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Review

What are the consequences of PM air pollution exposure on elderly behavior? A systematic review

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ABSTRACT

Environmental pollution poses a significant risk to human health. Particulate matter (PM) found in polluted air is particularly of concern due to its ability to penetrate the blood-brain barrier (BBB) and impact the central nervous system (CNS), affecting sensory, cognitive, and emotional well-being. The aim of this review is to provide a comprehensive overview on the latest evidence regarding the association between PM exposure and behavioral outcomes in adult and older populations. Searches were conducted across PubMed, Web of Science, and Scopus up to August 2023, with articles selected and screened following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. A total of 27 articles meeting the criteria were included, and their risk of bias was evaluated using the Newcastle Ottawa Scale. The studies primarily focused on PM2.5 and PM10 in regions such as Europe, the USA, and Asia. While data on the impact of PM exposure on sensory variables were limited, suggesting an adverse effect, overall findings indicated a link between PM exposure and worsened cognitive function, increased risk of dementia, depressive symptoms, and anxiety. Some studies highlighted sex-dependent effects of PM exposure, with women experiencing a higher prevalence of adverse effects. This review underscores the importance of further research to understand the specific cognitive aspects affected by PM exposure, particularly in relation to dementia risk.

Glossary

Abbreviations	
AGEB	Basic Geostatistical Areas
ANT	Animal Naming Test
AOD	Aerosol Optical Depth
AD	Alzheimer's disease
APOE	Apolipoprotein E
BBB	Blood-brain barrier
BDAE	Boston Diagnostic Aphasia Exam
BNT-30	Boston Naming Test
BioShaRE-EU	Biobank Standardisation and Harmonisation for Research Excellence in the European Union
B-SIT	Brief Smell Identification Test

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CAMDEX	Cambridge Examination for Mental Disorders in the Elderly
CANUE	Canadian Urban Environmental Health Research Consortium
CESD-R	Center for Epidemiologic Studies Depression Scale (Revised)
CHAP	China High Air Pollutants
CIND	Cognitive Impairment No Dementia
COWAT	Controlled Oral Word Association Test
CMAQ	Community Multiscale Air Quality
CNS	Central Nervous System
Co	Covariables
COWAT	Controlled Oral Word Association Test
CTT	Color Trails Test
CVLT	California Verbal Learning Test
DSM	Diagnostic and Statistical Manual of Mental Disorders

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EPA	Environmental Protection Agency
ESCAPE	European Study of Cohorts for Air Pollution Effects
EQ-5D-3L	European Quality of Life 5 Dimensions 3 Level Version
EURAD-CTM	European Air Quality and Dispersion Chemistry Transport Model
FDT	Frontotemporal Dementia
GDP	Gross Domestic Product
GEOS	Goddard Earth Observing System
GIS	Geographical Information System
GMS	Geriatric Mental Schedule
GWR	Geographically Weighted Regression
ICD-9	International Classification of Diseases 9th version
IR and DR	immediate recall and delayed recall
IT tool	Information Tecnology tool
JoLO-B	Judgment of Line Orientation, form B
LDST	Letter Digit Substitution Test
LNS	Letter-Number Sequencing
LUR	Land use Regression
MCI	Mild Cognitive Impairment
MESA	Multi-Ethnic Study of Atherosclerosis and Air Pollution Study
MMSE	Mini-Mental State Examination
MoCa	Montreal Cognitive Assessment
MODIS	Moderate Resolution Imaging Spectroradiometer
MS	Multiple Sclerosis
MSP	Medical Services Plan
NAD	Non-Alzheimer's dementia
NAMIS	National Ambient Air Monitoring Information System
NAMP	National Air Quality Monitoring Programme
NASA	National Aeronautics and Space Administration
NOMAS	Northern Manhattan Study
NOx	Nitrogen Oxides
O_3	Ozone
PAHs	Polycyclic Aromatic Hydrocarbons
PD	Parkinson's disease
PM	Particulate Matter
PPT	Purdie Pegboard Test
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SDMT/SDM	Symbol Digit Modalities Test
SGDS	Short Geriatric Depression Scale
Shipley-2	Shipley Institute of Living Scale
SPMSQ	Short portable Mental State Questionnaire
SRT	Selective Reminding Test
STET model	Space–Time Extremely randomized Trees
SVF	Semantic Verbal Fluency
TICS-M	Telephone Interview for Cognitive Status Survey (modified)
TMT-B	Trail Making Test-B
UFPM	Ultrafine Particulate Matter
VAD	Vascular Dementia
VFT	Verbal Fluency Test
VOCs	Volatile Organic Compounds
WAIS	Wechsler Adult Intelligence Scale
WHICAP	Washington Heights-Inwood Columbia Aging Project
WHO	World Health Organization
15-WLT	15-Word Learning Test
WMS	Wechsler Memory Scale
3-WMT test	Three-word Memory Test

1. Introduction

According to the World Health Organization (WHO), air pollution poses a significant risk to public health (World Health Organization, n.d.). Millions of individuals are exposed to air pollutants at levels surpassing legal safety standards throughout their lives (Block and Calderón-Garcidueñas, 2009; Cipriani et al., 2018; Watson et al., 2015). The WHO reports that 99 % of the global population breathes air exceeding contamination limits, with lower-income countries bearing the brunt of these exposures (World Health Organization, n.d.). This contamination is far from benign, as both indoor and outdoor pollution have been associated with increased morbidity and mortality, contributing to nearly 7 million premature deaths annually (World Health Organization, n.d.).

Air pollution is derived from different sources, such as motor vehicles, industrial facilities, forest fires, agriculture and homes among others (López-Granero et al., 2023b). The origin and composition of polluted air is diverse. It could be a mix of particulate matter (PM) gases such as nitrogen oxides (NOx) and ozone (O_3) and volatile organic compounds (VOCs) and polycyclic aromatic hydrocarbons (PAHs) produced in outdoor and/or indoor air (World Health Organization, n.d.). PM is one of the most hazardous air pollutants due to its impact on human health (Bates et al., 2019; Watson et al., 2015), and it is present in both urban and suburban air (Cipriani et al., 2018). PM is composed of solid and liquid particles suspended in the air, and its composition is variable (Liu et al., 2019).

The origin of PM is from natural sources (sea salt, naturally suspended dust, pollen, and volcanic ash) (European Environment Agency [EEA] (Copenhague, 2013) or anthropogenic sources such as motor vehicles, factories, or power plants (Zundel et al., 2022). The most common sites of PM exposure are roads with heavy traffic (Cipriani et al., 2018). These particles are classified according to their aerodynamic diameter: coarse particles (aerodynamic diameter of 2.5–10 μm, known as PM_{10}), fine particles of less than 2.5 μm, (known as $PM_{2.5}$) and ultrafine particles (less than of 0.1 μm, known as $PM_{0.1}$ or UFPM) (Cipriani et al., 2018; You et al., 2022). Within PM, $PM_{2.5}$ and $PM_{0.1}$ are the most harmful to human health given their ability to penetrate tissues, including the brain (Costa et al., 2019), and due their inefficient elimination (You et al., 2022). In addition, $PM_{2.5}$ can be suspended in air for long periods of time and travel over long distances (Chang et al., 2016).

PM affects human health (Bates et al., 2019; Fajersztajn et al., 2017; Garcia et al., 2023) and it has been associated with higher mortality rates (Chen and Hoek, 2020; Kianizadeh et al., 2022; Liu et al., 2019; Thompson, 2018), cancer mortality (Coleman et al., 2021), cardiovascular and lung diseases (Kianizadeh et al., 2022), bladder, kidney and urinary tract cancer risk (Zare Sakhvidi et al., 2020), diabetes mellitus and adverse birth outcomes (Feng et al., 2016). The mechanism/s by which PM affect the central nervous system (CNS) have yet to be fully characterized, but it has been hypothesized that PM can elicit neuroimmune and neuroinflammatory processes (Costa et al., 2019; Zundel et al., 2022).

PM can disrupt the blood–brain barrier (BBB) and translocate into the central nervous system (CNS), and thus impact behavioral and cognitive function (Costa et al., 2020; López-Granero et al., 2023b). PM can alter human behavior and affect sensory, cognitive and emotional activities (Braithwaite et al., 2019; Genter and Doty, 2019; Thompson, 2018). Behavior is characterized by complex amalgamation of various systems which result in different functions and activities (López-Granero et al., 2023a). It is the product of various functions: associative, motor, and sensory. PM can adversely affect one or more of these functions, leading to altered learning and memory processes, anxiety and depressive behavior (Heusinkveld et al., 2016; Weuve, 2012; Younan et al., 2020). Several epidemiological studies have indicated a greater risk of psychological and psychiatric diseases such as depression (Braithwaite et al., 2019; Liu et al., 2021), anxiety (Braithwaite et al., 2019; Trushna et al., 2021), psychological stress (Trushna et al., 2021), bipolar disorder (Braithwaite et al., 2019), psychosis (Braithwaite et al., 2019), suicide risk (Braithwaite et al., 2019; Liu et al., 2021) and neurological disorders (Hyunyoung Kim et al., 2020b) in humans exposed to PM during adulthood and senescence. Moreover, at the cognitive level, several studies have found associations between exposure to PM and lower cognitive functioning (Ailshire et al., 2017; Cipriani et al., 2018; Lee et al., 2022), greater cognitive decline (Kulick et al., 2020) and the prevalence of neurodegenerative diseases, such as Alzheimer's disease (Cheng et al., 2022), Parkinson's disease (Shin et al., 2018; Yuchi et al., 2020) and vascular dementia (Cheng et al., 2022).

In 2016, Clifford and colleagues (Clifford et al., 2016) conducted a review on the general effects of air pollution exposure on cognitive function across the lifespan. Our present systematic review emphasizes the importance of delving into the impact of air pollution and its potential health effects, particularly among vulnerable populations (Lee et al., 2022). People over 65 years of age have a greater risk of suffering the harmful effects of air pollution (Shumake et al., 2013) due to the degradation of physiological processes typical of age. Previously, our research team has focus on the influence of air pollution in developmental animal models (Rodulfo-Cárdenas et al., 2023; Ruiz-Sobremazas et al., 2023). Here, we aimed to identify those publications which analyzed associations between exposure to air pollutants (especially PM), with behavioral variables in the adult and elderly population. Our purpose was to broaden the understanding on specific activities and behavioral alterations upon PM exposure to incentivize future research in this field.

2. Materials and methods

2.1. Research methodology

Systematic searches were carried out according to Preferred Reporting Items for Systematic reviews and Meta-Analyses Statement (PRISMA) (See Fig. 3) (Shamseer et al., 2015). Furthermore, the protocol was preregistered in PROSPERO (registration code: CRD42023468892).

