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Association of ambient air pollution exposure and its variability with subjective sleep quality in China: A multilevel modeling analysis[☆]

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ABSTRACT

Growing epidemiological evidence has shown that exposure to ambient air pollution contributes to poor sleep quality. However, whether variability in air pollution exposure affects sleep quality remains unclear. Based on a large sample in China, this study linked individual air pollutant exposure levels and temporal variability with subjective sleep quality. Town-level data on daily air pollution concentration for 30 days prior to the survey date were collected, and the monthly mean value, standard deviations, number of heavily polluted days, and trajectory for six common pollutants were calculated to measure air pollution exposure and its variations. Sleep quality was subjectively assessed using the Pittsburgh Sleep Quality Index (PSQI), and a PSQI score above 5 indicated overall poor sleep quality. Multilevel and negative control models were used. Both air pollution exposure and variability contributed to poor sleep quality. A one-point increase in the one-month mean concentration of particulate matter with aerodynamic diameters of ≤2.5 μm ($PM_{2.5}$) and ≤10 μm (PM_{10}) led to 0.4% (95% confidence interval (CI): 1.002–1.006) and 0.3% (95% CI: 1.001–1.004) increases in the likelihoods of overall poor sleep quality (PSQI score >5), respectively; the odds ratios of a heavy pollution day with $PM_{2.5}$ and PM_{10} were 2.2% (95% CI: 1.012–1.032) and 2.2% (95% CI: 1.012–1.032), respectively. Although the mean concentrations of nitrogen dioxide, sulfur dioxide, and carbon monoxide met the national standard, they contributed to the likelihood of overall poor sleep quality (PSQI score >5). A trajectory of air pollution exposure with maximum variability was associated with a higher likelihood of overall poor sleep quality (PSQI score >5). Subjective measures of sleep latency, duration, and efficiency (derived from PSQI) were affected in most cases. Thus, sleep health improvements should account for air pollution exposure and its variations in China under relatively high air pollution levels.

1. Introduction

Poor sleep quality is a growing public health issue, and air pollution exposure may be one of the potential triggers for poor sleep quality (Stranges et al., 2012; Ohayon, 2002). Thus far, poor sleep quality has affected more than 40% of the Chinese population (Liu et al., 2016), and has been well recognized as a contributor to a series of adverse health outcomes, including cognitive dysfunction, behavioral and emotional dysregulation, cancer, diabetes, and cardiovascular disease (Liu et al., 2020; Crowley, 2011). Therefore, a comprehensive understanding of relevant influencing factors is required to improve sleep quality. Ambient air pollutant exposure is considered to affect sleep quality via disparate mechanisms, including, but not limited to, central ventilator control centers and the central nervous system (Cao et al., 2021).

Growing epidemiological evidence has shown a positive association between air pollutant exposure and various sleep problems in

Abbreviations: PSQI, pittsburgh sleep quality index; $PM_{2.5}$, particulate matter with aerodynamic diameters ≤2.5 μm; PM_{10}, particulate matter with aerodynamic diameters ≤10μm; NO_2, nitrogen dioxide; SO_2, sulfur dioxide; CO, carbon monoxide; O_3, ozone; SD, standard deviation; OR, odd ratio; CI, confidence interval.

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populations across different age groups and countries; however, the results remain inconclusive (Liu et al., 2020; Liu et al., 2021a; Cao et al., 2021; Li et al., 2020a; Wang et al., 2020a; Wang et al., 2020b; Tang et al., 2020; Yu et al., 2021b). The effects of exposure to particulate matter (PM) have been the focus of most epidemiological studies (Wang et al., 2020a; Yu et al., 2021b; Tang et al., 2020). Other air pollutants include nitrogen dioxide (NO_2), ozone (O_3), sulfur dioxide (SO_2), and carbon monoxide (CO). Sleep assessments include both objective (e.g., actigraphy and polysomnography) and subjective (e.g., self-reported) measures. Previous studies have objectively analyzed sleep duration and efficiency; however, varying results have been obtained. For example, Li et al. (2020a, 2020b) assessed sleep duration and efficiency using wrist actigraphy. O_3 was found to be associated with a longer sleep duration but not with an improved sleep efficiency, while $PM_{2.5}$, SO_2, NO_2, and CO were not associated with sleep duration or efficiency. Nevertheless, in the Multi-Ethnic Study of Atherosclerosis study, the average baseline single-day $PM_{2.5}$ level was not associated with sleep efficiency averaged over the subsequent seven days of actigraphy recording (Billings et al., 2019). The study population was drawn from patients suspected to have sleep disorders, which may have led to an inadequate representation and divergence in results.

Self-reported questionnaires allow for a large sample, and a series of sleep quality indicators (e.g., sleep duration, sleep latency, daytime dysfunction, daytime sleepiness, and overall sleep quality) have been subjectively assessed (Cheng et al., 2019; Cassol et al., 2012; Weinreich et al., 2015; Laratta et al., 2020; Billings et al., 2019). However, the relationship between air pollution exposure and subjective sleep quality remains uncertain. For example, opposing associations were observed between sleep duration and PM exposure, with a study demonstrating shorter sleep durations with higher PM exposure among UK middle-aged adults (Li et al., 2020a); meanwhile, another study based on a large sample of young Chinese adults displayed longer sleep durations with increased PM exposure (An and Yu, 2018). This divergence may be partly due to the temporal variability in air pollution exposure across populations during the study period. Substantial temporal variability in air pollution exposure has been well documented, but its implications for sleep quality have been neglected (Zhou et al., 2022; Liu et al., 2021b). The potential risks of variability in air pollution exposure to sleep quality have to date only been suggested by a recent epidemiological study (Xue et al., 2019) that linked air pollution variability with mental health. Moreover, current studies have used correlation analyses and are subject to the possibility of endogeneity issues (e.g., unmeasured confounding and measurement error) or sampling biases, which may partly explain the variations in the effects of ambient air pollution exposure across studies (Cheng et al., 2019). Liu et al. (2021a) summarized the associations between exposure to air pollutants and various subjective measures of sleep for children and adults from 14 studies; their review showed that 9 studies had sample bias issues or did not account for confounders, and samples in 8 studies were non-representative. Heyes and Zhu (2019) attempted to apply the instrumental variable model to solve this issue using city-level exposure and outcome measures. However, it is not always easy to find an appropriate instrumental variable.

