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Review

Air Pollution Effects on Mental Health Relationships: Scoping Review on Historically Used Methodologies to Analyze Adult Populations

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Abstract: Air pollution's effects on physical health, especially cardiovascular and respiratory, are well known. Exposure to air pollution may damage every organ and cell in the human body. New evidence is emerging showing that air pollution adversely affects human mental health. Current research suggests that high air pollution levels have long-term mental health effects, such as reduced mental capacity and increased cognitive decline, leading to increased stress, anxiety, and depression. Objectives: This scoping review aims to provide a comprehensive overview of the methods used in epidemiological literature to ascertain the existence of links between outdoor particulate matter (PM) and multiple adverse mental health (MH) effects (depression, anxiety, and/or stress). A better understanding of the practical research methodologies could lead to improved air quality (AQ) management and enhanced well-being strategies. Methods: This paper undertakes a scoping review. PubMed and EMBASE databases from 2010 to 2024 were searched for English-language human cohort observational studies stating methodologies used in analyzing the link between outdoor particulate matter (ultrafine (UFT) (<0.1 μm), fine (<2.5 μm), and course (<10 μm)) and mental health outcomes (depression, anxiety, and stress) in adults (>18 years), excluding vulnerable populations (i.e., elderly, children, and pregnant women). The study focuses on urban, suburban areas, and rural areas. Results: From an initial search of 3889 records, 29 studies met the inclusion criteria and were included in the review. These studies spanned various countries and employed robust quantitative methodologies to assess AQ and MH. All included studies investigated the impact of PM on mental health, with some (n = 19/65.52%) also examining nitrogen oxides (NO_x), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), ozone (O_3), and carbon monoxide (CO). Depression was the most frequently studied outcome (n = 10/34.48%), followed by anxiety and depression (n = 6/20.69%), and anxiety, stress, and depression, and stress (n = 4/13.79%, each). Depression, anxiety, and stress together were examined in a single study (n = 1/3.45%). Standardized questionnaires involving psychological scales such as Patient Health Questionnaire (PHQ) (n = 7/24.14%) and The Center for Epidemiological Studies-Depression (CES-D) (n = 3/10.34%) for depression and Generalized Anxiety Disorder Questionnaire (GAD) (n = 2/6.90%) for anxiety were commonly used MH tools. 27 out of 29 studies found a significant negative impact of air pollution on mental health, demonstrating a solid consensus in the literature. Two studies did not find a significant correlation. The results consistently indicated that higher levels of air pollution were associated with increased symptoms of depression, anxiety, and stress. Conclusion: Of the 3889 identified studies, 29 were suitable for inclusion in the scoping review per inclusion criteria. The results show the most preferred methods in assessing air quality and mental health in relevant studies, providing a detailed account of each method's strengths and limitations used in studies. This scoping review was conducted to assist future research and relieve the decision-making process for researchers aiming to find a correlation between air quality and mental health. While the inclusion criteria were strict and thus resulted in few studies, the review found a gap in the literature concerning the general adult population, as most studies focused on vulnerable populations. Further exploration of the methodologies used to find the relationship between air quality and mental health is needed, as reporting on these outcomes was limited.

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Keywords: air pollution; mental health; stress; depression; anxiety; methodology; scoping review

1. Introduction

Air pollution is responsible for millions of premature deaths and lost years of healthy life annually around the globe [1]. According to the World Health Organization (WHO), over 90% of the global population is exposed to toxic air pollution [1]. Most commonly, air pollution affects human health and is associated with respiratory and cardiovascular diseases [1–4]. However, as of recent years, more research is emerging considering the effects on mental health. More attention has been paid to understanding whether air quality relates to emotional and psychological well-being and the complexity of the brain. Mental health is a fast-growing cause of morbidity and a leading cause of disability among young people worldwide [5,6]. People with mental health disorders have poorer social outcomes than the general population in several areas of life. Yet, environmental health issues brought by continuous improvement of people's life quality and development via industrialization and urbanization have affected the lives of residents [7,8]. Recent research showed that air pollution is associated with suicide, increased drug usage, self-harm, work incapacity and lower productivity, memory impairment, poor mood, annoyance, lower physical activity, poor sleep, schizophrenia, depression, anxiety, and stress among various ages in the urban area, especially amongst the vulnerable population [6,9–14]. Certain pollutants, such as PM, can penetrate the lung's small airways and alveoli, entering the bloodstream and activating multiple pathophysiological mechanisms, potentially causing neuroinflammation and oxidative stress [9–11]. The brain is susceptible to environmental factors due to high metabolic demands, environmental inflammation, and oxidative stress [11–14]. Oxidative stress results from an imbalance between free radicals and antioxidants in the body, leading to cellular damage [11,15,16] that can affect neural pathways involved in mood regulation [13,15,17,18], even if the pollution levels are not exceedingly high [19].

Several studies suggest adverse pregnancy outcomes related to stress, depressive and anxiety episodes, which have an impact on fetal growth [20–22]. Other research found this association negatively impacting children's development, including developmental delays in children, especially in children exposed under 1 year of age, including at prenatal development, and behavioral, learning, and emotional problems, conduct disorder, attention-deficit hyperactivity, as well as resulting in anxiety and depression in later years (>18 years) [23–28]. Campbell [29] states that the risk for the onset of psychopathology is highest in childhood and adolescence.

Epidemiological evidence of air pollution and adult mental health problems is still limited and tends to be mainly concentrated on analyzing the effects on more susceptible populations, such as children, pregnant women, and the elderly. The purpose of this scoping review is to examine the existing literature and explore the methods used by researchers to determine the air pollution effects on mental health, mainly focusing on stress, anxiety, and depression symptoms. This scoping review focused on PM—a complex, heterogeneous mixture of natural and anthropogenic sources [30,31]. $PM_{2.5}$, also known as fine particulate (<2.5 μm), is responsible for the most significant proportion of air pollution's health impact, especially for premature deaths [1,32]. The review investigates various scientific methodologies used to analyze the exposure of PM (ultrafine (UFT) (<0.1 μm), $PM_{2.5}$, PM_{10} (also known as course particulate, <10 μm) exposure to adults' (18–69 years) mental health (depression, anxiety, and stress) in publications between 2010 and 2024. The review excludes vulnerable populations, such as the elderly and children, to derive standardized findings broadly applicable to the general adult population. Mental health alone can be analyzed using different strategies and tools, including medical analyses and psychological scales, involving cohorts. This paper aims to determine the most preferred and sound ways of collecting data for the study to find the relationship between mental health and air pollution, essentially welcoming more opportunities for other research, air

pollution reduction, and mental health awareness intervention strategies. Addressing air pollution and mental health in countries can reduce the burden of mortality and morbidity and contribute towards greater knowledge sharing and community development.

In this review, we define "depression" as a mood disorder causing persistent depressed mood or sadness, profound loss of interest in usually enjoyable activities, and frequent thoughts of suicide. In this review, "depression" in literature will be considered relating to clinical and general depressive symptoms, including those of major depressive disorder (MDD), dysthymia, now known as persistent depressive disorder (PDD), bipolar disorder, seasonal affective disorder (SAD), and atypical depression. Still, it will not consider postpartum depression (PPD) as it relates to pregnancy and vulnerable adults. "Anxiety" in this paper is defined not only as a temporary feeling but a disorder related to intense, excessive, and persistent worry, fear, and panic about everyday activities, which usually would be perceived as standard, including generalized and significant anxiety disorder, social anxiety disorder (social phobia), and substance-induced anxiety disorder. "Stress" is defined as a negative worry or mental tension that lasts for either a short (acute) or long (chronic) period. Articles containing other mental health disorders or stressors, including learning difficulties, schizophrenia, autism, or others, and suicide-related articles will not be considered. Literature containing sleep and mood disorders will be reviewed as there is a direct association between anxiety and depression. Literature in urban, suburban, and rural areas will be selected for review, and literature that does not mention any specific location will be taken for a more thorough investigation and conclusion. The existing literature will consider only methodologies used to collect data to analyze air quality and mental health together. A comprehensive review of the methods used in research will be discussed, offering insightful knowledge to researchers and policymakers in their decision-making processes.

2. Methods

2.1. Research Strategy

To conduct this scoping review, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist and the Arksey and O'Malley [33] methodological framework were used principally. The PRISMA-ScR framework and flow diagram were used to optimize the review's quality and allow readers to explore critical findings discovered from various selected research.

