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Sex differences in the association between air pollution and obesity: a systematic review and meta-analysis

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ABSTRACT

Background: Obesity contributes to non-communicable disease burden, and air pollution may promote adiposity, but sex differences are unclear.
Objectives: To quantify sex-specific associations between air pollution and obesity in adults, and to assess modification by sex.
Methods: Following a registered protocol (PROSPERO CRD420251065352), we searched Embase and MEDLINE to 20 June 2025 for observational studies in adults (≥18 years) reporting sex-specific or sex-stratified estimates for ambient pollutants and obesity (BMI, WC, general or abdominal obesity). Risk of bias was assessed using Joanna Briggs Institute (JBI) tools. Effect estimates were standardised to a 10 $\mu g/m^3$ increment and pooled using random-effects models. Sex differences were summarised as ratio of odds ratios (ROR, OR_female/OR_male) for categorical outcomes and $\Delta\beta$ for continuous outcomes.
Results: We included 28 studies (≈800,000 adults). Sixteen contributed to the meta-analysis, 10 of which were conducted in China. Air pollution was associated with higher odds of general and abdominal obesity in both females and males. For general obesity, pooled associations were slightly stronger in females for O_3 (ROR 1.06, 95% CI 1.02 to 1.11) and NO_2 (ROR 1.03, 95% CI 1.01 to 1.06). Sex differences for abdominal obesity and continuous outcomes were generally small and imprecise.
Conclusions: Air pollution was associated with higher adiposity, with broadly similar effects in females and males and modest pollutant- and phenotype-specific differences. For general obesity, females appeared more susceptible to O_3 and NO_2 exposure than males. Evidence was dominated by studies from China and some pollutant-outcome combinations were based on few studies, underscoring the need for adequately powered sex-stratified analyses and improved exposure and outcome harmonisation.

1. Introduction

Obesity is a major contributor to the global burden of non-communicable disease and to health inequality (World Health Organization. World Health Organization [Internet], 2025; World Health Organization. World Health Organization [Internet]. World Health Organization, 2024a; Tiwari and Balasundaram, 2023; Abad-Jiménez and Vezza, 2025; Xie et al., 2025; Ng et al., 2025). Its consequences extend beyond medical complications to substantial social and economic costs (Sweis, 2024; Revels et al., 2017). In research and practice, obesity is commonly defined using body mass index (BMI) and waist circumference (WC), although the thresholds used to define general and abdominal obesity vary by region, ethnicity and sex (World Health Organization. World Health Organization [Internet], 2025;

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Choo, 2002; World Health Organization, 2008). In some countries, females are disproportionately affected and the prevalence of obesity is rising more rapidly, whereas in others obesity is more common among males (Ng et al., 2025; Muscogiuri et al., 2023). This heterogeneity reflects a complex interplay of biological, behavioural and sociocultural factors (Cooper et al., 2021; Koceva et al., 2024; Kim et al., 2025a; Gavin and Bessesen, 2020; Mauvais-Jarvis, 2015; Lovejoy and Sainsbury, 2009), and underscores the need for sex-sensitive approaches to the prevention, diagnosis and management of obesity.

Ambient air pollution is one such ubiquitous exposure. It is recognised as a widespread environmental risk factor, and almost all individuals globally are exposed to pollutant concentrations that exceed the air quality guidelines set by the World Health Organization (WHO) (World Health Organization. World Health Organization [Internet]. World Health Organization, 2024b). Emerging evidence suggests that ambient air pollution may also contribute to the development of obesity, with systematic reviews reporting positive associations between long-term exposure and increased BMI, overweight and obesity (Lin et al., 2022; Huang et al., 2020; An et al., 2018; Luo et al., 2024; Lucio and Wang, 2023; Stojchevski et al., 2024; Pryor et al., 2022). However, methodological differences in study design, exposure assessment and population characteristics generate uncertainty and limit the robustness and comparability of these quantitative syntheses (Lin et al., 2022; Huang et al., 2017, 2020; An et al., 2018; Ma et al., 2024). Most importantly, whether these associations differ by sex remains largely unclear.

Considering sex is essential both for scientific accuracy and for health equity (EASE, 2024; MESSAGE Writing Group WA Woodward et al., 2024). Biological sex influences disease susceptibility, metabolism and treatment response (Sara Della Torre, 2017; Colineaux et al., 2022). If sex is not adequately accounted for, true associations may be masked, the external validity of findings restricted, and the effectiveness of public health interventions reduced (MESSAGE Writing Group WA Woodward et al., 2024; Lee, 2025; Kim et al., 2025b; Galea et al., 2020). Although there is increasing recognition of the importance of integrating sex into all stages of research (EASE, 2024; MESSAGE Writing Group WA Woodward et al., 2024), persistent biases remain: females are often underrepresented, results are frequently reported only for pooled samples, and when sex is included as a covariate, differential risks are rarely explored in depth (Sara Della Torre, 2017; Alwhaibi and Balkhi, 2025). Behavioural patterns and exposure profiles may further contribute to sex differences; for instance, females may experience higher indoor pollutant exposure because of traditional household roles, whereas males may have higher levels of occupational exposures (Biswas et al., 2021; Clougherty, 2010).

It is also important to distinguish between sex and gender (EASE, 2024; MESSAGE Writing Group WA Woodward et al., 2024). Both concepts are relevant for obesity and environmental exposures, but the present review focuses on sex. Experimental studies further suggest that females and males may differ in their metabolic responses to air pollution, raising the possibility of sex-specific susceptibility to its obesogenic effects (Woodward et al., 2019; Li et al., 2020). Clarifying whether sex modifies the health effects of environmental exposures is necessary to build a robust evidence base and to support equitable public health interventions (EASE, 2024; MESSAGE Writing Group WA Woodward et al., 2024; Colineaux et al., 2022; Dwivedi et al., 2022).

Although there is growing evidence linking ambient air pollution to obesity, potential sex-specific susceptibilities remain insufficiently explored. Previous systematic reviews have not examined whether the associations between air pollution and obesity-related outcomes vary by sex (Lin et al., 2022; Huang et al., 2020; An et al., 2018; Luo et al., 2024). Addressing this gap is both feasible and timely, as more recent epidemiological studies increasingly report sex-specific estimates or make individual-level data available (Karp, 2025). The outcomes examined in this review, including BMI and WC, are directly relevant to clinical practice and public health policy, and the findings are likely to be important for healthcare providers, policymakers and affected communities (Wu et al., 2024). This question is particularly pertinent for disadvantaged or marginalised populations, including females, who may face higher baseline obesity risk and greater exposure to air pollution (Rod et al., 2023; Hajat et al., 2015).

Therefore, the aim of this systematic review and meta-analysis is to assess sex-specific associations between selected ambient air pollutants and obesity in adults, and to determine whether sex modifies the relationship between these environmental exposures and obesity.

2. Methods

We conducted a systematic review in accordance with the updated Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and the Cochrane Handbook (Page et al., 2021; Higgins and Thomas, 2019). The completed PRISMA 2020 checklist is provided in Appendix 1. Study identification and selection followed the Population, Exposure, Comparator, Outcomes and Study Design (PECOS) framework, which is widely used in environmental health research (Morgan et al., 2018). The protocol was prospectively registered with PROSPERO (CRD420251065352).

Study selection, application of inclusion and exclusion criteria, risk of bias assessment and data extraction were carried out independently and in duplicate by two reviewers (XW and WL). Discrepancies were resolved through discussion or, when required, by consultation with a third reviewer (ACPG). We did not use automation tools, because of feasibility constraints and the moderate number of records; instead, we relied on manual dual-reviewer procedures to maintain methodological rigour.

2.1. Search strategy

We systematically searched Embase Classic + Embase (1947 to 20 June 2025) and MEDLINE (1946 to 20 June 2025) via the Ovid platform. The search strategy combined terms for ambient air pollution with terms for obesity related outcomes. Searches were restricted to human studies published in English because of resource constraints and concerns about the accuracy of translation (Appendix 2).

All search results were imported into Covidence, where duplicates were removed automatically. Reference lists of included articles and relevant systematic reviews were screened manually, but this did not identify additional eligible records. Full texts of studies selected for detailed review were imported into Zotero for organisation, annotation and citation management.

2.2. Eligibility criteria and study selection

Study selection proceeded in two stages: first, title and abstract screening, then full text review to confirm eligibility.

Inclusion criteria were defined according to PECOS:

- Population: adults aged ≥18 years;
- Exposure: ambient air pollution, including particulate matter (PM), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), ozone (O_3), and traffic-related air pollution;
- Comparator: not prespecified; studies were eligible irrespective of the specific reference group or exposure contrast used by the original investigators;
- Outcomes: obesity, including BMI and WC;
- Study design: primary observational studies (cross-sectional, cohort and case-control);
- Sex-specific reporting: studies reporting effect estimates by sex or stratified by sex;
- Language: publications in English.

Exclusion criteria:

- studies limited to children or restricted to a single-sex population;
- studies lacking relevant exposure or outcome data, or without sex-stratified results;
- studies in which primary outcomes were limited to mechanistic or intermediate physiological markers;
- reviews, meta-analyses, commentaries, conference abstracts, editorials or letters;
- animal studies, cell-based research or mechanistic studies;
- studies of exposures unrelated to air pollution, such as green space only.

We restricted the review to adults to enhance comparability, because paediatric sex differences are developmentally unstable, depend on age and sex standardised adiposity metrics, and reflect mechanisms that are not directly comparable with those in adults (Etchell et al., 2018). If adult specific results could not be obtained, or data for adults were combined with those for children without stratification, the study was excluded.

The primary outcomes were general and abdominal obesity, defined according to locally used categorical BMI and WC thresholds. Secondary outcomes were BMI and WC analysed as continuous variables. When studies reported combined overweight and obesity outcomes, these were included to avoid loss of data, because disaggregation was not possible. Metabolic syndrome (MetS) was not extracted as an overall outcome owing to variability in its definitions and the inconsistent inclusion of abdominal obesity (Kassi et al., 2011). However, studies reporting MetS were examined to determine whether results for individual components, such as abdominal obesity, were available.

2.3. Data extraction and risk of bias assessment

We developed a standardised form to extract data on study characteristics, population demographics, exposure and outcome measures, and adjusted covariates (Appendix 3). For each study, we collected details of pollutant type, measurement unit and outcome, together with sex specific effect estimates and their 95% confidence intervals (CI) or standard error (SE). Studies that reported sex stratified results without extractable effect estimates were included in the qualitative synthesis only, to maximise completeness.

When a single study population was reported in multiple publications, or when multiple eligible reports used the same or overlapping study population, we treated these as multiple reports from the same underlying study rather than as independent studies. We collated information across reports where necessary, but ensured that each underlying study contributed only once to any given pollutant–outcome–sex meta-analysis. For report selection, we prioritised the report that provided the most directly relevant pollutant–outcome pair, the largest analytic sample, and, for cohort studies, the longest follow-up. The largest analytic sample criterion was applied to both cross-sectional and cohort studies, whereas follow-up duration was considered only for cohort studies. Companion reports were used to supplement study characteristics or methodological details where needed.