To address these gaps, based on a large and representative sample in Shandong Province, China, this study calculated the monthly mean concentrations and standard deviations (SD) of daily pollutant exposure, the number of heavily polluted days, and pollutant trajectories to measure ambient air pollution exposure and its variations; subsequently, these indicators were linked to multiple dimensions of subjective sleep quality. Following a multilevel regression model, a negative control model was used to control for unobserved confounders that satisfied certain conditions (Yu et al., 2021a). The air pollution level in Shandong Province is relatively high compared with that in developed countries. Our research helps enhance the understanding of the relationship between air pollutants and sleep health.

2. Methods

2.1. Enhanced semi-individual design

This study proposed an enhanced semi-individual design to estimate the effects of air pollution exposure. A series of sleep indicators were collected from a large sample of healthy residents in Shandong Province. In contrast with typical semi-individual studies, the interviews for participants living in the same township were conducted at different dates. We then linked the temporal characteristics of individual exposure with township-level air pollution to include personal modifiers of exposure and reduce nondifferential exposure misclassification.

2.2. Shandong Province Mental Disorders Epidemiological Survey

This study used cross-sectional survey data from the Shandong Province Mental Disorders Epidemiological Survey (SMDES) 2015. SMDES 2015 employs a representative sample of people 18 years and older in Shandong Province using stratified cluster sampling, and the final samples include 102 townships of 17 cities across Shandong Province. One neighborhood was randomly selected from each township-level unit, and 300 households within each neighborhood were randomly chosen. One resident aged 18 years or older from each selected household was randomly interviewed face-to-face by household investigators in 2015 (Zhang et al., 2021). Written informed consent was obtained from all participants, and the Shandong Mental Health Institute review board approved the survey. Overall, 28,534 individuals were identified at these sites, with a response rate of 98.8%. The SMDES 2015 was implemented from September to December 2015. A more detailed description of the study design and sampling procedure can be found in the study of Zhang et al. (2021). After excluding 639 participants who did not complete the Pittsburgh Sleep Quality Index (PSQI) survey and 2294 participants who had missing values, 25,601 participants were obtained for analysis.

2.3. Pittsburgh Sleep Quality Index

The overall subjective sleep quality of the participants 30 days prior to the survey date was measured using the PSQI. The PSQI is a standardized self-rated questionnaire developed to measure overall sleep quality and alert physicians to the need for further assessments of individuals showing symptoms of sleep problems (Buysse et al., 1989). The 24-item questionnaire generates seven component scores—sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medications, and daytime dysfunction—with subscale scores ranging from 0 to 3. The total score (ranging from 0 to 21) was obtained by calculating the sum of the seven factors, with a higher score indicating worse sleep quality. The details are presented in Table S1. The Chinese version of the PSQI is also widely used in a large number of Chinese studies, with good reliability and reproducibility (Tang et al., 2017; Wang et al., 2021a; Xie et al., 2020; Zhang et al., 2019a). In the present study, Cronbach's alpha, employed to assess internal consistency, was 0.77. A total PSQI score above 5 is clinically considered to indicate overall poor sleep quality (Buysse et al., 1989; Wang et al., 2021a). Additionally, the PSQI score was used as a continuous variable to measure the symptoms of poor sleep quality. Following Yu et al. (2019) and Wei et al. (2017), we separated the PSQI into seven dimensions of sleep quality.

2.4. Ambient air pollution data source and measurement

Exposure to ambient air pollution was measured using the mean concentration of six common pollutants for 30 days prior to the survey date in the selected townships where the participants lived.

Step 1: Extraction of daily air pollution data. Ambient air pollution data for China were collected from a high-resolution and high-quality dataset of ground-level air pollutants (CHAP, available at https://weijing-rs.github.io/product.html), including six kinds of species—particulate matter with aerodynamic diameters $\leq$2.5 μm ($PM_{2.5}$), particulate matter with aerodynamic diameters $\leq$10 μm (PM_{10}), CO, NO_2, SO_2, and O_3. Each air pollutant was estimated at a uniform grid of 0.1° × 0.1° (≈10 × 10 km^2) from big data, including ground-based measurements, satellite remote sensing products, atmospheric reanalysis, and model simulations, using the developed space-time extra-trees model. The pollutant estimations are reliable since they exhibit high R^2 values of 0.80–0.91, with reference to surface observations obtained by adopting the independent ten-fold cross-validation approach (Wei et al., 2021a, 2021b; Wei et al., 2022a, 2022b). The pollution values were determined by collocating the nearest grid for each participant's physical address based on its unique longitudinal and latitudinal information. We extracted daily air pollution data for 30 days starting from the survey date and moved backward in time for each sampled township using the above dataset and map of Shandong Province.

Step 2: Calculation of one-month air pollution exposure and its temporal variations. The average exposure to air pollution, including PM_{10}, $PM_{2.5}$, NO_2, SO_2, CO, and O_3, in one-month was calculated based on the daily values. Variation in air pollution was assessed using the SD of the daily concentrations and number of heavy pollution days for 30 days prior to the survey date. Following Wang et al. (2021b), heavy pollution days with common pollutants were defined according to the daily exceeded multiples (EM):

$$EM = \frac{C - S}{S}.100\% \tag{1}$$

where c is the daily concentration and s is the national ambient air quality standard (MEE, 2012) (Table S2). We defined days with EM > 0 as being polluted and days with EM ≥ 20% as being heavily polluted (Wang et al., 2021b).

Step 3: The trajectory of each pollutant concentration for 30 days was calculated using group-based trajectory modeling (GBTM), which was applied to measure the joint effects of air pollution exposure level and variation. Based on the GBTM, the trajectory for air pollution exposure was grouped into the following statuses integrating the mean concentration and variation: good air quality and stable, light pollution and stable, and medium-to-heavy pollution with regular or irregular fluctuations. The details to obtain the trajectory for air pollution exposure by GBTM are provided in Supplementary Material.

