air pollutants were moderately to strongly positively correlated with each other, with the highest correlation being found for NOx and PNC (*rho* = 0.9). O_3 was weakly positively correlated with PM_{10} (*rho* = 0.1) and PM_{coarse} (*rho* = 0.2), but negatively correlated with $PM_{2.5}$, $PM_{2.5abs}$, PNC, NO_2, and NOx (*rho* ranged from -0.2 to -0.1).

3.3. Regression results

3.3.1. Health-related quality of life

Regression results for the EQ-5D index value and EQ-VAS are shown in Fig. 1 and Table S2 (supplementary materials). In the main model, we found adverse associations between the EQ-5D index value and most air pollutants, particularly for O_3 (% change: -0.91% [95% CI: -1.76; -0.06]). After adjustment for additional covariates, associations were strengthened for O_3 in extended model 1 and for $PM_{2.5abs}$ in extended model 2 (Fig. S2). We found that each IQR increase in air pollutant concentration was associated with decreased EQ-VAS for PM_{10} (-1.38% [-2.37; -0.38]), PM_{coarse} (-1.25% [-2.28; -0.23]), $PM_{2.5abs}$ (-1.57% [-2.69; -0.45]), PNC (-0.89% [-1.68; -0.10]), NO_2 (-1.30% [-2.36; -0.23]), and NO_X (-0.96% [-1.83; -0.10]). Most of these associations were attenuated in extended model 1 but remained robust in extended model 2 (Fig. S2). Details of the absolute changes in EQ-VAS are available in Table S3.

In our analysis of dichotomized EQ-5D-5L dimensions, the dimension "usual activities" had the strongest associations with increasing air pollution, though not all associations were statistically significant (Table S4, Fig. S3). Participants had higher odds of reporting difficulties in their usual activities when exposed to higher concentrations of PM_{10} (OR: 3.46 [95% CI: 1.32; 9.10]), $PM_{2.5abs}$ (1.65 [0.96; 2.84], PNC (1.53 [1.07; 2.19]), and NO_X (1.31 [0.98; 1.75]). Those exposed to higher levels of $PM_{2.5abs}$ had higher odds of reporting pain/discomfort, and those exposed to higher levels of $PM_{2.5}$ had higher odds of reporting difficulties with self-care. For the other two dimensions, we observed only some null tendencies towards increased odds of having problems.

3.3.2. Self-rated health

The long-term effects of air pollution on poor SRH are presented in Fig. 2 and Table S5. In the main model, we consistently observed increased odds of reporting poor SRH with increased exposure to PM_{10} (2.67 [1.07; 6.67]), PM_{coarse} (1.70 [1.14; 2.54]), $PM_{2.5abs}$ (1.60 [0.96; 2.67]), PNC (1.42 [1.01; 1.99]), NO_2 (1.24 [0.98; 1.58]) and NO_X (1.36 [1.04; 1.79]). Aside from PM_{coarse} and O_3, most of these associations slightly decreased in the extended model 1, with the extended model 2 similarly leading to lower estimates (Fig. S4).

Table 1
Descriptive analysis of KORA-Fit & INGER studies (N = 2610).