When a single publication reported multiple eligible estimates, we treated estimate selection as a separate decision. For quantitative extraction, we first prioritised sex-specific or sex-stratified estimates for the pollutant–outcome pair of interest. To avoid double counting, only one estimate from each study contributed to any given pollutant–outcome–sex meta-analysis. When several eligible estimates were available within the same publication, we selected the estimate corresponding to the obesity phenotype and definition used in the relevant synthesis, prioritising the most locally relevant BMI or WC threshold for the primary analysis. Alternative BMI or WC thresholds, where available, were examined in alternative-definition sensitivity analyses. These criteria were applied before considering the direction, magnitude, or statistical significance of the estimates.

If several models were presented, we extracted the most comprehensively adjusted model unless there was evidence of over-adjustment. Where reported, we also noted whether the extracted estimate came from a single-pollutant model or from a model that additionally adjusted for other environmental factors. Potential over-adjustment was considered to refer to adjustment for variables likely to lie on the causal pathway between air pollution and obesity, such as metabolic conditions or related intermediates. When data differed across sections or reports, we gave preference to values reported in tables or results sections; if discrepancies remained unresolved, we used the most complete and internally consistent source.

For each study, we extracted sex specific effect estimates that were adjusted for age and other available confounders, but not for sex, because our aim was to evaluate sex specific associations and sex differences rather than to control for sex as a covariate.

We coded exposure assessment methods into three mutually exclusive categories (World Health Organization, 2023; Hoek et al., 2008; Cesaroni et al., 2014; Beelen et al., 2014; Kloog et al., 2011; Di et al., 2019; van Donkelaar et al., 2015):

- simple assignment (for example, assigning city or postal code directly to monitoring data without spatial modelling);
- traditional spatial models (for example, land use regression, Kriging or spatiotemporal interpolation without satellite or machine learning inputs);
- advanced models (for example, remote sensing, chemical transport models, machine learning algorithms or hybrid approaches).

To harmonise exposure across studies, we extracted the most comparable long-term residential exposure estimates and rescaled effect estimates to a common increment in pollutant concentration, typically 10 $\mu g/m^3$ where harmonisation was possible.

The data extraction form was aligned with the review objectives and piloted on a subset of studies to ensure clarity and consistency. Extracted data were stored in a structured database with version control to facilitate future re-analysis and updates.

Risk of bias was assessed using the Joanna Briggs Institute (JBI) critical appraisal tools, with the appropriate checklist selected for each study design (Moola et al., 2020), and the study design-specific checklists are provided in Appendix 4. We did not calculate or present a single overall score for each study. Instead, we retained item-level judgements and summarised recurring concerns narratively.

2.4. Data synthesis

Where possible, we standardised effect estimates to represent associations per 10 $\mu g/m^3$ increase in pollutant concentration, to improve comparability across studies. When concentrations were reported in other units (for example, gaseous pollutants in ppb), we converted values using established formulas (Lin et al., 2022). Unless otherwise stated, all effect sizes in this review refer to a 10 $\mu g/m^3$ increase in pollutant concentration. When exposure metrics could not be harmonised because they captured fundamentally different physical properties, we analysed estimates separately and presented them in their original units. Following previous air pollution-obesity meta-analyses, categorical associations reported as odds ratios (ORs), risk ratios (RRs), or hazard ratios (HRs) were analysed as binary relative effect estimates on the log scale and rescaled to a common exposure increment where possible (Huang et al., 2020).

To quantify sex differences, we combined sex specific associations using ratio of odds ratios (RORs) for binary outcomes and differences in β coefficients for continuous outcomes. We treated the ROR as the primary relative measure of sex difference, defined as OR_female/OR_male and estimated on the log scale as log(OR_female) − log(OR_male), with pooled ROR obtained by exponentiating the combined log differences (Woodward, 2019). For continuous outcomes such as BMI or WC, we

calculated β_female − β_male, so that positive values indicate stronger associations in females (Appendix 5).

2.5. Statistical analysis

All statistical analyses were conducted in R using the metafor package.

For studies reporting multiple obesity definitions, only one estimate per study was included in any given pollutant–outcome–sex meta-analysis to avoid double counting. The primary analysis used the most locally relevant BMI or WC threshold, while alternative thresholds were assessed in alternative-definition sensitivity analyses where available.

Meta-analyses were undertaken only when at least three studies were available for a given pollutant–outcome–sex combination, to ensure adequate statistical power, to allow estimation of between study heterogeneity and to support meaningful interpretation of pooled estimates (Higgins and Thomas, 2019). To examine potential sex based differences, we extracted sex stratified effect sizes and ran separate meta-analyses for females and males.

We used random effects meta-analyses with the restricted maximum likelihood (REML) estimator. Forest plots were generated to display pooled estimates with their 95% CI. Statistical heterogeneity was assessed using Cochran's Q, the I^2 statistic (percentage of total variation attributable to heterogeneity) and τ^2 (between study variance). Wald type CI were used to quantify uncertainty around pooled effect sizes.

Subgroup analyses were prespecified and conducted only when at least three studies were available per subgroup (Higgins and Thomas, 2019). Potential subgroup variables included exposure assessment method (advanced vs simple/traditional), obesity definition, geographic region (China vs non-China), effect measure type (OR vs RR/HR), and study design (cohort vs cross-sectional), where feasible. These subgroup analyses estimated pooled effects within each subgroup and were interpreted as exploratory because of the small number of studies available for each comparison. When subgroup analysis was not feasible because one subgroup contained fewer than three studies, the relevant comparability issue was assessed through sensitivity analyses where possible.

Sensitivity analyses were performed using a leave-one-out approach, sequentially omitting each study to assess its influence on the pooled estimate. When two or more potentially less comparable estimates were present and at least three studies remained after excluding them, we repeated the meta-analysis after excluding those estimates. When only one potentially less comparable estimate was present, the corresponding leave-one-out analysis was considered to address this concern. For studies that reported multiple estimates because of differing definitions of obesity, we carried out alternative analyses by substituting the primary effect size with alternative definitions and repeating the meta-analysis to explore the range of possible effects. These decisions were informed by the distribution and characteristics of included studies after data extraction.

For combinations with ten or more studies, we assessed potential publication bias using funnel plots and Egger's regression test, following recommended guidance (Higgins and Thomas, 2019). We then applied the trim and fill method to further evaluate the impact of publication bias and generated adjusted funnel plots.

All meta-analyses were conducted separately by pollutant and outcome; any cross-pollutant summary was considered descriptive and interpreted cautiously because estimates from the same cohorts may be correlated and therefore not statistically independent.

All statistical tests were two-sided, and $P < 0.05$ was considered statistically significant unless stated otherwise (Fig. S1).

2.6. Summary of findings

We also assessed certainty of evidence for the main exposure–outcome associations using the GRADE approach and summarised these assessments in a Summary of Findings table.

3. Results

3.1. Study selection

The search identified 6963 records. After removal of duplicates, 5142 titles and abstracts were screened, 54 full texts were assessed for eligibility, and 28 studies met all inclusion criteria and were included in the systematic review. 19 studies contributed to the quantitative synthesis and 16 to the meta-analysis (Fig. 1).

3.2. Study characteristics

The 28 included studies were conducted in Austria (n = 1) (Altug et al., 2024), China (n = 21) (Liu et al., 2020, 2021, 2022, 2023, 2025; Kuang et al., 2025; Wang et al., 2023; Pan et al., 2023; Yang et al., 2019, 2023; Ye et al., 2023; Li et al., 2015, 2022, 2023; Han et al., 2023; Yu et al., 2023; Guo et al., 2022; Huang et al., 2021; Cao et al., 2021; Zhang et al., 2019; Chen et al., 2023), Germany (n = 1) (Niedermayer et al., 2024), Mexico (n = 1) (Tamayo-Ortiz et al., 2021), South Korea (n = 2) (Shin et al., 2019; Hwang et al., 2019), and the United States (n = 2) (Zhang et al., 2020; Li et al., 2016), and together included approximately 800,000 adults. Most of the sex-stratified or sex difference estimates that contributed to the meta-analyses were derived from Chinese studies. Twelve studies were cohort designs (Altug et al., 2024; Liu et al., 2022, Liu et al., 2025; Kuang et al., 2025; Wang et al., 2023; Yang et al., 2023; Ye et al., 2023; Li et al., 2023; Han et al., 2023; Yu et al., 2023; Huang et al., 2021; Chen et al., 2023) were cross-sectional (Pan et al., 2023; Liu et al., 2020, 2021, 2023; Guo et al., 2022; Li et al., 2015, 2016, 2022; Cao et al., 2021; Yang et al., 2019; Zhang et al., 2019, 2020; Niedermayer et al., 2024; Tamayo-Ortiz et al., 2021; Shin et al., 2019; Hwang et al., 2019), with mean ages mostly in the fifth or sixth decade of life.

Exposure assessment relied on advanced modelling approaches in 17 studies (Kuang et al., 2025; Pan et al., 2023; Yang et al., 2023; Ye et al., 2023; Li et al., 2016, 2022, 2023; Han et al., 2023; Yu et al., 2023; Liu et al., 2020, 2021, 2022, 2023; Guo et al., 2022; Huang et al., 2021; Cao et al., 2021; Tamayo-Ortiz et al., 2021), simple approaches in 8 (Altug et al., 2024; Liu et al., 2025; Yang et al., 2019; Zhang et al., 2019, 2020; Li et al., 2015; Shin et al., 2019; Hwang et al., 2019), and traditional monitoring methods in 3 (Wang et al., 2023; Chen et al., 2023; Niedermayer et al., 2024). Risk of bias assessment focused on epidemiological and analytical features, and the accuracy and performance of pollutant-specific exposure models, particularly for SO_2 and PM_1, could not be systematically evaluated because exposure models varied substantially across studies and comparable validation metrics were not reported consistently. Most item-level concerns were limited to cohort studies and related to uncertainty about baseline outcome status (Liu et al., 2022, 2025; Huang et al., 2021), follow-up completeness (Liu et al., 2025; Wang et al., 2023; Li et al., 2023; Han et al., 2023; Yu et al., 2023), and strategies to address incomplete follow-up (Yang et al., 2023; Ye et al., 2023; Li et al., 2023; Han et al., 2023; Yu et al., 2023). In cross-sectional studies, most JBI items raised little concern, although outcome measurement was unclear in one study (Shin et al., 2019). Detailed item-level JBI assessments are presented in Appendix 6: Table S1–S2. The primary outcomes were obesity-related indicators (n = 22) (Altug et al., 2024; Wang et al., 2023; Pan et al., 2023; Yang et al., 2019, 2023; Ye et al., 2023; Li et al., 2015, 2016, 2022, 2023; Han et al., 2023; Yu et al., 2023; Guo et al., 2022; Huang et al., 2021; Cao et al., 2021; Liu et al., 2020, 2021; Zhang et al., 2019, 2020; Niedermayer et al., 2024; Tamayo-Ortiz et al., 2021; Hwang et al., 2019), metabolic syndrome or its components (n = 5) (Liu et al., 2022, 2023, 2025; Kuang et al., 2025; Chen et al., 2023), and cardiometabolic outcomes (n = 1) (Shin et al., 2019) (Table 1).