The search for this systematic review was carried out on August 2023 in three databases (Web of Science, Scopus, and PUBMED) using the following keywords: "Particulate matter", "Behavi*", "Neuro*", "Cognition", "Emotion", "Brain", "Elderly", "Adulthoood", "Adults", "Older people" and "Humans". The search formula in Scopus was: "TITLE-ABS-KEY ("Particulate Matter") AND TITLE-ABS-KEY ("Behav*" OR "Cognition" OR "Emotion" OR "Neuro*" OR "Nervous System" OR "Bioch*") AND TITLE-ABS-KEY ("Adult*" OR "Elderly" OR "older people") AND TITLE-ABS-KEY ("human") not TITLE-ABS-KEY ("Rat*" OR "Mice" OR "Animal*") AND (LIMIT-TO (DOCTYPE, "ar"))". The search formula in PubMed was: "(("Particulate Matter") AND (("Behavi*") OR ("Neuro*") OR ("Cognition") OR ("Emotion") OR ("Brain")) AND (("Elderly") OR ("Adulthood") OR ("adults") OR ("older people")) AND ("human"))". And, finally, the search formula in Web of Science was: ": (TI= ("Particulate Matter" NOT ("Rat" OR "Mice")) OR AB= ("Particulate Matter" NOT ("Rat" OR "Mice")) OR AK= ("Particulate Matter" NOT ("Rat" OR "Mice"))) AND (TI= ("Behav*" OR "Cognition" OR "Emotion" OR "Neuro*" OR "Nervous System" OR "Bioch*" NOT ("Rat" OR "Mice")) OR AB= ("Behav*" OR "Cognition" OR "Emotion" OR "Neuro*" OR "Nervous System" OR "Bioch*" NOT ("Rat" OR "Mice")) OR AK= ("Behav*" OR "Cognition" OR "Emotion" OR "Neuro*" OR "Nervous System" OR "Bioch*" NOT ("Rat" OR "Mice"))) AND (TI = ("Adulthood" OR "Elderly" OR "older people" OR "adults") OR AK= ("Adulthood" OR "Elderly" OR "older people" OR "adults") OR AB= ("Adulthood" OR "Elderly" OR "older people" OR "adults")) AND (TI = ("human") OR AK = ("human") OR AB = ("human"))". All works were included in the review, and none were excluded based on publication date.

Figs. 1 and 2 shows the current state of the relationship between exposure to PM and the most researched aspects of behavior.

2.2. Eligible criteria for inclusion

The aim of this work was to review the epidemiological literature on behavioral alterations in human elderly and adults exposed to PM. The IT tool, "Rayyan", was used for removing duplicated publications along the different databases used (Cho et al., 2023; Lee et al., 2022). Three independent reviewers analyzed all the identified articles. We applied different filters by reading the titles and abstracts to determine eligibility. Review articles and experimental studies in animal models were excluded, and only original research in humans was included. All articles were written in English. In addition, study subjects included were

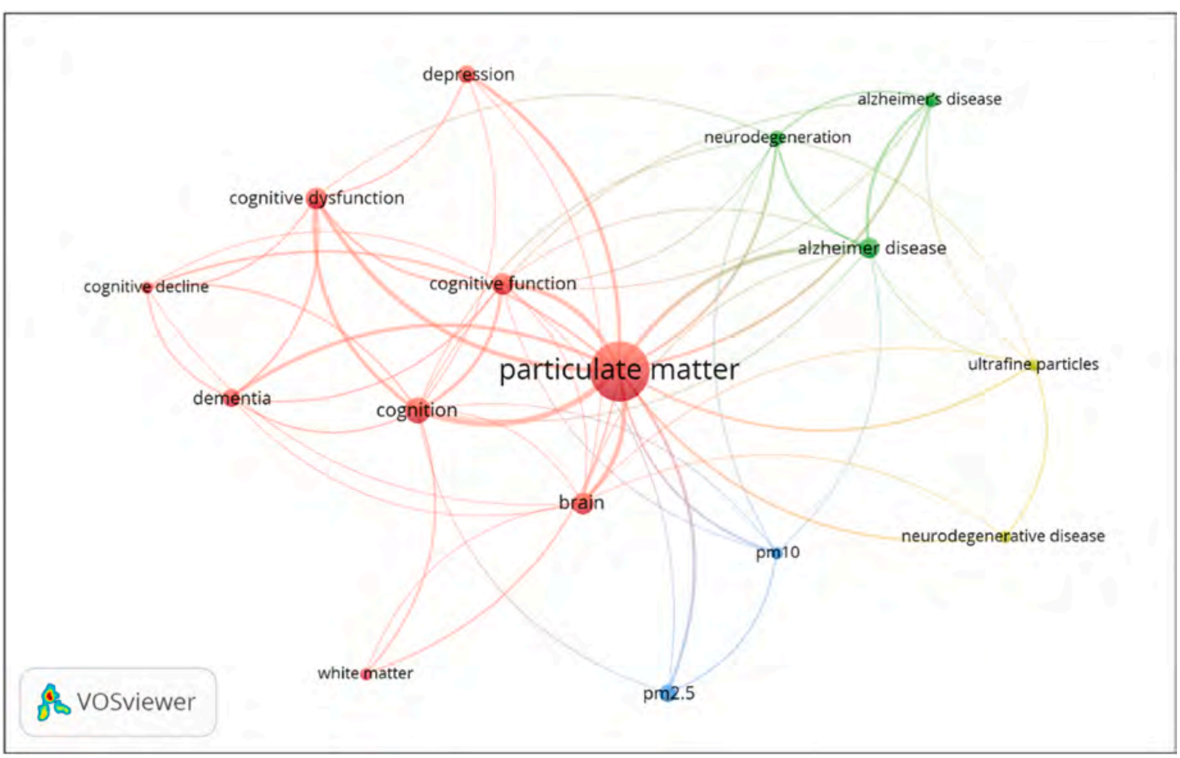

Fig. 1. Summary of the current state of knowledge on the topic under our review. We have included in the VOSViewer program the more than 300 articles that our searches returned in the PubMed, Scopus and Web of science databases. For the analysis, a minimum of 3 occasions in which the keywords appeared has been established. Thus, of the 521 total words, 73 have met the criteria for inclusion. Subsequently, we have selected those words that were relevant to our work. The larger the keyword size, the more weight that word has. The colors indicate the cluster groupings that the program automatically establishes. They highlight the numerous connections and emphasis on the connection between PM and cognitive problems. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

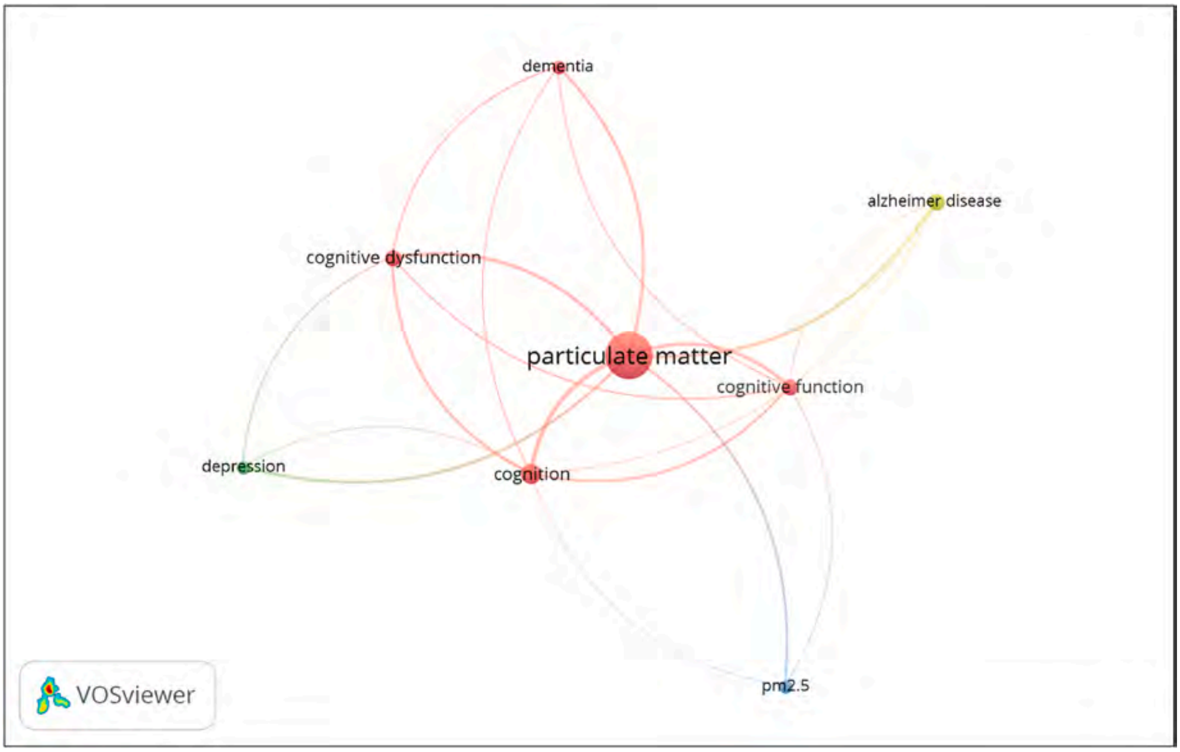

Fig. 2. This image shows more clearly the relevance of $PM_{2.5}$ on the relationship of PM with the rest of the variables. It has done establishing a minimum criterion of five occurrences and, again, filtering by those keywords relevant to our work.

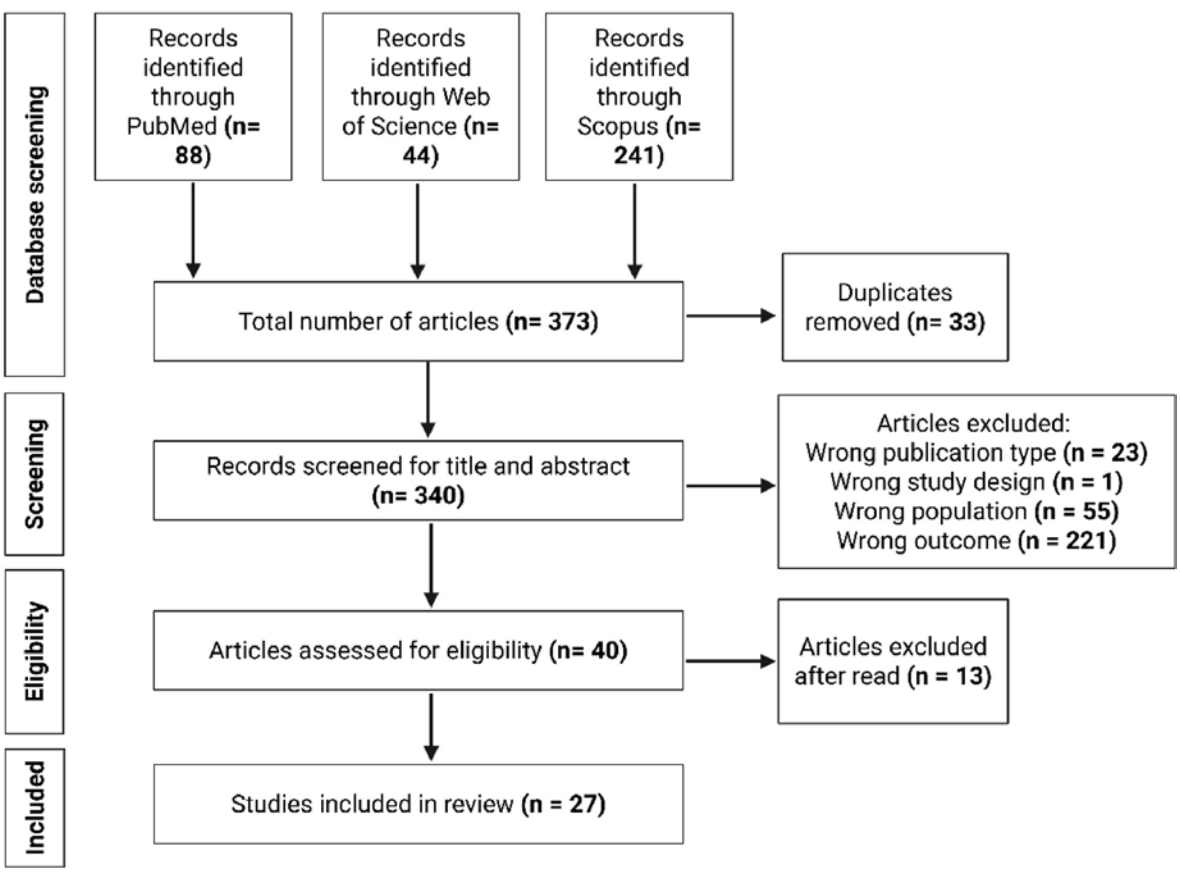

Fig. 3. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow chart.

