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Research article

Perception matters: How air pollution influences life satisfaction in China

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ABSTRACT

Academic studies on environmental pollution have convincingly acknowledged the salient relevance of ambient pollutant emissions on individual life satisfaction. However, an understanding of how the different dimensions of air pollution influence public self-assessment of their living condition is required. This research investigates whether objective pollutant emissions and subjective evaluation influence individual life satisfaction. The findings were based on data from the China Environment Yearbook and China Social Survey in 2019. The multi-level linear regression model found that air pollutants emissions, including particulate matter (PM) and sulfur dioxide (SO_2), failed to explain the variations in public life satisfaction because of the lag effect of public perception. A significant nexus between perceived air pollution and public life satisfaction was observed at a significance level of 0.01. Specially, as the perceived air pollution by the public increased by one-point, life satisfaction decreased by 0.22 on a scale of 1–10, on average. Heterogeneous analysis based on income further suggested the salient negative effect of PM emissions on life satisfaction only occurred in the high-income group. The findings were robust after various methodological analyses. This study has theoretical implications for understanding the effects of air pollution on public subjective perception and provides guidance for how the government can manage the relationship between environmental governance and life satisfaction.

1. Introduction

Research on life satisfaction has received continuous attention in recent decades. Shin, D. C. and D. M. Johnson [1] considered life satisfaction as a subjective assessment of an individual's quality of life-based on self-set criteria. Diener, E., R. A. Emmons, R. J. Larsen and S. Griffin [2] viewed it as how people assess their quality of life from a cognitive and global perspective. Currently, plenty of studies established theoretical discussions and empirical evidence concerning the impacts of life satisfaction and the factors that contribute to it. One body of literature explored the positive effects of life satisfaction, namely residents with higher life satisfaction tend to be more productive and beneficial to society [3]. Another body of literature examined how factors such macro-level as economic development, social stability, and cultural dimensions, as well as income, gender, and age at the micro level, influence life satisfaction [2,4–8]. Of the determinants, the external environment, particularly air pollution, captures much scholarly attention as one driving force impacting life satisfaction [9,10], because it is a trigger for activity participation and psychological well-being [11,

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12]. Research revealed that the "deprivation effect" of air pollution [13] is an essential precipitating mechanism that lowers residents' satisfaction with their lives. Exposure of residents to air pollutants directly endangers human health [14,15] by suffering from stimulation of nerves and brain and affecting physical and emotional states [16–18]. Consequently, this undoubtedly diminishes public life satisfaction gradually [10,19,20].

The consensus that the negative effects of air pollution on life satisfaction can be basically reached, with evidence based on numerous countries such as the United States [20,21], Australia [10], and Europe [12,22,23]. However, previous findings were primarily based on the salient relevance of the objective dimension of air pollution normally measured by air quality index [24] or pollutants concentrations, still obviously lacking a deep exploration of how subjective perceptions of air pollution exerts influence on life satisfaction [25]. Public perceptions of air pollution, essentially a risk perception, are a subjective judgment of risk characteristics and severity [26]. This is applied in the field of environmental pollution to represent the level of public awareness of the severity of air pollution status. Nonetheless, it has not investigated the differential impacts of pollution conditions and perceived air pollution in an integrated manner.

To fill the research gap, we incorporate perceived air pollution when investigating the relationship between ambient pollution and life satisfaction, intending to examine the differentiated effects of air pollution on life satisfaction by arguably categorizing air pollution into actual objective pollution conditions and perceived air pollution.

2. Literature review and hypotheses

Published studies have demonstrated that objective air pollution status has direct and indirect adverse consequences on human society, including lowering working efficiency [27,28], and reducing trustiness in government [29,30]. This is more salience among the vulnerable or marginalized group [31–34]. Existing studies elaborately illustrated three mechanisms through objective air pollution conditions influence individual life satisfaction [35]. First, air pollution exerts a direct negative influence on human physical health [36,37], probably leading to lower assessment of life satisfaction [38]. Much well-documented epidemiologic evidence demonstrated the potential effects of air pollution on cardiovascular, respiratory, and cancer diseases that may cause morbidity and mortality [39,40]. The higher levels of outdoor air pollution were significantly associated with lower life expectancy, as it may cause several chronic illnesses that increase the death rate in many nations [41]. Second, the human brain and the autonomous nervous system may be damaged due to long-term exposure to air pollution, resulting in changing physiology and emotional status [42]. Third, air pollution negatively affects individual assessment of their life quality. Coping behaviors, such as staying indoors rather than engaging in outdoor activities aiming to avoid the adverse effects of air pollution have the potential of inducing psychological stress and anxiety [43]. Overall, the findings are fundamentally consistent in that objective environmental pollution conditions are associated with people's health and quality of life [44], relatively low PM concentrations can even reduce residents' assessment of well-being because of the potential impact of greater physical and psychological stress, annoyance, and frustration [17]. Hence, we lead to the first hypothesis.

Hypothesis 1a. (Adverse Effects Hypothesis): Objective air pollution condition is significantly negatively related to life satisfaction.

The other side of the coin needs to caution that the lag effect of perception may result in the effect of objective air pollution conditions on public life satisfaction being weakened and even reversed from statistically significant to insignificant. Specially, the lag effect of public perception refers to the phenomenon that the public naturally may not readily detect minor changes in environmental quality within a short period, not to mention that it affects their life satisfaction. Over the past decades, studies on citizen subjective performance heatedly sparked a debate on whether increased public service provision inevitably enhances citizen satisfaction with government [45,46]. Stipak, B [45]. early noted that public performance evaluation was affected and changed only when the quantity and quality of public service were extremely good or poor. So is ambient pollution. Except for such sudden emergencies and disasters as nuclear pollution and leakage, most environmental pollution is a slow and continuous process. We thus argue objective air pollution status is more likely not to significantly influence the public's level of life satisfaction, and then hypothesize.

Hypothesis 1b. (Lag Effects Hypothesis): Objective air pollution conditions may be insignificantly related to life satisfaction.

Besides launching a substantial exploration of the association between objective air pollution status and life satisfaction, current scholarly literature also probes the mediating role of perceived air condition [47,48]. Perceived air pollution allows residents to link life satisfaction to external environmental conditions (including air pollution, climate deterioration, etc.) [49,50], and to consciously build the possible causal relationship between quality of life (QOL) and environmental pollution. Or try to help reduce air pollution if present in their area [51]. According to their risk perception, residents located in areas with serious air pollution normally rate the environmental quality lower than those living in better environments [52], leading to a change in emotional state and reducing the level of life satisfaction or happiness [53–56]. For instance, Xu, G., X. Feng, Y. Li, X. Chen and J. Jia [56] indicated that environmental risk perceptions exert a direct passive influence on individuals' overall well-being. Also, a study on China's mining areas found that the higher the individual's perceived risk of air pollution, the lower their subjective well-being. Scholars have primarily explored the mediating role of subjective environmental evaluations between objective environmental quality and life satisfaction [55,57]. It is reasonable and acceptable to build a substantial linkage between perceived air pollution and life satisfaction when examining the variability in life satisfaction. Given these research findings, we hypothesize.