This scoping review was intended to review the existing methodologies for data collection from available literature on the relationship between air quality and mental health. The topic of assessment has not been comprehensively reviewed in the past and is heterogeneous. To the author's knowledge, there are limited scoping reviews on air quality and mental health assessment methodologies. However, other reviews, such as systematic reviews, have analyzed air quality and mental health relationships in the past [18,34–38].

2.2. Search Criteria

The literature search across EMBASE [39] and PubMed Central [40] databases was selected for the search, as they catalog the most extensive range of studies related to the topic of this scoping review. All articles considered were published in the English language. A manual internet search was also carried out. The combination of search terms used was based on previous review studies that focused on air quality and mental health methodologies to acquire a broad range of results. Keywords such as "air quality", "air pollution", "ambient pollution ", air contaminants", "outdoor air pollution", "air"," air quality monitoring", "air quality modelling", and "particulate matter" were combined with search terms associated with "mental health" such as "stress", "anxiety", and "depression", can be fully viewed in Table 1.

Table 1. Search keywords and terms shown were used to find relevant literature in EMBASE and PubMed databases.

Keyword	Search Terms Used
Urban	"Urban" OR "city"
Suburban	"Suburban" OR "Neighbourhood" OR "Residential"
Air Quality	"Air Quality" OR "Air Pollution", OR "ambient pollution ", OR "air contaminants", OR "outdoor air pollution", OR "air pollutants" OR "particulate matter", OR "PM" OR "$PM_{2.5}$" OR "PM_{10}" OR "Fine particulates" OR "course particulates" OR "Ultrafine particulates" OR "environmental effects" OR "environmental stressors"
Mental Health	"Mental health" OR "anxiety" OR "depression" OR "stress" OR "anxiety disorder" OR "Anxious neurosis" OR "Depressive neurosis" OR "Nervous" OR "Feeling of anxiety" OR "Worry" OR "Depression test" OR "Mental stress" OR "Occupational stress" OR "Psychological pressure" OR "Stress management" OR "bipolar disorder" OR "suicide" *
Population	"adults" OR "young adults"

* Suicide has been reported to be correlated with depression in previous studies [41,42]. Patients with depression may be more likely to attempt violent means of suicide [43]. Therefore, all publications related to suicide will be categorized as depression-related.

2.3. Inclusion and Exclusion Criteria

The review was based on literature published between 1 January 2010 and 31 December 2024 (scheduled for release). Considerable literature had to be in the English language. We included observational studies, including cohort studies (longitudinal and cross-sectional), clinical, controlled studies, case studies, and articles. Publications that include scoping reviews, meta-analyses, systematic reviews, literature and general reviews, any studies that do not involve humans, pilot studies, conference abstracts and letters, or any other publications that do not include methodology in their work were not considered and excluded from the study. Studies in urban, suburban, and rural areas focused on outdoor PM were considered. More details on inclusion and exclusion can be found in Table 2 below.

2.4. Screening Criteria and Quality

The screening aimed to identify publications investigating the relationship between air quality/air pollution and mental health. These publications contained methodologies explaining how the authors performed the investigations to achieve the results. Whether the study successfully found the link between the two subjects or not, the results did not matter. Discussions on the inclusion/exclusion criteria were delivered via email and project meetings, and excluded publications included text explaining the reasoning behind exclusion from the review using MS Excel.

The authors included the inductive approach separately and screened all retrieved citations' titles and abstracts first. If the articles were deemed suitable for this review, they were reviewed fully. This was performed by examining a detailed summary/abstract of the article's aims and objectives, methodology, and results provided by the authors of the studies. The Covidence app was used to arrange and store the available literature.

Details recorded during the review included:

- Descriptive summary of the publication (including the authors' names, year of publication, publication name, country of origin, publication type, publication design, types of setting (urban, suburban, or rural), participants of interest (e.g., adults, young adults, elderly, children, etc.), study aim)
- Content analysis (methodologies used for mental health and air pollution, as well as how the two subjects were linked)
- Results analysis (was the link between air quality/pollution and mental health achieved when experimentation was used)
- Decision (whether the article is deemed suitable or not for the review)

Table 2. Inclusion and exclusion criteria were used in the scoping review to find the most preferred methods for analyzing the relationship between air pollution and mental health.

Inclusion Criteria	Exclusion Criteria
Published in English	Published in languages other than English
Location: Worldwide—any country or studies including more than one country.	Studies do not specify the location.
Environment: Urban, suburban, AND/OR rural setting; outdoor AQ only.	Focusing only on indoor AQ.
Cohort: Includes adults (18–69) with or without existing mental health disorders, including various socioeconomic backgrounds and lifestyles.	Includes vulnerable populations (elderly (>69), children (<18), only people with disabilities, and/or only pregnant women).
Mental health: depressive AND/OR anxiety symptoms, AND/OR stress	Any other mental health-related issue, relating to other health-related complications and diseases such as cardiovascular or respiratory, economic and political indicators, and generally any publication that does not analyze depressive, anxiety and stress symptoms in their studies and primarily focuses on other health issues, identities, aggressive behavior, alcohol, tobacco and similar products, and/or drug consumption/addiction, sleeping disorders, general wellbeing (not defining MH), school performances and/or learning difficulties, physical activity, obesity, image distortion and/or eating disorders, recovery, financial security, growth, community belonging and social security, rights/respect, personal relationships, cultural differences and awareness strategies, politics, people's perspectives, without including the relationship between AQ and MH.
Air quality: Relating to PM.	Any other pollutants excluding PM in the literature.
Explores the relationship between PM and mental health.	Sources that focus only on mental health or air quality/pollution without exploring the possible relationship between the two subjects.
Any available full-text research that includes methodology and involves human cohorts, observational studies (e.g., cohort studies, case-control studies, cross-sectional studies, longitudinal, structured observations, and participant observation), controlled studies, major clinical studies, case studies, time series, etc.	Review publications such as scoping reviews, systematic reviews, meta-analyses, literature reviews, general narrative reviews, non-human related studies and reviews, practice guidelines, protocols, conference abstracts, letters, or any other publication that does not specify the methodology used.
Study design: qualitative, quantitative, or mixed methods.	-
Date: Sources published between 2010 and 2024.	Any study published before 2010.
Results: Makes or does not make a connection between air pollution and mental health in the end—methodologies are key.	Any studies that do not specify the methodology used in their publication to achieve results, whether successful or not.

2.5. Data Analysis

Article characteristics were tabulated and organized according to air pollution and mental health information. The selected articles were analyzed in more detail using MS Excel, and the methodologies used were established.

3. Results

The original search was conducted in February of 2024. A comprehensive search was conducted across PubMed and EMBASE. The initial search yielded 3889 (1328 from PubMed and 2561 from EMBASE). After adjusting the search settings for diseases (mental health, depression, and anxiety disorders were selected), publication design, and publication type (article), 622 articles were chosen for records during title and abstract screening.

After a title and abstract screening of 622 selected articles, 32 duplicates and four articles were found in different languages, which were removed in the identification step.

A total of 586 articles were further investigated, 472 of which were deemed irrelevant to the study (i.e., 192 studies had no mental health or air quality aspect, 139 studies included vulnerable populations (elderly, children, pregnant women), 40 studies were reviews (systematic reviews, meta-analyses, scoping reviews), 26 studies included other mental health disorders (other than stress, anxiety or depression) or had generalized mental health (was unclear which mental health disorder was studied), 22 studies only had mental health aspect but did not address air quality, 18 studies only had air quality aspect but did not analyze mental health, 16 were animal studies, 13 studies did not include particulate matter, six studies only focused on indoor air quality. Further, 24 studies were removed as they were not open-access publications.

The remaining 90 studies were further analyzed, and 61 were unsuitable for inclusion. Figure 1 visually describes the article selection process using the Prisma flow diagram for scoping reviews.