2.5. *Control variables*

Interpersonal, social, and environmental factors that contribute to sleep health were adjusted in our multilevel models (Wang et al., 2021a; Kim et al., 2022). Demographic characteristics included age, sex (reference group: men), and marital status (reference group: married and living with their spouse; common-law marriage was considered married; unmarried included single, divorced, and separated). Individual socioeconomic status was measured based on education level and occupation. Participants were asked to select one of the following categories for the educational level: (1) elementary school and below, (2) junior high school, or (3) senior high school and above. The "elementary school and below" group served as the reference group. Occupation was classified into five groups: unemployed, retired, peasants, self-employed, and administrators.

In addition, several area-level indicators, including urbanicity (proportion of urban population), gross domestic product (GDP) per capita (log), greenspace coverage, and artificial light at night exposure (ALAN) (log), were also adjusted (Liu et al., 2021a; Kim et al., 2022; Obayashi et al., 2019). The details of area-level control variables are provided in Supplementary Material.

2.6. *Data analysis*

Weighted descriptive statistics, including percentages for categorical variables and means for continuous variables, were reported based on the subjective sleep quality. Although we differentiated between the individual interview dates, some participants living in the same township were interviewed on the same day. Thus, a multilevel logistic model adjusted for a series of influencing factors was employed to estimate the association between air pollution exposure and sleep quality. The intraclass correlation coefficient also suggests that the multilevel models were well fitted (see the Supplementary Material for the intraclass correlation coefficient of the multilevel model). Sleep quality measures included overall poor sleep quality (PSQI score >5), sleep latency, sleep medication use, daytime dysfunction, sleep disturbance, sleep duration, sleep efficiency, and subjective sleep quality, which were assessed and derived from the PSQI (Table S1). For the sensitivity analysis, the PSQI score, being a continuous variable, was used as the dependent variable; samples were categorized by age, sex, and physical health (Davies, 2019). Participants were asked whether they had been hospitalized or visited the hospital frequently for physical illness in the last three years. Those who responded "yes" were coded as having poor physical health. As a robustness check, we conducted multiple imputations for the samples that completed the PSQI (n = 28,534–639 = 27,895).

Subsequently, the negative control model developed by Yu et al. (2021a) was applied. Assuming that post-outcome exposure does not affect prior outcomes, no causal effects among time-varying exposures exist, and the proportional effects of the unobserved confounders on exposures do not change over time, post-outcome exposure was used as a negative control exposure (e.g., adjustment for pre- and post-outcome exposure simultaneously) in the negative control model. Thus, the negative control model could control for unobserved confounders, of which the proportional effects on exposures did not change over time (e.g., curtains for bedroom windows and the use of a sleeping mask) (Yu et al., 2021a; Bjorvatn et al., 2018). According to the negative control logistic model, three categorical variables of ambient air pollution exposure—the monthly mean concentration exceeding the pollution level, the occurrence of exposure to heavily polluted days, and the SD of daily air pollution surpassing the medium level—were constructed as the pre- and post-outcome exposures. Since the monthly mean concentrations of CO, SO_2, NO_2, and O_3 did not reach the standard pollution level, we did not construct a categorical variable measuring if the monthly mean was above the national standard. In addition, there were no days of heavy pollution with SO_2 and O_3. The details of the negative-control model are presented in Supplementary Material.

There was a disproportionately high number of women and elderly individuals in our sample, since women and older people were more likely to stay at home (e.g., at the scene of the investigation) and, thus, be selected. Therefore, we weighted the data by considering sample weights and post-stratification adjustment weights. The sample weights consisted of different sampling rates, as implied by the sample design. The post-stratification weights further accounted for the oversampling issue by adjusting the design weights in such a way that they replicated the age-by-sex distribution of the 2015 Demographic Census (Holt and Smith, 1979; Zhang et al., 2019b). The details of sample weighting are available in Supplementary Material. Odds ratios (ORs) with 95% confidence intervals (CIs) for the multilevel logistic regression estimates and estimated effect sizes with 95% CIs for the negative control logistic model were reported. STATA 14 and R 4.0.5 were used for all calculations.

3. Results

3.1. Basic characteristics of selected individuals

Table 1 presents weighted descriptive statistics. The total number of participants had a weighted mean [SD] age of 44.90 [26.86] years, and 52.81% of the participants were women. Almost 18% of participants reported poor sleep quality (PSQI >5), with approximately 9% having poor subjective sleep quality (PSQI score >5) and 50% taking over 15 min to fall asleep. Approximately 22% and 44% of the participants reported daytime dysfunction and sleep disturbance, respectively, and less than 5% used medication to help them sleep. The bedtime and wake-up time for most participants were earlier than 12:00 a.m. and later than 6:00 a.m., respectively, and the sleep duration was over 7 h daily. However, 15% of the participants reported sleep efficiency lower than 75%. Regarding the socioeconomic statuses of the individuals, approximately 17% of the participants had completed senior high school, almost 66% were peasants, and 7% were unemployed. More than 25% of participants lived in urban areas.

Table 1
Statistical description by sleep quality.