Table 1
Summary of studies included, methods and results.

Reference & Bias	Exposure protocol: Population and Molecule origin	Exposure protocol: Molecule size & measurements	Exposure protocol: Variables and covariables (CO)	Results: Sensory variables (Sensory), Cognitive variables (Cognitive), Emotional variables (Emotional), Covariables (CO)
(Ailshire et al., 2017) Bias → 7/9	USA: 779 men and women over 55 years (mean = 67.94)	**$PM_{2.5}$:** Annual average calculated using the National Air Quality Monitoring Programme [NAMP]; quarterly measurements calculated with 24-hours mean concentrations.	Cognitive function: abbreviated form of the SPMSQ. **CO:** sociodemographic characteristics, socioeconomic factors.	**Sensory:** no reference. **Cognitive:** $PM_{2.5}$ exposure linked with ↓ cognitive function. **Emotional:** no reference. **Gender:** no differences. **CO:** stronger relationship for participants who lived in high-stress neighborhoods.
(Ajmani et al., 2016b) Bias → 6/9	USA: 2,221 men and women aged 57 to 85 years (mean = 67.9)	**$PM_{2.5}$:** 1, 3, 6, 9 and 12 months exposure estimation using GIS with monitoring sites, specific characteristics of location, meteorological and spatial smoothing of $PM_{2.5}$ average levels.	Olfactory function: short version of the Sniffin'Sticks. **CO:** sociodemographic characteristics, lifestyle variables, comorbidities, and cognitive function.	**Sensory:** $PM_{2.5}$ ↓ olfaction (6-month exposure). **Cognitive:** no reference. **Emotional:** no reference. **Gender:** no differences. **CO:** ↑ effect on: the youngest age group, those who lived in the northeast or the south, and workers (employment status).
(Altuğ et al., 2020) Bias → 6/9	Germany: 821 older women over 65 years (mean = 73.5)	**PM_{10}, $PM_{2.5}$, PM_{coarse}, $PM_{2.5abs}$:** Air pollution measures calculated using LUR models: 2008-2009 (ESCAPE project); data collected in 20 sites at different seasons (cold, warm and intermediate). Covariables, derived from GIS models, were also controlled.	(CESD-R). **CO:** sociodemographic characteristics, anthropogenic measurements, lifestyle variables, comorbidities, cognitive function.	**Sensory:** no reference. **Cognitive:** no reference. **Emotional:** PMcoarse, $PM_{2.5}$ and $PM_{2.5abs}$ were associated with self-reported diagnosis of depression. PM_{10} and $PM_{2.5}$ were associated with ↑ depressive symptoms. **Gender:** Only women. **CO:** ↑ risk of depressive symptoms for participants with ↓ cognitive scores and ↑ risk of self-reported diagnosis and depressive symptoms for those who live near to major roads (<100m).
(Cao et al., 2023) Bias → 4/9	USA: 3,345 older women over 50 years (mean = 54.3)	**$PM_{2.5}$:** 900 monitors and 200 geographic covariates were used to calculate $PM_{2.5}$ 2-week average and annual concentrations from 2006 to 2017.	Olfactory function: The B-SIT. **CO:** sociodemographic characteristics, anthropogenic measurements, lifestyle variables and socioeconomic factors, depression.	**Sensory:** exposure to $PM_{2.5}$ not associated with ↓ olfaction in primary analysis.$PM_{2.5}$ linked with ↓ olfaction within the younger age group (<54.2 y). **Cognitive:** no reference. **Emotional:** no reference. **Gender:** Only women. **CO:** baseline $PM_{2.5}$ was associated with ↓ olfaction among younger women.
(Cho et al., 2023) Bias → 6/9	South-Korea: 640 men and women over 50 years (mean = 67.4)	**PM_{10}:** Calculated for five years prior to enrollment of each participant using Kriging model and air quality monitoring data in approximately 300 sites (Kim & Song, 2017). **$PM_{2.5}$:** long-term exposure to $PM_{2.5}$ was estimated as 1-year average concentrations in 2015.	MoCA-K. **CO:** sociodemographic characteristics, anthropogenic measurements, comorbidities, mean cortical thickness and cortical atrophy.	**Sensory:** no reference. **Cognitive:** ↑ PM_{10} and $PM_{2.5}$ linked with ↓ MoCA score and PM_{10} was associated with the risk of suspected MCI. PM_{10} and $PM_{2.5}$ linked with ↓ cortical thickness and PM_{10} linked with ↑ AD-like cortical atrophy. **Emotional:** no reference. **Gender:** no differences. **CO:** Mean cortical thickness and AD-like cortical atrophy z-score mediated the associations between PM_{10} and MoCA score and suspected MCI. Mean cortical thickness mediated the association between $PM_{2.5}$ and MoCA score.
(Cullen et al., 2018) Bias → 5/9	UK: 86,759 men and women aged 40 to 69 years (mean = 56.86)	**PM_{10}, $PM_{2.5}$ to $_{10}$ and $PM_{2.5}$:** Air pollution measures were calculated using LUR models: 2005-2007 (LUR based on BioShaRE-EU maps combined with EU-wide air pollution maps and EuroAirnet monitoring sites) 2010 (LUR based on ESCAPE project) PM_{10} calculated in 2007, $PM_{2.5}$ to PM_{10} and $PM_{2.5}$ calculated in 2010.	Cognitive function: numeric memory (maximum digits remembered), reasoning (verbal-numerical reasoning), reaction time (programmed task: Snap), visuospatial memory (pairs-matching), prospective memory (programmed task: prospective memory) via computerized touchscreen interface. **CO:** sociodemographic characteristics, socioeconomic variables, lifestyle variables and environmental factors.	**Sensory:** no reference. **Cognitive:** Weak association between air pollution and cognitive performance and barely significant results (or positive relationship between PM and cognitive performance). **Emotional:** no reference. **Gender:** no differences. **CO:** no differences.

(de Crom et al., 2023) Bias → 8/9	Netherlands: 7,511 men and women (mean = n.s.)	**PM_{10}, $PM_{2.5}$ and $PM_{2.5abs}$:** Annual averages were calculated using LUR models between February 2009 and February 2010 (ESCAPE project; 40 locations in the Netherlands and Belgium in 14 days of cold, intermediate, and warm seasons). Covariables (traffic, land use, population density, and altitude) were calculated with GIS.	**Dementia:** MMSE and the GMS organic level. CAMDEX for participants with lower score. Final diagnosis established by a consensus panel. **Cognitive function:** MMSE, LDST, word fluency test, Stroop test, 15-WLT, and the PPT. **CO:** anthropogenic measurements, socioeconomic variables, lifestyle variables, depression and APOE genotype.	**Sensory:** no reference. **Cognitive:** No clear associations were found between PM and risk of dementia or cognitive impairment. For $PM_{2.5}$, the highest risk of dementia was for those in the second and fourth quartiles compared to those in the first or third. **Emotional:** no reference. **Gender:** no differences. **CO:** Risk slightly higher in APOE ε4 carriers and in participants <70 years.
(Gatto et al., 2014) Bias → 6/9	USA: 1,496 men and women (mean = 60.5)	**$PM_{2.5}$:** Air pollution calculated with GIS-based system including a 24-hour range for PM2.5. Data supplemented with monthly average $PM_{2.5}$ concentration in Southern California Children's Health Study (Peters et al., 2004). Detection performed using Federal Reference Methods and Federal Equivalent Methods.	Cognitive function: executive function (SDMT; TMT-B; Letter-Number Sequencing and Shipley-2, Abstraction Subtest), verbal learning (CVLT-II: IR and DR), logical memory (Paragraph Recall-IR and DR (WMS-III), visual processing: JoLO-B and Block Design (WAIS-III), visual epi. Memory (Faces, IR and DR (WMS-III), and semantic memory (ANT and BNT-30). **Co:** sociodemographic characteristics, socioeconomic variables, comorbidities.	**Sensory:** no reference. **Cognitive:** $PM_{2.5}$ exposure was not significantly associated with general cognitive function but yes with less verbal learning. **Emotional:** no reference. **Gender:** no differences. **CO:** no differences.
(He et al., 2020) Bias → 7/9	China: 7,311 men and women over 60 years (mean = 68.6)	**$PM_{2.5}$ and PM_{10}:** Daily concentrations measured between 2013-2015 were used from the Department of Ecology and Environment of Zhejiang Province.	Cognitive function: Chinese version of the MMSE. **CO:** sociodemographic characteristics, anthropogenic measurements, socioeconomic variables, lifestyle variables, comorbidities.	**Sensory:** no reference. **Cognitive:** Exposure to $PM_{2.5}$ and PM_{10} ↑ the risk of cognitive impairment. **Emotional:** no reference. **Gender:** no differences. **CO:** No differences.
(Hu et al., 2023) Bias → 5/9	China: 12,481 men and women over 45 years (mean = 59)	**$PM_{2.5}$:** Data calculated starting at March 2000 until the month prior evaluation, using a machine learning algorithm based on AOD, land use information, and gridded meteorological parameters from MODIS.	Cognitive function: TICS-M (orientation, numeric ability, word recall and visuospatial ability). **CO:** sociodemographic characteristics and socioeconomic variables.	**Sensory:** no reference. **Cognitive:** lower and higher $PM_{2.5}$ intensity ↑ cognitive function (U-shaped association). Second PM2.5 exposure duration group (13-60 months) ↓ cognitive function. **Emotional:** no reference. **Gender:** ↓cognitive function in women. **CO:** relationship between cumulative $PM_{2.5}$ exposure and cognitive function ↑ significant in rural areas. ↑ age related with ↑ effect of PM.
(Hu et al., 2022) Bias → 6/9	China: 8,536 men and women over 45 years (mean = 58.6)	**PM_1, $PM_{2.5}$ and PM_{10}:** Daily PM_1 and $PM_{2.5}$ obtained from spatiotemporal approaches, air monitoring stations, meteorology, and land use characteristics; PM_{10} concentrations obtained from air monitors placed by the State Environmental Protection Administration of China in Beijing. Average concentrations were calculated prior 2015.	Cognitive function: episodic memory (instant and delayed word recall), orientation and attention TICS, and visuospatial ability (The figure drawing test). **CO:** sociodemographic characteristics, anthropogenic measurements, blood measures, lifestyle variables and comorbidities, domestic solid fuel use, lung function.	**Sensory:** no reference. **Cognitive:** Improved air quality in PM_1, $PM_{2.5}$ and PM_{10} linked with ↓ prevalence of cognitive impairment. Stronger association for $PM_{2.5}$. The cumulative effect ↑ the benefit of cognitive function. **Emotional:** no reference. **Gender:** reduction of PM_1 was more beneficial for men. **CO:** no differences.
(Ji et al., 2022) Bias → 7/9	China: 9,231 men and women over 65 years (mean = 82.5)	**$PM_{2.5}$:** Ground-level $PM_{2.5}$ concentrations were calculated using Atmospheric Composition Analysis Group combining AOD, Multi-angle Imaging Spectro-Radiometer, and Sea-viewing field-of-view Sensor satellite instruments.	MMSE. **CO:** sociodemographic characteristics and lifestyle variables.	**Sensory:** no reference. **Cognitive:** ↑ $PM_{2.5}$ was associated with a ↓ MMSE score and a ↑ risk of cognitive impairment. **Emotional:** no reference. **Gender:** The negative association between $PM_{2.5}$ and MMSE score was stronger in women **CO:** ↓ exposures to $PM_{2.5}$, homozygous minor alleles showed higher MMSE score.
(Hyunmin Kim et al., 2020) Bias → 6/9	South-Korea: 2,729 men and women over 50 years (mean =68.22 in women	**PM_{10}:** a prediction model, for five years, developed by Kim and Song (2017) based on the kriging prediction approach. Covariables (geography, traffic, etc.) were considered. **$PM_{2.5}$:**	Depression and depressive symptoms: SGDS-K. Depressive symptoms as the cut-off 8 point. **CO:** Anthropogenic measurements, socioeconomic variables, lifestyle variables and comorbidities.	**Sensory:** no reference. **Cognitive:** no reference. **Emotional:** Positive relationship between PM_{10} and depressive symptoms or SGDS-K in metropolitan areas, but negative relationship between $PM_{2.5}$ and depressive symptoms or SGDS-K in non-metropolitan areas. **Gender:** Men (married) lower depressive symptoms.