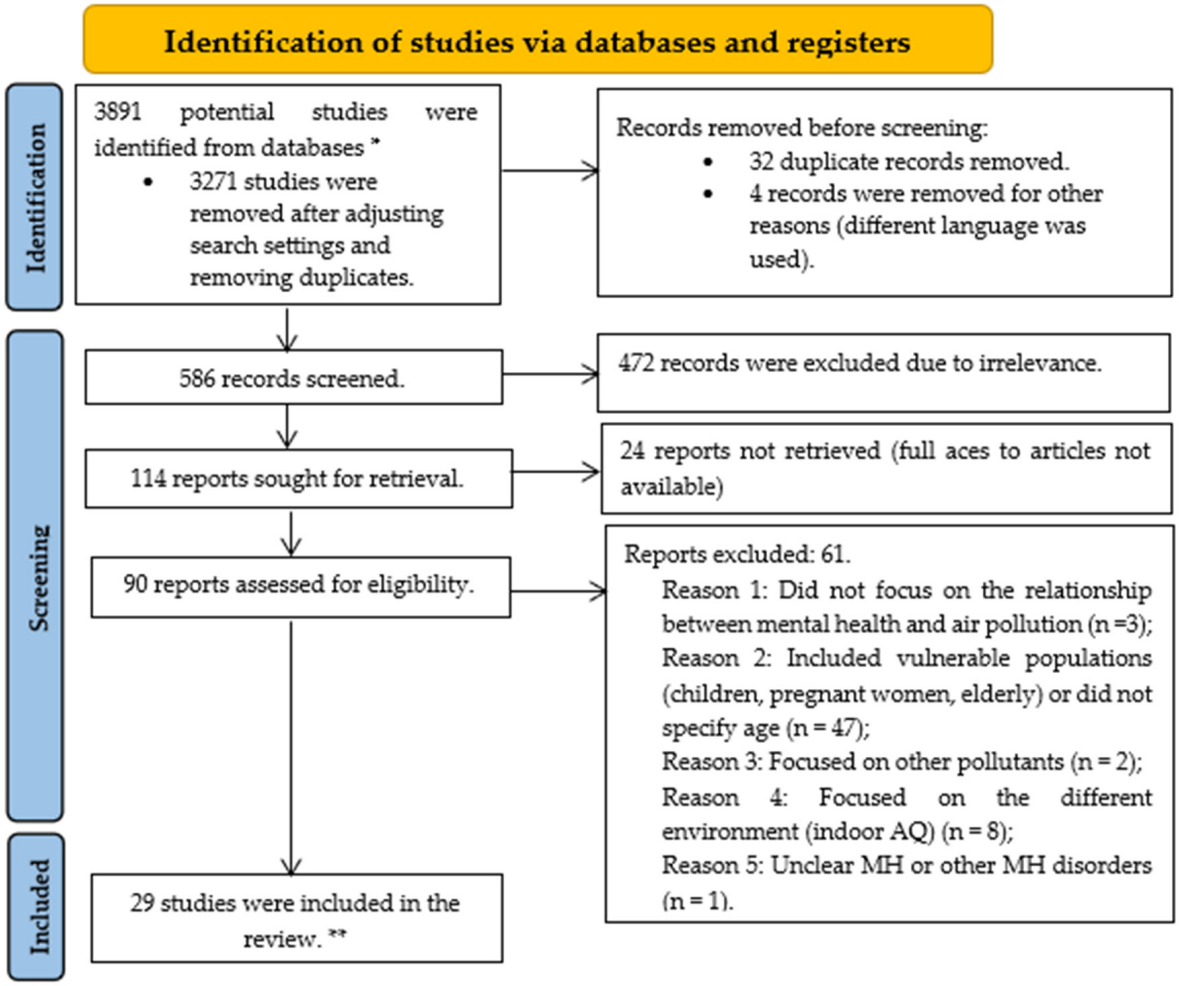

Figure 1. The study selection process is summarized according to the PRISMA flow diagram, which displays eligible study selection per inclusion criteria. * 1328 from PubMed and 2561 from EMBASE. ** Studies not acknowledging exact age but a mean age of 57 were included in the study, as well as studies stating "Adults" as a cohort, but the ages were still <69.

Ultimately, 29 articles met the inclusion criteria and were included in the scoping review.

Table 3 uses descriptive statistics to summarize the data and the general characteristics of selected studies. It further explores the characteristics of the selected studies and summarizes the findings.

Table 3. Lists the studies selected for the scoping review and details their methodologies for analyzing the relationship between particulate matter and mental health outcomes (stress, anxiety, and depression). Commonly used AQ analysis methods include air quality monitoring station data (inventories, databases, and AQI) and land-use models, such as land use regression (LUR) and the air pollution model (TAPM). For MH, various questionnaires and in-built psychological scales were used: self-reported questionnaires and surveys, Generalized Anxiety Disorder Questionnaire (GAD, GAD-7), Beck Anxiety Inventory (BAI) and Fear Questionnaire (FQ) for anxiety disorder and fear; The structured Clinical Interview for Diagnostic and Statistical Manual of Mental Disorders (SCID-I), Inventory of De-pression Symptomatology (IDS), Centre of Epidemiologic Studies Depression Questionnaire (CES-D) and the Patient Health Questionnaire (PHQ) (PHQ-4, PHQ-8 and PHQ-9) scales for measuring self-reported severity of depression; Altman Self-Rating Mania (ASRM) scale for mania; WHO-5 Wellbeing Index for general wellbeing; Short Warwick-Edinburgh Mental Wellbeing Scale (SWEMWBS), Ecological Momentary Assessment (EMA) and Eysenck Personality Questionnaire-Revised Short Form (EPQR-Short) for social behavior, feelings and mood; EuroQol-5 dimensions (EQ-5D) index for both anxiety and depression; Chinese version of the Perceived Stress Scale (CPSS) for stress; including medical/healthcare data, and Internet search behavior were also used in selected studies. For statistical analyses to find the relationship between AQ and MH, linear regression, including multiple, multilevel, Generalized Additive Models (GAMs), generalized linear models (GLMs), and multivariable regressions; logistic regressions, including multiple, multilevel and multivariable regressions; survival analysis models, including Cox proportional hazard analysis and time-varying Cox proportional hazard analysis; and other statistical approaches, such as two-way FE, negative binomial, GEE, and mix (multiple and linear regression), were incorporated. The table also indicates which study controlled for meteorological conditions (e.g., temperature, precipitation, wind speed, wind direction, humidity), demographics (e.g., sex, age, family status, occupation, cultural background), and socioeconomic factors (e.g., income, education level, living conditions, resources, etc.) to find the results.

Study	Study Name	Authors	Year	Country	Methodology—AQ	Methodology—MH	Controlled			Statistical Analysis
							Meteorological	Demographics	Socioeconomic Status	
Study 1	Relationship of emergency department visits for suicide attempts with meteorological and air pollution conditions	Miyazaki et al. [43]	2023	Japan	Monitoring stations	Medical (ED) data	Yes	Yes	No	Multivariate Poisson regression
Study 2	Residential greenspace and anxiety symptoms among Australian women living in major cities: A longitudinal analysis	Mouly et al. [44]	2023	Australia	Land-use regression (LUR) model	GAD	Yes	Yes	Yes	Generalized estimating equation (GEE)
Study 3	How People's COVID-19-Induced-Worries and Multiple Environmental Exposures Are Associated with Their Depression, Anxiety, and Stress during the Pandemic	Huang et al. [45]	2023	Hong Kong	Portable air pollutant sensors.	PHQ-4 and self-reported scale of stress symptoms.	No	Yes	Yes	Linear regression models
Study 4	Real-time air pollution and bipolar disorder symptoms: a remote-monitored cross-sectional study	Kandola and Hayes [46]	2023	UK	Air quality index (AQI)	PHQ-8 and ASRM scale	Yes	Yes	No	Linear regression

Table 3. *Cont.*

Study	Study Name	Authors	Year	Country	Methodology—AQ	Methodology—MH	Controlled			Statistical Analysis
							Meteorological	Demographics	Socioeconomic Status	
Study 5	Long-term Exposure to Multiple Ambient Air Pollutants and Association with Incident Depression and Anxiety	Yang et al. [47]	2023	UK	LUR	Medical data	No	Yes	Yes	Cox proportional hazards models
Study 6	Multiple environmental exposures along daily mobility paths and depressive symptoms: A smartphone-based tracking study	Roberts & Helbich [48]	2021	Netherlands	LUR	PHQ-9	No	Yes	Yes	Multiple regression analyses
Study 7	Daily space-time activities, multiple environmental exposures, and anxiety symptoms: A cross-sectional mobile phone-based sensing study	Lan et al. [49]	2022	Netherlands	LUR	GAD-7	No	Yes	Yes	Multiple linear regressions, including the Random Forest (RF) model
Study 8	Association between traffic-related air pollution and anxiety hospitalizations in a coastal Chinese city: are there potentially susceptible groups?	Ji et al. [50]	2022	China	Monitoring stations	Medical data	Yes	Yes	No	Generalized additive model (GAM)
Study 9	Spatial Variability of the Relationship between Air Pollution and Well-Being	Li & Managi [51]	2022	Japan	Database	Survey	No	Yes	Yes	Linear analyses
Study 10	Air pollution and anti-social behavior: Evidence from a randomized lab-in-the-field experiment	Lohmann et al. [52]	2023	China	Air Quality Index (AQI)	• Antisocial behavior: using incentivized economic games. • Risk and time preferences: lottery choice task and a convex time budget task. • Cognitive ability and well-being: Raven's Matrices, Numerical Stroop Task, and self-reported scales	Yes	Yes	No	Linear regression