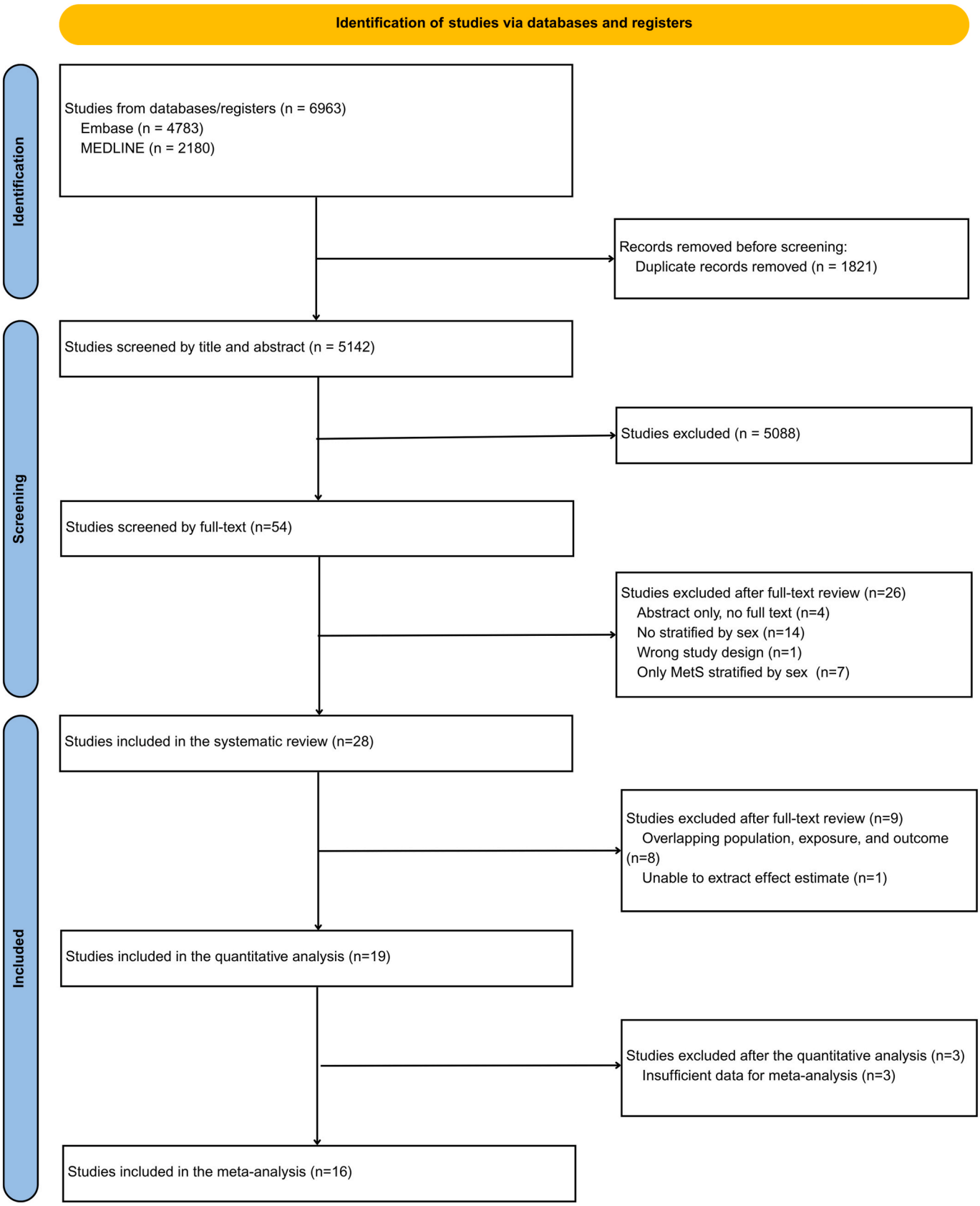


Fig. 1. PRISMA flow diagram of study selection.

Table 1
Characteristics of included studies Table 1 provides a descriptive overview of the characteristics of the 28 studies included in this review. The 16 studies that contributed data to the meta-analysis are specifically highlighted.

Author Year	Study design	Time period	Country Study name	Age	Sample size (Female%)	Exposure Type	Exposure assessment[1]	Outcome assessment	Effect measure type	Adjusted covariates
Liu et.al 2025	Cohort	2011-2015	China CHARLS[2]	60.91 ±8.93	6125 (54.3)	$PM_{2.5}$	Simple assignment (city-level annual $PM_{2.5}$ average)	MetS and components (categorical; WC ≥90 cm in male, ≥80 cm in female)	OR and β coefficient	Sex, age, education level, marital status, registration type, province, and physical exercise
Kuang et.al 2025	Cohort	2011-2015	China CHARLS	58.9± 8.9	3658 (46.3)	$PM_{2.5}$ and its components	Advanced model (CTM[3]/satellite /monitor/ML[4] hybrid)	MetS and components (categorical; WC ≥90 cm in male, ≥80 cm in female)	HR	Age, sex, marital status, educational level, employment status, residence type, alcohol consumption, smoking status, sleep duration, social activity participation, physical activity intensity, self-rated health, disability in activities of daily living, treatment for moderate blood pressure, high triglycerides, elevated fasting blood glucose, annual income categorized by quartiles, and type of cooking fuel used
Altug et.al 2024	Cohort	2011-2022, 2017-ongoing	Austria LEAD[5] Study	44.6± 17.1 51.3± 16.6	15882 (52.6)	PM_{10}[6], NO_2, transportation noise	Simple assignment (modeled annual concentration at residence)	BMI (continuous)	B coefficient	Age, educational level, smoking status, physical activity, alcohol consumption, and nutrition status
Niedermayer et.al 2024	Cross-sectional	2018-2019	Germany KORA[7] Fit study	63.2± 5.5	3034 (53.7)	NO_2, NOx[8], O_3, PM_{10}, PMcoarse[9], $PM_{2.5}$, $PM_{2.5}$abs[10], PNC[11], annual temperature, winter temperature, summer temperature, NDVI[12]	Traditional spatial model (LUR)	BMI/WC (continuous) and obesity (categorical; BMI ≥30 kg/m²; WC ≥94 cm in male, ≥80 cm in female)	OR and β coefficient	Age, physical activity, alcohol, smoking, and education

[1] Simple assignment refers to approaches assigning exposure using city-level averages, monitoring data, Air Quality Index (AQI), postal code, or road proximity without full spatial modelling. Traditional spatial model refers to approaches such as land-use regression (LUR), interpolation, or spatiotemporal prediction models. Advanced model refers to satellite-based, machine-learning, chemical transport, or hybrid modelling approaches.
[2] CHARLS: China Health and Retirement Longitudinal Study
[3] CTM: Chemical Transport Model
[4] ML: Machine Learning

[5] LEAD: Lung, hEart, sociAl, boDy
[6] PM_{10}: Fine Particulate Matter with an Aerodynamic Diameter ≤10 μm
[7] KORA: Cooperative Health Research in the Region Augsburg
[8] NOx: Nitrogen Oxides
[9] PMcoarse: Coarse Particulate Matter, defined as particulate matter with aerodynamic diameter 10-2.5 μm
[10] $PM_{2.5}$abs: Particulate Matter 2.5 Back Carbon Proxy, an absorbance-based indicator of soot/black carbon, measured from the reflectance of $PM_{2.5}$ filters
[11] PNC: Particle Number Concentration, the number concentration of particles (ultrafine/total count)
[12] NDVI: Normalized Difference Vegetation Index

Wang et.al 2023	Cohort	2011-2015	China CHARLS	60.8±9.4	34854 (53.4)	$PM_{2.5}$, NO_2, O_3	Traditional spatial model (spatiotemporal prediction)	Body weight and WC change (continuous)	B coefficient	Age, sex, education level, marital status, employment status, residence, and city-level GDP[13], smoking status, alcohol consumption, sleep duration, and physical activity, prevalence of diabetes and hypertension, annual household income and cooking fuel type, annual average temperature, and relative humidity
Chen et.al 2023	Cohort	2006-2016	China MJ Health Research Database	40.2±11.6	77862 (52.4)	$PM_{2.5}$, NO_2	Traditional spatial model (hybrid Kriging/LUR)	MetS and components (categorical; WC ≥90 cm in male, ≥80 cm in female)	HR	Age, sex, BMI, region, marital status, education, sleep duration, smoking habits, alcohol use, physical activity, fried/processed food consumption, and baseline values of MetS components
Pan et.al 2023	Cross-sectional	2015	China CHARLS	Median 60	11766 (52.8)	SO_2, NO_2, O_3, PM_1[14], $PM_{2.5}$, PM_{10}, and fuel	Advanced model (satellite/ML; STET)	BMI/WC (categorical; BMI ≥28 kg/m²; WC ≥90 cm in male, ≥80 cm in female)	OR	Gender, age, educational attainment, smoking status, and drinking status
Yang et.al 2023	Cohort	2018-2019	China CMEC[15]	30-79 years	68914 (60.8)	$PM_{2.5}$ and its components	Advanced model (GEOS-Chem + GWR[16])	BMI/WHR17 (categorical; BMI ≥28 kg/m²; WHR >1.0 in male, >0.9 in female)	OR	Age, sex, ethnicity, education, income, smoking, secondhand smoke, indoor air pollution, alcohol, physical activity, diet, NDVI, and urban/rural status

[13] GDP: Gross Domestic Product
[14] PM_1: Fine Particulate Matter with an Aerodynamic Diameter ≤1 μm
[15] CMEC: China Multi-Ethnic Cohort
[16] GWR: Geographically Weighted Regression
[17] WHR: Waist-to-hip Ratio

Ye et.al 2023	Cohort	2000-2018	China CLHLS[18]	87.5±11.3	21355 (62.6)	$PM_{2.5}$ and NDVI	Advanced model (satellite-based atmospheric composition model)	Overweight/obesity (categorical; BMI ≥24 kg/m²)	HR and β coefficient	Age, sex, education, residence, ethnicity, marital/living status, income, smoking, alcohol, physical activity, sugar/meat/staple food intake, visual ability, ADL[19] disability, social/leisure activity index, heart disease, hypertension, diabetes, cerebrovascular diseases, respiratory diseases, and geographical region
Li et.al 2023	Cohort	2011-2013	China CHARLS	≥45 years	5710 (51.7)	$PM_{2.5}$ components	Advanced model (CMAQ[20] + XGBoost calibration)	BMI categories (categorical; overweight 24-28 kg/m²; obesity ≥28 kg/m²)	OR	Age, sex, education, occupation, household income, smoking status, drinking status, time of exercise per week, region, mean temperature, and mean relative humidity
Han et.al 2023	Cohort	2011-2015	China CHARLS	≥45years	7424 (48.2)	NDVI, $PM_{2.5}$, NO_2, O_3	Advanced model (city-level population-weighted satellite/model estimate)	Overweight/obesity (categorical; BMI >24 kg/m²)	HR	Age, sex, education, alcohol, smoking, marital status, region, income, physical activity, and chronic disease
Yu et.al 2023	Cohort	2011-2015	China CHARLS	59.0±8.8	7204 (53.3)	$PM_{2.5}$	Advanced model (satellite/meteorology/land use)	BMI (continuous)	β coefficient	Age, gender, ethnicity, education level, marital status, living standard (high, medium, and low), residence, smoking and drinking status, and physical activity
Liu et.al 2023	Cross-sectional	2011-2015	China CHARLS	≥45years	14097 (54.9)	NO_2, PM_1, PM_{10}, $PM_{2.5}$	Advanced model (spatiotemporal random forest)	MetS and components (categorical; WC ≥90 cm in male, ≥80 cm in female)	OR	Age, gender, BMI, education level, marital status, smoking, drinking, social activity frequency, disability, health insurance, wage income, and health status