	and 69.58 in men)	average concentrations of 2015.		**CO:** Married lower depressive symptoms in non-metropolitan areas.
(Kulick et al., 2020) Bias → 7/9	USA: Two samples: 5,330 men and women over 65 years (mean = 75.2) in WHICAP and 1,093 men and women over 40 years (mean = 70.3) in NOMAS	**$PM_{2.5}$ and PM_{10}:** PM data obtained with EPA Air Quality System data using Kriging regression; sensitivity analyses calculated in a subsample of WHICAP using MESA Air data.	Memory (Modified CVLT [in NOMAS] and SRT [in WHICAP]); executive function (CTT), COWAT [in both] and Odd Man Out and Digit Reordering [in NOMAS] and Identities and Oddities; similarities subtest WAIS [in WHICAP]; language (BNT (15-item), ANT and CTT [both] and Grooved Pegboard, LNS, SDM [in NOMAS] and Comprehension subtest from BDAE [in WHICAP]. **CO:** sociodemographic characteristics, socioeconomic factors.	**Sensory:** no reference. **Cognitive:** $PM_{2.5}$ and PM_{10} linked with ↓ global cognitive function and ↑ rates of decline in cognitive function (WHICAP) No significant association found in NOMAS. **Emotional:** no reference. **Gender:** no differences. **CO:** no differences.
(Lee et al., 2022) Bias → 5/9	South-Korea: 4,175 men and women aged over 50 years (mean = 67.8)	**$PM_{2.5}$ and PM_{10}:** Short (1-14 days), medium (1, 3, and 6 months) and long-term (1, 2, and 3 years) exposure was calculated using CMAQ model was selected to measure air quality.	Cognitive function: K-MMSE. **CO:** sociodemographic characteristics, anthropogenic measurements, lifestyle variables, comorbidities, season.	**Sensory:** no reference. **Cognitive:** ↑ $PM_{2.5}$ exposure (short, medium, and long-term) is linked with ↓ cognitive scores. ↑ PM_{10} exposure (medium, and long-term) is linked with ↓ cognitive scores. **Emotional:** no reference. **Gender:** The effects of long-term exposure to $PM_{2.5}$ and PM_{10} were ↑ in women. **CO:** adverse effects of long-term exposure to PM in the group that was over 75 years old, in non-drinkers, in those who did not exercise and in those who had never smoked.
(Ogurtsova et al., 2023) Bias → 8/9	Germany: 2,554 men and women over 45 years (mean = 63.2)	**$PM_{2.5}$, PM_{10}, Source $PM_{2.5}$ PN_{acc} (accumulation mode particle number):** annual mean air pollution was calculated using LUR model: 2009 (ESCAPE project). Daily PN_{acc}, PM_{10} and $PM_{2.5}$ and source-specific fractions of $PM_{2.5}$ were estimated using EURAD-CTM model and then the estimates were validated using daily measurements from monitoring stations (PM_{10} and $PM_{2.5}$), TSI 3926 spectrometer (PN_{acc}) at the state monitoring station (2011-2014), and source suppression method (source $PM_{2.5}$).	Cognitive decline: verbal fluency (VFT, ANT), problem solving/speed of processing (labyrinth test), immediate and delayed verbal memory (verbal memory test), and abstraction/visual-spatial organization (clock-drawing test). **CO:** anthropogenic measurements, socioeconomic variables, lifestyle variables, depression, *APOE ε4* and MCI. Noise exposure (independent variable).	**Sensory:** no reference. **Cognitive:** PM_{10}, $PM_{2.5}$ and $PM_{2.5abs}$ linked with ↓ score on the immediate verbal memory test. **Emotional:** no reference. **Gender:** no differences. **CO:** stronger association between ap and more rapid decline in global cognition for *APOE ε4* allele carriers and participants with MCI.
(Parra et al., 2022) Bias → 9/9	UK: 187,194 men and women over 60 years (mean = 64.1)	**$PM_{2.5}$, PM_{10}, $PM_{2.5\text{-}10}$, $PM_{2.5abs}$:** Air pollution data were obtained from the Small Area Health Statistics Unit as part of the BioSHaRE-EU Environmental Determinants of Health Project. Annual average concentrations for 2010 was calculated using LUR models developed by ESCAPE and completed with monitoring of 20 different areas.	Dementia (AD, VAD and FDT): UK Biobank database: dementia cases identified by algorithm (Wilkingon et al., 2019) from participant self-reports and from record linkage in death records and hospital admissions. **CO**: sociodemographic characteristics, socioeconomic variables, lifestyle variables and comorbidities, APOE-ε4.	**Sensory:** no reference. **Cognitive:** Positive associations between $PM_{2.5}$ and all-cause dementia. **Emotional:** no reference. **Gender:** no differences. **CO:** no differences.
(Ran et al., 2021) Bias → 9/9	China: 57,775 men and women over 65 years (mean = n.s.)	**$PM_{2.5}$:** Annual $PM_{2.5}$ concentration between 1998-2011 was calculated with AOD from two NASA satellites. Ground-level $PM_{2.5}$ concentration was calculated with AOD from four general monitoring stations in Hong Kong.	Diagnosis of dementia (all-cause dementia, ADs and vascular dementia): registry of hospitalizations for dementia. The diagnosis of hospitalization was coded with the ICD-9. **CO:** sociodemographic characteristics, anthropogenic measurements, socioeconomic variables, lifestyle variables and comorbidities.	**Sensory:** no reference. **Cognitive:** ↑ $PM_{2.5}$ exposure linked with ↑ risk of all-cause dementia. **Emotional:** no reference. **Gender:** no differences. **CO:** ↓ intensity physical activity linked with ↑ risk of dementia from all causes, independent of $PM_{2.5}$ levels.

(Salinas-Rodriguez et al., 2018) Bias → 6/9	Mexico: 7,986 men and women over 60 years (mean = 69.9)	**$PM_{2.5}$:** Average concentrations calculated for five years with AOD information based on NASA and GEOS data. AGEB data was used to match the corresponding estimated PM2.5 concentrations.	Cognitive function: SVF and 3-WMT tests. **CO:** sociodemographic characteristics, socioeconomic variables, lifestyle variables, comorbidities, indoor air pollution, depression.	**Sensory:** no reference. **Cognitive:** $PM_{2.5}$ ↑ the likelihood of worse cognitive function using both the SVF and 3WMT. **Emotional:** no reference. **Gender:** no differences. **CO:** no differences.
(Shim et al., 2023) Bias → 9/9	South-Korea: 1,436,361 men and women over 65 years (mean = 70.9)	**PM_{10}:** Hourly concentrations between 2008 and 2019 were obtained from the NAMIS (186 monitoring stations) and confirmed by the National Institute of Environmental Research of South-Korea. 24-hour mean concentrations were calculated for the 137 districts. Also, averaged daily values over 12 months for each district was calculated.	ADs, vascular dementia and others: based on records in the neurology/psychiatry area (1 inpatient or 2 outpatient) and medications for dementia. **CO:** sociodemographic characteristics, anthropogenic measurements, socioeconomic variables, lifestyle variables, comorbidities, depression, and ecological factors.	**Sensory:** no reference. **Cognitive:** Long term exposure to PM_{10} linked with ↑ risk of vascular dementia, but not with ADs. **Emotional:** no reference. **Gender:** ↑ risk for men. **CO:** ↑ risk for people under 75 years of age.
(Shin et al., 2018) Bias → 9/9	USA: 2,194,519 men and women over 55 years (mean = 67)	**$PM_{2.5}$:** calculated using optimal estimation AOD satellite retrieval obtained from the NASA (annual concentrations between 1998-2012).	PD: was defined as the first qualifying health services contact for which a diagnosis of PD is confirmed. **CO:** sociodemographic characteristics, socioeconomic variables, comorbidities.	**Sensory:** no reference. **Cognitive:** $PM_{2.5}$ exposure was associated with PD but the relationship was attenuate with long lags (5 and 10 years). **Emotional:** no reference. **Gender:** no differences. **CO:** ↑ risk for participants with diabetes, stroke or brain injury.
(Tan et al., 2023) Bias → 6/9	China: 5,717 men and women over 65 years (mean = 71.85)	**$PM_{2.5}$ and PM_{10}:** STET model with AOD and CHAP datasets were calculated for 5 years annual ground-level concentrations.	Health-related quality of life: Chinese version of EQ-5D-3L (mobility, self-care, usual activities, pain/discomfort, and anxiety/depression). **CO:** sociodemographic characteristics, anthropogenic measurements, socioeconomic variables, lifestyle variables and comorbidities	**Sensory:** $PM_{2.5}$ exposure linked with ↑ pain/discomfort. **Cognitive:** no reference. **Emotional:** $PM_{2.5}$ and PM_{10} exposures linked with ↑ anxiety/depression. **Gender:** no differences. **CO:** Stronger associations for urban residents, high education level, high-income level and chronic conditions.
(Wang et al., 2020) Bias → 7/9	China: 13,324 men and women over 65 years (mean = 82.4)	**$PM_{2.5}$:** Exposure estimates were derived from a remote sensing provided by the Institute of Atmospheric Physics, University of Dalhousie (van Donkelaar et al., 2016; Boys et al., 2014). Data obtained with LUR model with AOD information, calibrated with GWR model. Air pollution data were since 2013.	Cognitive function: Chinese version of the MMSE **CO:** sociodemographic characteristics, socioeconomic variables, lifestyle variables and comorbidities.	**Sensory:** no reference. **Cognitive:** ↑ $PM_{2.5}$ linked with ↑ risk of poor cognitive function. **Emotional:** no reference. **Gender:** ↑ risk of poor cognitive function for men. **CO:** ↓ effect in cognitive function for ≥100 years group.
(Wu et al., 2022) Bias → 9/9	Sweden: 1,987 men and women over 60 years (mean = 71.6)	**$PM_{2.5}$ and PM_{10}:** Calculated using spatiotemporal dispersion modeling based on meteorological data and local emissions inventories for 1990, 1995, 2000, 2005, and 2011. Average annual levels obtained using linear interpolation compared with three different monitor stations at Stockholm. 2012 and 2013 data were the same as in 2011.	CIND and cognitive impairment in at least one: memory (free call), executive function (TMT-B), language (Category and Letter Fluency), visuospatial (mental rotation) or perceptual speed function (digit cancellation and pattern comparison). Dementia: DSM-IV and Swedish National Cause of Death Register and clinical medical records. **CO:** sociodemographic characteristics, socioeconomic variables, lifestyle variables.	**Sensory:** no reference. **Cognitive:** Exposure to $PM_{2.5}$ and PM_{10} linked with ↑ incidence of CIND (weak association for PM_{10}) and their progression to dementia, with pollution being a risk factor. **Emotional:** no reference. **Gender:** no differences. **CO:** no differences.
(Yao et al., 2022) Bias → 7/9	China: 2,812 men and women over 60 years (mean = 81)	**$PM_{2.5}$ and PM_{10}:** Annual average concentrations were taken from a database (Xiao et al., 2020) that used an atmospheric chemical transport model. Average concentrations of PM were calculated for 12 months prior survey. Land surface temperature also controlled.	MMSE. **CO:** sociodemographic characteristics, socioeconomic variables, lifestyle variables, environmental factors.	**Sensory:** no reference. **Cognitive:** Clean air policy group had smaller ↓ in MMSE scores. Inverse relationship between $PM_{2.5}$ and MMSE scores. **Emotional:** no reference. **Gender:** no differences. **CO:** The estimated effect of clean air on MMSE was better for participants <75 years, non-Han ethnicity, >5 years of education, married or exercised regularly.