Table 3. *Cont.*

Study	Study Name	Authors	Year	Country	Methodology—AQ	Methodology—MH	Controlled			Statistical Analysis
							Meteorological	Demographics	Socioeconomic Status	
Study 11	Do objective and subjective traffic-related pollution, physical activity, and nature exposure affect mental wellbeing? Evidence from Shenzhen, China	Huang, Tian & Yuan [53]	2023	China	NASA Sedac database	• WHO-5 Wellbeing Index • Short Warwick-Edinburgh Mental Wellbeing Scale (SWEMWBS) • Self-reported survey (single question)	No	Yes	Yes	Multivariate linear regression
Study 12	The effects of long-term exposure to air pollution on incident mental disorders among patients with prediabetes and diabetes: Findings from a large prospective cohort	Feng et al. [54]	2016	UK	UK Air database	Healthcare data	Yes	Yes	Yes	Time-varying covariates Cox model and generalized propensity score (GPS)
Study 13	The Impacts of Air Pollution on Mental Health: Evidence from the Chinese University Students	Zu et al. [55]	2020	China	The Air Quality Index (AQI) data	CES-D	No	Yes	Yes	Multivariable models
Study 14	Associations of co-exposures to air pollution and noise with psychological stress in space and time: A case study in Beijing, China	Tao et al. [56]	2021	China	The Airbeam sensor	EMA	Yes	Yes	Yes	Multilevel ordinal logistic regression models
Study 15	Effects of vitamin D on associations between air pollution and mental health outcomes in Korean adults: Results from the Korea National Health and Nutrition Examination Survey (KNHANES)	Kim et al. [57]	2023	S. Korea	Monitoring stations	Self-reported questionnaire	No	Yes	Yes	Multiple logistic regression
Study 16	Relationship between chronic exposure to ambient air pollution and mental health in Korean adult cancer survivors and the general population	Kim et al. [58]	2021	S. Korea	Monitoring stations	Self-reported questionnaire	No	Yes	Yes	Multiple logistic regression

Table 3. *Cont.*

Study	Study Name	Authors	Year	Country	Methodology—AQ	Methodology—MH	Controlled			Statistical Analysis
							Meteorological	Demographics	Socioeconomic Status	
Study 17	Ambient air pollution exposure and depressive symptoms: Findings from the French CONSTANCES cohort	Sakhvidi et al. [59]	2022	France	LUR	CES-D	No	Yes	Yes	Negative binomial regressions
Study 18	Associations of $PM_{2.5}$ and road traffic noise with mental health: Evidence from UK Biobank	Hao et al. [60]	2022	UK	LUR	PHQ and the SCID-I	No	Yes	Yes	Logistic regression model
Study 19	Associations between long term exposures to outdoor air pollution and indoor solid fuel use and depression in China	Zhang et al. [61]	2022	China	Monitoring stations	PHQ-9	No	Yes	Yes	Multiple logistic regression
Study 20	$PM_{2.5}$ exposure and anxiety in China: evidence from the prefectures	Chen et al. [62]	2021	China	Air Quality Online Monitoring and Analysis Platform	Internet search behavior	No	No	Yes	Two-way fixed effect (FE) regression model
Study 21	Short-term effects of traffic noise on suicides and emergency hospital admissions due to anxiety and depression in Madrid (Spain)	Díaz et al. [63]	2020	Spain	Monitoring stations	Medical (ED) data	Yes	No	No	Linear models and Poisson regression.
Study 22	The relationship between air pollution and depression in China: Is neighborhood social capital protective?	Wang et al. [64]	2018	China	Airborne Fine Particulate Matter and Air Quality Index	CES-D	No	Yes	Yes	Multilevel linear regression analyses
Study 23	Long-term exposure to ambient air pollutants and mental health status: A nationwide population-based cross-sectional study	Shin, Park & Choi [65]	2018	S. Korea	Monitoring stations	EQ-5D index	Yes	Yes	Yes	Multiple logistic regression
Study 24	Greenspace and mortality in the U.K. Biobank: Longitudinal cohort analysis of socio-economic, environmental, and biomarker pathways	Wan et al. [66]	2022	UK	LUR	PHQ-4 and EPQR-Short	Yes	Yes	Yes	Cox proportional hazards model

Table 3. *Cont.*

Study	Study Name	Authors	Year	Country	Methodology—AQ	Methodology—MH	Controlled			Statistical Analysis
							Meteorological	Demographics	Socioeconomic Status	
Study 25	Ambient temperature and air pollution associations with suicide and homicide mortality in California: A statewide case-crossover study	Rahman et al. [67]	2023	US	United States Environmental Protection's (US EPA's) AQ System	Healthcare (death) data	Yes	No	No	Conditional logistic regression models
Study 26	Impacts of coal mine fire related $PM_{2.5}$ on the utilization of ambulance and hospital services for mental health conditions	Carroll et al. [68]	2022	Australia	The Air Pollution Model (TAPM)	Medical (ED) data	Yes	No	No	GAMs
Study 27	Urban Air Pollution and Mental Stress: A Nationwide Study of University Students in China	Zhang et al. [69]	2021	China	National Bureau of Statistics	CPSS	No	Yes	Yes	Multilevel logistic regression
Study 28	Outdoor light at night, air pollution, and depressive symptoms: A cross-sectional study in the Netherlands	Helbich, Browning & Huss [70]	2020	Netherlands	LUR	PHQ–9	No	Yes	Yes	GAM
Study 29	Not urbanization level but socioeconomic, physical, and social neighborhood characteristics are associated with the presence and severity of depressive and anxiety disorders	Generaal et al. [71]	2019	Netherlands	LUR	IDS, BAI, and FQ	No	Yes	Yes	Multilevel logistic and linear regression

Findings from Table 4 suggest that most studies were carried out in 2023 (n = 10/34.48%), 2022 (n = 8/27.59%), 2021 (n = 5/17.24%), 2020 (n = 3/10.34%), 2018 (n = 2/6.90%), and 2019 (n = 1/3.45%)—indicating a recent surge in interest in the relationship between AQ and MH. No suitable studies were found before 2019 that fit the selection criteria. This trend suggests that the field is rapidly evolving, with increasing research output in recent years.

Table 4. The table shows the total number and percentages of studies using a particular methodology, publication country and year, publication type, whether publications found a link between AQ and MH, and studies containing PM and MH focus.

Study Characteristics (Total n = 29)		**Count n (%)**
Year of publication	2023	10 (34.48)
	2022	8 (27.59)
	2021	5 (17.24)
	2020	3 (10.34)
	2019	1 (3.45)
	2018	2 (6.90)
Continent	Asia	15 (51.72)
	Europe	11 (37.93)
	North America	1 (3.45)
	Australia or New Zealand	2 (6.90)
Results achieved (MH and AQ link realized)	Yes	27 (93.10)
	No	2 (3.45)
MH methods	Quantitative methods Healthcare/medical records Surveys/questionnaires and diagnostic classification/rating scales Other *	29 (100) 7 (24.14) 21 (72.41) 1 (3.45)
AQ methods	Monitoring data -Data from stationary (national/local) monitors -Portable AQ monitors	19 (65.52) 17 (58.62) 2 (6.90)
	Land-use models -LUR -TAPM	10 (34.48) 9 (31.03) 1 (3.45)
Study design	Cross-sectional	19 (65.52)
	Longitudinal	4 (13.79)
	Time series	2 (6.90)
	Case study	1 (3.45)
	Prospective cohort	1 (3.45)
	Randomized experiment	1 (3.45)
Statistical methods	Linear regression models **	14 (48.28)
	Logistic regression models ***	8 (27.59)
	Survival analysis models ****	3 (10.34)
	Other *****	4 (13.79)

Table 4. *Cont.*

Study Characteristics (Total n = 29)		**Count n (%)**
Studies including PM	Only PM	10 (34.48)
	Includes other pollutants ******	19 (65.52)
Studies MH focus	Anxiety	4 (13.79)
	Depression	10 (34.48)
	Stress	4 (13.79)
	-Anxiety & depression	6 (20.69)
	-Depression & stress	4 (13.79)
	-Depression, anxiety, and stress	1 (3.45)

* Includes other quantitative methods, such as Internet search behavior. ** Linear regression models, including multiple, multilevel GAMs, generalized linear models (GLMs), and multivariable regressions. *** Logistic regression models, including multiple, multilevel, and multivariable regressions. **** Survival models, including Cox proportional hazard analysis and time-varying Cox proportional hazard analysis. ***** Other, including two-way FE, negative binomial, GEE, and mix (multiple and linear regression). ****** Studies include PM as well as other pollutants.