18 CLHLS: Chinese Longitudinal Healthy Longevity Survey
19 ADL: Activities of Daily Living
20 CMAQ: Community Multiscale Air Quality model

Guo et.al 2022	Cross-sectional	2011-2012	China CEERHAPS-A[21]	48.8±14.8	84208 (42.9)	$PM_{2.5}$ (Low vs High)	Advanced model (satellite/CTM/monitor/ML)	Obesity (categorical; BMI ≥28 kg/m²)	OR and β coefficient	Age, gender, urbanicity, income, occupation, education, ethnicity, active and passive smoking, physical activity, diet, cooking/heating fuel type, ventilation, heating days, pollution sources near home, and air pollutants
Li et.al 2022	Cross-sectional	2020	China NA	52.7±15.3 50.9±13.0	8377 (48.6)	$PM_{2.5}$, PM_{10}, SO_2, NO_2, CO[22], O_3, NDVI	Advanced model (individual-level GLM[23]/random forest)	BMI/WC/WHR/WHtR24/body fat percentage/visceral fat index (categorical; BMI ≥28 kg/m²; WC ≥90 cm in male, ≥80 cm in female; WHR ≥0.90 in male, ≥0.85 in female; WHtR ≥0.50; body fat percentage ≥25% in male, ≥30% in female; visceral fat index ≥10)	OR	Sex, age, education level, career, annual household income, housing type, outdoor exercise frequency, distance to road, smoking, drinking, personal/family history of chronic diseases, mean temperature, and relative humidity
Liu et.al 2022	Cohort	2012-2017	China CLHLS - HABCS[25] subcohort	85.6±12.2	1755 (53.8)	$PM_{2.5}$ and NDVI	Advanced model (NASA satellite + GEOS-Chem)	MetS and components (categorical; WC ≥90 cm in male, ≥80 cm in female)	OR and β coefficient	Biomarker year, baseline age, sex, ethnicity, education, marital status, residence, exercise, smoking, alcohol drinking, and GDP per capita

[21] China CEERHAPS-A: Chinese Environmental Exposure Related Activity Pattern Research for Chinese Adults
[22] CO: Carbon Monoxide
[23] GLM: generalized Linear Model
[24] WHtR: Waist-to-height Ratio
[25] CLHLS - HABCS: Chinese Longitudinal Healthy Longevity Survey, specifically the Healthy Ageing and Biomarkers Cohort Study

Huang et.al 2021	Cohort	2007-2015	China China-PAR[26]	52.8±11.9	77609 (NA)	$PM_{2.5}$	Advanced model (satellite-based spatiotemporal model)	BMI (continuous) and overweight/obesity (categorical; BMI ≥25 kg/m²)	RR	Age, sex, smoking status, alcohol consumption, physical activity, diet, individual education level, urbanicity, county-level averaged years of education, geographic region, per capita monthly income of the family, and chronic disease status
Cao et.al 2021	Cross-sectional	2011-2012	China CEERHAPS-A	48.7±14.7	91052 (45.3)	$PM_{2.5}$	Advanced model (satellite/CTM/monitor/ML)	Obesity (categorical; BMI ≥28 kg/m²)	OR	Age, gender, urbanity, income level, occupation level, educational level, ethnic, active smoke exposure, passive smoke exposure, household cooking fuel type, household heating fuel type, cook ventilation, have pollution sources near home, physical activity time, food intake, and beverages intake
Liu et.al 2021	Cross-sectional	2018-2019	China CMEC	52.2±11.4	68254 (60.8)	PM_1, $PM_{2.5}$, PM_{10}	Advanced model (satellite-based spatiotemporal model)	BMI/WC/WHtR (continuous) and obesity (categorical; BMI ≥28 kg/m²; WC ≥90 cm in male, ≥85 cm in female; WHtR ≥0.5)	OR and β coefficient	Age, sex, ethnicity, residence, household income, educational level, physical activity level, smoking, secondary smoking, indoor air pollution, alcohol drinking, dietary intake, hypertension, and diabetes
Tamayo-Ortiz et.al 2021	Cross-sectional	2006 2012	Mexico ENSANUT[27]	42.9±16.4 44.9±16.3	2281(55.1) 2302(54.7)	$PM_{2.5}$	Advanced model (hybrid spatiotemporal AOD[28] + monitors)	Obesity (categorical; BMI ≥30 kg/m²)	OR / RRR	Sex, age, socioeconomic status, and smoking status

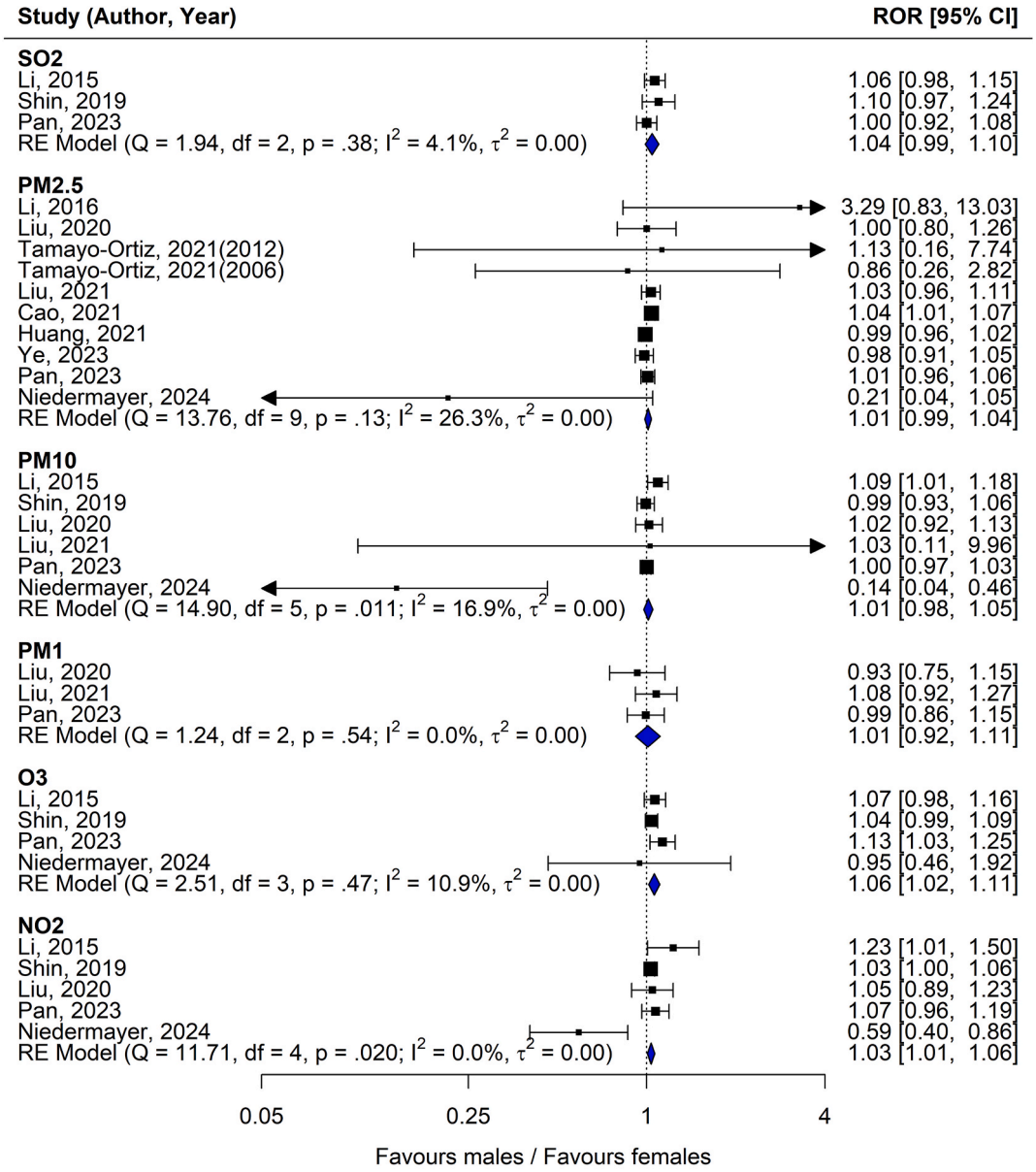
[26] China-PAR: the Prediction for Atherosclerotic Cardiovascular Disease Risk in China
[27] ENSANUT: Encuesta Nacional de Salud y Nutrición (National Health Survey Nutrition)
[28] AOD: Aerosol Optical Depth

Liu et.al 2020	Cross-sectional	2015-2017	China Henan Rural Cohort Study	55.6± 12.15	38824 (60.5)	NO_2, PM_1, PM_{10}, $PM_{2.5}$	Advanced model (AOD/meteorology/land use ML)	BMI/WC (categorical; BMI ≥28 kg/m²; WC ≥90 cm in male, ≥80 cm in female)	OR and β coefficient	Age, sex, education level, per capital monthly income, smoking status, alcohol drinking status, high fat diet, vegetable and fruit intake, and physical activity
Zhang et.al 2020	Cross-sectional	2008-2012	United States MAC[29]	38.0± 10.0	7826(54.3)	$PM_{2.5}$	Simple assignment (R-LINE + road proximity GIS[30])	Obesity (categorical; BMI ≥30 kg/m²)	OR and β coefficient	Age, gender, smoking status, household income, nativity, education level, and health insurance coverage
Yang et.al 2019	Cross-sectional	2015	China CHARLS	60.93 ±9.91	13414 (53.3)	AQI[31] ($PM_{2.5}$, PM_{10}, CO, O_3, NO_2, and SO_2)	Simple assignment (national monitoring network)	BMI (continuous) and obesity (categorical; Chinese ≥28, Asian ≥25, WHO ≥30 kg/m²)	OR and β coefficient	Sex, age, education level, marital status, insurance status, smoking, alcohol drinking, physical activity, plus stratified analyses by sex, age, and education
Shin et.al 2019	Cross-sectional	2003-2012	South Korea KCHS[32]	47.8± 0.06	100867 (50.0)	PM_{10}, SO_2, NO_2, CO, O_3	Simple assignment (national emissions service)	Obesity within cardiometabolic diseases (categorical; BMI >25 kg/m²)	OR	Age, sex, smoking status, alcohol consumption, physical activity, years of education, marital status, household income, place of residence, and history of other cardiometabolic diseases