Hypothesis 2. (Perception Hypothesis): Perceived air pollution is negatively related to life satisfaction.

Moreover, life satisfaction is essentially a psychological cognition of current life status, which primarily depends on one's income. Generally, the lower-income group may pay more attention to material aspects and put less priority on environmental issues compared to the higher-income group, resulting in attitudes toward environmental pollution varying among separate groups. To be more specific, some low-income workers are more likely to tolerate serious labor conditions while high-income earners not only desire stricter environmental standards but are willing to bear the cost of a better environment [20,58]. In particular, when the high-income group perceives a link between air pollution and adverse effects on human health, including a shortened life span, their sense of life satisfaction significantly decreases [41]. We thus argued that the effects of SO_2 and PM emissions on life satisfaction are contingent on income. Based on the aforementioned analysis, we develop the third hypothesis.

Hypothesis 3. (Income Heterogenous Effects Hypothesis): The negative correlation between objective air pollution conditions and life satisfaction is more salient among the high-income group.

Fig. 1 represents the research framework utilized in this study. We proposed several hypotheses regarding the relationship between objective pollutant emission, subjective perception, and life satisfaction. The heterogenous effects of income are also investigated.

3. Materials and methods

3.1. Research context: Why China

This article empirically examined the theoretical association between environment and life satisfaction based on China that substantially differs from Western countries in terms of economic, political, and cultural aspects. This is of great significance for enhancing understanding of the “environment-life satisfaction” nexus. Especially, along with remarkable economic development is the conflicting trend that Chinese life satisfaction has not been synchronized with great improvement in material living conditions, also called the China-style "Easterlin paradox" [59,60]. The reason comes from the fact that the fulfilment of rapid economic growth in China mainly relies on traditional energy consumption, industrial emissions [61,62], and the like. Consequently, this economic mode is always accompanied by seriously deteriorating environmental pollution. Wolf, M. J., D. C. Esty, H. Kim, M. L. Bell, S. Brigham, Q. Nortonsmith, S. Zaharieva, Z. A. Wendling, A. de Sherbinin and J. W. Emerson [63] discovered that China occupied one of the five countries where residents were most severely exposed to air pollution, after comparing pollutant concentrations in 171 countries from 2014 to 2018. A similar finding was also confirmed by Chen, J., C. Li, Z. Ristovski, A. Milic, Y. Gu, M. S. Islam, S. Wang, J. Hao, H. Zhang and C. He [64]. Moreover, air pollutants are regarded as the top four health risk factors among multiple environmental pollution factors in China [65], and verifiably generate more hazards in developing countries than in developed [66]. Therefore, to improve the quality of life and well-being of residents, environmental protection has been highly prioritized by the Chinese governments across all hierarchical levels in recent years. Since the 18th National Congress of the Communist Party of China held in 2012, the central government has gradually endeavored to improve air quality by modifying its target responsibility system, in which obligatory targets were introduced to evaluate the political achievements of local officials. However, air pollution in China is partial rather than total acceptance because it meets domestic regulations but does not reach the guideline limits of pollutants issued by the World Health Organization (WHO) [67]. For example, “China Air 2022: Air Pollution Prevention and Control Progress in Chinese Cities” [68] reported that while China’s air quality is improving at the fastest rate in the world over the last decade, only 70 % of cities meet $PM_{2.5}$ guideline limits of pollutants. Against this backdrop, it is necessary to re-examine the relationship between environment and life satisfaction, in other words, whether or not public life satisfaction increases and what role perceived air pollution will play under the condition that China makes great progress in environmental management and pollution reduction.

3.2. Data collection

3.2.1. Individual-level data

The micro-individual data used in this paper was from the China Social Survey (CSS), a large-scale nationwide continuous sample survey launched by the Institute of Sociology of the Chinese Academy of Social Sciences (CASS). This is a biennial survey since 2005. It obtains longitudinal information on labor, family, social life as well as social attitudes of the public during the transition period in China, providing detailed and useful information for social science research or government policymaking. What we selected was the seventh wave of CSS conducted in 2019, abbreviated as CSS2019, and the survey theme was "Social Quality and Social Class Change". Overall, CSS2019 includes multiple modules on households, living conditions, employment, socioeconomic status, social security and values, social and political participation, and volunteering. Over eleven thousand residents were interviewed in 596 villages/towns across 149 cities/counties/districts nationwide, resulting in a total of 10283 valid questionnaires being collected.[1]

3.2.2. Provincial-level data

This research also utilizes environmental and economic indicators for 30 of China’s provinces in 2018. (There are 31 provincial-level administrative regions in China mainland, and Xinjiang was not included in this research). The economic indicators were obtained from the China Statistical Yearbook (CSY) in 2019; the corresponding environmental pollutant emissions are available from the CSY of Environment for the same year. These two all provided the relevant data in the previous year. Besides, it bears noting that the timing of the macro-level and survey collections was not fully synchronized, potentially leading to a lag in participants’ perception of air pollution and the evaluation of government governance performance [69]. While prefecture- or county-level data are more

[1] Data can be available from the official website (http://csqr.cass.cn/. accessed on 5 August 2023) by registering.

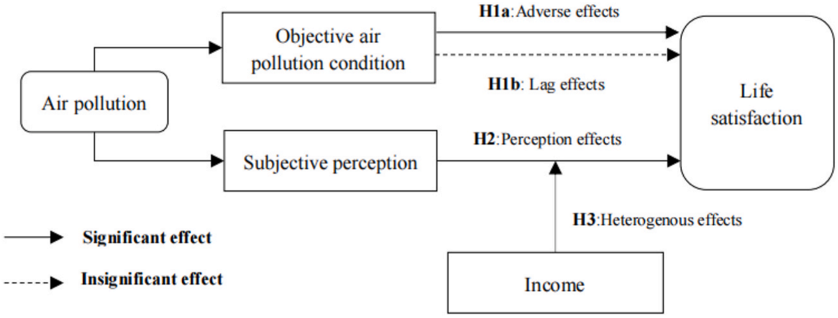

Fig. 1. Research framework.

accurate than provincial-level, it was not feasible to position the city or county where the respondent is located, due to the restriction of CSS2019 disclosures. Therefore, we only target the province. Due to CSS2019 being mainly implemented in 2018, we used provincial-level data from the corresponding year.

3.3. Variables specification

3.3.1. Dependent variable

The dependent variable of interest in this paper was the public satisfaction with their living conditions. Although prior research has begun to explore public life satisfaction using social media data in recent years [18], relying on the respondents' self-reported life satisfaction remains the mostly common choice by current academics [70,71]. In line with the current research, we captured life satisfaction with one question in CSS2019 described as "How satisfied are you with your current life in general?". Responses were scored on a ten-point scale ranging from 1 (strongly disagree) to 10 (strongly agree).