	Missing (%)	Overall	EQ-5D index value[a]			SRH[b]		
			Low (n = 806)	High (n = 1804)	*P*-value[c]	Poor (n = 437)	Good (n = 2173)	*P*-value[c]
			Mean ± SD/No. (%)	Mean ± SD/No. (%)		Mean ± SD/No. (%)	Mean ± SD/No. (%)	
Age, years	0 (0.0)	64.0 ± 5.4	64.3 ± 5.4	63.8 ± 5.5	**0.047**	63.9 ± 5.4	64.0 ± 5.5	0.881
	0 (0.0)				**<0.001**			**0.002**
Sex								
Female		1428 (54.7)	508 (63.0)	920 (51.0)		269 (61.6)	1159 (53.3)	
Male		1182 (45.3)	298 (37.0)	884 (49.0)		168 (38.4)	1014 (46.7)	
Living with a partner	0 (0.0)				**<0.001**			**<0.001**
Yes		2066 (79.2)	576 (71.5)	1490 (82.6)		311 (71.2)	1755 (80.8)	
No		544 (20.8)	230 (28.5)	314 (17.4)		126 (28.8)	418 (19.2)	
Pension	1 (0.0)				**<0.001**			**<0.001**
Yes		136 (5.2)	85 (10.6)	51 (2.8)		54 (12.4)	82 (3.8)	
No		2473 (94.8)	720 (89.4)	1753 (97.2)		383 (87.6)	2090 (96.2)	
Residential durations, years	0 (0.0)	19.1 ± 9.7	19.0 ± 9.8	19.1 ± 9.7	0.746	19.1 ± 9.7	19.1 ± 9.7	0.997
	9 (0.3)	14.9 ± 5.0	13.9 ± 4.7	15.3 ± 5.1	**<0.001**	13.7 ± 4.7	15.1 ± 5.0	**<0.001**
SES								
	9 (0.3)				**<0.001**			**0.001**
SES (tertiles)								
1.0–12.0		664 (25.5)	248 (31.0)	416 (23.1)		139 (32.0)	525 (24.2)	
≥12.0–16.5		1048 (40.3)	344 (43.0)	704 (39.1)		178 (40.9)	870 (40.2)	
≥16.5		889 (34.2)	209 (26.1)	680 (37.8)		118 (27.1)	771 (35.6)	
Self-perception of residential greenness	0 (0.0)				**<0.001**			**0.001**
Very green		2062 (79.5)	598 (74.7)	1464 (81.7)		320 (73.6)	1742 (80.7)	
Hardly green		532 (20.5)	203 (25.3)	329 (18.4)		115 (26.4)	417 (19.3)	
NDVI	1 (0.0)	0.4 ± 0.1	0.4 ± 0.1	0.4 ± 0.1	**0.022**	0.4 ± 0.1	0.4 ± 0.1	0.055
	0 (0.0)				**<0.001**			**<0.001**
Physical activity								
Very active		1017 (39.0)	256 (31.8)	761 (42.2)		105 (24.0)	912 (42.0)	
Moderately active		885 (33.9)	271 (33.6)	614 (34.0)		143 (32.7)	742 (34.2)	
Little active		320 (12.3)	115 (14.3)	205 (11.4)		70 (16.0)	250 (11.5)	
Inactive		388 (14.9)	164 (20.4)	224 (12.4)		119 (27.2)	269 (12.4)	
Alcohol consumption, g/day	1 (0.0)	14.8 ± 19.6	12.9 ± 19.0	15.6 ± 19.8	**0.001**	12.9 ± 20.0	15.1 ± 19.5	**0.030**
	1 (0.0)				**<0.001**			**0.003**
Alcohol consumption (category, g/day)								
None		675 (25.9)	258 (32.1)	417 (23.1)		141 (32.3)	534 (24.6)	
≥0-40		1261 (48.3)	463 (57.5)	1158 (64.2)		254 (58.1)	1367 (62.9)	
≥40-80		280 (10.7)	73 (9.1)	207 (11.5)		34 (7.8)	246 (11.3)	
≥80		33 (1.3)	11 (1.4)	22 (1.2)		8 (1.8)	25 (1.2)	
Smoking status	4 (0.2)				0.057			**0.007**
Non-smoker		1186 (45.4)	349 (43.5)	837 (46.4)		175 (40.1)	1011 (46.6)	
Ex-smokers		1075 (41.2)	329 (41.0)	746 (41.4)		186 (42.7)	889 (41.0)	
Current smokers		345 (13.2)	125 (15.6)	220 (12.2)		75 (17.2)	270 (12.4)	
BMI, kg/m^2	0 (0.0)	28.0 ± 5.2	29.2 ± 6.1	27.5 ± 4.7	**<0.001**	30.0 ± 6.3	27.6 ± 4.9	**<0.001**
	0 (0.0)	0.9 ± 0.1	0.9 ± 0.1	0.9 ± 0.1	0.861	0.9 ± 0.1	0.9 ± 0.1	**0.012**
Waist-Hip-Ratio								
	75 (2.9)	4.0 ± 0.6	3.9 ± 0.6	4.1 ± 0.5	**<0.001**	3.86 ± 0.7	4.1 ± 0.6	**<0.001**
Self-efficacy								
	124 (4.8)	14.3 ± 5.6	17.0 ± 5.8	13.1 ± 5.0	**<0.001**	18.0 ± 6.0	13.5 ± 5.2	**<0.001**
Perceived stress								

Abbreviations: EQ-5D-5L, European Quality of Life 5-dimensional questionnaire; EQ-5D index, index of EQ-5D-5L questionnaire; EQ-VAS, EuroQol group's visual analog scale; SRH, self-rated health; CSRH, comparative self-rated health; NDVI, normalized difference vegetation index; BMI, body mass index; SES, socioeconomic status; Self-efficacy, General Self-Efficacy Short Scale; Perceived stress, Perceived stress scale.

Note: Continuous variables are presented as means ± standard deviations (SDs), as well as their ranges (minimum, maximal), and categorical variables are presented as total numbers (percentages).

[a] Population was divided into groups according to the mean value of the EQ-5D index value (cutoff value = 0.90).

[b] Population was divided into groups according to the recorded SRH (poor/good).

[c] *P*-value was calculated by using the Kruskal-Wallis test or the Chi-square test.

Table 2
Results of correlation analysis for outcomes of interest.

	Missing (%)	Mean (SD)/n (%)	Correlation coefficients			
			EQ-5D index value	EQ-VAS	SRH	CSRH
EQ-5D index value	0 (0.0)	0.9 ± 0.1	1.0	–	–	–
EQ-VAS	0 (0.0)	79.2 ± 14.7	0.5[a,d]	1.0	–	–
SRH	0 (0.0)	–	−0.4[b,d]	−0.4[b,d]	1.0	–
Good	–	2173 (83.3)	–	–	–	–
Poor	–	437 (16.7)	–	–	–	–
CSRH	42 (1.6)	–	−0.3[b,d]	−0.4[b,d]	0.3[b,d]	1.0
Better	–	1287 (50.1)	–	–	–	–
Equal	–	1069 (41.6)	–	–	–	–
Worse	–	212 (8.3)	–	–	–	–
EQ-5D-5L Dimension (dichotomized)	0 (0.0)	–	–	–	–	–
Mobility, yes%	–	727 (27.9)	−0.5[b,d]	−0.3[b,c]	0.4[b,d]	0.3[b,d]
Self-care, yes%	–	85 (3.3)	−0.2[b]	−0.2[b]	0.3[b,d]	0.2[b]
Usual activities, yes%	–	366 (14.0)	−0.5[b]	−0.3[b]	0.4[b,d]	0.3[b]
Pain/ discomfort, yes %	–	1617 (62.0)	−0.7[b,d]	−0.4[b,d]	0.3[b,c]	0.2[b,c]
Anxiety/ depression, yes %	–	709 (27.2)	−0.4[b,c]	−0.3[b]	0.3[b,c]	0.2[b]