3.1. Regions of Studies

Table 4 outlines that geographically, studies are predominantly from Asia (n = 15/51.72%) *, Europe (n = 11/37.93%), Australia (n = 2/6.90%), and North America (n = 1/3.45%). There are no studies from South America or Africa. This geographic distribution highlights a potential research gap in underrepresented regions, particularly South America and Africa, where air pollution issues are also prevalent. The highest proportion of studies have been based in China (n = 9/31.03%), followed by the UK (n = 5/17.24%), the Netherlands (n = 4/13.79%), South Korea (n = 3/10.34%), Australia and Japan (n = 2/6.90%), and one study from France, Spain, Hong Kong, and the USA (n = 1/3.45%). This indicates that 31.03% of the studies are based in developing countries (China), while 68.97% are evaluated in developed countries.

* n represents the total number of studies in this review, followed by the selected studies' total percentage (%) ratio.

3.2. Types of Methodologies Used

3.2.1. Mental Health

All studies used quantitative methods (n = 29/100%) to collect MH data. Methods to assess mental health varied, with psychological scales and survey/questionnaire-based sampling methods being the most common (n = 21, 72.41%), with PHQ (n = 7/24.14%) scales and CES-D (n = 3/10.34%) being the most preferred tools to analyze depressive symptoms, and GAD (n = 2/6.90%) for anxiety. 24.14% (n = 7) of the studies used medical/healthcare records to attain MH data, while another method, internet behavioral search, only accounted for 3.45% (n = 1). There was no mention of direct qualitative face-to-face interviews, apart from one study that collected demographic/socioeconomic (SES) data in person (classroom), assuming all survey/questionnaire-based studies involving psychological scales were not directly assessed in person. The reliance on psychological scales indicates a focus on quantifiable and standardized mental health measures. Most studies focused on depression and depressive symptom analysis (n = 10/34.48%), including suicides (n = 2/6.90%), followed by anxiety and depression (n = 6/20.69%), anxiety, stress, and depression and stress, all accounting for four studies each (n = 4/13.79%), and a single study including all stress, anxiety, and depression (n = 1/3.45%).

3.2.2. Air Quality

Air quality assessment methods were diverse. Monitoring station data (fixed, i.e., databases, AQI, (n = 17/58.62%) and portable monitors (n = 2/6.90%) accounted for 65.52% (n = 19), followed by land-use regression models (LUR (n = 9/31.03%) and the air pollution model (TAPM), a prognostic meteorology and air pollution model developed by

an Australian governmental agency (n = 1/3.45%)), in 34.48% (n = 10) of the studies. No studies employed mixed methods, such as LUR with portable monitor data for comparison, to analyze AQ, apart from attaining this data to analyze other factors, such as green spaces. Although all studies included PM (either/or $PM_{2.5}$ or PM_{10}) in their studies, 34.48% (n = 10) focused solely on PM, while the remainder (n = 19/65.52%) included other pollutants in their studies as well. No studies included ultrafine PM.

3.2.3. Statistical Methods

Linear regression models were used the most (n = 14/48.28%) in the selected studies to find AQ and MH links, followed by logistic regression models (n = 8/27.59%), survival analysis (n = 3/10.34%), which included Cox proportional hazard analysis, and four other methods (two-way FE, negative binomial regression, GEE, and mixed methods (multivariate and linear regressions)) (n = 1/3.45%). For covariates, most of the studies included and controlled for cohort demographics (e.g., sex, age) ("Yes" n = 27/93.10%; "No" n = 2/6.90%), and SES ("Yes" n = 25/86.21%; "No" n = 4/13.79%), while very few considered to control for meteorological variables ("Yes" n = 12/41.38%; "No" n = 17/58.62%). However, most studies have found a relationship between AQ and MH (n = 27/93.10%), while two studies did not find a strong correlation (n = 2/6.90%).

3.3. Study Types and Design

The study designs varied, with cross-sectional studies being the most common (n = 19/65.52%), followed by longitudinal (n = 4/13.79%), time series studies (n = 2/6.90%), and the remainder (n = 1/3.45% each) case study, prospective cohort, and randomized experiment. The high percentage of cross-sectional studies indicates a focus on snapshot assessments rather than longitudinal follow-ups, though longitudinal designs are crucial for understanding long-term effects. All the studies were published in journals (100%), reflecting the rigorous peer-review process and the academic community's commitment to disseminating high-quality research.

4. Discussion

The methods described ensured thorough and straightforward investigation principles for finding the most preferred methodologies and limitations in the existing literature. Researchers and policymakers can use these to ease the research process, find missing information, and provide valuable investigative literature.

4.1. Principal Findings

We identified various methods for analyzing air quality and mental health outcomes among the included studies. Among them, the most common methods to collect data for air quality analysis are data from stationary monitoring stations [43,46,50,52] and LUR [44,47–49]. In contrast, for mental health studies, only quantitative methods, such as psychological scales, were used to analyze depression and/or anxiety symptoms [44–46,48,49,53,55], as well as attaining medical records for analysis [50], which may not include direct contact with the cohort and provide accurate data for analysis for broader cohort and area coverage. By using these methods, studies within this review found that higher concentrations of PM were linked with increased symptoms of depression and anxiety [44,45]. These findings align with previous research suggesting that air pollution can exacerbate mental health issues, contributing to the global burden of disease [72–75].

Although emerging research has started to explore the relationship between mental health and air pollution, as per a review of the selected studies, Zu et al. [55] explained that the mental health of young and working adults in urban and suburban areas has been neglected by stressing the importance of undergraduate students transitioning into adulthood and the challenges, such as sleep problems inflicted by environmental stressors, notably air pollution. Another study also addressed this gap in the literature: regional air

pollution is associated with students' mental stress and requires better learning resources to moderate the effects of stress [69].

The scoping review revealed a notable concentration of studies conducted in Asia and Europe, with fewer studies from North America and Australia and an absence of studies from South America and Africa. Specifically, 57.14% of the studies were based in Asia, 28.57% in Europe, and 7.14% in North America and Australia. It is estimated that Asia has the highest populations exposed to unsafe air pollution levels, with China and India alone accounting for 38% of global exposure to $PM_{2.5}$ above the WHO guidelines (>5 $\mu g/m^3$) [76]. Nine studies focused on China, with two studies analyzing AQ and MH in Beijing (Northern China) [52,56], one in Qingdao (Eastern China) [50], one in Shenzhen (Southeastern China) [53], one study in Northeast China (Liaoning, Jilin, Heilongjiang, and Inner Mongolia) [61], and four conducted a multicity study. China, the country with the most noted studies in the scoping review on the relationship between air pollution and mental health, has implemented strong AQ regulations [45,77–82] and AQ research [51], consequently reducing its $PM_{2.5}$ concentrations in cities, yet 42% of the population is exposed to annual average $PM_{2.5}$ concentrations above 35 $\mu g/m^3$ (the lowest of the three WHO interim target levels required) [77,80], primarily due to industrial activity, which has increased airborne pollutants in places near Japan, South Korea, and Taiwan, as well as in places as far away as California in the USA [83]. Four studies [55,62,64,69] analyzed multiple cities and provinces within China to understand how air pollution affects MH. However, only one study [62] identified that most anxiety indices were found in southern China (Guangdong Province). A study by Ji et al. [84] explained that good air quality cities in South China and East China are more sensitive to air pollution, while cities with poor air quality in Northwest and North China (e.g., Beijing [52,56]) are less sensitive. Clean regions may have heightened sensitivity to air pollutants as their respiratory and immune systems are less challenged by high pollution levels. Air pollution levels in China are approximately six to eight times higher than those in the United States [55], and Beijing is still 40% higher than the most polluted county in the United States (Plumas County in California, USA) [85].