3.3.2. Independent variables

Following WHO,[2] air pollution is defined as any contamination to indoor and outdoor environments by chemical, physical and biological factors that alter the natural characteristics of the atmosphere. Common air pollutants of public concern are solid particulate matter (PM, including respirable particulate matter, which is PM10, and fine particulate matter, which is PM2.5), gaseous mixtures (e.g., CO, NO_2, O_3, SO_2). When theoretically and empirically investigating the relation between ambient pollution and life satisfaction, it is reasonable to partition air pollution into two dimensions, namely objective air pollution condition and how the public view them, which is consistent with the empirical research of Liao, P.-s., D. Shaw and Y.-m. Lin [55] and Li, F. and T. Zhou [57].

Specifically, we employed both subjective and objective indicators to gauge air pollution in this work. Subjective evaluation refers to public perception toward air pollution ***(perceived air pollution)*** that was proxied by the following general question: "Do you think air pollution is serious in the present residential areas?" in the CSS2019. The answer was measured on a four-point scale, ranging from "not serious" (1) to "very serious" (4). A larger value indicates more serious air pollution perceived by the respondents.

Each atmospheric pollutant was given varying priorities by both academic scholars and practitioners from public organizations in China. Practically, as far back as 2013, the Notice of the Chinese State Council on the Issuance of the Action Plan for the Prevention and Control of Air Pollution[3] stressed the characteristics of regional atmospheric pollution was feathered by PM, and treated SO_2 emissions as an obligatory environmental indicator. The scholarship from public administration and environmental science also focused attention on these two pollutants [72–74], and viewed PM and SO_2 as the most widely-present air pollutants [75]. Following previous protocols, we also targeted SO_2 and PM.

Objective air pollution condition is measured by PM and SO_2 emissions rather than air quality index or pollutants concentrations because Chinese environmental governance normally focus on reducing pollutants emissions as main policy targets. We applied a logarithmic treatment to adjust them to conform to a normal distribution. Tang, X., Y. Wang and H. Yi [72] also log-transformed their data when exploring information manipulation in environmental governance.

3.3.3. Control variables

We included other potential macro- and micro-level factors in the statistical model to avoid omitting variables. Gross Domestic Product (GDP), constantly refers to the final product of the production activities of all resident units in a country (or region) over a certain period and is commonly used to measure economic development. We thus controlled China's GDP. The micro-level variables mainly comprised respondents' socioeconomic demographic characteristics. Education was transformed into the duration of school education by employing linear approaches. Specially, years of education were recoded according to participants' education experience; for instance, six years of education were recoded if the respondent reported their education background to have been in primary

[2] website: https://www.who.int/zh/health-topics/air-pollution#tab=tab_1. accessed on 5 August 2023.
[3] website: https://www.gov.cn/zhengce/zhengceku/2013-09/13/content_4561.htm. Access on 5 August 2023.

school. Similarly, middle school was recoded as "9", high school as "12", undergraduate as "16", and postgraduate and above as "19", and never attended school was coded as "0". The individual income was obtained from self-reported annual earnings in the questionnaire, which was logarithmically processed in order to conform to normal distribution. Gender, marital status, nationality, political membership, household registration, religion, and employment were all dummy variables with values of 1 for male, married, Han nationality, China Communist Party (CCP) membership, urban household registration, religious residents, and having a job; otherwise, they were 0. Age and age-squared were also included in the model [76]. In this article, we calculated percentages for dummy variables, medians and IQR for ordinal variables, and means and SD for continuous variables. Descriptive statistics of variables from the entire sample are reported in Table 1, Table 2, and Table 3, respectively.

Table 1 showed that among 10282 samples, the 25 %, 50 %, and 75 % quartiles of life satisfaction were 5, 7, and 9, respectively, while corresponding values for perceived air pollution were 1, 2, and 2 among 5067 samples.

As Table 2 demonstrated, 43 % of respondents in the sample were male and 81 % were married. The majority of respondents belonged to the Han nationality, with a value of 92 %. The percentage of respondents who had CCP membership was only 10 %. Residents with urban household registration account for 31 % of all samples. Thirteen percent and 65 % of the respondents in our sample claimed to be religious and employed, respectively.

Table 3 reported the summary statistics for the remaining variables. SO_2 emissions, PM emissions, and GDP were at the provincial-level, and so their observations were 30. After log-transformed, the mean, standard deviation (SD), minimum, and maximum of SO_2 emissions were 11.96, 0.88, 7.89, and 12.8, respectively. Respondents in our sample had an average age of 46.59 years old, with the oldest being 69 while the youngest 18. Overall, the age distribution was relatively uniform. Years of education ranged from 0 to 18, and the average value was 9.27. Individual income was also log-treated, and its mean, SD, minimum and maximum were 9.65, 1.44, 0, and 15.89.

3.4. Model specification

Explanatory variables (air pollutants emissions) and dependent variables (life satisfaction) pertained to different levels, i.e., the survey (CSS2019) was nested in the provincial data. This may lead to non-independence of respondents surveyed, which was not solved by traditional statistical model. Recently, the Hierarchical Linear Model (HLM) has gradually evolved to tackle this nested problem [77], and simultaneously contributed to a certain extent to causal inference.

Given that life satisfaction was measured by a 10-point scale, it was reasonable to treat it as a continuous variable. The formulas are set as follows, which we call equation (1) and equation (2).

$$\text{Individual} - \text{level}: Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \varepsilon_{ij};\ \varepsilon_{ij} \sim N(0, \sigma^2) \quad [1]$$

$$\text{Province} - \text{level}: \beta_{0j} = \gamma_{00} + \gamma_{01}W_j + \mu_{oj};\ \beta_{1j} = \gamma_{10} + \gamma_{11}W_j + \mu_{1j} \quad [2]$$

Y_{ij} is individual i nested within province j *($j \sim 1,2,3, \ldots 30$; because the number of provinces for statistical model is 30)*. It denotes dependent variables, mainly including individual self-reported life satisfaction and perceived air pollution in Table 5. X_{ij} denotes individual-level explanatory variables, including perceived air pollution as core micro-variable and a set of control variables. β_{0j} is the intercept, and β_{1j} is the coefficient, which two are functions of W_j, which denotes group-level variables, including air pollutants emissions and GDP at the province-level in this article. ε_{ij} represents the error term, assumed to be subject to normal distribution, with the mean of 0 and variance of σ^2. In the province-level, γ_{00} and γ_{01} denote the means of dependent variables when controlling for W_j, γ_{01} and γ_{11} are the coefficients of W_j. μ_{oj} and μ_{1j} represent error terms. In this article, we use a random intercept model to estimate the parameter, and γ_{11} is assumed to be equal to 0.

Moreover, to obtain more robust estimation results, we also treat life satisfaction as an ordinal variable. The formula is set as follows, which we call equation (3).

$$P(Y_{ij} \leq = K) = H(X_{ij}\beta_{1j} + \beta_{0j}) \quad [3]$$

Ordinal logit model is distinct from the linear probability model in terms of formula specification, with the former based on cumulative probability distribution function, that is $H(\cdot)$. K equals 10 because life satisfaction is measured on a ten-point scale ranging from 1 to 10. β_{1j} and β_{0j} are interpreted analogous to that of Individual-level and also influenced by province-level variables (W_j).

Table 1
Descriptive statistics of ordinal variables.