[29] MAC: Mano-a-Mano Mexican American Cohort
[30] GIS: Geographic Information System
[31] AQI: Air Quality Index, 0 to 500 index calculated from daily concentrations of six pollutants: SO_2, NO_2, PM_{10}, $PM_{2.5}$, CO, and O_3
[32] KCHS: Korean Community Health Survey

Hwang et.al 2019	Cross-sectional	2006-2014	South Korea NA	53.5± 9.2	5114 (29.1)	NO_2, PM_{10}	Simple assignment (nearest monitoring site by postal code)	BMI/WC/body fat percentage/TAT33/VAT34/SAT35 (continuous)	β coefficient	Age, sex, smoking status, alcohol consumption, physical activity, hypertension, diabetes, and dyslipidemia
Zhang et.al 2019	Cross-sectional	2015	China CHARLS	67.53 ±6.11	4364 (51.6)	AQI ($PM_{2.5}$, PM_{10}, CO, O_3, NO_2, and SO_2)	Simple assignment (city-level AQI/pollutant days)	Obesity (categorical; BMI ≥28 kg/m²)	Marginal effect	Age, sex, marital status, education level, disability, physical activity, household consumption per capita, GDP per capita, manufacturing share of GDP, number of hospital beds per 1000 population, region, and place of residence
Li et.al 2016	Cross-sectional	1998-2005	United States Framingham Offspring and Third Generation MDCT[36] substudy	53.9± 11.8	2372 (52.1)	$PM_{2.5}$	Advanced model (AOD + hybrid meteorology/land use/emissions)	BMI/SAT/VAT (continuous) and obesity (categorical; BMI ≥30 kg/m²)	OR and β coefficient	Age, sex, smoking status, pack-years of smoking, alcohol intake, educational level, physical activity index, antihypertensive medication use, statin use, median household income in the participant's census tract, cardiovascular disease, diabetes, and a cohort identifier
Li et.al 2015	Cross-sectional	2006-2009	China 33CCHS[37]	45.6± 13.3	24845 (49.0)	PM_{10}, SO_2, NO_2, O_3	Simple assignment (municipal monitoring stations)	BMI/WC/WHR/WHtR (categorical; BMI ≥30 kg/m²; WC ≥90 cm in male, ≥85 cm in	OR	Age, sex, race, education, income, smoking, drinking, physical activity, diet, family history of hypertension, and district

[33] TAT: Total Adipose Tissue
[34] VAT: Visceral Adipose Tissue
[35] SAT: Subcutaneous Adipose Tissue
[36] MDCT: Multidetector Computed Tomography
[37] 33CCHS: 33 Communities Chinese Health Study



(a) Sex differences

Fig. 2. Sex differences and sex-stratified pooled associations of all pollutants with general obesity. Random effects meta analysis. Cochran's Q tests for between study heterogeneity (df = k − 1), with the p-value assessing evidence against homogeneity. I^2 is the percentage of total variability attributable to heterogeneity rather than sampling error, and τ^2 is the estimated between study variance (larger I^2 and τ^2 indicate greater heterogeneity).

3.3. Meta-analysis results

Detailed reasons why eligible studies did not contribute to the meta-analysis are provided in Table S3. Study-level characteristics of estimates included in the categorical general and abdominal obesity meta-analyses are provided in Appendix 7: Tables S4–S5. Unless otherwise stated, pooled estimates reported below refer to a 10 μg/m^3 increase in pollutant concentration.

3.3.1. Sex differences in the association between air pollution and general obesity

Sex difference contrasts for general obesity were available for PM_1 (k = 3), SO_2 (k = 3), O_3 (k = 4), PM_{10} (k = 6), NO_2 (k = 5), and $PM_{2.5}$ (k = 10). For PM_1, SO_2, PM_{10}, and $PM_{2.5}$, the pooled RORs were close to one (PM_1 1.01, 95% CI 0.92 to 1.11; SO_2 1.04, 95% CI 0.99 to 1.10; PM_{10} 1.01, 95% CI 0.98 to 1.05; $PM_{2.5}$ 1.01, 95% CI 0.99 to 1.04) (Fig. 2a), with low to moderate heterogeneity ($I^2 \leq 26.3\%$). For O_3 and NO_2, the ROR indicated positive and more precise associations in females than in males (O_3 1.06, 95% CI 1.02 to 1.11; NO_2 1.03, 95% CI 1.01 to 1.06) (Fig. 2a). O_3 exposure metrics varied across studies, including 10-year average concentrations derived from hourly monitored data (Shin et al., 2019), annual average residential O_3 (Niedermayer et al., 2024), 3-year average daytime 8-h O_3 concentrations (Li et al., 2015), and 1-year average modeled O_3 exposure (Pan et al., 2023); therefore, the pooled O_3 estimate should be interpreted cautiously.

In the sex-stratified analyses, higher exposure to several air

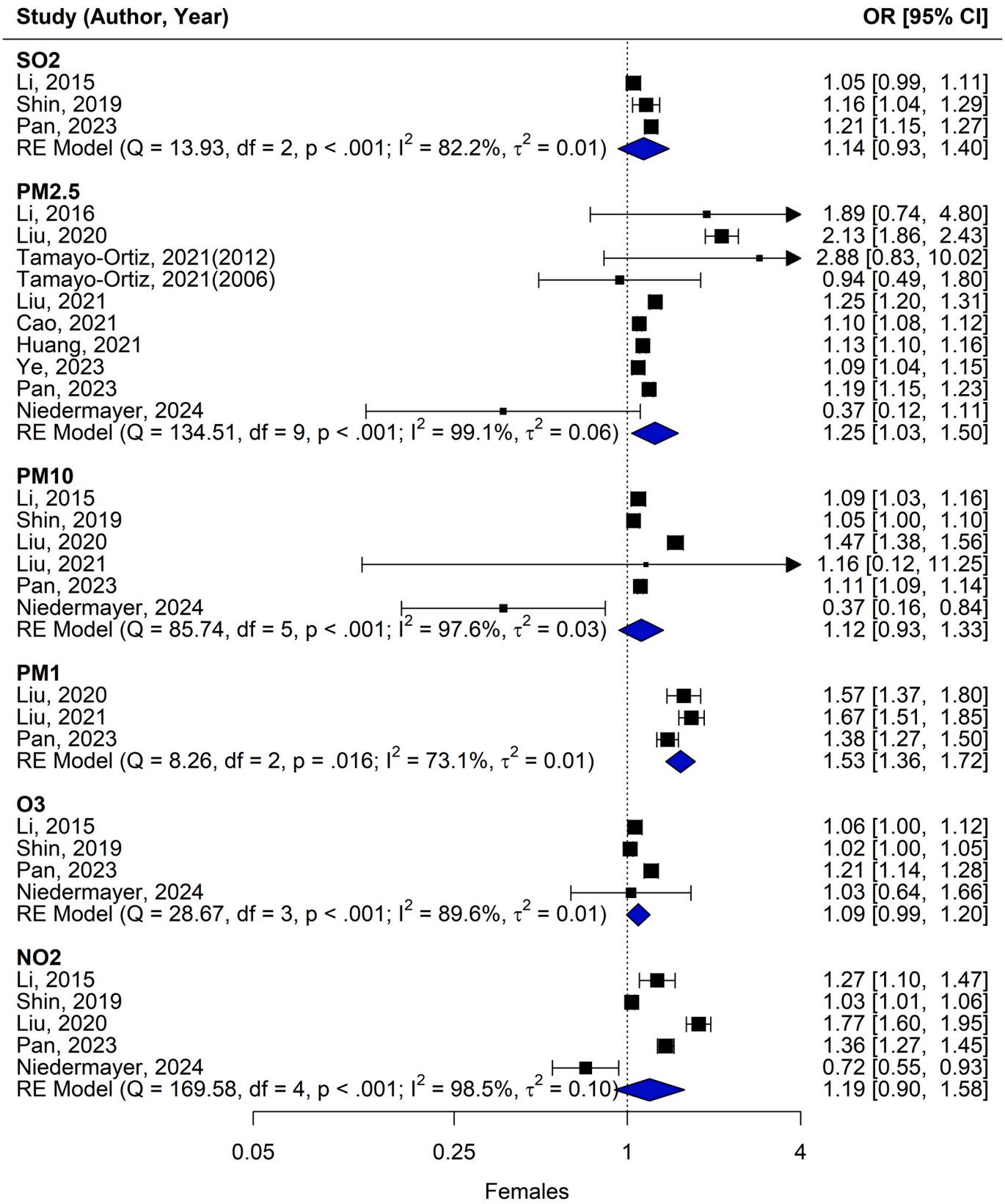
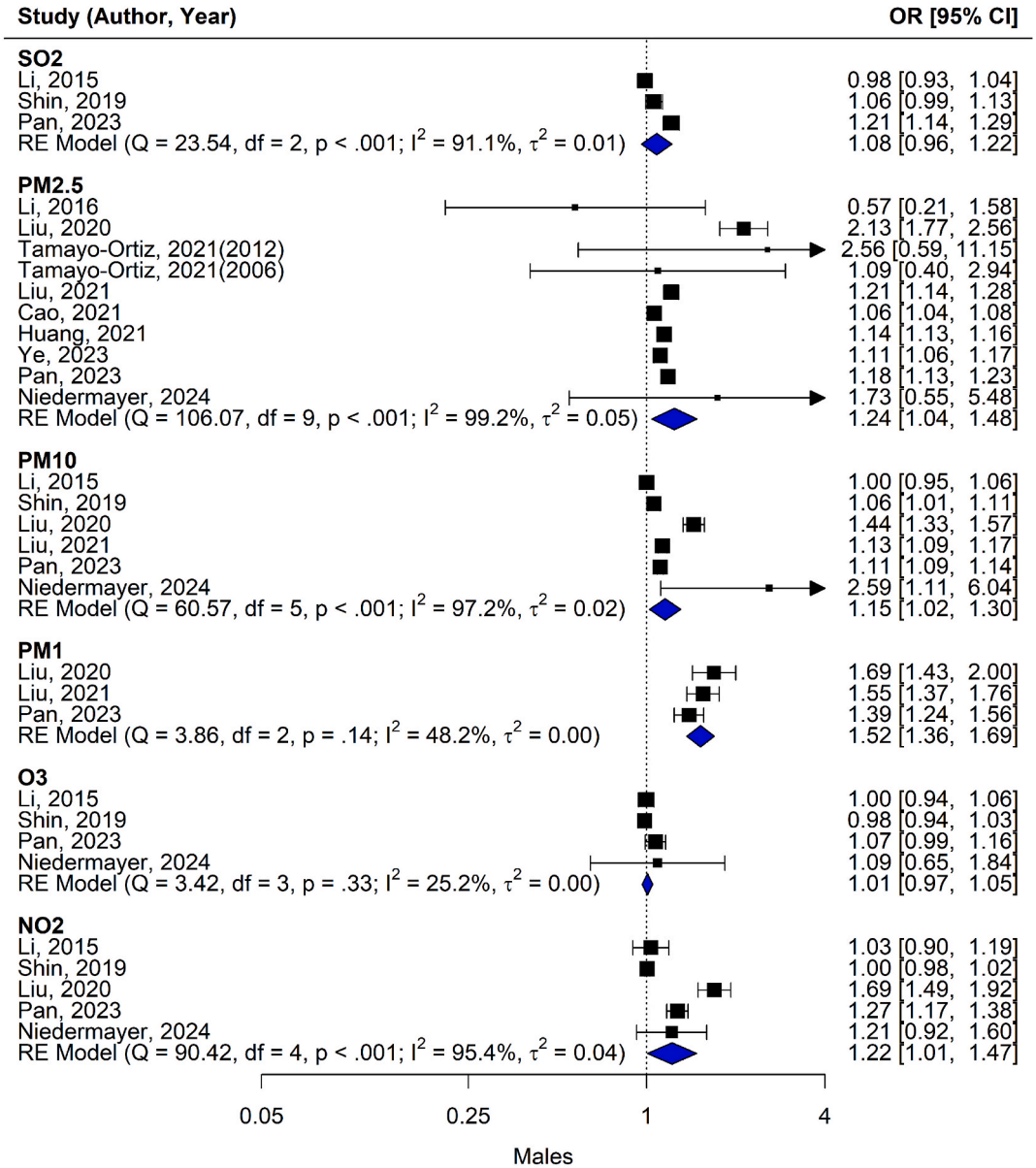


Fig. 2. (*continued*).