Abbreviations: SD, standard deviation; EQ-5D index value, the index of European Quality of Life 5-dimensional questionnaire; EQ-VAS, EuroQol group's visual analog scale; SRH, self-rated health; CSRH, comparative self-rated health.
Note.
[a] The correlation coefficients (*rho*) were calculated by Spearman correlation analysis.
[b] The correlation coefficients (*tau*) were calculated by Kendall correlation analysis.
[c] $P < 0.10$.
[d] $P < 0.05$.

In the case of CSRH, we found a tendency for decreased odds of equal CSRH when compared with better CSRH with increasing exposure to air pollution (Fig. 3, Fig. S5, Table S6). We also generally found increasing odds of worse CSRH compared to better CSRH with increasing exposure to air pollution, but there was no consistent pattern across pollutants. Each IQR increase in $PM_{2.5abs}$ was associated with increased odds of reporting worse CSRH (2.59 [1.12; 5.99]), with similar trends being found for PM_{coarse}, $PM_{2.5}$, and NO_2. All these effects were attenuated in the two extended models (Figs. S6–S7).

3.4. Sensitivity analyses

Given that the DAG plot (Fig. S8) shows that BMI and physical activity might be theoretical mediators in the causal pathway, we updated the main adjustment model excluding these two variables. However, as it is shown in Table S7 and Figs S9 – S12, the exclusion did not greatly alter the estimated effects. This supports the robustness of our findings regardless of the inclusion of physical activity and BMI, reducing concerns about over-adjustment. Figs. S13 and S14 show the exposure-response relationships of two continuous outcomes (EQ-5D index value and EQ-VAS) with the different air pollutants. Overall, most associations exhibited a generally linear trend, though associations between $PM_{2.5}$ and O_3 and the EQ-5D index showed several fluctuations. In two-pollutant models, most associations were consistent with those of the main analysis (Table S8). Further adjustments to the residential duration did not cause great changes in our results (Table S9).

3.5. Effect modification

Effect modification was solely performed for EQ-VAS because this outcome had the strongest association with air pollution in the main analysis. Results presented in Fig. 4 show that BMI and perceived stress modified the association between air pollution and EQ-VAS. Participants with a BMI below 30.0 kg/m^2 exhibited a stronger association between air pollution and EQ-VAS as compared to those with a BMI at or above 30.0 kg/m^2. Furthermore, participants with higher perceived stress (scale score ≥13.59) showed stronger effects compared to those with lower stress. We did not observe any considerable modification for other covariates (sex, age, self-perception of residential greenness, NDVI, and self-efficacy) (Table S10).

4. Discussion

Our cross-sectional study found that higher long-term exposure to air pollution was associated with worse HRQoL and worse SRH in German adults aged 54 and over. Additionally, effect modification was observed for BMI and perceived stress level. We found that the one-item measurements of self-perceived health status (EQ-VAS and SRH) may show higher sensitivity to air pollution compared to the multi-dimensional

Table 3
Distribution of ambient air pollutant concentrations.

	Mean (SD)	Min	P25	Median	P75	Max	IQR	Spearman correlation coefficients							
								PM_{10}	PM_{coarse}	$PM_{2.5}$	$PM_{2.5abs}$	PNC	O_3	NO_2	NO_X
PM_{10} (μg/m^3)	16.4 (1.4)	13.2	15.2	16.1	17.2	22.3	2.0	1.0							
PM_{coarse} (μg/m^3)	4.8 (1.0)	2.5	4.1	4.7	5.5	8.3	1.4	0.8	1.0						
$PM_{2.5}$ (μg/m^3)	11.7 (1.0)	8.3	11.1	11.8	12.4	14.3	1.4	0.5	0.5	1.0					
$PM_{2.5abs}$ (10^{-5}/m)	1.2 (0.2)	0.8	1.0	1.2	1.3	1.9	0.3	0.8[a]	0.8[b]	0.6	1.0				
PNC (10^3/cm^3)	7.1 (1.8)	3.2	6.1	7.1	8.0	14.6	1.9	0.8[a]	0.7	0.6	0.8	1.0			
O_3 (μg/m^3)	39.1 (2.4)	32.1	37.3	39.2	40.9	46.0	3.5	0.1	0.2	−0.2[b]	−0.1	0.0	1.0		
NO_2 (μg/m^3)	13.6 (4.2)	6.9	10.3	12.9	16.5	28.9	6.2	0.7	0.8[b]	0.7	0.9[b]	0.8	−0.1	1.0	
NO_X (μg/m^3)	21.3 (7.0)	3.8	17.0	22.0	25.5	47.2	8.4	0.7	0.7	0.8[b]	0.7	0.9[b]	−0.1[a]	0.8	1.0