(Younan et al., 2022) Bias → 8/9	USA: 2,232 women over 74 years (mean = n.s.)	**$PM_{2.5}$:** Kriging models with partial least squares regression of geographic covariables and EPA monitoring were used to obtained $PM_{2.5}$ concentrations from 1993 and updated biannually.	General cognitive status: TICS-M Episodic memory: CVLTm **CO:** sociodemographic characteristics, anthropogenic measurements, socioeconomic variables, lifestyle variables and comorbidities, use of any postmenopausal hormone treatment, depression, and *ApoE e4*.	**Sensory:** No reference. **Cognitive:** ↓ $PM_{2.5}$ linked with slower rates of decline in general cognitive status and episodic memory (equivalent to slower cognitive declines for TICSm and CVLT in women who were 0.9-1.2 years and 1.4-1.6 years younger at enrollment). **Emotional:** No reference. **Gender:** No reference (only women). **CO:** no differences.
(Yuchi et al., 2020) Bias → 8/9	USA: 678,000 men and women aged 45 to 84 years (NAD cases mean = 76; NAD Non-cases mean = 57; PD cases mean = 72; and PD non-cases mean = 58)	**$PM_{2.5}$:** Monthly air pollution measures (1994-1998) were calculated using LUR models based on 25 monitoring sites, along with 55 geospatial variables. Sensitivity analyses was performed with satellite-based $PM_{2.5}$ from LUR model (from the CANUE), and a GWR with the ground measurements for residual bias.	Cases of dementia: diagnosis from hospital records, physician visits from MSP and prescriptions from PharmaNet to identify incident cases of NAD, AD, PD, and MS. **CO:** sociodemographic characteristics, socioeconomic variables, comorbidities and environmental factors.	**Sensory:** no reference. **Cognitive:** $PM_{2.5}$ exposure linked with ↑ risk index for NAD and PD and MS. **Emotional:** no reference. **Gender:** risk slightly higher for women for PD and NAD. **CO:** living near major roads ↑ NAD, AD, MS and PD. ↑ effects on NAD y PD for people <65 y.

Note 1: Sociodemographic characteristics: age, gender, race/ethnicity, education, location, employment status, marital status, living alone, living conditions. Socioeconomic variables: income, insurance, expenditure, socioeconomic status (SES), annual regional gross domestic product (GDP). Lifestyle variables: smoking, physical activity, alcohol, fruit intake, vegetable intake, water, social contact, fish/shrimp consumption, exposure to environmental tobacco smoke, time outdoors. Environmental factors: temperature, major road proximity, traffic intensity and population density, noise, greenness. Comorbidities: diabetes, cerebrovascular disease, cancer, cardiovascular diseases, blood pressure, hyperlipidemia, hypertension, dementia, traumatic brain injury, pulmonary diseases, chronic liver disease, hypercholesterolemia, dyslipidemia, chronic lung disease, liver disease, chronic kidney disease, stomach disease, emotional problem, glucose, serum creatinine, blood urea nitrogen, cholesterol, triglycerides, cystatin C, uric acid, C-reactive protein, and glycosylated hemoglobin A1c and disability. Anthropogenic measurements: BMI, height, weight.

Note 2: NAPM = National Air Quality Monitoring Programme; SPMSQ = Short Portable Mental State Questionnaire; GIS = Geographical Information System; LUR = Land Use Regression; ESCAPE = European Study of Cohorts for Air Pollution Effects; CESD-R = Center for Epidemiologic Studies Depression Scale Revised; B-SIT = Brief Smell Identification Test; MoCA = Montreal Cognitive Assessment; AD = Alzheimer's disease ; MCI = ; BioShaRE-EU = ; GMS = Geriatric Mental Schedule; CAMDEX = Cambridge Examination for Mental Disorders in the Elderly; LDST = Letter-Digit Substitution Test; WLT = 15-Word Learning Test; PPT = Purdie Pegboard Test; SDMT = Symbol Digit Modalities Test; TMT-B = Trail Making Test-B ; CVLT = California Verbal Learning Test ; IR and DR = immediate recall and delayed recall; WMS = Wechsler Memory Scale; JoLO-B = Judgment of Line Orientation, form B; WAIS = Wechsler Adult Intelligence Scale; ANT = Animal Naming Test; BNT = Boston Naming Test; MMSE = Mini-Mental State Examination; AOD = Aerosol Optical Depth; MODIS = Moderate Resolution Imaging Spectroradiometer; TICS = Telephone Interview for Cognitive Status Survey; SGDS = Short Geriatric Depression Scale; EPA = Environmental Protection Agency; WHICAP = Washington Heights-Inwood Columbia Aging Project; MESA = Multi-Ethnic Study of Atherosclerosis and Air Pollution Study; NOMAS = Northern Manhattan Study; SRT = Selective Reminding Test; CTT = Color Trails Test; COWAT = Controlled Oral Word Association Test; LNS = Letter-Number Sequencing; SDM = Symbol Digit Modalities; BDAE = Boston Diagnostic Aphasia Exam; CMAQ = Community Multiscale Air Quality; EURAD-CTM = European Air Quality and Dispersion Chemistry Transport Model; VFT = Verbal Fluency Test; APOE = Apolipoprotein E; MCI = Mild Cognitive Impairment; VAD = Vascular Dementia; FDT = Frontotemporal Dementia; NASA = National Aeronautics and Space Administration; GEOS = Goddard Earth Observing System; AGEB = Basic Geostatistical Areas; SVF = Semantic Verbal Fluency; 3-WMT = Three-word Memory Test; NAMIS = National Ambient Air Monitoring Information System; PD = Parkinson's disease; STET = Space–Time Extremely randomized Trees; CHAP = ; EQ-5D-3L = European Quality of Life 5 Dimensions 3 Level Version; GWR = Geographically Weighted Regression; CIND = Cognitive Impairment No Dementia; TMT-B = Trail Making Test-B; DSM-IV = Diagnostic and Statistical Manual of Mental Disorders; CANUE = Canadian Urban Environmental Health Research Consortium ; MSP = Medical Services Plan; NAD = Non-Alzheimer's dementia; MS = Multiple Sclerosis; Shipley-2 = Shipley Institute of Living Scale; IV = Independent Variable; n.s. = Not specified.

Table 2
Summary of sensory functions altered by PM exposure.

Reference	Country	PM exposure	Sensory function affected	Sex-Dependent?
Ajmani et al. (2016b)	USA	$PM_{2.5}$	Olfactory function	No
Cao et al. (2023)	USA	$PM_{2.5}$	Olfactory function	Only women
Tan et al. (2023)	China	$PM_{2.5}$	Pain/discomfort	No

Note: No: no differences.

adults or older populations. Moreover, articles studying the effects of PM exposure on organs other than the brain were excluded. We also excluded articles that were limited to smoking exposure or other pollutants, not PM, and articles that used only indoor exposures. However, smoking exposure was included in some studies as a covariable.

Studies published from any country worldwide were included, with no restrictions based on the country studied. We focused on articles studying sensory, cognitive and emotional processes as well as brain structure. Finally, in a second reading, each study was carefully examined.

2.3. Quality assessment using the Newcastle-Ottawa scale for epidemiological studies

To assess risk of bias, the Newcastle-Ottawa scale (Wells et al., 2015) was used. This scale has already been used previously in different systematic reviews (e.g. (Paterson et al., 2021), and comprises three domains: selection (e.g.: "Selection of the non-exposed cohort", where come from the same community as the exposed cohort, if it is drawn from a different source or if it does no description of the derivation of the non-exposed cohort), comparability ("comparability of cohorts on the basis of the design or analysis" and is selected between whether they are study controls for the most important factor or whether controls are studied for any additional factors) and outcome (e.g., "Was follow-up long enough for outcomes to occur?" and select between yes or no). Each study could obtain up to one "star" for each element within the selection and results categories and up to a maximum of two in comparability. The total score was 9 points, with a higher score indicating a lower risk of bias.

Finally, the authors evaluated independently each study using the above mentioned scale. The differences were resolved by consensus. No studies were excluded due to their bias level.

3. Results

3.1. Study selection and risk of bias

The complete search strategy is shown in the flow chart in Fig. 3. After carrying out searches in the three databases (PubMed, Web of Science y Scopus), we found a total of 373 articles, of which we eliminated 33 because they were duplicates. Subsequently, according to the title and abstract, we eliminated a total of 300 articles for representing a different type of publication (other systematic reviews, meta-analysis, etc.), wrong study design (parametric computation to quantify prevalence), wrong sample (different to human samples of adult and older age) or wrong outcome (incidence of cancer, for example). The remaining 40 articles were carefully read, and we eliminated additional 13 of them following the same criteria by consensus. The final selection included 27 articles (Table 1).

With respect to bias assessment (See Table 1), the scale does not present cuts or categorize by levels. However, we found that 15 articles had a score between 7 and 9 points (the maximum contemplated by the scale), corresponding to 55.56 % of the articles; the other 44.44 % of the articles had a score between 4 and 6 points. None of the included articles scored below 4 points on the scale. We included colors to indicate the range of quality. The yellow color indicates a score on the scale in the range of 4–6 points. The green color indicates a score on the scale in the range of 7–9 points.

Table 3
Summary of cognitive functions altered by PM exposure.

Reference	Country	PM exposure	Cognitive function affected	Sex-dependent?
Ailshire et al. (2017)	USA	$PM_{2.5}$	Cognitive function	No
Cho et al. (2023)	South-Korea	$PM_{2.5}$, PM_{10}	Global cognitive function and suspected MCI	No
Cullen et al. (2018)	UK	PM_{10}, $PM_{2.5\ to\ 10}$, $PM_{2.5}$	No clear associations were found	No
de Crom et al. (2023)	Netherlands	PM_{10}, $PM_{2.5}$, $PM_{2.5abs}$	No clear associations were found	No
Gatto et al. (2014)	USA	$PM_{2.5}$	Verbal learning	No
He et al. (2020)	China	$PM_{2.5}$, PM_{10}	Chinese version of MMSE	No
Hu et al. (2022)	China	PM_1, $PM_{2.5}$, PM_{10}	Cognitive function	↓ in women for PM1
Hu et al. (2023)	China	$PM_{2.5}$	Cognitive function	↓ in women
Ji et al. (2022)	China	$PM_{2.5}$	Chinese version of MMSE	↓ in women
Kulick et al. (2020)	USA	$PM_{2.5}$, PM_{10}	In WHICAP cohort: Global Cognitive Function	No
Lee et al. (2022)	South-Korea	$PM_{2.5}$, PM_{10}	K-MMSE	↓ in women (long-term exposure)
(Ogurtsova et al., 2023)	Germany	$PM_{2.5}$, PM_{10}	Immediate verbal memory	No
Parra et al. (2022)	UK	$PM_{2.5}$,	$PM_{2.5}$ and all-cause dementia	No
Ran et al. (2021)	China	$PM_{2.5}$	All-cause dementia	No
Salinas-Rodríguez et al. (2018)	Mexico	$PM_{2.5}$	Semantic verbal fluency and free recall	No
Shim et al. (2023)	South-Korea	PM_{10}	Vascular dementia and Alzheimer's disease	↓ in men (VAD)
Shin et al. (2018)	USA	$PM_{2.5}$	Parkinson's disease	No
Wang et al. (2020)	China	$PM_{2.5}$	Chinese version of MMSE	↓ in men
Wu et al. (2022)	Sweden	$PM_{2.5}$, PM_{10}	CIND and dementia	No
Yao et al. (2022)	China	$PM_{2.5}$	MMSE	No
Younan et al. (2022)	USA	$PM_{2.5}$	General cognitive status and episodic memory	Only women
Yuchi et al. (2020)	USA	$PM_{2.5}$	Medical records of dementia	No

Note: ↓: poor performance; -: Not analyzed; No: no differences. MMSE = Mini-Mental State Examination; MCI = Mild Cognitive Impairment; CIND = Cognitive Impairment No Dementia.