(c) Males

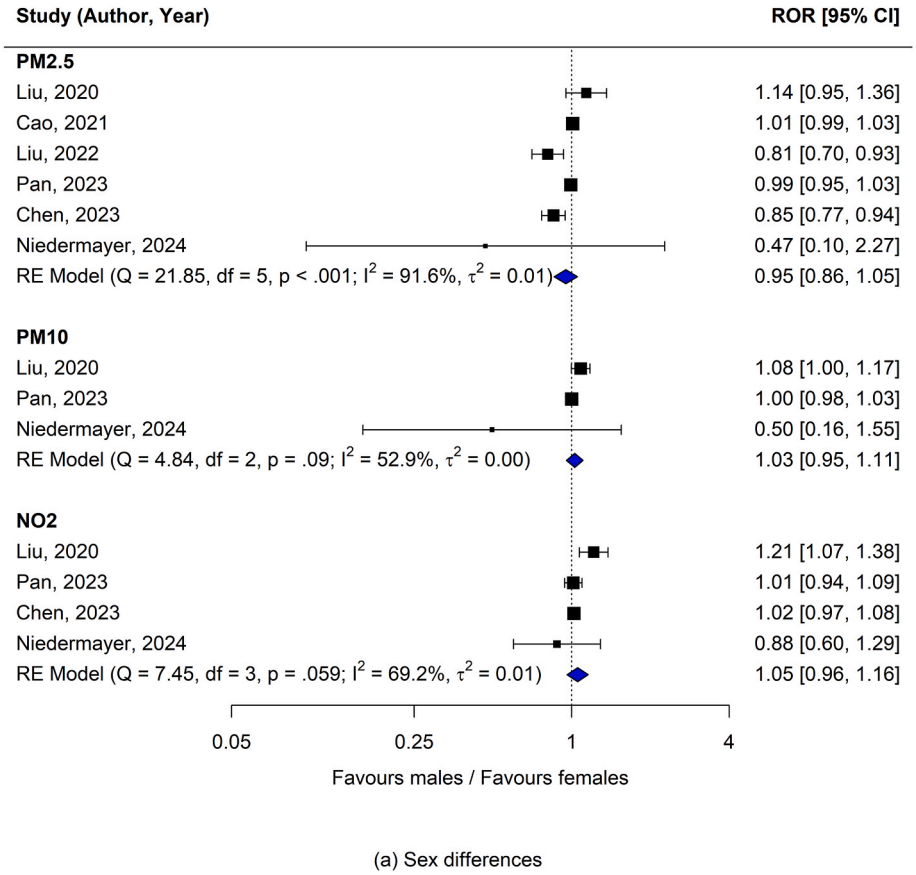
Fig. 2. (*continued*).

pollutants was generally associated with increased odds of general obesity in both females and males. Among females, significant positive associations were observed for SO_2 (OR 1.14, 95% CI 1.04 to 1.25), $PM_{2.5}$ (OR 1.25, 95% CI 1.03 to 1.50), and PM_1 (OR 1.53, 95% CI 1.36 to 1.72), whereas the pooled estimates for PM_{10}, O_3, and NO_2 were not statistically significant (Fig. 2b).

Among males, significant positive associations were found for $PM_{2.5}$ (OR 1.24, 95% CI 1.04 to 1.48), PM_{10} (OR 1.15, 95% CI 1.02 to 1.30), PM_1 (OR 1.52, 95% CI 1.36 to 1.69), and NO_2 (OR 1.22, 95% CI 1.01 to 1.47), while the pooled estimates for SO_2 and O_3 were not statistically significant (Fig. 2c). However, heterogeneity was substantial to considerable across most pollutant-specific, sex-stratified meta-analyses, particularly for $PM_{2.5}$, PM_{10}, and NO_2. These within-sex pooled estimates should therefore be interpreted with caution.

3.3.2. *Sex differences in the association between air pollution and abdominal obesity*

For abdominal obesity, sex difference estimates were available for PM_{10} (k = 3), NO_2 (k = 4), and $PM_{2.5}$ (k = 6). The pooled RORs did not show statistically significant differences between females and males (PM_{10} ROR 1.03, 95% CI 0.95 to 1.11; NO_2 ROR 1.05, 95% CI 0.96 to 1.16; $PM_{2.5}$ ROR 0.95, 95% CI 0.86 to 1.05), and heterogeneity was substantial (I^2 >50%) (Fig. 3a). In sex-stratified analyses, higher particulate exposure was associated with greater abdominal obesity in males. $PM_{2.5}$ was associated with higher odds of abdominal obesity in males (OR 1.38, 95% CI 1.06 to 1.80), whereas the corresponding estimates in females were similar in direction but not statistically significant (OR 1.29, 95% CI 0.92 to 1.81) (Fig. 3b and 3c).



(a) Sex differences

Fig. 3. Sex differences and sex-stratified pooled associations of all pollutants with abdominal obesity. Random effects meta analysis. Cochran's Q tests for between study heterogeneity (df = k − 1), with the p-value assessing evidence against homogeneity. I^2 is the percentage of total variability attributable to heterogeneity rather than sampling error, and τ^2 is the estimated between study variance (larger I^2 and τ^2 indicate greater heterogeneity).

3.3.3. Sex differences in the association between air pollution and BMI and WC

For continuous outcomes, we examined sex differences in the effects of $PM_{2.5}$ on BMI (k = 3) and of NO_2 on WC (k = 3). The pooled β difference for $PM_{2.5}$ and BMI was 2.06 (95% CI -5.48 to 9.60), and the pooled β difference for NO_2 and WC was −0.66 (95% CI -2.32 to 0.99). Pooled sex-stratified coefficients for both pollutants were small and not statistically significant, with moderate to high heterogeneity (Appendix 8: Figs. S2–S3).

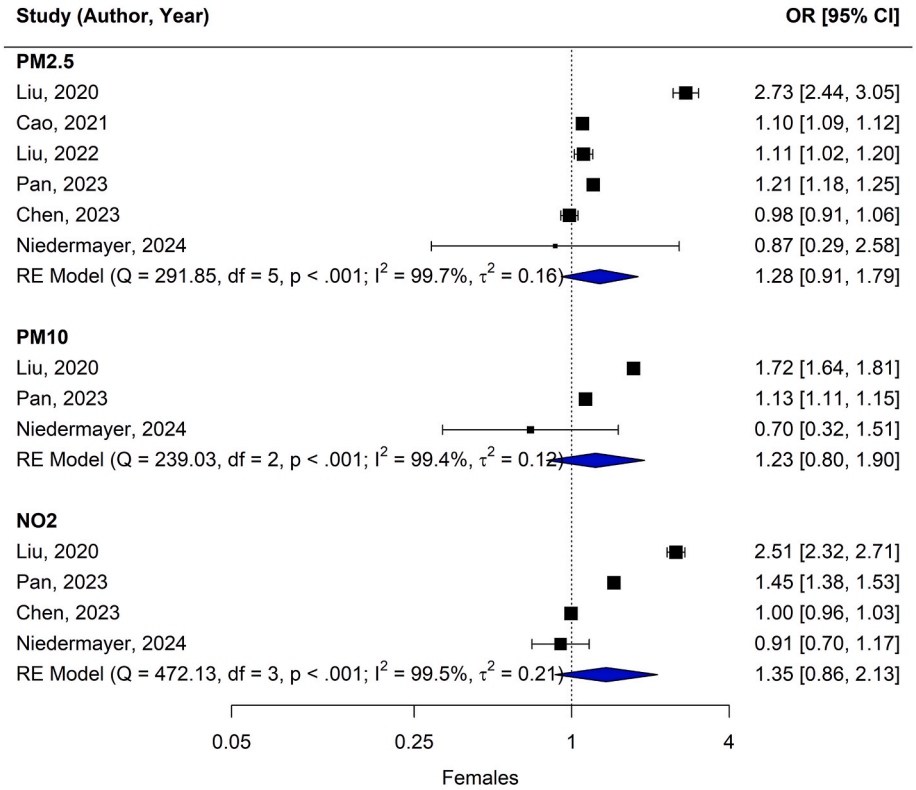
3.4. Subgroup analyses

Subgroup analyses by exposure assessment method and BMI threshold produced estimates that were similar to the main analyses. Stratification by exposure assessment method showed similar ROR for PM_{10} and general obesity in studies using advanced versus simple or traditional exposure assessment (Appendix 9: Fig. S4). Sex difference estimates for PM_{10} and $PM_{2.5}$ were also stable across different BMI thresholds (Appendix 9: Figs. S5–S6). Restricting analyses to studies from China or from other regions did not materially change the magnitude or direction of the associations between $PM_{2.5}$ and general obesity (Appendix 9: Fig. S7), although the small number of studies outside China limited the assessment of regional heterogeneity. Given the small number of studies within subgroup comparisons, these subgroup-specific pooled estimates were interpreted as exploratory. The feasibility of exploratory subgroup analyses and the corresponding sensitivity-analysis decisions are summarised in Table S6.

3.5. Sensitivity analyses

Leave-one-out analyses indicated that no single study materially altered the pooled estimates or their statistical significance (Appendix 10: Figs. S8–S18). Restricted sensitivity analyses were conducted to assess the robustness of pooled estimates to five potential sources of limited comparability: exposure assessment method, obesity definition including BMI/WC cut-offs, geographic region, effect-measure type, and study design, where formal subgroup analyses were not feasible (Appendix 11: Fig. S19–S24). The main exception was $PM_{2.5}$ and general obesity: after excluding two less comparable estimates that differed in effect-measure type, study design and obesity definition, the pooled ROR increased from 1.01 (95% CI 0.99 to 1.04) to 1.03 (95% CI 1.01 to 1.06), although the magnitude of the sex difference remained small. Additional analyses that used alternative definitions of general and abdominal obesity, and substituted combined overweight or obesity outcomes where available, yielded results that were highly consistent with the primary analyses (Appendix 12: Figs. S25–S32).