Variable	Obs	25 % quartile	50 % quartile.	75 % quartile
Life satisfaction	10282	5	7	9
Perceived air pollution	5067	1	2	2

Table 2
Descriptive statistics of dummy variables.

Variable	Obs	Proportion
Male	10283	43 %
Married	10278	81 %
Han nationality	10283	92 %
CCP	10283	10 %
Urban residents	10138	31 %
Religious residents	10283	13 %
Having job	10283	65 %

Table 3
Descriptive statistics of continuous variables.

Variable	Obs	Mean	Std.Dev.	Min	Max
SO_2 emissions (log; 10000 tons)	30	11.96	0.88	7.89	12.8
PM emissions (log; 10000 tons)	30	12.78	0.74	9.68	13.75
GDP (log; billions)	30	10.41	0.75	7.34	11.51
Age	10283	47	14.25	18	69
Age^2	10283	2374	1282.41	324	4761
Years of education	10266	9.27	4.43	0	18
Income (log; yuan)	8527	9.65	1.44	0	15.89

4. Results

4.1. Description of air pollutant emissions in China

To visually demonstrate the geographical differences between SO_2 and PM emissions among various provinces in China, we rendered the pollutants emissions distribution in Fig. 2.

As illustrated in Fig. 2, air pollutant emissions varied among Chinese provinces in 2018. The left panel shows that SO_2 pollution was most serious in the traditional industrially developed provinces such as Hebei, Inner Mongolia, Liaoning, Shandong, and Jiangsu, with almost no emissions in Tibet, Hainan, and Qinghai. This follows a similar pattern of PM emissions in the right panel of Fig. 2 that were most severe in Inner Mongolia and Liaoning, with the lowest emissions in Tibet, Qinghai, Hainan, and Jilin. SO_2 and PM emissions in other provinces were at an intermediate level.

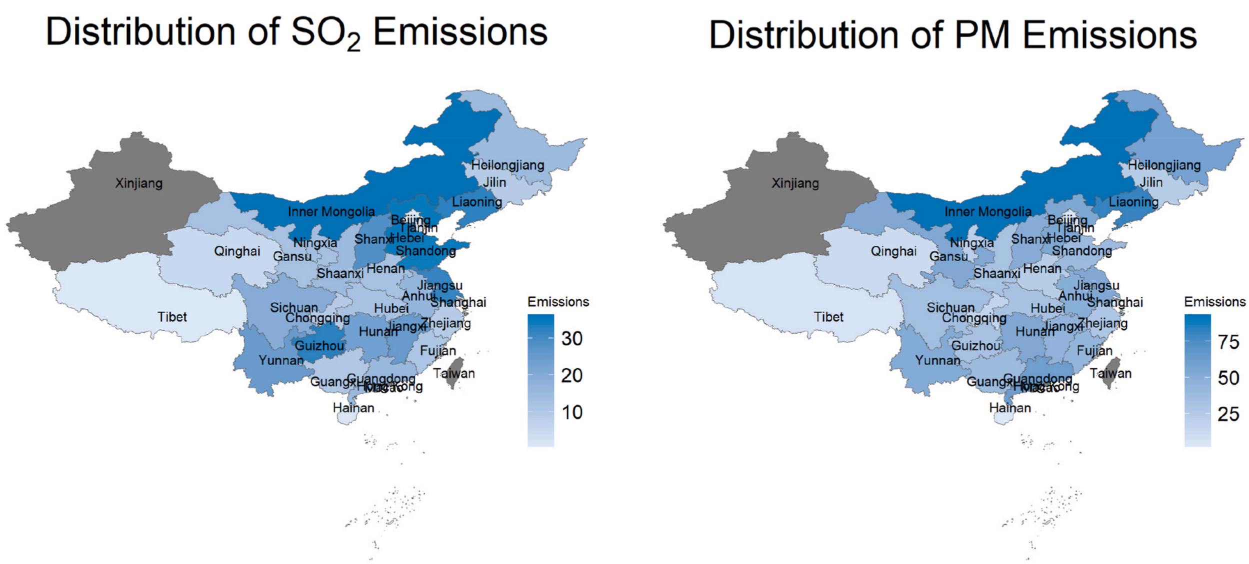

Fig. 2. Distribution of SO_2 and PM Emissions in China in 2018 *Note: The unit of air pollutant emissions is 10,000 tons. Darker blue indicates higher emissions. Gray areas represent missing values.
*Source: Map generated from the data from CSY of Environment in 2019.

4.2. Baseline regression results

4.2.1. Statistical tests for hypothesis 1 and 2

We sequent ran three multi-level linear regression models to empirically investigate the nexus between air pollution and life satisfaction (see Table 4). All three models contained perceived air pollution as well as controlling for macro- and micro-level variables such as GDP and a set of individual socioeconomic information. Model (1) only included SO_2 emissions (logged) while Model (2) only included PM emissions (logged). These two air pollutants were simultaneously added to Model (3). Three models in Table 4 are estimated based on equation (1), equation (2) and indicated that perceived air pollution influenced life satisfaction at a significance level of 0.01 while holding all other aspects constant. Specially, for each one-point increase in perceived air pollution, Chinese life satisfaction scores decrease by an average of 0.22 on a scale of 1–10. Our hypothesis 2 is supported by empirical evidence. Emissions of SO_2 and PM failed to significantly impact public life satisfaction, which supported lagged effects hypothesis (H 1b).

For micro-level control variables, there was significant variation in life satisfaction among different groups based on gender, marriage status, and party affiliation while nationality, household registration, religion, and employment status did not influence residents' satisfaction. Moreover, a nonlinear relationship between age and life satisfaction was observed by extant evidence. Both residents' years of education and income significantly enhanced their life satisfaction, but GDP had null effect on residents' life satisfaction.

To further validate the lag effect of public perception, we replicated baseline model but replaced life satisfaction with perceived air pollution as the dependent variable to examine whether SO_2 and PM emissions had a significant effect on it. If there was a significant effect, this explanation reasonably was refuted. If not, we convincingly acknowledged that the public may fail to detect changes in air pollutant emissions, even minor ones. In that case, lag effect of public perception was provided by empirical evidence. The results are shown in Table 5. Models (1) and (2) are estimated by equation (1)&2, and revealed that there was no significant relation between air pollutant (SO_2 and PM) emissions and perceived air pollution with or without the inclusion of control variables. This implied that the public was not sensitive to subtle air pollution changes, verifying the lag effect once again.

Table 4
Regression results for the effect of air pollution on life satisfaction.