3.2. Study population

The studies included in the analysis were primarily conducted in the USA (29.6 %) and China (29.6 %), with South Korea (14.8 %), Germany (7.4 %), UK (7.4 %), Netherlands (3.7 %), Mexico (3.7 %), and Sweden (3.7 %) also represented. The majority of studies included both men and women (88.9 %), while a minority focused solely on women (11.1 %). In terms of age groups, most studies included subjects over 65 years old (25.9 %). Other studies set the cut-off age at 60 years (18.5 %), 57 years (3.7 %), 55 years (11.1 %), 50 years (11.1 %), 45 years (14.8 %), or 40 years (3.7 %). One isolated study included subjects over 74 years of age (3.7 %).

3.3. Air pollution measurements and methods

Few studies incorporated data directly from air pollution monitors. Only 18.52 % of the articles included in the review collected and sampled $PM_{2.5}$ pollution data from the atmosphere with street monitors (Ailshire et al., 2017; Cao et al., 2023; He et al., 2020; Hu et al., 2022; Shim et al., 2023). Specifically, He and colleagues included street monitor data with spatiotemporal approaches and land use characteristics (He et al., 2020).

In contrast, 81.48 % of the articles used different models (Aerosol Optical Depth [AOD]; Land use Regression [LUR]; Kriging regression; Geographical Information System [GIS], spatiotemporal dispersion modeling; atmospheric composition group analyses) to calculate or estimate the $PM_{2.5}$, PM_{10} or any other PM measurement. Specifically, 27.27 % of the articles that did not use street monitors selected the AOD model to predict air pollution quantity (Hu et al., 2023; Ran et al., 2021; Salinas-Rodríguez et al., 2018; Shin et al., 2018; Tan et al., 2023; Wang et al., 2020). However, several articles did not only use AOD, but a combination of AOD with other models like Stet-model (Tan et al., 2023), land-use information, meteorological parameters from the NASA (Hu et al., 2023), and LUR model (Wang et al., 2020).

Only 27.27 % of the articles used LUR models to predict air pollution (Altuğ et al., 2020; Cullen et al., 2018; de Crom et al., 2023; Ogurtsova et al., 2023; Parra et al., 2022; Yuchi et al., 2020). In addition, several authors opted to complement LUR models with other methods such as GIS-modeling for covariables (de Crom et al., 2023), physical monitoring in different areas (Parra et al., 2022) or EURAC data (Ogurtsova et al., 2023). Following the LUR models, the Kriging model was used by only 18.18 % of the articles (Cho et al., 2023; Hyunmin Kim et al., 2020a; Kulick et al., 2020; Younan et al., 2022). Analogous to the above, several authors combined the Kriging regression modeling with other methods such as leas squares regression combined with EPA physical monitoring (Younan et al., 2022), or physical monitoring alone (Cho et al., 2023). GIS models were used in only 9.09 % of the studies (Ajmani et al., 2016b; Gatto et al., 2014), and were combined with other methods such as physical monitoring (Gatto et al., 2014).

Finally, 18.18 % of the articles relied on other less common methods such as other author's PM measurements (Yao et al., 2022), spatiotemporal dispersion modeling (Wu et al., 2022), atmospheric composition analysis group (Ji et al., 2022), and chemical transport modeling (calculated in the Community Multiscale Air Quality (CMAQ) (Lee et al., 2022).

3.4. Human behavioral system: sensory, cognitive and emotional alterations after PM exposure

3.4.1. Effects of PM on sensory process

From the total of the twenty seven analyzed articles, three analyzed the effects of PM exposure on sensory system, specifically on perception process. These articles evaluated $PM_{2.5}$ as environmental pollutant. Two studies (Ajmani et al., 2016b; Cao et al., 2023) analyzed the impact of $PM_{2.5}$ on olfactory ability, finding in both cases worsening olfaction associated with exposure to $PM_{2.5}$, although one of them (Cao et al., 2023) only in younger participants (54.2 years). Ajmani and colleagues found greater adverse effect of $PM_{2.5}$ in younger participants (that is in subjects between 57 and 64 (Ajmani et al., 2016b). The third article analyzed the relationship between air pollution and interoceptive perception, noting a positive relationship between $PM_{2.5}$ exposure and pain/discomfort perception (Tan et al., 2023). Table 2 shows a summary of the results on the sensory effects of PM.

3.4.2. Effects of PM on cognitive function

Most articles found worse cognitive performance in humans exposed to $PM_{2.5}$ (Ailshire et al., 2017; Cho et al., 2023; He et al., 2020; Ji et al., 2022; Kulick et al., 2020; Lee et al., 2022; Ogurtsova et al., 2023; Salinas-Rodríguez et al., 2018; Wu et al., 2022) and PM_{10} (Cho et al., 2023; He et al., 2020; Kulick et al., 2020; Lee et al., 2022; Ogurtsova et al., 2023; Wang et al., 2020; Wu et al., 2022). The studies corroborated that higher exposure to PM increased not only the risk of cognitive decline (Cho et al., 2023; Ji et al., 2022), but also the speed of cognitive decline (Kulick et al., 2020), showing a positive correlation between the degree of exposure and the degree of cognitive impairment (He et al., 2020).

In general, there were few articles that analyzed the impact of PM on specific cognitive functions, with aspects related to memory being more frequent (Cullen et al., 2018; Gatto et al., 2014; Ogurtsova et al., 2023; Salinas-Rodríguez et al., 2018; Younan et al., 2022). Table 3 shows a summary of the areas of cognition affected by PM exposure.

Moreover, the analyzed studies showed that higher exposure to PM increases the risk of dementia. Ran and collaborators in 2021 noted a positive relationship between exposure to $PM_{2.5}$ and the risk of all-cause dementia (Ran et al., 2021). Wu et al. also indicated positive associations between exposure to $PM_{2.5}$ and PM_{10} and Cognitive Impairment no Dementia [CIND] and progression to dementia (Wu et al., 2022). Yuchi and co-authors (2020) observed that higher exposure to $PM_{2.5}$ was associated with increased risk for non-Alzheimer's dementia, Parkinson's disease, and multiple sclerosis (Yuchi et al., 2020). Shim, Byun and Lee (2023) indicated that long term exposure to PM_{10} was associated with higher risk of vascular dementia, but not with Alzheimer's disease (Shim et al., 2023), and Shin et al. (2018) found an association between exposure to $PM_{2.5}$ and Parkinson's disease (Shin et al., 2018). Finally, Parra et al. (2022) found positive associations between $PM_{2.5}$ exposures and all dementia measures (that is all-cause dementia, Alzheimer's disease and incident vascular dementia), but not with incident frontotemporal dementia. Additionally, in the adjusted models both $PM_{2.5}$ and $PM_{2.5}$ had similar effects, and the risk for dementia was higher at the highest level of exposure. However, associations between $PM_{2.5\text{-}10}$ with any type of dementia were noted (Parra et al., 2022).

Nonetheless, there are also studies which failed to note significant associations between PM and cognitive function (Gatto et al., 2014; Kulick et al., 2020), or risk of dementia or cognitive impairment (de Crom et al., 2023). Several authors have even indicated that lower and higher $PM_{2.5}$ intensity was related with better cognitive function (Hu et al., 2023). Furthermore, Cullen and collaborators (2018) observed a positive relationship between exposure to PM and improved

Table 4
Summary of emotional functions altered by PM exposure.

Reference	Country	PM exposure	Emotional function affected	Sex-Dependent?
Altuğ et al. (2020)	Germany	$PM_{2.5}$, PM_{10}, $PM_{2.5abs}$, PMcoarse	Diagnosis of depression and depressive symptoms	Only women
(Hyunmin Kim et al., 2020a)	South-Korea	$PM_{2.5}$, PM_{10},	Depressive symptoms	↓ in women
Tan et al. (2023)	China	$PM_{2.5}$, PM_{10},	Anxiety and depression	No

Note: ↓: Worst emotional score; No: no differences.

performance in verbal-numerical reasoning (Cullen et al., 2018).

In this review, structural damage was included in the results as a supplement for cognitive effects. However, only one article included structural variables (Cho et al., 2023). This study utilized a sample of subjects over 50 years of age and found a relationship between increased PM_{10} exposure, decreased cortical thickness and increased AD-like cortical atrophy. Associations were also reported between increased PM_{10} exposure and decreased cortical thickness, although not with cortical atrophy (Cho et al., 2023). The structural results were obtained with magnetic resonance imaging. Furthermore, it was found that the effect of exposure to PM_{10} on the scores on the MoCA scale was mediated by mean cortical thickness and AD-life cortical atrophy scores, which could be a risk factor or related to lower cognitive function (Cho et al., 2023).

3.4.2.1. Cognitive task and processes evaluated. Questionnaires are commonly used to assess general cognitive function, with a better score being associated with better cognitive function. The most cited questionnaire is the MMSE (Folstein et al., 1975; He et al., 2020; Ji et al., 2022; Lee et al., 2022; Wang et al., 2020; Yao et al., 2022), its versions adapted to different languages, although others are included such as the TICS-M (Brandt, n.d.) (Hu et al., 2023; Younan et al., 2022) which evaluates orientation, numerical ability, word recall or visuospatial ability; the MoCA scale (Nasreddine et al., 2005; Cho et al., 2023) or the SPMSQ (Pfeiffer, 1975; Ailshire et al., 2017) among others. These questionnaires include exercises that evaluate different areas. The SPMSQ evaluates working memory and orientation (Pfeiffer, 1975); the MoCA orientation, attention, language abstraction, visuospatial/executive function, naming and episodic memory (Nasreddine et al., 2005); the MMSE orientation, concentration, attention, verbal memory, naming and visuospatial skills (Folstein et al., 1975).

In some cases, authors evaluated cognitive function using various questionnaires. Salinas-Rodriguez and collaborators used SVF (semantic verbal fluency test) and 3-WMT (three-word memory test) (Salinas-Rodríguez et al., 2018) or Gatto (et al., 2014), assessing six specific domains of cognitive functions (executive function, verbal learning, logical memory, visual processing, memory and semantic memory (Gatto et al., 2014). In addition, several studies included a sum of tests in different areas: for example, Kulick (et al., 2020) included task for memory, executive function and language (Kulick et al., 2020). Wu assessed cognitive impairment no dementia (CIND) and cognitive impairment with a battery of test about episodic memory, executive function, language, visuospatial or perceptual speed function (Wu et al., 2022). Hu and collaborators include episodic memory, orientation and attention and visuospatial ability (Hu et al., 2022). Ogurtsova et al. assessed verbal fluency, problem solving/speed of processing, immediate and delayed verbal memory, and abstraction/visual-spatial organization (Ogurtsova et al., 2023). De Crom et al. utilized MMSE, LDST, word fluency test, Stroop test, 15-WLT, and the PPT (de Crom et al., 2023). And finally, Cullen et al. included numeric memory, reasoning, reaction time, visuospatial memory and prospective memory (Cullen et al., 2018).