Variables	Weighted mean ± SD/N (weighted percent (%))			
	Total 25,601	Poor sleep quality (PSQI >5)		
		No 19,307 (82.03)	Yes 6249 (17.94)	P-value
PSQI	3.18 ± 4.55	1.96 ± 2.54	8.75 ± 3.39	0.00
Sleep latency >0	13,806 (49.35)	8042 (40.51)	5764 (89.67)	0.00
Sleep medication use	839 (2.19)	111 (0.45)	728 (10.13)	0.00
Daytime dysfunction >0	6240 (21.67)	2775 (14.00)	3465 (56.72)	0.00
Sleep disturbance >0	12,759 (43.51)	7246 (33.84)	5513 (87.67)	0.00
Sleep duration ≤7 h	8734 (25.70)	3783 (14.88)	4951 (75.15)	0.00
Sleep efficiency ≤85%	8496 (28.50)	3386 (17.44)	5110 (79.00)	0.00
Bad subjective sleep quality	3247 (9.19)	275 (0.94)	2972 (46.87)	0.00
Age	44.90 ± 26.86	42.82 ± 25.29	54.39 ± 26.76	0.00
Urbanicity	57.29 ± 12.59	57.19 ± 13.10	57.71 ± 9.89	0.56
GDP per capita (log)	11.02 ± 0.77	11.01 ± 0.80	11.02 ± 0.62	0.00
NDVI	0.28 ± 0.19	0.28 ± 0.20	0.28 ± 0.15	0.32
Artificial light at night exposure (log)	4.98 ± 13.61	5.21 ± 14.54	3.95 ± 7.96	0.00
Women	17,227 (52.81)	13,253 (53.38)	3974 (50.20)	0.00
Married	21,869 (89.81)	16,962 (91.59)	4907 (81.67)	0.00
Education				0.00
Elementary school and below	10,341 (32.89)	6947 (28.72)	3394 (51.91)	
Junior high school	11,190 (49.47)	8995 (52.17)	2195 (37.11)	
Senior high school and above	4070 (17.64)	3365 (19.11)	705 (10.98)	
Occupation				0.00
Unemployed	2213 (7.25)	1450 (6.50)	763 (10.65)	
Retired	2415 (2.65)	1783 (2.50)	632 (3.37)	
Peasants	16,425 (66.53)	12,168 (65.51)	4257 (71.24)	
Self-employed	3310 (17.44)	2830 (18.75)	480 (11.48)	
Administrators	1238 (6.13)	1076 (6.75)	162 (3.26)	

Note: SD: standard deviation; PSQI: the Pittsburgh Sleep Quality Index; NDVI: Normalized Difference Vegetation Index.

$PM_{2.5}$ and PM_{10} had high concentrations and dispersion degrees. The one-month mean concentration [SD] of $PM_{2.5}$ and PM_{10} were 104.84 [46.87] and 160.40 [70.80], respectively, exceeding the Chinese National Ambient Air Quality Standards for good quality (MEE, 2012). Over 70% and 40% of participants lived in a town where the monthly mean $PM_{2.5}$ and PM_{10} exposure surpassed the national standard for pollution, respectively (Table S3). On average, 15 and 10 days were labeled as heavy pollution days according to the monthly mean $PM_{2.5}$ and PM_{10} concentrations, respectively (Table 2). Approximately 20–30% of participants lived in a town with medium-to-heavy pollution pertaining to $PM_{2.5}$ and PM_{10} every day of the month (Fig. S1 and Table 2). The remaining four common pollutants met the national standards and rarely resulted in a heavily polluted day. We found that common pollutant exposure was highly correlated with each other because some pollutants shared their sources (Table S4). For example, PM mixtures and NO_2 are released from traffic and industrial emissions (Li et al., 2022). Air pollution exposure varied across communities, with the one-month mean $PM_{2.5}$ and PM_{10} concentrations ranging from 44.39 to 201.33 and 43.70 to 307.66, respectively. Meanwhile, the community-level prevalence of poor subjective sleep quality, measured by a PSQI score over 5, was also sparsely distributed, ranging from 5 to 50%. Compared to those with fair or good sleep quality, participants with poor sleep quality (PSQI >5) tended to be exposed to worse air quality, although the differences were small. Nevertheless, the concentration of O_3 did not differ across participants with different sleep qualities.

3.2. Association between air pollutant exposure and subjective sleep quality

The regression results of the associations between common pollutant exposure and subjective sleep quality are presented in Figs. 1 and 2. In addition to O_3 exposure, exposure to five other common pollutants tended to have a negative impact on subjective sleep quality. The association was not sensitive to different regression assumptions (e.g., multilevel and negative control models). Our results from the multilevel models suggest that a one-point increase in the one-month mean $PM_{2.5}$ and PM_{10} concentrations resulted in 0.4% (95% CI: 1.002–1.006) and 0.3% (95% CI: 1.001–1.004) increases in the possibility of overall poor sleep quality (PSQI score >5), respectively (Fig. 1a). Analogously, judging from the estimates of the negative control model, monthly mean $PM_{2.5}$ and PM_{10} concentrations exceeding the national standard led to 12.8% (95% CI: 0.104–0.152) and 7% (95% CI: 0.046–0.093) increases in the possibility of overall poor sleep quality (PSQI score >5) (Fig. 1b). Similarly, the concentrations of NO_2, SO_2, and CO were low, but they had effects on sleep quality, while O_3 was not significantly related to overall poor sleep quality (PSQI score >5) (Fig. 1).

3.3. Association between variability in air pollution exposure and subjective sleep quality

Our results show that the variability in air pollution exposure, measured by the SD of daily concentration for five common pollutants ($PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2), contributed to the likelihood of overall poor sleep quality (PSQI score >5). The greater the variability in air pollution exposure, the greater the possibility of poor sleep quality (PSQI score >5). The increase in days heavily polluted with PM was also significantly positively associated with the likelihood of overall poor sleep quality (PSQI score >5). According to the multilevel model results, a heavy pollution day with $PM_{2.5}$ and PM_{10} led to 2.2% (OR: 1.022; 95% CI: 1.012–1.032) and 2.2% (OR: 1.022; 95% CI: 1.012–1.032) increases in the likelihood of overall poor sleep quality (PSQI score >5) (Fig. 1a).

Table 2
One-month exposure to air pollution by sleep quality.