Abbreviations: SD, standard deviation; P25, 25th percentile; P75, 75th percentile; IQR, Inter-quartile range; PM_{10}, particulate matter (PM) with an aerodynamic diameter <10 μm (μg/m^3); PM_{coarse}, coarse particulate matter; $PM_{2.5}$, PM < 2.5 μm (μg/m^3); $PM_{2.5abs}$, the absorbance of $PM_{2.5}$; PNC, particle number concentration; O_3, Ozone (μg/m^3); NO_2, Nitrogen dioxide (μg/m^3); NO_X, Nitrogen oxide (μg/m^3).
Note.
The correlation coefficients (*rho*) were calculated by Spearman correlation analysis.
[a] $P < 0.10$.
[b] $P < 0.05$.

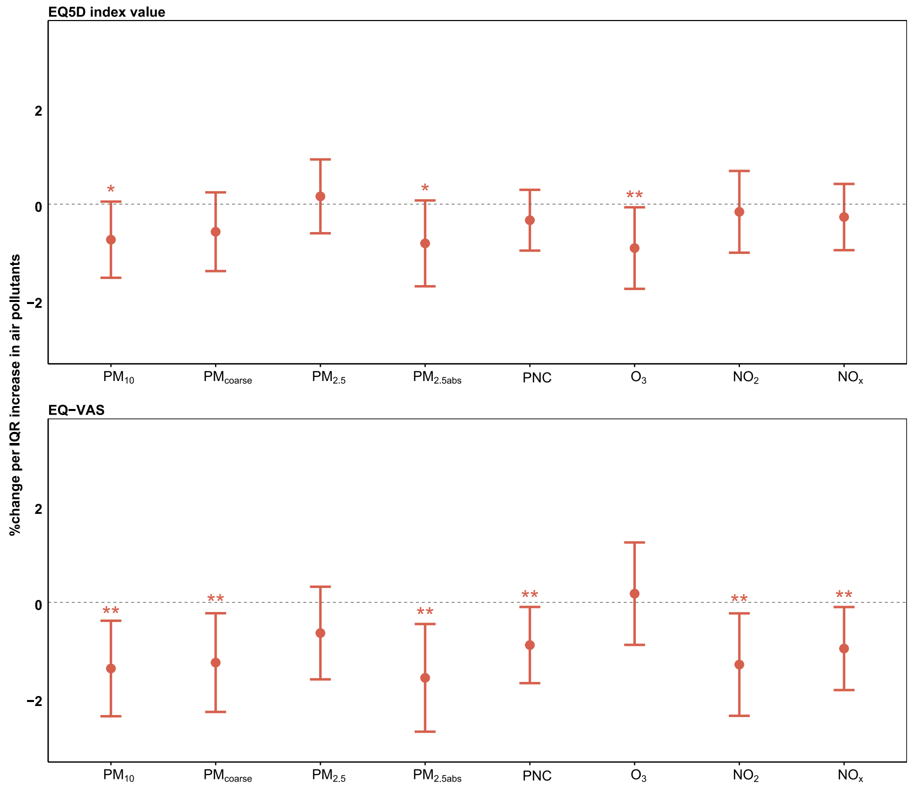

Fig. 1. Results of the main model of linear regression for the associations between air pollutants and EQ-5D index value and EQ-VAS.
Abbreviations: EQ-5D index value, the index of European Quality of Life 5-dimensional questionnaire; EQ-VAS, EQ visual analogue scale; IQR, interquartile range; PM_{10}, particulate matter (PM) with an aerodynamic diameter <10 μm (μg/m^3); PM_{coarse}, coarse particulate matter; $PM_{2.5}$, PM < 2.5 μm (μg/m^3); $PM_{2.5abs}$, the absorbance of $PM_{2.5}$; PNC, particle number concentration; O_3, Ozone (μg/m^3); NO_2, Nitrogen dioxide (μg/m^3); NO_X, Nitrogen oxide (μg/m^3). **Note:** Estimates represented as the percentage changes in EQ-5D index value/EQ-VAS mean for IQR increase in annual exposures to air pollutants (1.95 μg/m^2 for PM_{10}, 1.40 μg/m^2 for PM_{coarse}, 1.39 μg/m^2 for $PM_{2.5}$, 0.28 [10^{-5}/m] for $PM_{2.5abs}$, 1.92 [10^3/cm^3] for PNC, 3.54 μg/m^2 for O_3, 6.20 μg/m^2 for NO_2 and 8.41 μg/m^2 for NO_X).
The plots were developed based on the main model, which was adjusted for age at the survey, sex, socioeconomic status (SES), living with a partner, physical activity, and smoking status.

measure (EQ-5D index value).