3.4.2.2. Effects of cleaning air programs on cognitive process. Although most of the analyzed articles evaluated the impact of exposure to PM on behavior, there were three publications which addressed the benefit in reducing PM levels by air cleaning programs (Hu et al., 2022; Yao et al., 2022; Younan et al., 2022). The PM included in these studies were PM_1 (Hu et al., 2022), $PM_{2.5}$ (Hu et al., 2022; Yao et al., 2022; Younan et al., 2022) and PM_{10} (Hu et al., 2022; Yao et al., 2022). In all cases, they found that a decrease over time in exposure to PM and improvements in air quality reduced the prevalence of cognitive impairment.

Regarding $PM_{2.5}$, the three articles point to better cognitive performance associated by reducing exposure to $PM_{2.5}$ (Hu et al., 2022; Yao et al., 2022; Younan et al., 2022). Yao (et al., 2022) noted that the intervention group had a smaller decrease in MMSE scores compared to the control group, although in addition to PM2.5 other pollutants were included in the analyses (Yao et al., 2022). Finally, Younan (et al., 2022) found that women who experienced improvements in air quality had a slow cognitive decline in the Telephone Interview for Cognitive Status (modified version) and California Verbal Learning Test (telephone-based).

Several other studies with PM_1 and PM_{10} were identified. Hu et al. (2022) noted a protective effect of PM_1 reduction on prevalence of cognitive impairment. Finally, both, Hu et al. (2022) and Yao (2022) also analyzed the impact of reduction in PM_{10} exposure. Hu et al. (2022) found a protective effect of PM_{10} reduction with a lower prevalence of cognitive decline, while Yao et al. (2022) failed to note significant differences of PM_{10} reduction on MMSE scores (Hu et al., 2022; Yao et al., 2022).

3.4.3. Effects of PM on emotional variables

Only three articles considered emotional variables, specifically depression (Altuğ et al., 2020; Hyunmin Kim et al., 2020a; Tan et al., 2023) and anxiety symptoms (Tan et al., 2023). Two of these studies (Altuğ et al., 2020; Tan et al., 2023) found positive relationships between exposure to PM_{10} and $PM_{2.5}$ and depressive symptoms. Altuğ (et al., 2020) also found positive associations between $PM_{2.5abs}$ and PMcoarse and the diagnosis of depression (Altuğ et al., 2020). Tan (et al., 2023) found positive associations between exposure to $PM_{2.5}$ and PM_{10} and anxiety (Tan et al., 2023). Kim (et al., 2020) found a similar relationship, but only among those subjects who lived in metropolitan areas (Hyunmin Kim et al., 2020a).

Regarding other characteristics of these studies, although the three studies analyzing emotional variables in the aging process, one of them (Hyunmin Kim et al., 2020a) included participants over 50 years of age. The other two included samples of individuals older than 65 years of age (Altuğ et al., 2020; Tan et al., 2023). All three used different scales; the scales used by Altuğ (et al., 2020) and Kim (et al., 2020) focused on depressive symptoms (CESD-R and SGDS-K, respectively) (Altuğ et al., 2020; Hyunmin Kim et al., 2020a), while Tan (et al., 2023) used a scale that measures other variables such as mobility, self-care, usual activities and pain/discomfort (Tan et al., 2023). Table 4 shows a summary of the emotional functions affected by PM.

3.5. Human covariates related with air pollutants: sociodemographic, gender-dependent, age, physical and lifestyle analyses

3.5.1. Sociodemographic analyses

Most of the studies included in this review failed to find differences in the results by including covariates in their models (Gatto et al., 2014; Hu et al., 2022; Kulick et al., 2020; Parra et al., 2022; Salinas-Rodríguez et al., 2018; Wu et al., 2022; Younan et al., 2022). For example, in some studies, sex had no effect on the results of PM exposure (Ailshire et al., 2017; Ajmani et al., 2016b; Cho et al., 2023; Cullen et al., 2018; de Crom et al., 2023; Gatto et al., 2014; He et al., 2020; Kulick et al., 2020; Parra et al., 2022; Ran et al., 2021; Salinas-Rodríguez et al., 2018; Shin et al., 2018; Tan et al., 2023; Wu et al., 2022; Yao et al., 2022; Younan et al., 2022) or there were authors that used samples exclusively of women (Altuğ et al., 2020; Cao et al., 2023).

Despite of disparity in the results, other studies found a higher risk for women (Lee et al., 2022; Ogurtsova et al., 2023) for worsened cognitive scores or cognitive impairment upon PM exposure, as well as dementias such as Parkinson's disease and non-Alzheimer's dementia (Yuchi et al., 2020). Hu and co-authors (2022) found that PM_1 reductions were more beneficial for men (Hu et al., 2022). Other authors indicated mixed results. For example, Ji (et al., 2022) found that the negative association between $PM_{2.5}$ exposure and MMSE scores is stronger in women over 80 and men under 80 (Ji et al., 2022). Other studies noted an opposite relationship, pointing to a higher risk for men for developing vascular dementia (Shim et al., 2023) or increased risk of

Country	# Studies
USA	8
Germany	2
South-Korea	4
UK	2
Netherlands	1
China	8
Mexico	1
Sweden	1

Fig. 4. Geographical distribution of studies included.

lower cognitive function (Wang et al., 2020). In addition, being married has been seen in some studies as a protective effect (Hyunmin Kim et al., 2020a; Yao et al., 2022), but Kim (et al., 2020) found a protective effect in relationship to PM exposure only for men. In addition, several studies indicated a higher impact of PM exposure in younger compared to aged populations (Ajmani et al., 2016b; Cao et al., 2023). Specifically, Cao and colleagues found higher impact of $PM_{2.5}$ exposure on olfactory function in younger women (under 54 years old). Shim et al. (2023) found a higher risk of vascular dementia in youngest section of the sample (men under 75 years of age) (Shim et al., 2023) and De Crom et al. (2023) found increased association between PM exposure and Alzheimer's disease in participants under 70 years of age (de Crom et al., 2023).

However, other studies indicated an opposite relationship. For example, He (et al., 2020) indicated a higher rate of cognitive decline in older people (He et al., 2020) and Yao et al. (2022) better MMSE scores for participants under 75 years of age (Yao et al., 2022). Lee et al. (2022) found a greater risk of PM exposure on cognitive function in the group of participants over 75 years of age (Lee et al., 2022). Wang et al. (2020) noted a stronger association between $PM_{2.5}$ and cognitive deterioration in the youngest group (65–79 years old) and in the oldest group ($\geq$100 years old) (Wang et al., 2020). And finally, Yuchi et al. (2020), found a higher risk of non-Alzheimer's disease and Parkinson's disease in participants over 65 years of age.

Another widely studied variable was years of education. Yao et al. (2022) found that participants with education beyond primary school had higher scores on the MMSE (Yao et al., 2022). Tan et al. (2023), on the other hand, found stronger adverse effects among those participants with a higher educational level (Tan et al., 2023). Related to education, three studies found differences in other variables such as current employment situation and socioeconomic level. Ajmani and colaborators found a greater impact of $PM_{2.5}$ for workers compared to those who did not work (Ajmani et al., 2016b). A greater impact of $PM_{2.5}$ exposure on cognitive function was seen for those with decreased prefecture-level GDP (Wang et al., 2020). Tan et al. (2023) found stronger adverse effects among those with high levels of income (Tan et al., 2023).

3.5.2. *Lifestyle analyses*

Ran (et al., 2021) (Ran et al., 2021) found a greater risk of dementia from all causes in those participants with lower intensity physical activity level. Yao et al. observed that those who exercise regularly scored higher on MMSE (Yao et al., 2022). Lee et al. indicated that the effect of PM exposure was more harmful in non-drinkers and in non-smokers (Lee et al., 2022).

3.5.3. *Environmental measures*

Among environmental variables, differences in location have also been noted, related to where the participants resided. Wang et al. (2020) found that the relationships between $PM_{2.5}$ and poor cognitive function were stronger for those living in western China compared to those in eastern and central China (Wang et al., 2020). Ajmani and colaborators found that the association between $PM_{2.5}$ and poor olfaction was stronger for those living in the northeast or southern US compared to those who living in West or Midwest (Ajmani et al., 2016b). Tan et al. (2023) found that the impact of pollution had stronger adverse effects for those living in urban areas (Tan et al., 2023).

Related to location, Altuğ et al. (2020) found a higher risk of depressive symptoms for those who lived near main roads (Altuğ et al., 2020) and Yuchi et al. (2020) noted that living in green areas is a protective factor for non-Alzheimer's disease and Parkinson's disease (Yuchi et al., 2020). Furthermore, Ailshire et al. (2017) suggested stronger relationships between $PM_{2.5}$ and worsened cognitive function in subject living in neighborhoods with high levels of stress (Ailshire et al., 2017). Yuchi et al. (2020) also found a higher risk for non--Alzheimer's disease in those living in neighborhoods with a percentage of Chinese population greater than 10 % (Yuchi et al., 2020). Finally, Yao (et al., 2022) found better MMSE scores in non-Han ethnicity population compared to people of Han ethnicity (Yao et al., 2022).

3.5.4. *Comorbidities and genotype*

Comorbidities such as stroke, diabetes or brain injury have also been associated with a higher risk for Parkinson's disease (Shin et al., 2018). Tan et al. (2023) found associations between PM and quality of life were stronger among those participants with chronic conditions such as diabetes, cardiovascular disease, hypertension or cancer (Tan et al., 2023).

Another variable is APOE ε4. Ji et al. (2022) found that at low levels of exposure to $PM_{2.5}$, those participants with homozygous minor APOE ε4 alleles had better cognitive scores (Ji et al., 2022). On the other hand, De Crom et al. (2023) found that those who were APOE ε4 carriers had a higher risk of cognitive impairment associated with exposure to PM (de Crom et al., 2023) and Ogurtsova et al. (2023) showed that they had a more rapid cognitive decline (Ogurtsova et al., 2023).

4. Discussion

The aim of this work was to analyze the published literature on PM and behavioral changes in the adult and elderly population. Our main objective was to characterize the complex and specific effects of PM on behavioral functions. In general, the analyzed literature revealed sensory, emotional and cognitive alterations related to poor air quality. Some of the studies found greater susceptibility in women, although this was inconsistent across the various articles. $PM_{2.5}$ was the PM most analyzed in the literature. It can readily cross the lungs and enter into the circulatory system, causing systemic and neuronal inflammation characterized by oxidative damage (Bates et al., 2019; Liu et al., 2021).

Three of the analyzed articles (Ajmani et al., 2016b; Cao et al., 2023; Tan et al., 2023) indicated a relationship between PM and olfactory function (see Table 2). The impact on the olfactory system aligns with the primary route for PM entry into the body. PM can affect the CNS through several pathways, and one of them is inhalation (Costa et al., 2019). In turn, PM can be deposited in the lungs as well as in the olfactory cortex and other brain regions (Ajmani et al., 2016a; Costa et al., 2019). Notably, PM can also directly enter the brain from inhaled air via the olfactory neuroepithelum (Genter and Doty, 2019). While the composition of PM was not specifically addressed in this review, it is probable that the olfactory system is influenced by repeated exposure to environmental particles containing substances like aluminum, cadmium, nickel, chromium, lead, manganese, and zinc, among others (Genter and Doty, 2019).

Regarding the origin of the analyzed studies, it is noteworthy that all of them were conducted in the Northern Hemisphere (USA, China, South Korea, Germany, UK, Netherlands, Mexico and Sweden). This highlights the lack of representation of studies from the Southern Hemisphere or developing countries (see Fig. 4). These results may be due to the fact that most developed countries have access to technology and systems that allow for air quality monitoring, which are later used to implement air quality policies (United Nations Environment, 2019). On the other hand, developing or underdeveloped countries do not have the same level of access to such technology, and research in this field is therefore limited (United Nations Environment, 2019). In this regard, some authors (Martin et al., 2019) have reported a higher proportion of PM2.5 monitors per million inhabitants in Northern Hemisphere countries compared to those in the Southern Hemisphere.