Variables	Weighted Mean ± SD/N (weighted percent (%))			
	Total 25,601	Poor sleep quality (PSQI>5)		
		No 19,307 (82.03)	Yes 6294 (17.94)	P-value
One-month $PM_{2.5}$ exposure				
Monthly mean concentration	104.84 ± 46.87	104.55 ± 49.22	106.2 ± 34.03	0.00
SD of daily $PM_{2.5}$ concentration	47.35 ± 29.05	47.21 ± 30.40	48.00 ± 21.78	0.01
Number of heavily polluted days	15.96 ± 11.06	15.86 ± 12.79	16.46 ± 19.50	0.00
$PM_{2.5}$ trajectory				0.00
Good air quality and stable	7438 (27.33)	5893 (28.22)	1545 (23.26)	
Light pollution and stable	12,152 (56.29)	8974 (55.50)	3178 (59.92)	
Medium-heavy pollution and medium variation	6011 (16.38)	4440 (16.28)	1571 (16.82)	
One-month PM_{10} exposure				
Monthly mean concentration	160.4 ± 70.80	159.99 ± 74.43	162.29 ± 51.12	0.00
SD of daily PM_{10} concentration	67.55 ± 40.20	67.36 ± 42.21	68.38 ± 29.34	0.00
Number of heavily polluted days	10.01 ± 10.42	9.92 ± 12.04	10.43 ± 18.54	0.00
PM_{10} trajectory				0.00
Good air quality and stable	4649 (15.65)	3746 (16.08)	903 (13.70)	
Light pollution and stable	9444 (40.50)	7109 (40.62)	2335 (39.96)	
Medium-heavy pollution and rising	5984 (27.92)	4328 (27.38)	1656 (30.37)	
Medium-heavy pollution and regular fluctuations (Wavy-shape)	2919 (7.20)	2254 (7.46)	665 (5.99)	
Great variability	2605 (8.73)	1870 (8.45)	735 (9.98)	
One-month CO exposure				
Monthly mean concentration	1.74 ± 0.78	1.73 ± 0.82	1.78 ± 0.57	0.00
SD of daily CO concentration	0.51 ± 0.34	0.51 ± 0.35	0.52 ± 0.26	0.01
Number of heavily polluted days	0.15 ± 0.72	0.15 ± 0.84	0.13 ± 1.28	0.01
CO trajectory				0.00
Good air quality and stable	5286 (16.59)	4222 (17.06)	1064 (14.43)	
Light pollution and stable	7848 (36.24)	5982 (36.97)	1866 (32.89)	
Medium pollution and medium variation	7119 (27.01)	5172 (26.08)	1947 (31.24)	
Medium-to-heavy pollution and medium variation	3713 (15.19)	2736 (14.91)	977 (16.46)	
Heavy pollution and regular fluctuations (Wavy-shape)	1635 (4.97)	1195 (4.97)	440 (4.98)	
One-month NO_2 exposure				
Monthly mean concentration	48.35 ± 16.64	48.22 ± 17.55	48.94 ± 11.66	0.00
SD of daily NO_2 concentration	12.28 ± 5.63	12.24 ± 5.90	12.44 ± 4.21	0.00
Number of heavily polluted days	0.20 ± 0.92	0.21 ± 1.07	0.17 ± 1.60	0.01
NO_2 trajectory				0.00
Good air quality and stable	4779 (15.40)	3789 (15.71)	990 (13.98)	
Light pollution and stable	11,672 (54.92)	8755 (54.98)	2917 (54.63)	
Medium-to-heavy pollution and medium variation	4653 (11.52)	3583 (11.79)	1070 (10.28)	
Medium-to-heavy pollution and great variation	4497 (18.16)	3180 (17.52)	1317 (21.11)	
One-month SO_2 exposure				
Monthly mean concentration	50.82 ± 22.59	50.58 ± 23.61	51.9 ± 17.12	0.00
SD of daily SO_2 concentration	15.87 ± 7.61	15.83 ± 7.92	16.04 ± 5.95	0.00
Number of heavily polluted days	0.01 ± 0.14	0.01 ± 0.17	0.00 ± 0.11	0.00
SO_2 trajectory				0.00
Good air quality and stable	4390 (14.50)	3478 (14.93)	912 (12.53)	
Light pollution and stable	12,910 (60.06)	1687 (60.02)	3223 (60.24)	
Medium-heavy pollution and medium variation	8301 (25.44)	6142 (25.05)	2159 (27.23)	
One-month O_3 exposure				
Monthly mean concentration	47.89 ± 27.56	48.14 ± 28.65	46.79 ± 21.89	0.01
SD of daily O_3 concentration	13.91 ± 10.03	13.99 ± 10.38	13.55 ± 8.26	0.00
O_3 trajectory				0.00
Good air quality and stable	1113 (3.49)	942 (3.71)	171 (2.48)	
Light pollution and stable	14,701 (57.27)	10,865 (56.05)	3836 (62.78)	
Low-to-medium pollution and stable	7493 (30.57)	5726 (31.37)	1767 (26.93)	
Medium-to-heavy pollution and stable	2294 (8.68)	1774 (8.87)	520 (7.80)	

Note: SD: standard deviation; PSQI: the Pittsburgh Sleep Quality Index.

The results of the negative control models were consistent (Fig. 1b). However, the number of days with heavy NO_2, SO_2, and CO pollution seemed insignificantly associated with an increased likelihood of overall poor sleep quality (PSQI score >5), which may be because the levels of the three pollutants were rarely defined as being heavy (Fig. 1). Subsequently, a trajectory of the air pollution exposure was constructed to integrate the mean concentration and variation, and the differences in the possibility of overall poor sleep quality (PSQI score >5) across these trajectories were estimated using a multilevel model (Fig. 2). Compared with the group exposed to a good air quality and stable trajectory, those exposed to a light pollution and stable trajectory were more likely to report overall poor sleep quality (PSQI score >5). A trajectory of air pollution exposure characterized by great variability in air pollution exposure was associated with a higher likelihood of overall poor sleep quality (PSQI score >5).