The results findings noted that most of the studies controlled the SES and in their studies. This encompasses income, educational attainment, financial security, and subjective perceptions of social status and social class. The SES is a reliable and consistent predictor of many life outcomes, including physical and psychological health, which, when controlled, could explain an association with mental disorders [86]. These predictors were attained from the cohort, mostly via surveying, and adjusted in statistical models with AQ and MH results. Huang et al. [45] and Zu et al. [55] showed that worries about job loss and financial hardship are significantly associated with depression, anxiety, and stress. Huang et al. [45] and Huang, Tian, and Yuan [53] studies showed that open space, recreational land, or green space did not influence them. Wan et al. [66] found it particularly beneficial for low and medium-SES individuals. Mouly et al. [44] did not adjust for area-level socio-economic variables besides the individual-level information on income and education. Helbich, Browning, and Huss [70] controlled for SES variables but did not include the observations in the study. Ji et al. [50] did not include SES factors, and Kandola and Hayes [46] stated that socioeconomic position confounders may not have been measured. Lan et al. [49], Li and Managi [51], Lohmann et al. [52], and Yang et al. [47] controlled the demographic and socioeconomic characteristics of the sample but did not discuss the findings on these results relating to AQ and MH. Roberts and Helbich [48] observed no significant associations. Lohmann et al. [52] found that individuals with higher income levels indicated better mental well-being and experienced less stress than their lower-income counterparts. Similarly, Sakhvidi et al. [59] and Generaal et al. [71] also found that those with low incomes and lower educations, who were younger and living in highly deprived areas, as well as those who were not married or in a civil partnership, were more exposed to depressive symptoms associated with air pollution. Additionally, those living in high-rise housing and apartments reported higher levels of mental well-being than the

dwellers of urban villages and multi-story housing [52]. This evidence could be related to tall buildings that are densely placed, interfering with wind patterns and reducing air pollutant dispersion [87].

The demographics, such as gender, were also controlled in all the studies. Gender as a variable contributes to differences in the biological and behavioral systems, enhancing accuracy in human studies [88]. For instance, Ji et al. [50] found stronger associations between short-term exposure to air pollutants and anxiety hospitalizations in females. Mouly et al. [44] only focused on the female cohort living in significant cities and similarly found that anxiety symptoms were associated with elevated $PM_{2.5}$ levels. Similar findings were assessed in other literature [12,18,89–94]. This could be primarily linked to sex differences in biological susceptibility [93,95–97], genetic and hormonal factors, physiological stress responsivity, cultural aspects, and/or environmental risk factors [98–100]. Whereas Zu et al. [55] and Yang et al. [47] found that men had greater odds of increased mental health problems than women, relating to their place of birth and current living locations. Other studies also found cognitive decline more pronounced in men than women [82,101–103]. Meteorological conditions can worsen air quality and damage human health, yet very few studies considered meteorological factors for control in their studies [43,44,46,50,52,56,66,67]. Some studies included meteorological variables to predict and analyze air quality in a particular area. Miyazaki et al. [43] observed a significant relationship between higher temperatures, $PM_{2.5}$, and suicide attempts by violent means, like Rahman et al. [67], although the association with AQ was not found. Similarly, Mouly et al. [44] investigated major cities with temperate or subtropical climates and found an association between AQ and MH. This association was found previously in other studies [75,92]. However, Ji et al. [50] and Lohmann et al. [52] found that PM effects on MH were significant during colder seasons. Díaz et al. [63] found that cold temperatures are significantly associated with emergency hospital admissions for anxiety. Other studies found strong associations between cool seasons and AQ on MH [104,105] related to coal combustion and heating during the colder months [106]. Tao et al. [56] The surveys were controlled for the weather but did not consider seasonal variations, as they were completed in winter, with higher air pollution than other seasons.

4.2. Method Suitability

4.2.1. Air Quality Methods

AQ Monitors and Databases—Stationary and Portable

Most of the analyzed studies relied on monitoring station data. Miyazaki et al. [43], Ji et al. [50], Li and Managi [51], Huang, Tian, and Yuan [53], Feng et al. [54], Zu et al. [55], Kim et al. [57], Kim et al. [58], Chen et al. [62], Díaz et al. [63], Wang et al. [64], Shin, Park, and Choi [65], Rahman et al. [67], and Carroll et al. [68] used air quality data from environmental/government organization databases, which attain data from monitoring stations, in their research. Nationwide/local monitoring stations are operated by a governing body, such as the Environmental Protection Agency (EPA), which is responsible for environmental monitoring and protection. Data attained from environmental organizations and governmental databases typically provide high-quality, standardized, and verified data, using strict regulatory guidelines ensuring consistency, legal compliance, and reliability in air quality measurements [107–109]. The Air Quality Index (AQI) is based on the monitoring station data. In the findings, the AQI data was used by Kandola and Hayes [46], Lohmann et al. [52], and Zu et al. [55]. They provide extensive and accurate data on a given location, offering a broad understanding of air quality trends and pollution levels across different regions, depending on how densely populated the area is. Large datasets from monitoring stations can support extensive and reliable research for long-term trend analyses, offer public access, and be collected for AQ regulatory purposes [110,111]. For instance, satellite data uses data from various sources but is mainly derived from monitoring stations and provides extensive spatial coverage at higher resolution, allowing detailed assessments of air pollution and air quality monitoring over large, remote areas where

ground-based monitoring stations may be sparse or nonexistent [112–115] yet may have limitations in vertical resolution, making it challenging to distinguish between ground-level and upper-atmosphere pollutants and may require specialized skills for rigorous calibration and validation against ground-based measurements to ensure accuracy, which can be resource-intensive [115–120]. However, some monitoring stations may be in population hotspots but not where people live.

Stationary monitoring stations may not be sufficiently selective or sensitive to target pollutants [110,121], monitoring personal exposure to pollutants and typically accounting for outdoor air quality only. Nationwide networks may not provide detailed local data, potentially missing small-scale variations in air quality and localized pollution hotspots, particularly in remote areas [121–124]. Therefore, local monitoring data can be attained but limited to specific locations. Other means, such as LUR models, are incorporated to better understand the air quality in a larger geographical area and for spatial variation. Resources, such as field professionals, specific data communication methods, and laboratory analysis, are required to attain accurate results, which can be expensive. The process of collecting, validating, and releasing data and communicating can be slow due to bureaucratic procedures, leading to delays in data availability [121,125–127].

Portable/mobile or manual air pollutant sensors, as employed by Huang et al. [45] and Tao et al. [56], offer real-time data collection, capturing short-term exposure and its immediate assessment of air pollution levels and impact [128,129]. These monitors provide a reasonable estimate and insight for personal exposure and are easy to use and maintain [130,131]. Compared to stationary AQ monitoring stations, portable monitors are lightweight and mobile, do not require training to use, enabling users to measure air quality at various locations, including indoors, and do not require specific data communication methods, and data can be easily transferred to a mobile phone and computer for analysis [132,133]. Additionally, portable monitors are relatively inexpensive, making them accessible for individuals and community-based monitoring projects, allowing engagement and empowering the public by involving such monitors in data collection, consequently raising awareness about air quality issues [130,134–137]. However, these monitors are far less accurate and precise than stationary AQ monitors. Furthermore, they are not used for regulatory monitoring and may require an additional means to measure meteorological data [128–132,137]. Similarly, satellite data may also be affected by weather conditions such as cloud cover and adverse weather conditions obstructing satellite sensors and reducing data quality and reliability [112,120] and have limited temporal resolution, providing only near real-time imagery, while data collection occurs only once a day or less frequently, potentially missing short-term pollution events [114,138].

Land Use Models

LUR models were widely used in studies by Mouly et al. [44], Yang et al. [47], Roberts and Helbich [48], Lan et al. [49], Sakhvidi et al. [59], Hao et al. [60], and Generaal et al. [71]. These models are used in research, especially in urban and large-scale environments, due to their ability to estimate fine spatial scales down to individual buildings or small neighborhoods for detailed, long-term exposure assessments [139–141]. Helbich, Browning and Huss [70] did not address the type of land use model the study used, and Carroll et al. [68] used TAPM. Air quality models make use of existing air data from multiple sources (e.g., satellite data, monitoring station data, and geographic information system (GIS) data) in their development, offering flexibility, adaptability, and versatility when incorporating various types of environmental data (e.g., noise data, greenspace, traffic counts, industrial emissions, etc.) for different settings, identifying multiple sources of pollution, and producing comprehensive pollution maps with precision [138–140,142–144]. The LUR accuracy depends heavily on the quality and availability of input data. It requires correct and extensive data to work appropriately, requiring existing air quality data and relying on static predictors [140,141,145]. The model's effectiveness and reliability may be compromised in areas with sparse monitoring networks or poor-quality data [139,142,143,145]. LUR models often

provide spatial data limited to a plane close to the ground without capturing temporal variation in pollution levels. These models developed for one geographical area may not directly apply to another without significant modifications, limiting their generalizability, and may not produce exposure concentrations [139,143].