Variables	Model (1) Life satisfaction	Model (2) Life satisfaction	Model (3) Life satisfaction
SO_2 emissions (log)	−0.02		0.11
	(0.05)		(0.18)
PM emissions (log)		−0.06	−0.18
		(0.05)	(0.19)
Perceived air pollution	−0.22***	−0.22***	−0.22***
	(0.05)	(0.05)	(0.05)
GDP(log)	0.03	0.04	0.04
	(0.10)	(0.10)	(0.10)
Male	−0.16**	−0.16**	−0.16**
	(0.07)	(0.07)	(0.07)
Age	−0.16***	−0.16***	−0.16***
	(0.02)	(0.02)	(0.02)
Age^2	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Education	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
Married	0.40***	0.40***	0.40***
	(0.07)	(0.07)	(0.07)
Han nationality	−0.08	−0.08	−0.09
	(0.20)	(0.20)	(0.20)
CCP	0.55***	0.55***	0.55***
	(0.11)	(0.11)	(0.11)
Urban household registration	0.06	0.06	0.06
	(0.07)	(0.07)	(0.07)
Religious resident	−0.13	−0.13	−0.12
	(0.10)	(0.10)	(0.10)
Having job	0.04	0.04	0.04
	(0.07)	(0.07)	(0.07)
Income(log)	0.15***	0.14***	0.15***
	(0.03)	(0.03)	(0.03)
Constant	7.60***	7.95***	8.17***
	(1.32)	(1.33)	(1.30)
lns1_1_1_cons	−1.16***	−1.18***	−1.23***
	(0.22)	(0.22)	(0.24)
lnsig_e_cons	0.74***	0.74***	0.74***
	(0.02)	(0.02)	(0.02)
N	4181	4181	4181

*Robust standard errors in parentheses; level of significance: *p < 0.1, **p < 0.05, ***p < 0.01.

Table 5
Regression results for the effect of SO_2 and PM emissions on perceived air pollution.

	Model (1) Perceived air pollution	Model (2) Perceived air pollution
SO_2 emissions (log)	0.11	0.02
	(0.12)	(0.09)
PM emissions (log)	−0.06	0.03
	(0.12)	(0.09)
Controls		Y
Constant	3.43***	4.66***
	(0.60)	(0.67)
lns1_1_1_cons	−1.58***	−1.76***
	(0.17)	(0.17)
lnsig_e_cons	−0.09***	−0.10***
	(0.01)	(0.01)
N	5067	4156

*Robust standard errors in parentheses; level of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

4.2.2. Statistical test for Hypothesis 3

To statistically test hypothesis 3, we conduct separably multi-level linear model by segmenting individual income into two groups. Empirically, we first calculated the 75 % percentile individual income (log-transformed), which is served as a cut-off criterion to divide the respondents surveyed into two groups in the entire sample, i.e., low-income group and high-income group. Subgroup regressions were then performed to examine the differential effects of SO_2 and PM emissions on life satisfaction among the two groups. The findings are presented in Table 6, of which two models are estimated based on equation (1) and equation 2.

Model (1) indicated that SO_2 and PM emissions still lacked a remarkable impact on the public's self-reported life satisfaction after controlling for macro- and micro-variables in low-income group. However, there was a significant negative correlation between PM emissions and life satisfaction in the high-income group with a significance level of 0.1, as demonstrated by the model (2). As PM emissions increased by 1 unit in the log term, individual satisfaction with his/her life decreased by 0.31 on a scale of 1–10, on average. Hypothesis 3 is partially supported by empirical evidence.

4.3. Robustness checks

Considering that the dependent variable was measured by a scale of 1–10, we employed a multilevel ordinal logit model as a robust test, and the results are presented as Model (1) to Model (3) of Table 7, which is estimated by equation (1)&2. Additionally, CSS2019 applied a stratified sampling approach that may incur biased estimation if lacking weighting regression. Therefore, the multilevel regression model by weighting was rerun to obtain a robust parameter. The results are shown as models (4) to (6) in Table 7, which is estimated by equation (3).

All models in Table 7 found that SO_2 and PM emissions did not significantly affect life satisfaction, while there was a significant correlation between perceived air pollution and life satisfaction. Compared with the unweighted model, the coefficients of Model (4) to Model (6) were smaller than those of the baseline regression model in Table 4. Overall, the findings were consistent with our baseline results.

Table 6
Regression results for the heterogeneous effect of life satisfaction based on income.

	Model (1)	Model (2)
	Life satisfaction (Lower Income)	Life satisfaction (Higher Income)
SO_2 emissions (log)	0.17	0.26
	(0.22)	(0.16)
PM emissions (log)	−0.28	−0.31*
	(0.22)	(0.17)
Perceived Air pollution	−0.22***	−0.20***
	(0.05)	(0.04)
Controls	Y	Y
Constant	11.79***	7.84***
	(1.37)	(1.42)
lns1_1_1_cons	−1.17***	−1.39***
	(0.22)	(0.26)
lnsig_e_cons	0.80***	0.67***
	(0.02)	(0.02)
N	3106	1911

*Robust standard errors in parentheses; level of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 7
Robustness tests for the effect of air pollution on life satisfaction.

	Multi-level ordinal logit regression			Multi-level linear regression with weighting		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
SO_2 emissions (log)	−0.01		0.11	−0.04		−0.00
	(0.04)		(0.16)	(0.06)		(0.19)
PM emissions (log)		−0.04	−0.15		−0.06	−0.05
		(0.04)	(0.17)		(0.06)	(0.20)
Perceived air pollution	−0.18***	−0.18***	−0.18***	−0.24***	−0.24***	−0.24***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Controls	Y	Y	Y	Y	Y	Y
Constant				7.77***	7.95***	7.94***
				(1.56)	(1.62)	(1.55)
var(constant[province])	0.07**	0.07**	0.06**			
	(0.03)	(0.03)	(0.03)			
lns1_1_1_cons				−1.10***	−1.11***	−1.11***
				(0.22)	(0.23)	(0.23)
lnsig_e_cons				0.71***	0.71***	0.71***
				(0.02)	(0.02)	(0.02)
N	4181	4181	4181	4181	4181	4181

Robust standard errors in parentheses; level of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

4.4. Sensitivity analysis

There could be still concerns that some important confounding variables - those related to both the dependent and independent variables but not controlled for - were not observed and thus not included in the model. To address this issue, we performed a sensitivity analysis to prove that the main findings were insensitive to potential, unobserved confounding variables. The basic idea of sensitivity analysis is to show the extent to which an unobserved potential confounder would need to be correlated with the treatment and outcome variables to make the treatment effects statistically non-significant.

The R sensemakr package [78] was used to implement the sensitivity analysis and the results are described in Fig. 3. The y-axis is the partial correlation between the outcome variable (life satisfaction) and the hypothetical confounding factors, and the x-axis is the partial correlation between a treatment variable (perceived air pollution) and the hypothetical confounding factors. The red dashed contour line is the threshold line. Any red point referring to controls in our article on or beyond the line would make the observed treatment effect for perceived air pollution non-significant at the 1 % significant level. Fig. 3 illustrates that all observed control variables, including gender, age, and education, were well below the threshold line. This implied that the unobserved confounding factors would need to be more closely related to the dependent and independent variables than the observed covariates to make the effect of perceived air pollution irrelevant, which seems highly unlikely.

5. Discussion

Our empirical findings concerning the relationship between air pollution and life satisfaction added new theoretical contributions to existing academic studies by examining the differential impacts of air pollution on public life satisfaction, namely partitioning air pollution into subjective and objective indicators, which has seldom been empirically investigated in preceding research. This work not only provides theoretical insight for existing studies but further is also valuable to prompt better policies and guiding practice in the practical term.