Table 2 shows that differences in the pollutant exposure level were minor between the groups with a PSQI above and below 5. It is possible that the effects of air pollution could be spurious and cannot be easily converted into a poor–good sleep quality metric. The results should be interpreted with caution. While trajectory analysis shows that the likelihood of poor sleep quality (PSQI score >5) varied significantly by trajectory groups of air pollution exposure. As robust check, subsample analyses by age, sex, and physical health were performed (Table S5), and they obtained similar results. Thereafter, the PSQI score was used as a continuous variable, and the association between air pollution exposure and PSQI score was maintained (Table S6). Taking $PM_{2.5}$ and PM_{10} as examples, a 10-point increase in their monthly mean concentrations was associated with increases of 0.05 (95% CI: 0.03–0.07) and 0.04 (95% CI: 0.02–0.05) PSQI scores, respectively, and the effect size of a heavy pollution day with $PM_{2.5}$ and PM_{10} were 0.03 (95% CI: 0.02–0.04) and 0.03 (95% CI: 0.02–0.04), respectively. Although the effects of monthly air pollution exposure on possibility of overall poor sleep quality (PSQI score >5) were minor, it is likely to affect sleep quality. Since these were estimates of population effects, combined with a series of theoretical

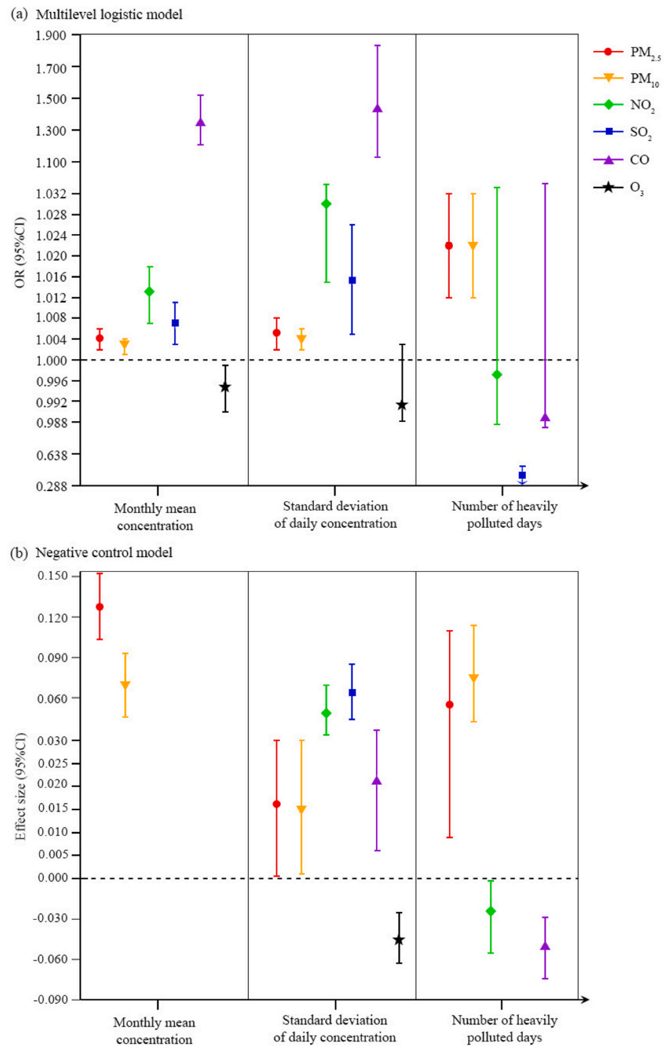

Fig. 1. Association between one-month air pollution exposure and overall poor sleep quality (PSQI >5) using (a) multilevel model and (b) negative control model. OR: odds ratio; CI: confidence intervals. Age, sex, marital status, education, occupation, urbanicity, GDP per capita, greenspace coverage, and artificial light at night exposure were controlled in multilevel models.

supports and previous studies, they cannot be ruled out as irrelevant. The descriptive statistics between the imputed data and complete case were quite similar (Table S7), and the estimated association with imputed data were similar with those using raw data (Table S8).

3.4. Association between air pollution exposure and sleep dimensions

When we further analyzed our evidence, including the association between air pollution exposure and different dimensions of sleep, consistent results were obtained. Air pollution exposure and its variations contributed to multiple problems with sleep quality, judging from the multilevel model (Tables S9–11). However, in the negative control model, the likelihood of experiencing poor subjective sleep quality, daytime dysfunction, sleep medication use, and sleep disturbance were seldom affected by variations in common pollutant exposure, whereas the likelihood of sleep latency, sleep duration, and sleep efficiency continued to be affected by common pollutants in air (Table S10). Comparing the results from the multilevel model with those of the negative control method, the direction of air pollution remained constant, but the effect size in the negative control models changed, suggesting that the correlation results may be biased owing to uncontrolled measures (Tables S9 and S11).

4. Discussion

4.1. Association between air pollution exposure and subjective sleep quality

We estimated the association between ambient air pollution exposure and subjective sleep quality by using a large sample of healthy residents in Shandong Province, China. Exposure to air pollution contributed to an increased likelihood of overall sleep quality (PSQI score >5). Sleep latency, duration, and efficiency were the sleep indicators affected in most cases. Nevertheless, associations between air pollution and sleep quality have been explored with inconsistent results. Many previous studies have been based on correlation analyses, and there is likely to be an endogeneity issue, resulting in inconsistent results (Heyes and Zhu, 2019). Many other factors associated with alterations in sleep quality have not been controlled in correlation studies, including our regression analysis. For instance, we did not ask about noise pollution, the presence of curtains for bedroom windows, or the use of sleeping masks (Connelly et al., 2020; Bjorvatn et al., 2018). An extra bias is introduced by measurement error. For example, people staying indoors for long periods could lead to measurement errors owing to a lack of consideration for indoor conditions when assessing air pollution exposure (Li et al., 2020b). Although ambient air pollution is associated with indoor air quality, personal exposure to air pollution differs according to the indoor ventilation status, meteorological factors, and individual time-activity patterns (Gil et al., 1995; Lawrence et al., 2005; Li et al., 2020b). Owing to data limitations, we could not measure air pollution exposure accounting for indoor conditions.