One of the primary effects of PM is on cognitive processing. Results across studies were generally consistent (see Table 3). The vast majority of the studies reported inverse relationships between PM exposure and cognitive functioning (Ailshire et al., 2017; Cho et al., 2023; He et al., 2020; Ji et al., 2022; Kulick et al., 2020; Lee et al., 2022; Ogurtsova et al., 2023; Salinas-Rodríguez et al., 2018; Wang et al., 2020; Wu et al., 2022) and between PM exposure and dementia (Parra et al., 2022; Ran et al., 2021; Shim et al., 2023; Shin et al., 2018; Wu et al., 2022; Yuchi et al., 2020). Within cognitive functioning, memory was most analyzed in the articles included in this review (for example, (Cullen et al., 2018; Ogurtsova et al., 2023; Younan et al., 2022). Although most articles calculated total scores or used scales that evaluate general cognitive functioning, there were some that provided results on the impact of PM on specific functions of cognition, in most cases various types of memory (Cullen et al., 2018; Ogurtsova et al., 2023). In this respect, the importance of episodic memory as a factor related to the development of Alzheimer's disease has been previously informed (Gallagher and Koh, 2011). Several authors documented the importance of episodic memory as a factor related to the development of Alzheimer's disease. Notably, Alzheimer's disease is the most common dementia among older people (H. Niu et al., 2017a) and its incidence, as well as that of other dementias, has been increasing in recent years due to increased life expectancy and aging, which represent the greatest risk factors for the development of dementia (H. Niu et al., 2017a). However, other reasons might be ascribed to protracted exposure to pollutant concentrations exceeding established safe limits (Block and Calderón-Garcidueñas, 2009), in turn, leading to higher rates of dementia or cognitive impairment, as noted in this review.

Nevertheless, there are some studies that failed to find significant associations between PM exposure and cognitive function (de Crom et al., 2023; Gatto et al., 2014), or found contradictory results. For example, both low and high levels of $PM_{2.5}$ intensity were related to weak improved cognitive function (Cullen et al., 2018; Hu et al., 2023). Nevertheless, the number of these studies is limited and may be ascribed to limitations such as small study areas, samples without cognitive impairment, or errors in the measurement of cognitive tests. In this context, the authors have highlighted certain factors that need to be considered, including the absence of individual-level pollutant measures and the use of air pollution data from different years (Cullen et al., 2018). These limitations stablish the relevance of time interval between the exposure of PM and cognitive evaluation.

Emotional processes were also analyzed in this systematic review. The published literature indicated a positive relationship between PM exposure and the risk of depression or anxiety (Altuğ et al., 2020; Tan et al., 2023). Kim et al. found similar relationships with depression, but only for those living in metropolitan areas (Hyunmin Kim et al., 2020a) (see Table 4). Depression is the emotional factor related to cognitive decline, which has received most academic attention. In geriatric samples, depression frequently occurs along with a measured cognitive decline (Modrego and Ferrández, n.d.; Rapp et al., 2011). Geriatric depression can be considered as a risk factor for Alzheimer's disease (Rapp et al., 2011) and raise the risk for dementia (Barnes et al., 2012; Ownby et al., 2006). Depression is also associated with cognitive decline and with the incidence of mild cognitive impairment (Feola et al., 2013; Wilson et al., 2014). These distinct pathologies are frequently confused (Dillon et al., 2014). On the other, it has been observed that social networks and social activity led to a positive self-evaluation concerning health, i.e. subjective well-being in elderly subjects residing in rural areas by evaluating the number of years spent in education and the level of social support (Tobiasz-Adamczyk and Zawisza, 2017). However, this subjective well-being lessened in rural areas when related to perceived levels of loneliness (Tobiasz-Adamczyk and Zawisza, 2017). In addition, being married was invoked as a protective factor, especially for men (Hyunmin Kim et al., 2020a,b). Furthermore, exposure to air pollution was lower in rural areas compared to urban areas, and the effects of air pollution appeared to be more significant in cities (Zhou et al., 2022).

Regarding covariates analyses, sex appeared as a significant variable in the relationship between exposure to PM and behavioral alterations; however, the results were not consistent. Several studies failed to note association between sex and PM exposure (Ailshire et al., 2017; Ajmani et al., 2016b; Cho et al., 2023; Cullen et al., 2018; de Crom et al., 2023; Gatto et al., 2014; He et al., 2020; Kulick et al., 2020; Parra et al., 2022; Ran et al., 2021; Salinas-Rodríguez et al., 2018; Shin et al., 2018; Tan et al., 2023; Wu et al., 2022; Yao et al., 2022; Younan et al., 2022). However, others found a sex-dependent increase between PM exposure and cognitive function in women, (Ji et al., 2022; Lee et al., 2022; Ogurtsova et al., 2023; Yuchi et al., 2020). In contrast, two of analyzed studies revealed a greater risk for men for lower cognitive function (Wang et al., 2020) or developing vascular dementia (Shim et al., 2023). Mo and co-authors found a greater vulnerability to the effect of PM on cognitive aging in women (Mo et al., 2023). Bell and colleagues found that the number for hospitalization were higher in women exposed to $PM_{2.5}$ (Bell et al., 2015). Furthermore, Gong et al. found a higher risk of dementia in women, especially in places with low-income levels (Gong et al., 2023). In general, socioeconomic level, years of education, educational level or GDP (Gross Domestic Product) (Tan et al., 2023) and lower level of income (Tan et al., 2023; Wang et al., 2020) were associated with declined cognitive function regardless of gender. The results about education are desirable and worthy of study given that learning and cognitive training during life can reduce cognitive decline (Baumgart et al., 2015). This effect is such that even levels of formal education and literacy (measured through level of education reached) have been associated with a lower risk of dementia (Baumgart et al., 2015; Beydoun et al., 2014).

Among the covariates, APOE ε4 must be considered for its relationship with Alzheimer's disease. Although only a few studies included it as a covariate (de Crom et al., 2023; Ji et al., 2022; Ogurtsova et al., 2023; Parra et al., 2022; Younan et al., 2022), and two of them did not find differences (Parra et al., 2022; Younan et al., 2022). Other studies suggested a greater risk of developing cognitive impairment in APOE ε4 carriers upon PM exposure (de Crom et al., 2023; Ogurtsova et al., 2023). *APOE* is a polymorphic gene in humans, and among the three human ApoE alleles (ε2, ε3, ε4), the apoE4 confer increased risk for AD and cognitive impairment after injury (Michaelson, 2014). Interestingly, it was shown that the ε4 allele was expressed in greater than half of AD patients, and is the most prevalent genetic risk factor for sporadic AD especially in females. This is especially relevant yet the proportion of ε4 carriers in general population are about 25 %. They also found that the risk of AD for this reason was greater for women (Riedel et al., 2016). Taken together, the literature corroborates that a genetic factor mediates the relationship between PM and neurodegeneration. This might also be related to results reported herein, which indicated a greater susceptibility to the effects of PM in women, where a multifactorial relationship exists, where each of the factors is interrelated with the other.

In summary, future research should aim to characterize the composition of particulate matter (PM) and its specific effects on human health. In particular, there is a pressing need to investigate the impact of PM exposure on distinct cognitive domains, such as attention and various subdomains of memory. Prior studies have reported associations between PM exposure and impairments in specific cognitive functions, including immediate verbal memory (Ogurtsova et al., 2023) and episodic memory (Younan et al., 2020). Additionally, evidence suggests a high prevalence of attention deficits correlated with poorer air quality (Min and Min, 2017). Conversely, other research (Chen et al., 2021) indicates that PM exposure is associated with deficits in domains such as language and overall cognitive performance, but not in orientation or recall. A comprehensive analysis of these cognitive subdomains may provide a more nuanced understanding of the cognitive repercussions of PM exposure and help identify the functions most susceptible to its deleterious effects.

Moreover, assessing the impact of air quality and generating robust evidence in this domain is essential for guiding governmental strategies aimed at mitigating pollution. Countries such as China and the United States have already implemented air pollution reduction policies, which have been associated with decreased rates of cognitive impairment (Yao et al., 2022), depression (Xue et al., 2021), and even dementia (Nethery et al., 2021). These findings suggest that the formulation and execution of targeted public health and environmental policies may significantly reduce population-level exposure to air pollutants, thereby lowering the incidence of neurodegenerative and psychiatric disorders. Additionally, early detection strategies for neurological deficits could be incorporated into these policies, as proposed by Chen et al. (2021), facilitating more efficient use of healthcare resources. Economically, the burden of PM exposure is substantial; for instance, in China—the world's largest developing nation—annual economic losses attributable to pollution-related health outcomes are estimated in the millions of dollars (Niu et al., 2017a,b). Importantly, the implementation of pollution control measures has been projected to yield not only public health benefits, including a reduction in pollution-related mortality, but also significant decreases in national healthcare expenditures (Chen et al., 2017).

Amongst the strengths of this systematic review, we highlight the following (1) the search of the literature in three databases; (2) the analyses of the evidence on the relationship between PM and behavioral systems and some of its subdomains, including sensory, cognitive or emotional variables in the aging process; (3) the entire search and selection process were carried out by three authors, to avoid researchers' own biases and; (4) this systematic review covered a broad spectrum of both cognitive and emotional health outcomes, facilitating a broader psychological view of the impact of PM. Nonetheless, several limitations should be noted, (1) there are other variables, such as noise, green areas, stress or variables of lifestyle that have not been considered in the analyses; (2) not all articles took into account other pollutants that may have synergistic effects with PM; (3) the use of questionnaires whose results were grouped into a single score making it difficult to determine the effect of PM in a particular behavioral subdomain, and (4) finally, the composition of the PM was not taken into account. We are aware that PM are mixtures of solid and liquid particles found in the air and whose composition is heterogeneous, and may include (among others) carbon, metals, sulfates or nitrates. Future works should analyze the composition of these PM and their impact on human health.

5. Conclusions

This study compiled current evidence on the relationship between exposure to particulate matter (PM) and the behavioral system, focusing on sensory, cognitive, and emotional variables in adulthood and aging. Contemporary evidence suggests links between PM exposure and sensory, cognitive, and emotional systems in human health across various countries in Europe, Asia, and North America. While a consensus is lacking, most publications suggest a higher susceptibility to PM effects in women. It is important to note that factors such as educational level, marital status, social interactions, residential areas, and genetic influences also play a role in the outcomes of PM exposure. When considering these variables in the context of PM exposure, there appears to be increased vulnerability to cognitive impairment, potentially leading to a higher risk of dementia. This systematic review underscores the need for a detailed examination of changes in the behavioral system and its subdomains as a foundation for future research into the effects of PM on specific aspects of cognition and their underlying mechanisms. Finally, further research in this field could contribute to the implementation of air quality improvement policies, which, in turn, may help reduce the future incidence of cognitive impairment, dementia, and other related conditions in our society.

CRediT authorship contribution statement

Blanca Cativiela-Campos: Writing – original draft, Validation, Conceptualization. **Diego Ruiz-Sobremazas:** Validation, Conceptualization. **Rocío Rodulfo-Cárdenas:** Validation, Conceptualization. **Angel Barrasa:** Supervision, Conceptualization. **Fernando Sánchez-Santed:** Validation, Supervision, Conceptualization. **Maria Teresa Colomina:** Validation, Supervision, Conceptualization. **Michael Aschner:** Writing – review & editing, Supervision. **Caridad López-Granero:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

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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.

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Data availability

No data was used for the research described in the article.

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