To improve transparency regarding heterogeneity in obesity definitions, study designs, and effect-measure types, we summarised the main and robustness estimates for categorical obesity outcomes in Table 2. The main pooled estimates combined studies using locally defined BMI or WC thresholds, because these thresholds reflect population- and region-specific clinical standards and were the definitions used in the original studies. However, because these thresholds were not identical across studies and some comparisons also included different study designs or effect-measure types, the main pooled estimates should be interpreted as exploratory summaries rather than definitive estimates based on identical outcome definitions.



(b) Females

Fig. 3. (*continued*).

Where at least three comparable studies were available, greater interpretive weight was placed on restricted or robustness estimates based on more comparable obesity definitions, study designs, exposure assessment methods, geographic regions, or effect-measure types. When fewer than three comparable studies remained after restriction, no additional pooled estimate was calculated, and the direction, magnitude, and precision of study-specific estimates were interpreted narratively. Therefore, pooled estimates combining different outcome definitions or effect-measure types should be considered hypothesis-generating, whereas estimates that remain consistent across the main and restricted analyses provide stronger support for future inference.

3.6. Publication bias

Formal assessment of small-study effects was possible only for the $PM_{2.5}$ and general obesity cluster. The funnel plot was broadly symmetrical, Egger's test did not indicate small-study effects ($z = -0.29$, $P = 0.77$), and trim-and-fill analysis had minimal impact on the pooled estimate. However, because this assessment was feasible for only this single evidence cluster and the number of studies was limited, these findings should be interpreted cautiously. The funnel plot and trim-and-fill analysis are presented in the Supplementary material (Appendix 13: Figs. S33–S34).

3.7. Certainty of evidence

Certainty of evidence for the main exposure–outcome associations was assessed using the GRADE approach. $PM_{2.5}$, PM_{10}, and NO_2 were included in the Summary of Findings table because these were the only pollutants with meta-analyses available for both general and abdominal obesity. Overall, certainty was moderate for $PM_{2.5}$ and NO_2 in relation to general obesity, but low for PM_{10} and for all abdominal obesity outcomes. Downgrading mainly reflected inconsistency and imprecision, with additional concerns related to the limited number of studies and the possibility of publication bias in some evidence clusters (Table S7).

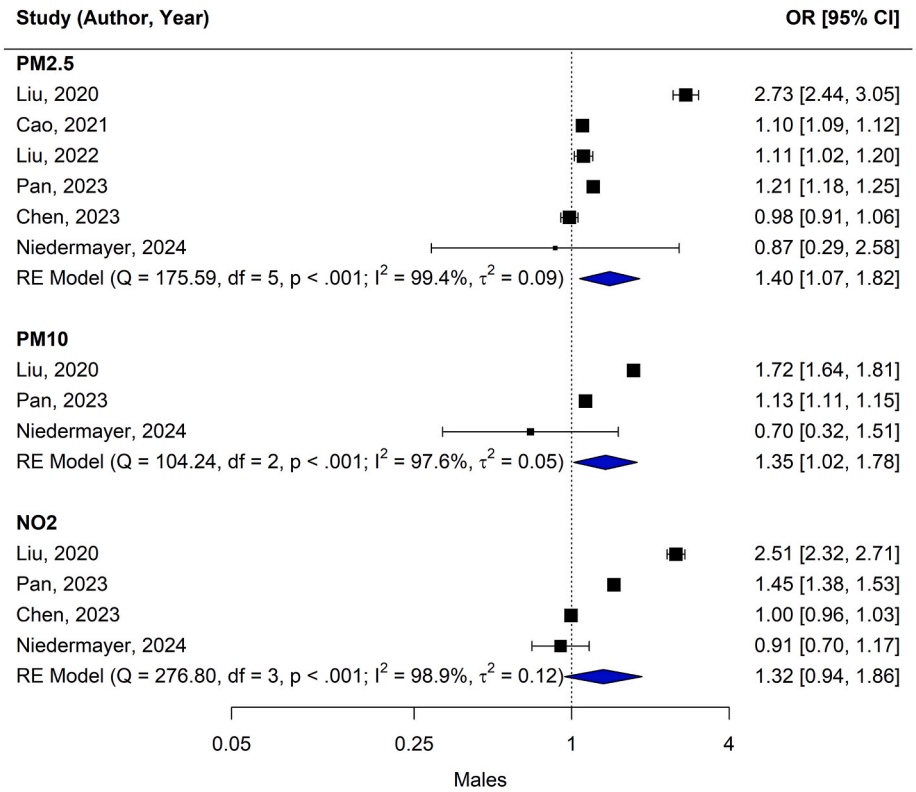
3.8. Narrative synthesis

For pollutants and exposure metrics that could not be meta-analysed, the narrative synthesis showed broadly similar patterns. Most additional pollutants yielded ROR close to one, with CI spanning unity, indicating little evidence for large or consistent sex differences. Sex-stratified estimates for PM_1 and SO_2 showed positive associations with abdominal obesity in both females and males, whereas associations for other pollutants were smaller and often imprecise (Appendix 14: Tables S8–S11).

4. Discussion

This systematic review and meta-analysis of 28 observational studies, including roughly 800,000 adults, indicates that higher concentrations of several common ambient air pollutants are associated with increased general and abdominal obesity in both females and males, and that overall these associations are broadly similar by sex. For most pollutant–outcome combinations, the RORs were close to 1 and the 95% CI included the null, suggesting largely shared pollution-related adiposity risks in females and males.

Against this background of similarity, we identified some pollutant-specific and outcome-specific differences. For general obesity, O_3 and NO_2 were associated with slightly higher risks in females than in males, with pooled RORs of 1.06 and 1.03, respectively. In contrast, for abdominal obesity, sex-stratified analyses suggested that particulate matter, particularly $PM_{2.5}$, might be more strongly associated with larger WC in males, although CIs were wide and ROR estimates were not



(c) Males

Fig. 3. (*continued*).

Table 2
Summary of main and robustness estimates for sex-difference meta-analyses of categorical obesity outcomes.

Pollutant	Outcome	Main analysis: k and contributing studies	BMI/WC definitions in main analysis	Study design/effect measure type	Main pooled ROR	Sensitivity/robustness pooled estimates	Interpretation for inference
PM_1	General obesity	k = 3; Pan et al., 2023, Liu et al., 2021, Liu et al., 2020	BMI thresholds 28 and 30 kg/m^2	Cross-sectional; OR	1.01 (0.92–1.11)	Leave-one-out analyses did not materially alter the estimate. No restricted pooled estimate was feasible.	Exploratory; limited number of studies.
SO_2	General obesity	k = 3; Pan et al., 2023, Shin et al., 2019, Li et al., 2015	BMI thresholds 25, 28, and 30 kg/m^2	Cross-sectional; OR	1.04 (0.99–1.10)	Alternative-definition analysis substituting BMI >25 for BMI >30: 1.00 (0.97–1.03). Leave-one-out analyses did not materially alter the estimate.	Positive direction in the main analysis, but imprecise and sensitive to obesity definition; hypothesis-generating.
O_3	General obesity	k = 4; Niedermayer et al., 2024, Pan et al., 2023, Shin et al., 2019, Li et al., 2015	BMI thresholds 25, 28, and 30 kg/m^2	Cross-sectional; OR	1.06 (1.02–1.11)	Alternative-definition analysis substituting BMI >25 for BMI >30: 1.04 (0.97–1.11). Leave-one-out analyses did not materially alter the estimate.	Positive female-to-male contrast, but should be interpreted cautiously because exposure metrics varied.
PM_{10}	General obesity	k = 6; Niedermayer et al., 2024, Pan et al., 2023, Liu et al., 2021, Liu et al., 2020, Shin et al., 2019, Li et al., 2015	BMI thresholds 25, 28, and 30 kg/m^2	Cross-sectional; OR	1.01 (0.98–1.05)	Exposure-assessment subgroup: advanced models 1.00 (0.97–1.03); simple/traditional methods 0.61 (0.20–1.93). BMI-definition subgroup: BMI >30, 0.54 (0.13–2.18); BMI >25/28, 1.00 (0.97–1.03). China-only restricted analysis: 1.03 (0.97–1.09). Alternative-definition analysis substituting BMI >25 for BMI >30: 1.00 (0.98–1.03).	Overall close to null; greater weight should be placed on the more comparable OR-based, cross-sectional estimates.

(*continued on next page*)

Table 2 (*continued*)

Pollutant	Outcome	Main analysis: k and contributing studies	BMI/WC definitions in main analysis	Study design/effect measure type	Main pooled ROR	Sensitivity/robustness pooled estimates	Interpretation for inference
NO_2	General obesity	k = 5; Niedermayer et al., 2024, Pan et al., 2023, Liu et al., 2020, Shin et al., 2019, Li et al., 2015	BMI thresholds 25, 28, and 30 kg/m^2	Cross-sectional; OR	1.03 (1.01–1.06)	Alternative-definition analysis substituting BMI >25 for BMI >30: 1.03 (1.00–1.06). Leave-one-out analyses did not materially alter the estimate.	Positive and relatively precise female-to-male contrast; still interpreted as exploratory because obesity definitions varied.
$PM_{2.5}$	General obesity	k = 10; Niedermayer et al., 2024, Pan et al., 2023, Ye et al., 2023, Huang et al., 2021, Cao et al., 2021, Liu et al., 2021, Tamayo-Ortiz et al., 2021 (2006), Tamayo-Ortiz et al., 2021 (2012), Liu et al., 2020, Li et al., 2016	BMI thresholds 24, 25, 28, and 30 kg/m^2	Cross-sectional and cohort; OR, RR, and HR	1.01 (0.99–1.04)	BMI-definition subgroup: BMI >30, 1.03 (0.96–1.11); BMI >24/25/28, 1.01 (0.98–1.04). Geographic subgroup: China 1.01 (0.99–1.04); other countries 0.60 (0.23–1.54). Restricted analysis excluding two less comparable estimates: 1.03 (1.01–1.06). Restricted BMI comparison: BMI >30, 1.03 (0.96–1.11); BMI >28, 1.03 (1.01–1.06). Alternative-definition analyses: substituting BMI >25 for BMI >28, 1.01 (0.99–1.03); substituting BMI >30 for BMI >28, 1.01 (0.98–1.04). Leave-one-out analyses did not materially alter the estimate.	Main estimate is exploratory because definitions, study designs, and effect-measure types varied. Greater weight should be placed on restricted estimates based on more comparable definitions and effect metrics.
PM_{10}	Abdominal obesity	k = 3; Niedermayer et al., 2024, Pan et al., 2023, Liu et al., 2020	WC thresholds 90/80 and 94/80 cm	Cross-sectional; OR	1.03 (0.95–1.11)	Leave-one-out analyses did not materially alter the estimate. No further restricted pooled estimate was feasible.	Exploratory; limited number of studies.
NO_2	Abdominal obesity	k = 4; Niedermayer et al., 2024, Chen et al., 2023, Pan et al., 2023, Liu et al., 2020	WC thresholds 90/80 and 94/80 cm	Cross-sectional and cohort; OR and HR	1.05 (0.96–1.16)	Leave-one-out analyses did not materially alter the estimate. No restricted pooled estimate was calculated where fewer than three comparable studies remained.	Exploratory; heterogeneity by study design and effect-measure type remains.
$PM_{2.5}$	Abdominal obesity	k = 6; Niedermayer et al., 2024, Chen et al., 2023, Pan et al., 2023, Liu et al., 2022, Cao et al., 2021, Liu et al., 2020	WC thresholds 90/80, 90/85, and 94/80 cm	Cross-sectional and cohort; OR and HR	0.95 (0.86–1.05)	Advanced-model restricted analysis: 0.98 (0.88–1.09). WC 90/80 cm restricted analysis: 0.93 (0.82–1.07). Cross-sectional-only analysis: 1.01 (0.99–1.02). Alternative-definition analyses: substituting WC 94/80 cm for WC 90/85 cm, 0.94 (0.86–1.04); substituting WC 90/80 cm for WC 90/85 cm, 0.95 (0.86–1.05). Leave-one-out analyses did not materially alter the estimate.	Main estimate is imprecise and heterogeneous; greater weight should be placed on restricted estimates based on comparable study design and WC definitions.