Due to potential endogeneity issues, we should be careful not to overinterpret the results. Heyes and Zhu (2019) used the instrumental variable method to solve this issue in a city-level analysis and identified air pollution as a cause of sleeplessness. Nevertheless, the assumptions of the instrumental variable are difficult to elucidate in the presence of strong confounding factors; therefore, the validity of the instrumental variable might be reduced (Martens et al., 2006). Our study used a negative control model to adjust for some unobserved confounders, of which the proportional effects on exposures did not change over time (Yu et al., 2021a). It is easy to obtain pre- and post-outcome exposures from environmental studies. Nevertheless, this method cannot eliminate unmeasured confounding issues and measurement error. Previous studies have found that humans, especially the elderly and women, spend more time indoors (Li et al., 2020b; Chen et al., 2019). For a robustness check, subgroup analyses found that overall poor sleep quality (PSQI score >5) was negatively affected by air pollution exposure, regardless of age, sex, or physical condition.

Combined with a series of theoretical data and previous studies, air pollution exposure could negatively affect sleep quality. There are three potential pathways that could be involved. First, air pollution exposure may alter sleep through its effects on the central nervous system where it alters the expression and dysregulation of neurochemicals. $PM_{2.5}$ exposure could lead to lower serotonin levels, which modulate wakefulness and circadian rhythms, and, in turn, is linked with increased sleepiness and sleep disturbances (Liu et al., 2020). In addition, central nervous system changes triggered by CO exposure may interrupt cell signaling in multiple brain regions and affect neural functions, presenting as increased frequency of arousal and light sleep. Another potential pathway from air pollution exposure (such as PM, NO_2 and SO_2) to sleep may arise from the effects on the physiology of the respiratory system, including cell damage, irritation, and obstruction of the airways. This creates restriction and obstruction of normal airflow, increasing the risk of apnea and hypoxia, thereby compromising sleep quality (Tang et al., 2020; Li et al., 2022). Furthermore, cohort studies have revealed that exposure to PM_{10}, $PM_{2.5}$, CO, and NO_2 can reduce sleep quality by increasing depression and anxiety (Lo et al., 2021). Potential heterogeneity in the effects of O_3 has been reported in previous studies (Zhao et al., 2018), which may be partly explained by the strong association

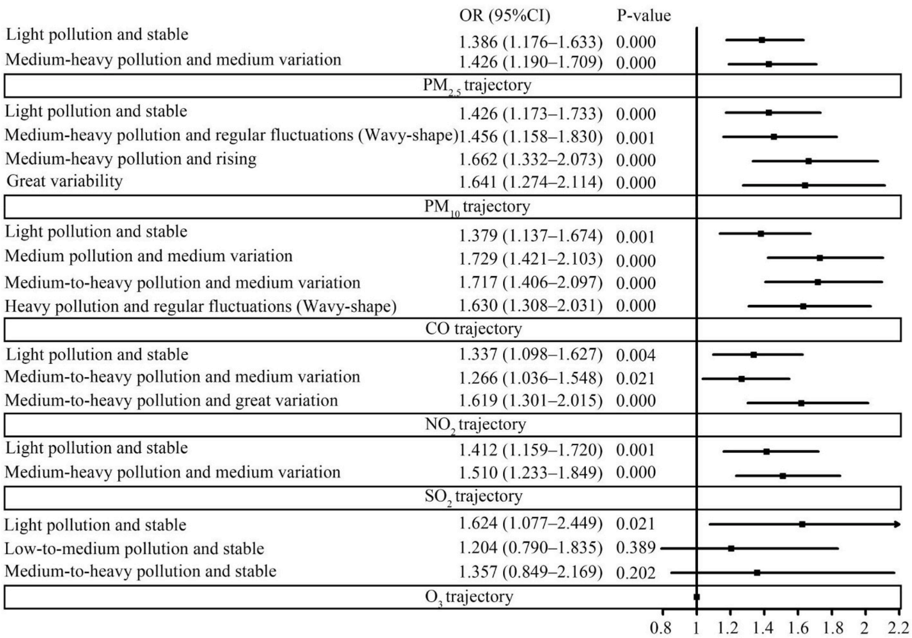

Fig. 2. Associations between trajectory of one-month air pollution exposure and overall poor sleep quality (PSQI >5). Reference group for each air pollution exposure trajectory: good air quality and stable. In each panel, black dots with error bars: odds ratios (OR) of the air pollution with their 95% confidence intervals (CI) estimated by the multilevel logistic model. Age, sex, marital status, education, occupation, urbanicity, GDP per capita, greenspace coverage, and artificial light at night exposure were controlled in multilevel models.

between O_3 concentrations and the intensity of solar radiation. Exposure to sunlight has been shown to improve mental health (Wang et al., 2017; Son and Shin, 2021). Since inflammatory responses in the central nervous system and upper airway could occur due to air pollution within one month, and sleep quality of the participants 30 days prior to the survey date was measured in our study, we assessed the association between one-month air pollution exposure and sleep health (Tang et al., 2020; Li et al., 2022).

Notably, different mechanisms behind these results exist. Air pollution is known to have significant day-night variations (Jalava et al., 2015; Singh et al., 2020). Despite the mixed results obtained, studies have found heterogeneous intraday effects of air pollution. For example, $PM_{2.5}$ exerted greater risks of upper respiratory infections and emergency department visits for acute myocardial infarction during the nighttime than during the daytime (Cheng et al., 2021a, 2021b). These health shocks may be related to the acute changes in sleep quality. As such, there could be differences between the daytime and nighttime effects of air pollution exposure on sleep quality. However, owing to data limitations, we only have daily air pollution data and cannot split the data into night and day air pollution exposure. Other hypotheses revealed that the relevance of long-term air pollution exposure to chronic health outcomes may lead to poor sleep quality (Cao et al., 2021; Liu et al., 2021a). A sensitivity analysis using the annual average values of air pollution exposure was consistent with the proposed hypotheses (Table S12).