The findings theoretically provide a nuanced understanding of the relationship between environmental pollution and life satisfaction. When explaining the variations in life satisfaction, subjective perception rather than actual pollutant emissions matter, as evidenced by Tables 4–6. This helps to reconceptualize the traditional concern of how environmental pollution and life satisfaction are shared within environmental science, public administration, and many other disciplines. Additionally, heterogeneity analysis based on income demonstrated that the effect of air pollutant emissions among higher-income groups is more pronounced than in lower-income groups, highlighting the important role of material living conditions. This implied that the relation between environmental pollution and life satisfaction was non-linear rather than linear. Further studies should extensively explore this topic within countries featuring different political systems, economic conditions, and cultures.

Practically, our research also carries implications for policy formulation and implementation on the environment and quality of life for many other countries with institutional backgrounds and traditions similar to China. Firstly, the ambient effects of pollution vary across different material conditions, especially distinct income groups. The government's attention should be more focused on balancing the association between environmental protection and economic growth that constitutes the main driver for increasing personal income. Particularly, large-scale pollution controls at least are placed on equal status as economic growth. Secondly, the public's subjective perception of environmental quality deserves more attention. We thus suggest that relevant sectors should jointly promptly publish and update accurate environmental quality monitoring information so that the public have access to actual air pollution status and understand the beneficial efforts made by the government.

A few limitations of our research should be addressed. it is widely accepted that the dispersion of pollutants varies not only

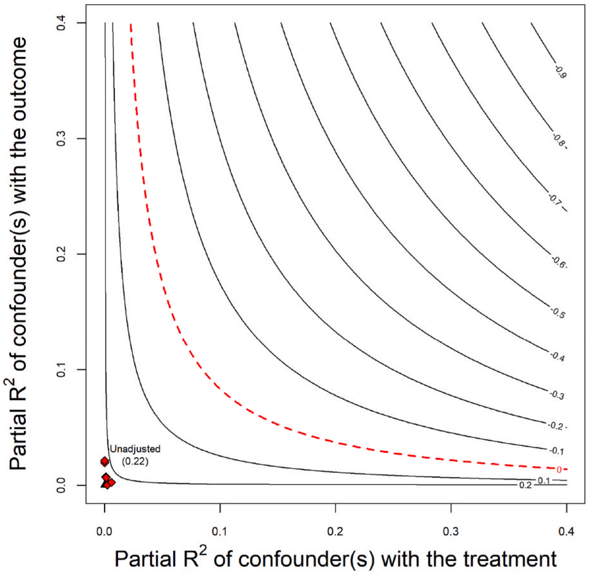

Fig. 3. Sensitivity analysis for the effect of perceived air pollution on life satisfaction.

depending on black carbon [79], VOCs, HAPs, and many other contaminants but also location and specific activities. This was not explored in our study. Moreover, most air pollutant emissions data were mainly gathered in the urban area rather than rural area, whereas individual life satisfaction was collected in "villages/towns and cities/country". It resulted in a potential mismatch so that the model explanatory variable may not accurately represent the variability in the explained variable. We utilized weighting regression as robust test to tackle this potential issue for ensuring the research result is reliable. However we still regard it as a deficiency in the research.

6. Conclusion

There is a heated discussion about the association between air condition and individual life satisfaction. We enthusiastically joined this surging trend by comprehensively probing how air pollution influenced individual life satisfaction by categorizing air pollution into two dimensions. We were theoretically inspired by insightful views concerning the lag effect of public perception and the heterogeneous effect of income, to develop three hypotheses for statistical test. We then empirically use China's case to validate the complex association between air pollution and life satisfaction by combining provincial- (e.g., PM and SO2 emissions) and individual-level (e.g., self-reported life satisfaction and perceived air pollution) data based on non-Western context. Empirical results showed that the public assessment of life satisfaction was directly affected by their subjective perceptions of air pollution rather than objective pollution conditions gauged by PM and SO_2 emissions. The findings remained plausible after robustness checks and sensitivity analysis. Our research theoretically offers a nuanced understanding of how air pollution influences life satisfaction, simultaneously guides China's environmental governance in the practical term, and serves as a reference for other countries with similar social backgrounds and development modes.

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Data availability statement

Data can be available from the official website. China Social Survey: http://csqr.cass.cn/. China Environment Yearbook: http://cnki.nbsti.net/CSYDMirror/area/Yearbook/Single/N2022030234?z=D26.