There is an increasing number of studies on the long-term health effects of air pollution. However, only two identified studies to date have assessed HRQoL using the EQ-5D (Shin et al., 2018; Tan et al., 2023). Measuring HRQoL with the three-level version of the EQ-5D (EQ-5D-3L), Tan et al. found that per 1 μg/m^3 increase in long-term exposures to $PM_{2.5}$ and $PM_{10,}$ the EQ-5D-3L index value among their study population in Shandong decreased by 0.002 and 0.001, respectively (Tan et al., 2023). In a study in South Korea, Shin et al. dichotomized the EQ-5D-3L index values based on a fourth quartile cut-off, defining participants above the fourth quartile as having poor quality of life. They found that poor quality of life was associated with increased exposures to PM_{10} and NO_2, particularly in younger people (<65.0 years) (Shin et al., 2018). Another study used the Short Form-36 Health Survey (SF-36) Physical and Mental Component Summary scores to assess HRQoL (Boudier et al., 2022). This European population-based study reported that higher $PM_{2.5}$, PM_{10}, and NO_2 concentrations were associated with lower Mental Component Summary scores, but no consistent association was found for Physical Component Summary scores (Boudier et al., 2022).

In terms of the general SRH, there is sparse evidence regarding the long-term effect of air pollution on EQ-VAS. In China, Li et al. found a positive association between annual air pollution (PM_{10}, $NO_{2,}$ and O_3) and worse SRH among 5172 individuals aged >60.0 years from 123 Chinese cities (Li et al., 2023). Another study in China consistently observed that a higher air pollution index was associated with a greater likelihood of having poor SRH among 7358 residents aged ≥65 years from 171 Chinese cities (Sun and Gu, 2008). Supporting evidence has also been found in European populations, including a cross-sectional study of 16,455 participants aged ≥15 years in Belgium (Hautekiet et al., 2022), a study including 354,827 Dutch citizens aged ≥19 years (Klompmaker et al., 2019), and an analysis of over 500,000 residents aged 37–73 years from the UK Biobank (Mutz et al., 2021). In general, these studies observed the detrimental effect of air pollution on self-perceived health status, in agreement with our results. Until now, however, there has been no evidence linking long-term air pollution with CSRH.

Several biological mechanisms may explain our findings. Self-perceived health is a measurement of both overall subjective physical and mental well-being (EuroQol-Group, 2023). Within the body, long-term air pollution exposure is connected to a variety of diseases (de Bont et al., 2022; Hansel et al., 2016) by producing reactive oxygen species and causing endothelial dysfunction, which may be related to worse HRQoL (Akor et al., 2020; Phyo et al., 2021), poor SRH (Farkas et al., 2009; Ko and Boo, 2016), and worse CSRH (Dong et al., 2018; Verhoeven et al., 2021). Air pollution toxicity can also damage the central nervous system or cause neurodegenerative diseases by altering miRNAs, telomeres, gene expression, and signaling pathways (Costa et al., 2020; van der Meulen et al., 2018). These neurodegenerative diseases may further worsen HRQoL. Air pollution also affects the subjective experience of physical and mental health. For example, people living in areas with higher chronic air pollution exposure may be more stressed and fearful of getting sick (Zhu and Lu, 2023). This high subjective stress in response to ambient air pollution may be related to the abnormal secretion of hormones (e.g., dopamine) (Pereyra-Muñoz et al., 2006), metabolism of neurotransmitters (e.g., serotonin) (Zhao et al., 2018), and stimulation of hippocampal pro-inflammatory cytokine

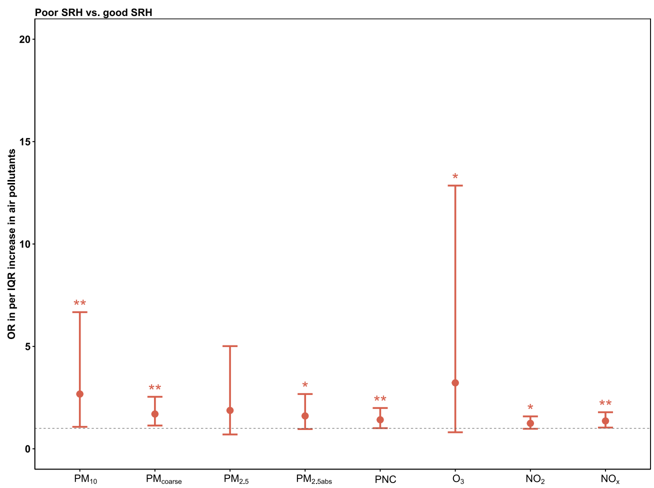

Fig. 2. Results of the main model of logistic regression for the association between air pollutants and the odds of reporting poor SRH.

Abbreviations: SRH, self-rated health; IQR, interquartile range; OR, odds ratio; 95% CI, 95% confidence interval; PM_{10}, particulate matter (PM) with an aerodynamic diameter <10 μm (μg/m^3); PM $_{coarse}$, coarse particulate matter; $PM_{2.5}$, PM < 2.5 μm (μg/m^3); $PM_{2.5abs}$, the absorbance of $PM_{2.5}$; PNC, particle number concentration; O_3, Ozone (μg/m^3); NO_2, Nitrogen dioxide (μg/m^3); NO_X, Nitrogen oxide (μg/m^3). **Note:** With those reported “good SRH” as reference group, estimates represented as ORs (with 95% CIs) of poor SRH for IQR increase in annual exposures to air pollutants (1.95 μg/m^2 for PM_{10}, 1.40 μg/m^2 for PM_{coarse}, 1.39 μg/m^2 for $PM_{2.5}$, 0.28 [10^{-5}/m] for $PM_{2.5abs}$, 1.92 [10^3/cm^3] for PNC, 3.54 μg/m^2 for O_3, 6.20 μg/m^2 for NO_2 and 8.41 μg/m^2 for NO_X).