4.2. Association between variations in air pollution exposure and subjective sleep quality

A key result of this study is that increases in air pollution variability can have a similar effect on sleep quality as do increases in mean concentrations. Several studies have found that daily exposure to air pollution is associated with poor sleep health. Moreover, the effects can last for several days. For example, based on a large healthcare record system, Tang et al. (2020) observed that daily air pollution exposure was associated with sleep disorders in the elderly, with the strongest associations occurring for $PM_{2.5}$, PM_{10}, and NO_2 and for SO_2 and O_3 2–3 and 5 days prior to hospital visits for sleep disorders. As such, the sleep risks derived from air pollution could not only be associated with the one-month exposure level but also with temporal variation in daily air pollution exposure within the study period.

As expected, we found that variability in common air pollutant concentrations ($PM_{2.5}$, PM_{10}, NO_2, SO_2, and CO) contributed to an increased likelihood of overall poor sleep quality (PSQI score >5). Our results are consistent with those of Xue et al. (2019), who found that a decline in mental health was associated with air pollution variability in China. As depression and anxiety may cause sleep problems, the biological mechanism between sleep quality and air pollution variability may be mediated by increases in depression and anxiety (Wang et al., 2021a; Geoffroy et al., 2020). Furthermore, discrepancies in sleep quality were found across trajectories of air pollution exposure. Participants were more sensitive to a trajectory of air pollution exposure with great variation, whereas they were less likely to be affected when the trajectory of air pollution exposure had a regular shape. A potential explanation for the divergence in sleep across air pollution trajectories is that it is easy to adapt to air pollution trajectories with a regular shape (Ji et al., 2022; Smithers and Smit, 1997; Madureira et al., 2021). When air pollution trends are predictable and depict a regular trend, people were more likely to take action to avoid air pollution, which could alleviate the health risks (e.g., depression and anxiety) resulting from air pollution exposure (Smithers and Smit, 1997; Madureira et al., 2021). This, in turn, reduces the likelihood of sleep disorders (Ji et al., 2022; Lo et al., 2021).

4.3. Policy implications

First, the question of whether and to what extent air pollution in developing countries with relatively high pollution levels can cause sleep problems remains unanswered (Liu et al., 2021a). This study offers evidence that air pollution management can improve sleep quality. Because sleep latency, sleep duration, and sleep efficiency may be more likely to be affected by ambient air pollution, particular attention should be paid to these indicators. Second, our findings highlight the fact that fluctuations in ambient air quality can lead to changes in sleep quality. As such, our findings provide justification for interventions that target variations in air quality and alert individuals to these irregular changes. Third, given that the common pollutant exposure in air pollution has different impacts on sleep, more precise measures should be determined and implemented according to the characteristics of these pollutants. The concentrations of PM_{10} and $PM_{2.5}$ were significantly higher than the national standard, and they should be more strictly controlled by properly implementing the existing protection standards. Meanwhile, the monthly mean concentrations of CO, SO_2 and NO_2 met the national standard criteria but still negatively impacted sleep quality. We may need to announce their potential to jeopardize sleep quality to the public.

4.4. Contributions and limitations

To the best of our knowledge, this study makes three major contributions to the existing literature. First, the association of air pollution concentration and its temporal variability with sleep health was assessed for the first time, which helped us to comprehensively understand the association with sleep health. Second, we proposed an enhanced semi-individual study linking individual survey dates with township-level air pollution data to differentiate individual environmental exposures. This is an attempt to collect individual ecological exposures for a large sample of healthy community dwellers. Third, the effects of multiple pollutants on sleep quality were estimated using the same sampled population, with a negative control model used to adjust for unobserved confounders that satisfied certain conditions.

However, this study has some limitations. First, we used Shandong Province, China, as the research area, which is not nationally representative. However, from east to west in Shandong Province, the environmental and sociodemographic characteristics are similar to those in China as a whole. Data spanning a wide range of economies and environments provide a good sample for analyzing the association between air pollution and sleep. Second, the indicators used to measure sleep quality were obtained through a retrospective self-evaluation. Future studies using objective sleep measures should improve the generalizability of these results. Third, owing to limited available data, we could not identify long-term effects and the divergence resulting from day-night variations and indoor-outdoor stays. This limitation may have led to biased results and unclarified mechanisms. Finally, the results of this study, in which the air pollution level was high, may not be generalizable to other countries. Although a negative relationship between air pollution exposure and sleep health was found in populations across different age groups, countries, and measures, conducting a comparison of the effect sizes was not plausible because of the mixed study methods.

5. Conclusion

To the best of our knowledge, this is the first study to document an association between variability in ambient air pollution exposure and subjective sleep quality. $PM_{2.5}$ and PM_{10} had high concentrations. A one-point increases in the one-month mean concentration of $PM_{2.5}$ and PM_{10} led to 0.4% (95% CI: 1.002–1.006) and 0.3% (95% CI: 1.001–1.004) increases in the likelihood of overall poor sleep quality (PSQI score >5), respectively. For NO_2, SO_2, and CO, the mean concentrations met the national standard; however, NO_2, SO_2, and CO exposure contributed to the likelihood of overall poor sleep quality (PSQI score >5). Furthermore, variability in air pollution exposure increased the likelihood of overall poor sleep quality (PSQI score >5). The odds ratios of a heavy pollution day with $PM_{2.5}$ and PM_{10} were 2.2% (95% CI: 1.012–1.032) and 2.2% (95% CI: 1.012–1.032), respectively. A trajectory of air pollution exposure with great variability was associated with the highest likelihood of overall poor sleep quality (PSQI score >5). Sleep latency, duration, and efficiency were affected in most cases. Our findings on the effects of variability in ambient air pollution exposure suggest that air quality guidelines based on the mean concentrations of air pollutants may be inadequate to protect sleep health.

Author statement

Lingli Wang: Data curation, Software, Visualization, Writing - original draft. Jingxuan Zhang: Investigation, Validation, Resources. Jing Wei: Resources, Writing - review and editing. Jingru Zong: Data curation, Resources. Chunyu Lu and Yajie Du: Investigation. Qing Wang: Conceptualization, Methodology, Writing - original draft, review, and editing, Supervision, Project administration. Lingli Wang, Jingxuan Zhang and Jing Wei contributed equally to this work and should be considered co-first authors.

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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.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2022.120020.

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