Note: ROR indicates the female-to-male ratio of relative effect estimates. Values above 1 indicate that the pollutant–obesity association was relatively larger in females than in males. Main pooled estimates were based on locally defined obesity thresholds used in the original studies. Where multiple thresholds were available from the same study, only one estimate contributed to the primary meta-analysis; alternative thresholds were assessed in alternative-definition analyses. Restricted pooled estimates were calculated only when at least three comparable studies remained. Continuous BMI and WC outcomes are not shown because they did not involve categorical BMI/WC thresholds.

statistically significant. These subtle and sometimes inconsistent patterns, together with the small effect sizes, suggest that any true sex modification is likely to be modest. At the same time, they illustrate how sex-stratified analyses can reveal potential differences that would be masked in pooled models, even when the main message is one of largely shared susceptibility.

This review extends previous systematic reviews that have examined associations between ambient air pollution and adiposity but have not systematically assessed sex differences or have treated sex only as a covariate in multivariable models (Lin et al., 2022; Huang et al., 2020; An et al., 2018; Luo et al., 2024). To our knowledge, this is the first meta-analysis to quantify sex-specific associations between air pollution and obesity. By separating sex-specific estimates and then combining them using RORs and differences in regression coefficients, our approach distinguishes more clearly between overall pollution-obesity associations and relative risks in females and males, and therefore represents a methodological advance over analyses that treat sex solely as a confounder.

Control of confounding is central to interpreting these results. Most effect estimates included in our meta-analyses were adjusted for age and, in many cases, for smoking and some indicators of socioeconomic position. However, adjustment for diet, physical activity and other

behavioural risk factors for obesity was inconsistent, and very few studies incorporated neighbourhood-level characteristics or co-exposures such as noise and green space. Some models also adjusted for potential mediators, including hypertension or diabetes, which may have resulted in partial over-adjustment. Importantly, no study systematically measured gender-related behaviours or social roles, and none examined whether confounding structures differed between females and males. These patterns suggest that residual confounding is likely and that unmeasured behavioural or socioeconomic factors may have influenced the sex-specific estimates. In some studies, the most comprehensively adjusted model may also have involved a smaller analytic sample because of missing covariate data, which could have reduced comparability across estimates. In addition, most extracted estimates were derived from single-pollutant models, whereas adjustment for co-exposures or other environmental factors was inconsistent across studies, limiting inference in the presence of correlated exposures.

Biological and behavioural mechanisms may nonetheless help to interpret the small sex differences observed. Experimental and observational studies suggest that air pollution can induce systemic inflammation, oxidative stress and metabolic dysregulation, which in turn may promote weight gain and central fat accumulation (Lucio and Wang, 2023; Stojchevski et al., 2024; Pryor et al., 2022; Woodward et al., 2019; Li et al., 2020). These pathways could plausibly operate differently in females and males because of differences in body fat distribution, hormonal milieu and cardiometabolic profiles. For example, oestrogen has complex effects on adipose tissue and inflammatory responses, and women generally have a higher percentage of body fat, which might make them more responsive to oxidative and inflammatory insults. Behavioural factors such as commuting patterns, occupational exposures and time spent in domestic environments may further modify individual contact with ambient pollutants (Biswas et al., 2021; Clougherty, 2010). Our data do not allow discrimination between specific biological pathways, and mechanistic inferences should remain cautious.

This review also has several strengths. It was conducted according to a prospectively registered protocol with explicit eligibility criteria, dual independent screening and standardised data extraction. Wherever possible, we harmonised effect estimates to a common exposure contrast of 10 μg/m^3 and prioritised the most comprehensively adjusted models that did not include sex as a covariate. By considering both BMI-based general obesity and WC-based abdominal obesity, we were able to explore whether any sex modification differed by adiposity phenotype. In addition, we used meta-analytic techniques to compare females and males, including RORs and differences in regression coefficients, and we undertook exploratory subgroup analyses, leave-one-out checks, restricted sensitivity analyses, alternative-definition analyses, and publication bias assessments, where feasible, to examine the robustness of the findings.

There are, however, several limitations that should be considered when interpreting these findings. First, all included studies were observational, and many were cross-sectional. This limits causal inference and means that reverse causation cannot be ruled out. Second, although the JBI-based risk of bias assessment captured key epidemiological and analytical features, it did not formally assess the predictive performance of exposure models. For some pollutants, particularly those estimated using model-based approaches, exposure measurement error may therefore have influenced the observed associations. Third, most studies assigned exposure on the basis of residential address and could not account for individual time–activity patterns, indoor exposures, or residential mobility. Such non-differential misclassification would be expected to bias associations towards the null and may also have reduced our ability to detect small sex-specific differences. Residual confounding also remains possible, because adjustment for behavioural, socioeconomic and environmental co-exposures varied across studies.

Additional limitations relate to the structure and comparability of the evidence base itself. For several pollutant–outcome combinations, the number of contributing studies was small, often only three or four, and in some meta-analyses the pooled estimates were heavily influenced by one or two large Chinese studies with narrow confidence intervals. As a result, subgroup analyses had limited statistical power, and subgroup findings should be interpreted cautiously. The evidence base was also geographically unbalanced, with most studies conducted in China and relatively few from Europe, North America, or other regions. Given cross-country differences in pollutant mixtures, exposure levels, obesity patterns, and wider social and healthcare contexts, the generalisability of these findings to under-represented settings remains uncertain. Although standardising estimates to a common 10 μg/m^3 increment improved comparability, the relative meaning of this increment is unlikely to be equivalent across pollutants and settings; the same absolute increase may represent a different proportional exposure contrast in high- and low-exposure environments, which may have contributed to between-study heterogeneity.

Another important limitation is that obesity outcomes were pooled as reported by the primary studies. BMI and WC thresholds often reflect locally relevant or population-specific definitions of general and abdominal obesity, but these thresholds were not identical across studies. Therefore, the pooled estimates should be interpreted as syntheses of locally defined obesity outcomes rather than strictly identical outcome definitions. This may have introduced imprecision and contributed to outcome-definition heterogeneity. Similarly, some categorical estimates were reported as ORs, RRs or HRs. Although these were analysed as binary relative effect estimates and sensitivity analyses were conducted where feasible, these measures are not strictly interchangeable, particularly when outcomes are common. These limitations are reflected in the GRADE assessment, which indicated lower certainty for several pollutant–outcome combinations, mainly because of heterogeneity, imprecision, and limitations in the size and completeness of the evidence base.

These strengths and limitations indicate that the main conclusion of this review should be interpreted with caution. The available evidence is most consistent with broadly similar pollution-related obesity risks in females and males, with at most modest sex differences that vary by pollutant and adiposity measure. At the same time, gaps in confounder control, uncertainties about exposure model performance, the small number of studies for some pollutants and the dominance of data from a single country mean that more substantial sex modification in other contexts cannot be ruled out. In this sense, the evidence base is sufficient to support a cautious conclusion of largely shared susceptibility, but not to close the question of sex differences entirely.

Our findings also have several implications for future research. First, investigators should routinely plan and report sex-stratified analyses in environmental epidemiology, in line with recommendations on sex and gender equity in research (EASE, 2024; MESSAGE Writing Group WA Woodward et al., 2024). This includes presenting sex-specific effect estimates with measures of precision and formally testing interactions, rather than adjusting for sex as a covariate only. Second, future studies would benefit from more consistent and comprehensive measurement of key confounders, including diet, physical activity, smoking, socioeconomic position and co-exposures, and from considering whether these factors operate differently in females and males. Third, there is a need for well-designed longitudinal studies and collaborative meta-analyses in regions outside China to improve generalisability. Where new large-scale cohorts are not feasible, reanalysis of existing datasets with harmonised protocols and individual participant data meta-analyses may offer a cost-effective way to strengthen the evidence base. Finally, mechanistic research that combines experimental and epidemiological approaches could clarify whether specific biological pathways differ by sex, and under what conditions any such differences are clinically meaningful.

Policy implications should likewise be framed cautiously. If the associations between ambient air pollution and obesity are causal,

reducing population-level exposure has the potential to support obesity prevention in both females and males, in addition to well-established cardiovascular and respiratory benefits. Our findings do not suggest that air pollution control policies need to be targeted by sex, because both sexes appear susceptible. Rather, they reinforce the rationale for stringent air quality standards, such as those recommended by WHO, as part of broad strategies to improve population health. At the same time, the relatively small effect sizes and the limitations of the evidence mean that air pollution should be regarded as one component of a multifactorial approach to obesity, alongside interventions that address diet, physical activity and the social determinants of health.

5. Conclusion

This review indicates that sex differences in the association between ambient air pollution and obesity are modest and vary by both pollutant and adiposity measure. For general obesity, females appeared somewhat more susceptible to O_3 and NO_2 than males. In contrast, sex-stratified analyses suggested that higher $PM_{2.5}$ exposure was more clearly associated with higher odds of abdominal obesity in males. Although these effect sizes were small, they were directionally consistent and stable across multiple analyses, supporting their epidemiological relevance and indicating distinct patterns of sex-specific vulnerability.

These findings support the continued use of sex-disaggregated surveillance and the design of longitudinal studies with adequate power to test interaction, clarify underlying mechanisms and, where appropriate, inform targeted prevention within broader population-wide strategies to reduce air pollution exposure.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author(s) used ChatGPT (OpenAI) to improve the clarity and readability of the manuscript (e.g., language editing, rephrasing, and grammar checking). After using this tool, the author(s) reviewed and edited the content as needed and take (s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Xunziyin Wan: Data curation, Formal analysis, Methodology, Project administration, Software, Visualization, Writing – original draft. **Wen Li:** Data curation, Formal analysis. **Edward Mullins:** Conceptualization, Supervision, Writing – review & editing. **Fujian Song:** Methodology, Writing – review & editing. **Mark Woodward:** Methodology, Writing – review & editing. **Ana-Catarina Pinho-Gomes:** Conceptualization, Methodology, Software, Supervision, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Mark Woodward is a consultant to Perisphere.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2026.125053.

Data availability

Data will be made available on request.

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