The plot was developed based on the main model, which was adjusted for age at the survey, sex, socioeconomic status (SES), living with a partner, physical activity, and smoking status.

production (Fonken et al., 2011). Moreover, individuals exposed to higher air pollution are more likely to experience headaches, dizziness, nausea, and feelings of ill health, ultimately affecting their mental well-being (Zhao et al., 2018). Other symptoms related to air pollution exposure (shortness of breath, cough, wheezing, and phlegm) are also likely to interrupt the performance of daily activities and work (D’Oliveira et al., 2023), while also resulting in lower physical capacity and worse self-perceived health (Lopez-Campos et al., 2013). In addition, health risk perception is the psychosocial determinant of health and could also be affected by personal perceptions of air quality (Borbet et al., 2018), neighborhood stigma (King, 2015), and individual’s knowledge of air pollution (Cori et al., 2020). As there are fewer studies of the clear specific mechanisms linking air pollution to self-reported health status, more research is needed to validate our findings due to the complex etiology of mental and subjective health outcomes.

Our results related to the association between various sizes of PM and self-perceived health status were somewhat unclear in comparison to other air pollutants. First, the associations between worse self-perceived health status and PM_{10}, $PM_{coarse,}$ and $PM_{2.5}$ gradually disappeared as their particle sizes decreased. This may be because the size fraction of PM plays a significant role in determining its health effects because PM deposits in different parts of the respiratory system and enters the circulatory system depending on its aerodynamic diameters (Zhang et al., 2022). Larger particles lodge in the upper airways, which may cause more obvious symptoms that affect self-perceived health more significantly. Smaller particle sizes and deeper deposit locations are less likely to result in immediate and noticeable symptoms, which may explain why we did not find an association between $PM_{2.5}$ and self-perceived health. Second, PNC contributes most to UFP, which, due to their small size, can diffuse into the most distal lung regions and additionally penetrate all organ systems including the central nervous system (Calderón-Garcidueñas and Ayala, 2022; Oberdörster et al., 2007). This is unlikely to be the scenario for ambient $PM_{2.5}$ as it mainly affects the respiratory and cardiovascular systems (Henning, 2023), and this inconsistency may also be reflected in self-perceived health outcomes. Apart from their size, UFPs are more toxic than larger PMs as they have a larger relative surface area and are highly reactive, meaning that they can absorb more hazardous metals and toxic organic compounds (Kwon et al., 2020). In summary, our mixed results for PM suggest that large-scale scientific studies are needed to determine the effects of $PM_{2.5}$ on self-perceived health status in more detail.

Within our study, ‘one-item’ measures (EQ-VAS and SRH) were more affected by air pollution than multi-dimensional measures (EQ-5D index value). In the EQ-VAS and SRH, respondents’ perceptions of health on the day of the survey are presented straightforwardly, whereas the EQ-5D rates specific dimensions based on a certain weight (coefficient). In general, the EQ-VAS provides more granular information but is less focused on impairments in specific dimensions of health than the EQ-5D (EuroQol-Office, 2023). As a result, the EQ-VAS may be more sensitive when used in a general population sample than the EQ-5D. In addition, our less pronounced results for poor CSRH as compared to our results for poor SRH may be explained by a lack of clarity as to which people the participants were comparing themselves with, and detecting air pollution effects would be challenging if participants compared themselves to people in the same residential area since they would be exposed to air pollution at the same levels. As a result, worse CSRH might be underestimated. There were wider intervals of worse CSRH for $PM_{2.5abs}$ than for other air pollutants, likely due to the relatively narrow range of annual $PM_{2.5abs}$ levels and the gap in sample sizes across the three categories of CSRH.

We detected significant modification effects for the association between air pollution and EQ-VAS, with the effect modification being most apparent for BMI, with the detrimental impacts of ambient air pollution being stronger among those with a lower BMI. A similar higher susceptibility to air pollution among those with lower BMI was also found for cardiovascular and cerebrovascular diseases (Zhang et al., 2011). In contrast to our results, a previous study measured HRQoL using the EQ-5D-3L index value and revealed a stronger adverse health effect of air pollution in those with higher BMI (Tan et al., 2023). A higher susceptibility to air pollution among study participants with other diseases (type 2 diabetes, high blood pressure, and brain tumours) was also found among those with higher BMI (Jørgensen et al., 2016; Li et al., 2021; Liu et al., 2016). Exposed to short-term PM, overweight or obese people release a smaller amount of extracellular vesicles (particles released by cells in response to stimuli) which is associated with a lower risk of narrowing of the coronary arteries (Rota et al., 2020). A potential explanation for the attenuated effect of BMI is the obesity paradox, which suggests that obese people of advanced age have a better prognosis for chronic diseases due to their persistent low-grade inflammation, which is less likely to lead to chronic illnesses (Blum et al., 2011; Rota et al., 2020). Validating this finding will require further research.