CRediT authorship contribution statement

Xinghua Zhao: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Software. **Yumei Cao:** Writing – original draft, Data curation, Conceptualization. **Zheng Cheng:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] D.C. Shin, D.M. Johnson, Avowed happiness as an overall assessment of the quality of life, Soc. Indicat. Res. 5 (1978) 475–492.
[2] E. Diener, R.A. Emmons, R.J. Larsen, S. Griffin, The satisfaction with life scale, J. Pers. Assess. 49 (1985) 71–75.
[3] C.H. DiMaria, C. Peroni, F. Sarracino, Happiness matters: productivity gains from subjective well-being, J. Happiness Stud. 21 (2020) 139–160.
[4] B.L. Neugarten, R.J. Havighurst, S.S. Tobin, The measurement of life satisfaction, J. Gerontol. 16 (1961) 134–143.
[5] E. Palmore, C. Luikart, Health and social factors related to life satisfaction, J. Health Soc. Behav. (1972) 68–80.
[6] J.N. Edwards, D.L. Klemmack, Correlates of life satisfaction: a re-examination, J. Gerontol. 28 (1973) 497–502.
[7] R. Veenhoven, The Study of Life-Satisfaction, 1996.
[8] W. Pavot, E. Diener, The satisfaction with life scale and the emerging construct of life satisfaction, J. Posit. Psychol. 3 (2008) 137–152.
[9] T. Vinson, M. Ericson, The social dimensions of happiness and life satisfaction of a ustralians: evidence from the world values s urvey, Int. J. Soc. Welfare 23 (2014) 240–253.
[10] C.L. Ambrey, C.M. Fleming, A.Y.-C. Chan, Estimating the cost of air pollution in south east queensland: an application of the life satisfaction non-market valuation approach, Ecol. Econ. 97 (2014) 172–181.
[11] Y. Song, M. Li, M. Zhang, X. Sun, Study on the impact of air pollution control on urban residents' happiness from microscopic perspective, J. Clean. Prod. 229 (2019) 1307–1318.
[12] H. Welsch, Environment and happiness: valuation of air pollution using life satisfaction data, Ecol. Econ. 58 (2006) 801–813.
[13] H. Liu, T. Hu, How does air quality affect residents' life satisfaction? Evidence based on multiperiod follow-up survey data of 122 cities in China, Environ. Sci. Pollut. Control Ser. 28 (2021) 61047–61060, https://doi.org/10.1007/s11356-021-15022-x.
[14] N.A.B. Mabahwi, O.L.H. Leh, D. Omar, Human health and wellbeing: human health effect of air pollution, Procedia-Social and Behavioral Sciences 153 (2014) 221–229.
[15] Q. Wang, Z. Yang, Industrial water pollution, water environment treatment, and health risks in China, Environ. Pollut. 218 (2016) 358–365.
[16] S. Marques, M.L. Lima, Living in grey areas: industrial activity and psychological health, J. Environ. Psychol. 31 (2011) 314–322.
[17] K. Orru, H. Orru, M. Maasikmets, R. Hendrikson, M. Ainsaar, Well-being and environmental quality: does pollution affect life satisfaction? Qual. Life Res. 25 (2016) 699–705.
[18] S. Zheng, J. Wang, C. Sun, X. Zhang, M.E. Kahn, Air pollution lowers Chinese urbanites' expressed happiness on social media, Nat. Human Behav. 3 (2019) 237–243.
[19] H. Welsch, Environmental welfare analysis: a life satisfaction approach, Ecol. Econ. 62 (2007) 544–551.
[20] A. Levinson, Valuing public goods using happiness data: the case of air quality, J. Publ. Econ. 96 (2012) 869–880.
[21] C. Schmiedeberg, J. Schröder, Does weather really influence the measurement of life satisfaction? Soc. Indicat. Res. 117 (2014) 387–399, https://doi.org/10.1007/s11205-013-0350-7.
[22] S. Ferreira, A. Akay, F. Brereton, J. Cuñado, P. Martinsson, M. Moro, T.F. Ningal, Life satisfaction and air quality in europe, Ecol. Econ. 88 (2013) 1–10.
[23] G. MacKerron, S. Mourato, Life satisfaction and air quality in london, Ecol. Econ. 68 (2009) 1441–1453.
[24] L. Yuan, K. Shin, S. Managi, Subjective well-being and environmental quality: the impact of air pollution and green coverage in China, Ecol. Econ. 153 (2018) 124–138.
[25] I. Sulemana, L. McCann, H.S. James Jr., Perceived environmental quality and subjective well-being: are african countries different from developed countries? Int. J. Hydropower Dams 3 (2016) 64–87.
[26] P. Slovic, Perception of risk, Science 236 (1987) 280–285.
[27] J.G. Zivin, M. Neidell, The impact of pollution on worker productivity, Am. Econ. Rev. 102 (2012) 3652–3673.
[28] J. Archsmith, A. Heyes, S. Saberian, Air quality and error quantity: pollution and performance in a high-skilled, quality-focused occupation, Journal of the Association of Environmental and Resource Economists 5 (2018) 827–863.
[29] Q. Shi, F. Guo, Do people have a negative impression of government on polluted days? Evidence from Chinese cities, J. Environ. Plann. Manag. 62 (2019) 797–817.
[30] A. Heyes, N. Rivers, B. Schaufele, Pollution and politician productivity: the effect of pm on mps, Land Econ. 95 (2019) 157–173.
[31] R. Sun, D. Gu, Air pollution, economic development of communities, and health status among the elderly in urban China, Am. J. Epidemiol. 168 (2008) 1311–1318.
[32] S. Wang, J. Zhang, X. Zeng, Y. Zeng, S. Wang, S. Chen, Association of traffic-related air pollution with children's neurobehavioral functions in quanzhou, China, Environ. Health Perspect. 117 (2009) 1612–1618.
[33] Y. Zeng, D. Gu, J. Purser, H. Hoenig, N. Christakis, Associations of environmental factors with elderly health and mortality in China, Am. J. Publ. Health 100 (2010) 298–305.
[34] T. Schikowski, M. Vossoughi, A. Vierkötter, T. Schulte, T. Teichert, D. Sugiri, K. Fehsel, L. Tzivian, I.-s. Bae, U. Ranft, Association of air pollution with cognitive functions and its modification by apoe gene variants in elderly women, Environ. Res. 142 (2015) 10–16.
[35] M. Abed Al Ahad, Air pollution reduces the individuals' life satisfaction through health impairment, Applied Research in Quality of Life (2024) 1–25.
[36] B. Ambade, The air pollution during diwali festival by the burning of fireworks in jamshedpur city, India, Urban Clim. 26 (2018) 149–160.
[37] N. Gouveia, M. Maisonet, Health effects of air pollution: an overview, Air quality guidelines: Global update 2005. Particulate matter, ozone, nitrogen dioxide and sulfur dioxide (2006) 87–109.
[38] M. Abed Al Ahad, U. Demšar, F. Sullivan, H. Kulu, The spatial–temporal effect of air pollution on individuals' reported health and its variation by ethnic groups in the United Kingdom: a multilevel longitudinal analysis, BMC Publ. Health 23 (2023) 1–25.
[39] N. Ab Manan, A.N. Aizuddin, R. Hod, Effect of air pollution and hospital admission: a systematic review, Annals of global health 84 (2018) 670.
[40] M. Abed Al Ahad, F. Sullivan, U. Demšar, M. Melhem, H. Kulu, The effect of air-pollution and weather exposure on mortality and hospital admission and implications for further research: a systematic scoping review, PLoS One 15 (2020) e0241415.
[41] O.S. Ebhota, Y. Hongxing, A.K. Sampene, Air pollution and life expectancy: new evidence from the mint economies, Heliyon 9 (2023) e22396, https://doi.org/10.1016/j.heliyon.2023.e22396.
[42] A.M. Dzhambov, I. Markevych, B. Tilov, Z. Arabadzhiev, D. Stoyanov, P. Gatseva, D.D. Dimitrova, Pathways linking residential noise and air pollution to mental ill-health in young adults, Environ. Res. 166 (2018) 458–465.