4.2.2. Mental Health Methods

Qualitative and Quantitative Methods

Qualitative methods (e.g., self-reported questionnaires and scales, interviews, and observations) can explain the "why" and "how" behind quantitative results, providing rich, detailed insights into participants' experiences, beliefs, and behaviors [146], offering a deeper understanding of health phenomena and a comprehensive picture that includes environmental, social, and cultural factors from the viewpoint of those directly impacted by them, which can help provide more flexibility and profound insights in exploring complex subjects, such as mental health [146–152]. As a result, qualitative research has become the leading research method in many studies, especially in psychological studies in recent times [153].

Quantitative methods provide broad, reproducible, and generalizable results that allow statistical analysis to identify patterns, correlations, and causal relationships [154,155]. These methods offer a solid basis for evidence-based conclusions in a structured manner.

Quantitative methods in mental health research encompass various tools and techniques, such as ecological momentary assessment (EMA) and psychometric tools, such as standardized scales and tests. These methods are widely used in studies focusing on mental health literacy and measuring constructs such as depression and anxiety [156–162]. Quantitative studies offer valuable insights into the incidence of mental health disorders, the effectiveness of interventions, and the relationship between different variables [160,163], including the built environment and urban settings on mental health [164,165].

While the selected studies predominantly use quantitative methods, integrating qualitative approaches could provide additional depth and context, especially on an individual level, and provide a more comprehensive view of the impact of environmental factors on mental health [166,167]. Qualitative research often lays the groundwork for subsequent quantitative studies, guiding the selection of study instruments and validating the results obtained quantitatively [168,169].

Surveying

Most studies, such as Li and Managi [51], Lohmann et al. [52], Kim et al. [57], Kim et al. [58], and Helbich, Browning, and Huss [70] incorporated surveying into their research to analyze mental health from the selected literature. Surveying and questionnaires can be quantitative and qualitative measurement tools used to understand the population, draw informed decisions or conclusions from the collected data, and make explanatory assertions about a population widely used to gather data on mental health from diverse populations [170,171]. In this study, Mouly et al. [44] and Lan et al. [49] used GAD to analyze anxiety disorders, PHQ scores were used by Huang et al. [45], Wan et al. [66], (PHQ-4), Kandola and Hayes [46] (PHQ-8), Hao et al. [60], Roberts and Helbich [48] and Helbich, Browning and Huss [70] (PHQ-9) to monitor the severity of depression and anxiety, EQ-5D by Shin, Park and Choi [65], WHO-5 Wellbeing Index by Huang, Tian and Yuan [53] to assess current mental wellbeing, CES-D scale by Zu et al. [55], Sakhvidi et al. [59], and Wang et al. [64] for self-reported depressive symptoms, and EMA repeated sampling was performed by Tao et al. [56] to analyze momentary and in-situ behaviors, moods, and experiences. ASRM, SWEMWBS, SCID-I, EPQR-Short, and CPSS scales were also used by Kandola and Hayes [46], Huang, Tian and Yuan [53], Hao et al. [60], Wan et al. [66], and Zhang et al. [69], respectively. Huang et al. [45] also used a 4-item (6-point) scale to analyze stress and a 5-item (6-point) scale to analyze worries related to COVID-19 in their study. Generaal et al. [71] used IDS, BAI, and FQ to assess the severity of depressive and anxiety disorders. These methods are highly structured with closed-ended

questions to ensure consistency and ease of data analysis. The data collected is numerical, allowing for calculating means, medians, variances, and other statistical measures to test hypotheses and draw conclusions from large sample populations [171–173]. They are often used to quantify subjective psychological states and traits, ensuring consistency and reliability in measuring mental health symptoms and facilitating the assessment of changes in mental health over time on persons' personal experiences and perceptions [171,173,174]. Qualitative surveys collect textual data for thematic analysis to identify patterns and themes, typically involving a smaller cohort size [175,176]. This method is relatively inexpensive to administer [177,178]. It has significantly increased since the COVID-19 pandemic researchers due to the ease of accessing online data and rapid response collection over traditional face-to-face methods, such as interviews, adhering to restrictions at the time [177]. Surveys can collect data from large and diverse population samples, offering a broad and inclusive range of data-enhancing generalizability of the findings and providing insight into individuals' perspectives and experiences [170,179]. These sampling methods are generally anonymized and confidential, protecting participants' personal information and identity, which in turn encourages participation honestly and openly about their mental health conditions.

While self-reporting surveying can offer anonymity, this method may feel impersonal and dissociated. The subjective nature of qualitative data collection and analysis can lead to biases and variability in interpretations, challenging the reliability and validity of the findings [146,180], such as respondents not reporting symptoms accurately to present themselves favorably, doubting the existence of mental illness, and online surveys by those who have access to the internet [181,182], which may affect the data's accuracy and reliability [183]. Huang et al. [45] used self-reported diaries during the AQ monitoring; however, they noted that data was affected by participants' bias, who conveniently and quickly wrote down the locations and times when conducting their daily activities, which could have led to biases due to inaccurate data input.

The researcher may create bias in surveys and psychological scales by ignoring certain personal attributes, such as respondent demographics and cultural groups, limiting the representativeness of the findings [178,182,184]. For instance, Mouly et al. [44] started the data collection in 1996, with follow-ups in 2000, 2003, 2006, 2009, 2012, 2015, and 2018. However, the GAD instrument used in the analysis was only introduced in 2003 in the study 3 stage, when women were already 25 to 30. Therefore, some anxiety symptoms were not analyzed in these women at ages 18 and 23 and 22–27 years in Study 1 and Study 2, creating biases and potentially losing a portion of the results. Huang, Tian, and Yuan [53] used three quantifying instruments to assess mental well-being, but all were limited and were closed-ended questions. Happiness was assessed with a single question— "In general, how happy would you say you are on a scale from 1 (extremely unhappy) to 10 (extremely happy)?" which may not provide a broad picture of the overall MH on the assessed cohort, despite incorporating other methods [53]. Roberts and Helbich [48] used the PHQ-9 scale to measure depressive symptoms. However, few studies have assessed its factor structure, and the results have been inconsistent [179].

Face-to-Face Sampling/Assessment

While only Generaal et al. [71] used this sampling method to analyze the presence of current depressive and anxiety disorders, incorporating the Composite International Diagnostic Interview (WHO version 2.1) in person, Huang et al. [45] assessed personal and household socioeconomic attributes. It is worth noting the importance of incorporating this method in the research. The study incorporated predetermined questions associated with quantitative methods.

Direct face-to-face assessment research data are obtained verbally between the interviewer and the respondent, allowing open-ended or closed-ended questions for comprehensive and in-depth data collection, providing richer, personal, and more nuanced information about mental health conditions than other methods and can include psycholog-

ical scales and observational assessments [185–187]. In qualitative methods-based research, the participants' thoughts, feelings, and beliefs, sometimes sensitive, about a particular topic are explored, building rapport even in highly structured and standardized interviews [188]. During face-to-face assessments, it is also possible to observe non-verbal cues such as body language, facial expressions, or tone of voice, which can provide additional context and insight into the participant's answers and mental health [186].

However, face-to-face assessments require resources, such as training on conducting the interviews, which may require time and training, which can be costly [185,186]. Lastly, it can limit the number of participants assessed within a given timeframe if the assessments are one-on-one rather than large groups such as focus groups [186] and sharing negative views about the study or too much personal information may harm rapport building and thus lower the response rate, introduce dishonesty, and introduce potential bias into the data [187,189].

Medical/Healthcare Data

Medical/healthcare data, or "real world data", is central to any healthcare activity involving collecting, analyzing, or using patient health information to direct insights into patients' health status and needs at a large scale, often spanning over several years [190]. In the results, Mouly et al. [44] used a random female cohort from the Australian Universal Healthcare System (Medicare) database to assess anxiety symptoms further following a GAD. Yang et al. [47] used inpatient data, self-reported data (based on physician diagnosis and subsequently checked with nurses), and death records for depression and anxiety, while Ji et al. [50] used hospital admission data for anxiety. Other studies involved in the scoping review also used this type of data [43,54,60,62,63,68].

These data are considered quantitative due to the wealth of numerical data, such as lab and assessment results, medication dosages, and vital signs that can be measured and quantified. The digitalization of health records has significantly helped to improve healthcare delivery with improved management, surveillance, and accessibility of patient data [191]. Medical records data offer high systematic accuracy and reliability, offering detailed clinical information, and allow for data linkages, which provide passive follow-ups for participant research and outcomes to be collected cost-effectively with minimal drop-out [192]. This provides a better phenotypic classification in predicting relevant outcomes [192–194]. Moreover, this data can validate self-reported data from surveys or scales, increasing research findings' overall accuracy and feasibility [195].