Previous research has also found that people with a higher stress level appeared to be more vulnerable to air pollution (Schwartz et al., 2011). We also found that the perceived stress modified the association between air pollutants and EQ-VAS, with stronger adverse effects on EQ-VAS being found in the higher perceived stress group. Psychosocial stress increases vulnerability to the health effects of environmental hazards (Mehta et al., 2015). A higher self-perceived stress level might damage general feelings of optimism or promote pessimism about the future, worsening dynamic feelings of health (Smith et al., 2004). However, a cross-sectional study in the Arab-American community found no evidence of effect modification of perceived stress (Suleiman et al., 2021). As there is limited conclusive evidence accounting for comorbidity or stress-related vulnerability, more in-depth studies are required regarding their modification effects.

There are several strengths in the present study. First, this study was conducted based on the KORA-Fit cohort, a well-characterized study

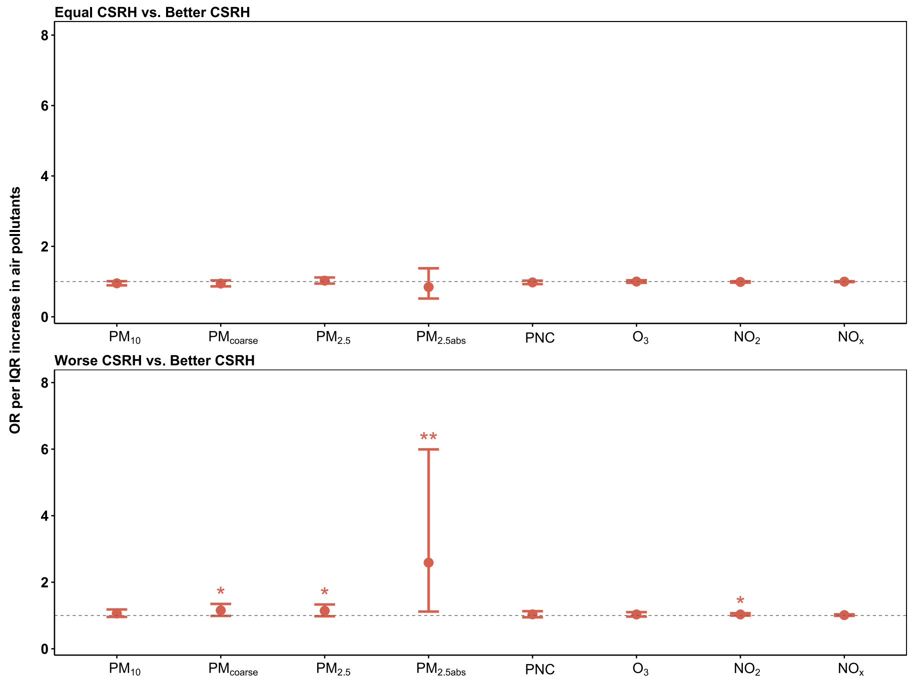

Fig. 3. Results of the main model of multinominal regression for the association of air pollution with the odds of reporting equal CSRH or worse CSRH. **Abbreviations**: CSRH, comparative self-rated health; OR, odds ratio; 95% CI, 95% confidence interval; IQR, interquartile range; PM_{10}, particulate matter (PM) with an aerodynamic diameter <10 μm (μg/m^3); PM_{coarse}, coarse particulate matter; $PM_{2.5}$, PM < 2.5 μm (μg/m^3); $PM_{2.5abs}$, the absorbance of $PM_{2.5}$; PNC, particle number concentration; O_3, Ozone (μg/m^3); NO_2, Nitrogen dioxide (μg/m^3); NO_X, Nitrogen oxide (μg/m^3). **Note:** With those reported "better CSRH" as reference group, estimates represented as ORs (with 95% CIs) of equal CSRH or worse CSRH for IQR increase in annual exposures to air pollutants (1.95 μg/m^2 for PM_{10}, 1.40 μg/m^2 for PM_{coarse}, 1.39 μg/m^2 for $PM_{2.5}$, 0.28 [10^{-5}/m] for $PM_{2.5abs}$, 1.92 [10^3/cm^3] for PNC, 3.54 μg/m^2 for O_3, 6.20 μg/m^2 for NO_2 and 8.41 μg/m^2 for NO_X). The plots were developed based on the main model, which was adjusted for age at the survey, sex, socioeconomic status (SES), living with a partner, physical activity, and smoking status.

with standardized and comprehensive information regarding subject characteristics and outcomes, which enhanced the reliability of our results. Second, our study examined the potential effect of eight commonly measured air pollutants, after checking for potential multicollinearity. This enables us to conclude consistent patterns across various air pollutants and to explore potential differences in sources and aerosol properties.

Our study also has some limitations. First, using spatial models, we estimated the annual average concentrations of air pollutants for 2014/2015, while outcome data were collected in 2018/2019. Yet, we believe these exposure estimates are valid since previous studies have shown that spatial variation in exposure over time is stable for historical spatial contrasts (de Hoogh et al., 2018; Wang et al., 2013). Second, we focused only on self-perceived 'physical' health states by asking the participants two SRH-related questions, rather than assessing 'general' health status. In part, this could be compensated by using the EQ-5D-5L instrument, which measures the self-perceived health from both physical and mental health (anxiety/depression) perspectives. Our use of EQ-VAS also helps to determine general health (EuroQol-Office, 2023). Third, our data may not be generalizable to other populations since KORA-Fit participants were mainly of European descent. Finally, the cross-sectional design prevented us from assessing the causality between self-perceived health status and air pollution.