[43] M. Abed Al Ahad, U. Demšar, F. Sullivan, H. Kulu, Air pollution and individuals' mental well-being in the adult population in United Kingdom: a spatial-temporal longitudinal study and the moderating effect of ethnicity, PLoS One 17 (2022) e0264394.
[44] M. Sørensen, P. Lühdorf, M. Ketzel, Z.J. Andersen, A. Tjønneland, K. Overvad, O. Raaschou-Nielsen, Combined effects of road traffic noise and ambient air pollution in relation to risk for stroke? Environ. Res. 133 (2014) 49–55.
[45] B. Stipak, Citizen satisfaction with urban services: potential misuse as a performance indicator, Publ. Adm. Rev. (1979) 46–52.
[46] K. Brown, P.B. Coulter, Subjective and objective measures of police service delivery, Publ. Adm. Rev. 43 (1983) 50–58.
[47] A.-S. Claeson, E. Lidén, M. Nordin, S. Nordin, The role of perceived pollution and health risk perception in annoyance and health symptoms: a population-based study of odorous air pollution, Int. Arch. Occup. Environ. Health 86 (2013) 367–374.
[48] S. Gong, J.G. Lu, J.M. Schaubroeck, Q. Li, Q. Zhou, X. Qian, Polluted psyche: is the effect of air pollution on unethical behavior more physiological or psychological? Psychological science 31 (2020) 1040–1047.
[49] M. Zeidner, M. Shechter, Psychological responses to air pollution: some personality and demographic correlates, J. Environ. Psychol. 8 (1988) 191–208.
[50] S.A. Ajayi, C.A. Adams, G. Dumedah, O.A. Adebanji, A. Ababio-Donkor, W. Ackaah, A. Kehinde, Public perceptions of vehicular traffic emissions on health risk in lagos metropolis Nigeria: a critical survey, Heliyon 9 (2023) e15712, https://doi.org/10.1016/j.heliyon.2023.e15712.
[51] Kester S. Ardvin, Y.T.P. Ong, Poonyawat Kusonwattana, Klint Allen Mariñas, Nattakit Yuduang, Thanatorn Chuenyindee, Kirstien Paola E. Robas, Fadil Persada Satria, Nadlifatin Reny, Determining factors affecting the perceived usability of air pollution detection mobile application "airvisual" in Thailand: a structural equation model forest classifier approach, Heliyon 8 (2022) e12538, https://doi.org/10.1016/j.heliyon.2022.e12538. https://www.cell.com/heliyon/fulltext/S2405-8440(22)03826-9#secsectitle0010.
[52] D.O. Atari, I.N. Luginaah, K. Fung, "The relationship between odour annoyance scores and modelled ambient air pollution in sarnia,"chemical valley", ontario." International Journal of Environmental Research and Public Health 6 (2009) 2655–2675.
[53] K. Rehdanz, D.J. Maddison, Local environmental quality and life-satisfaction in Germany, Ecol. Econ. 64 (2008) 787–797.
[54] Z. Li, H. Folmer, J. Xue, To what extent does air pollution affect happiness? The case of the jinchuan mining area, China, Ecol. Econ. 99 (2014) 88–99.
[55] P.-s. Liao, D. Shaw, Y.-m. Lin, Environmental quality and life satisfaction: subjective versus objective measures of air quality, Soc. Indicat. Res. 124 (2015) 599–616.
[56] G. Xu, X. Feng, Y. Li, X. Chen, J. Jia, Environmental risk perception and its influence on well-being, Chin. Manag. Stud. 11 (2017) 35–50.
[57] F. Li, T. Zhou, Effects of objective and subjective environmental pollution on well-being in urban China: a structural equation model approach, Soc. Sci. Med. 249 (2020) 112859, https://doi.org/10.1016/j.socscimed.2020.112859. https://www.sciencedirect.com/science/article/pii/S0277953620300782.
[58] A. Diekmann, A. Franzen, The wealth of nations and environmental concern, Environ. Behav. 31 (1999) 540–549.
[59] R.A. Easterlin, R. Morgan, M. Switek, F. Wang, China's Life Satisfaction, 1990–2010, vol. 109, Proceedings of the National Academy of Sciences, 2012, pp. 9775–9780.
[60] L. Li, L. Shi, Economic growth and subjective well-being: Analyzing the formative mechanism of easterlin paradox, The Journal of Chinese Sociology 6 (2019) 1–19.
[61] R. Di Tella, R. MacCulloch, Gross national happiness as an answer to the easterlin paradox? J. Dev. Econ. 86 (2008) 22–42.
[62] X. Zhang, X. Zhang, X. Chen, Happiness in the air: how does a dirty sky affect mental health and subjective well-being? J. Environ. Econ. Manag. 85 (2017) 81–94.
[63] M.J. Wolf, D.C. Esty, H. Kim, M.L. Bell, S. Brigham, Q. Nortonsmith, S. Zaharieva, Z.A. Wendling, A. de Sherbinin, J.W. Emerson, New insights for tracking global and local trends in exposure to air pollutants, Environ. Sci. Technol. 56 (2022) 3984–3996, https://doi.org/10.1021/acs.est.1c08080.
[64] J. Chen, C. Li, Z. Ristovski, A. Milic, Y. Gu, M.S. Islam, S. Wang, J. Hao, H. Zhang, C. He, A review of biomass burning: emissions and impacts on air quality, health and climate in China, Sci. Total Environ. 579 (2017) 1000–1034.
[65] M. Zhou, H. Wang, X. Zeng, P. Yin, J. Zhu, W. Chen, X. Li, L. Wang, L. Wang, Y. Liu, Mortality, morbidity, and risk factors in China and its provinces, 1990–2017: a systematic analysis for the global burden of disease study 2017, Lancet 394 (2019) 1145–1158.
[66] R.P. Kumar, C. Samuel, S. Gautam, A bibliometric and scientometric: analysis towards global pattern and trends related to aerosol and precipitation studies from 2002 to 2022, Air Quality, Atmosphere & Health 16 (2023) 613–628.
[67] S. Gautam, A.K. Patra, P. Kumar, Status and chemical characteristics of ambient pm2. 5 pollution in China: a review, Environ. Dev. Sustain. 21 (2019) 1649–1674.
[68] China air 2022, Air Pollution Prevention and Control Progress in Chinese Cities, 2022, p. 116.
[69] Y. Lu, Y. Wang, J. Zuo, H. Jiang, D. Huang, R. Rameezdeen, Characteristics of public concern on haze in China and its relationship with air quality in urban areas, Sci. Total Environ. 637 (2018) 1597–1606.
[70] Z. Dankulincova Veselska, I. Jirasek, P. Veselsky, M. Jiraskova, I. Plevova, P. Tavel, A. Madarasova Geckova, Spirituality but not religiosity is associated with better health and higher life satisfaction among adolescents, Int. J. Environ. Res. Publ. Health 15 (2018) 2781.
[71] Z. Sun, J. Li, The effects of performance of public sector health system on quality of life in China: evidence from the cgss2015, Int. J. Environ. Res. Publ. Health 17 (2020) 2896.
[72] X. Tang, Y. Wang, H. Yi, Data manipulation through patronage networks: evidence from environmental emissions in China, J. Publ. Adm. Res. Theor. 33 (2023) 342–356.
[73] S. Chen, Performance feedback, blame avoidance, and data manipulation in the public sector: evidence from China's official city air quality ranking, Publ. Manag. Rev. (2023) 1–21.
[74] J.J. Schreifels, Y. Fu, E.J. Wilson, Sulfur dioxide control in China: policy evolution during the 10th and 11th five-year plans and lessons for the future, Energy Pol. 48 (2012) 779–789.
[75] Y. Wang, Q. Ying, J. Hu, H. Zhang, Spatial and temporal variations of six criteria air pollutants in 31 provincial capital cities in China during 2013–2014, Environ. Int. 73 (2014) 413–422.
[76] Z.S. Zhao Xinghua, The effect of satisfaction with environmental performance on subjective well-being in China: Gdp as a moderating factor, Sustainability 12 (2020) 1745, https://doi.org/10.3390/su12051745.
[77] T.A. Blakely, A.J. Woodward, Ecological effects in multi-level studies, J. Epidemiol. Community Health 54 (2000) 367–374.
[78] C. Cinelli, C. Hazlett, Making sense of sensitivity: extending omitted variable bias, J. Roy. Stat. Soc. B Stat. Methodol. 82 (2020) 39–67.
[79] A.J. Hussain, T.K. Sankar, M. Vithanage, B. Ambade, S. Gautam, Black carbon emissions from traffic contribute sustainability to air pollution in urban cities of India, Water, Air, Soil Pollut. 234 (2023) 217.