5. Conclusions

Worse HRQoL (assessed with the EQ-5D index value and EQ-VAS), poor SRH, and worse CSRH were associated with increasing exposure to air pollution. These associations were modified by BMI and perceived stress level. In studies of the effects of air pollution, a single-item SRH indicator may be more suitable for assessing self-perceived health status among older people than multidimensional indicators.

CRediT authorship contribution statement

Minqi Liao: Writing – original draft, Visualization, Formal analysis. **Siqi Zhang:** Visualization, Software, Formal analysis. **Kathrin Wolf:** Writing – review & editing. **Gabriele Bolte:** Writing – review & editing. **Michael Laxy:** Writing – review & editing. **Lars Schwettmann:** Writing – review & editing. **Annette Peters:** Supervision. **Alexandra Schneider:** Supervision, Methodology, Conceptualization. **Ute Kraus:** Writing – review & editing, Methodology, Conceptualization.

Ethics statement

The use of data for this project was approved by the ethics board of the Bavarian Chamber of Physicians (KORA-Fit EC No.17040) in adherence to the declaration of Helsinki. All study participants gave written informed consent.

Data availability

Data will be made available on request.

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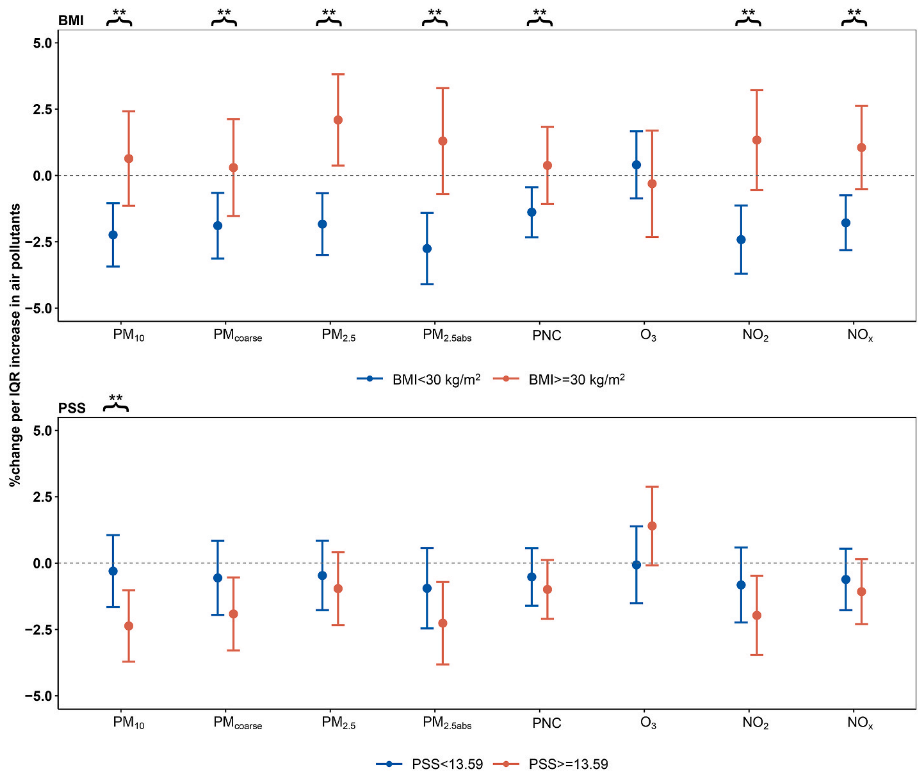

Fig. 4. Multiple linear regression results for the associations between annual air pollutant exposures and EQ-VAS modified by BMI and perceived stress.
Abbreviations: EQ-VAS, EuroQol group's visual analog scale; OR, odds ratio; 95% CI, 95% confidence interval; IQR, Interquartile range; PM_{10}, particulate matter (PM) with an aerodynamic diameter <10 μm (μg/m^3); PM_{coarse}, coarse particulate matter; $PM_{2.5}$, PM < 2.5 μm (μg/m^3); $PM_{2.5abs}$, the absorbance of $PM_{2.5}$; PNC, particle number concentration; O_3, Ozone (μg/m^3); NO_2, Nitrogen dioxide (μg/m^3); NO_X, Nitrogen oxide (μg/m^3); BMI, body mass index. **Note:** Estimates expressed as the percentage change in EQ-VAS mean for IQR increase in annual exposures to air pollutants (1.95 μg/m^2 for PM_{10}, 1.40 μg/m^2 for PM_{coarse}, 1.39 μg/m^2 for $PM_{2.5}$, 0.28 (10^{-5}/m) for $PM_{2.5abs}$, 1.92 (10^3/cm^3) for PNC, 3.54 μg/m^2 for O_3, 6.20 μg/m^2 for NO_2 and 8.41 μg/m^2 for NO_X).
The plots were developed based on the main model, which was adjusted for age at the survey, sex, socioeconomic status (SES), living with a partner, physical activity, and smoking status.

Declaration of competing interest

Authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijheh.2024.114513.

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