Regulations such as the General Data Protection Regulation (GDPR) may restrict the reuse of health data across different activities, requiring specific patient consent. Due to this complex landscape of ethical and legal requirements, attaining this type of data is extremely difficult, restricting research by the lengthy, confusing, and time-consuming applications and communications processes, which may not guarantee permission to access the data to protect the patient's confidentiality and personal information rights [194,196]. Even in low-risk studies, compiling a consent form and its active management could be costly and time-consuming [196–198]. Concerns about data misuse, especially non-anonymized data, and data leakage can lead patients to overprotect their data and not give their consent for its reuse in research [197,198].

Health facilities often use varied electronic or paper health records, screening, and organizational styles, and a lack of technical interoperability between data systems can hinder efficient data aggregation and use, leading to failure to get a comprehensive view of the patient's health status [192,195]. For example, Kandola and Hayes [46] used juli, a digital healthcare platform, and stated that certain confounders, such as socioeconomic position and urbanicity, may not have been measured. Furthermore, evaluations of treatment outcomes at geographical, administrative, epidemiological, or facility levels often focus solely on mortality, readmission, and data such as medicine use and other uses of health services and may fail to capture treatment outcomes fully [193]. Lastly, there could be a data selection bias as not all individuals with mental health conditions seek medical

help, thus resulting in incomplete and underrepresented data on populations with existing mental health disorders [195].

4.3. Statistical Methods

Four studies used linear regression for their analysis [45,46,51,52]. Multiple regression was used in two studies [48,49]. However, the model of Lan et al. [49] incorporated a random forest model as it is useful for capturing nonlinear associations. Whereas the generalized additive model, used by Ji et al. [50], Carroll et al. [68], and Helbich, Browning, and Huss [70], is considered to be a general case of regression [199], multivariate linear regression, or the general linear model (GLM) used by one study [53], compactly uses multiple linear regression models, allowing for different kinds of responses, and, when applied with Poisson distribution [43,63], the model offers more flexibility for describing experiences by a set of correlated count variables [199,200]. While multivariate and multivariable terms are used interchangeably in research, multivariable analysis refers to statistical models with multiple independent or response variables [201], which Zu et al. [55] used. Multilevel linear regression, used by Wang et al. [64] and Generaal et al. [71], accounts for data nested within groups, which are given a probability model, providing more accurate estimates when a hierarchical structure exists [202,203]. Multilevel ordinal regression models are used for ordering categories, as Tao et al. [56] used this to control both within-individual and inter-individual differences in stress responses to environmental pollutants.

Logistic regression, a type of GLM modeling used by Hao et al. [60], is incorporated when a dependable variable may have a discrete value or only one of the two values. It shows a relationship between the target and independent variables via a sigmoid curve. It best uses large data sets to predict a dichotomous outcome [204]. This model can be extended to multiple variables to construct complex logistic regression to predict the outcome of a response variable and achieve a meaningful relationship [57,58,65,69]. Conditional logistic regression, used by Rahman et al. [67], differs from logistic regression only in that the estimates are conditional on the matched groups or the cases linked to a case-control study, requiring individually matched studies [205].

Yang et al. [47] and Wan et al. [66] used Cox proportional hazard models to estimate the hazard ratios of individual air pollutants and air pollution scores and to what extent the association between green space and mortality was attenuated, respectively. These models consider the time until events occur and whether the risk factor affects the age of onset of the disease or disorder [206].

The two-way fixed effect regression model estimates causal effects from panel data and adjusts for unobserved unit-specific and time-specific confounders [62]. This model by Chen et al. [62] allowed us to rule out any confounding effects from time-invariant factors at the city level. The negative binomial regression is usually used for overdispersed outcome variables when conditional variance exceeds the mean [207]. Sakhvidi et al. [59] used this model to find the association between exposure to air pollution and depressive symptoms. Time-varying covariates, the Cox model, and generalized propensity score, as used by Feng et al. [54], were created for cohort survival data where air pollution and age were assumed from year-to-year varying exposures to estimate the association and mental disorders among people with diabetes. The model estimates the hazard of each participant being treated at a certain time [208]. In contrast, the generalized propensity score balancing is based on the conditional density of the continuous exposure given the confounders [54]. The generalized estimating equation, as used by Mouly et al. [44], allowed for repeated observations from each female participant over time. As GEE estimates population-average effects, it is broadly used in longitudinal studies for large groups of predictors, and it was appropriate for the study's aims and data [44,209].

5. Limitations and Recommendations

Despite the methodologies observed in the scoping review, several limitations must be acknowledged:

(1) Most studies included in this review are cross-sectional, limiting the ability to draw causal inferences. Cross-sectional designs capture a snapshot in time and cannot establish temporality, making it difficult to determine whether air pollution exposure precedes the onset of mental health symptoms [49,50]. Meanwhile, some studies employed longitudinal designs [47,48], which are excellent in tracking changes in mental health over time but may also face significant challenges such as systematic biases, high costs, measurement consistency, data management, changing contexts, participant burden, complex analysis, and ethical considerations limiting the feasibility of the literature [210–213]. Instead, prospective cohort studies may be more helpful in establishing causality and understanding the long-term impacts of air pollution on mental health due to their focus on identifying risk factors for disease or health outcomes by following a healthy cohort over time and assessing effects for the future. It is also important to note the abundance of quantitative methods assessed in the scoping review and the lack of qualitative methods used in the selected studies. None of the studies included qualitative methods, which could provide deeper insights into the subjective experiences of individuals affected by air pollution. Qualitative data could help portray the mechanisms through which air pollution impacts mental health and provide a more holistic understanding of these relationships through individual cohort perspectives.

(2) The obtained literature is biased geographically. Most studies were conducted in Asia and Europe, lacking representation from other continents and countries. This leaves significant gaps in knowledge regarding the impact of air pollution on mental health in different regions, such as Africa and South America, where no studies were identified in the scoping review. There could be various reasons for a lack of similar research, including focusing on physical health outcomes, such as respiratory and cardiovascular diseases, rather than mental health [21,73,214,215]. Funding may prioritize other public health issues perceived as more immediate or severe, leading to fewer research resources linking air quality and mental health. For example, African countries combat health risks such as HIV/AIDS, malaria, and tuberculosis while lacking a public budget or immediate concern and dedication to mitigate air pollution and focus on mental health research [216]. Furthermore, awareness of the potential links between air quality and mental health is relatively recent compared to more established areas of environmental health research. As a result, the body of research is still growing, and fewer reviews might have been conducted to synthesize existing studies. Additionally, collecting reliable air quality and mental health data can be challenging due to limited access to high-quality, long-term air pollution data and comprehensive mental health records, especially in developing countries. In some parts of South America and Africa, limited research infrastructure and resources can impede conducting extensive research [217–221]. There might be a lack of local expertise or interest in the intersection of air quality and mental health. Mental health research, in general, might be underprioritized due to cultural stigmas or SES challenges in certain regions [222]. Addressing these challenges requires targeted efforts to enhance research infrastructure, foster interdisciplinary collaboration, increase funding for mental health research in environmental health contexts, and raise awareness about the importance of studying the links between air quality and mental health.

(3) Many studies relied on self-reported measures for assessing mental health outcomes, such as the CES-D and PHQ-9 scales. Although these are validated tools, they are subject to reporting biases due to predetermined closed-end questions, which can affect the accuracy and reliability of the data. A mixed-method approach, such as quantitative and qualitative methods in the study design, could enhance the accuracy and reliability of mental health evaluations.

(4) This study primarily focused on the link between PM and MH, while other pollutants such as O_3, volatile organic compounds (VOCs), SO_2, CO, and NO_2 have not been addressed. These pollutants warrant consideration in future research as their poten-

tial neurotoxic effects could contribute to a broader understanding of how various air pollutants impact the nervous system and, consequently, MH. For example, O_3 exposure has been linked to activated stress responses [92], psychiatric emergency services admissions, depression, and other MH disorders [223–225], including the use of antidepressants [226]. VOCs are neurotoxic and can damage the central nervous system and affect sleep [227]. However, the association between VOCs and certain MH disorders, such as depression, remains unclear and requires more research [228,229]. Augmented risk of MH when exposed to SO_2, CO, and NO_2, especially depression and stress, has been observed in numerous studies [65,92,230–233]. While CO is predominantly associated with suicide [234,235] and has been previously used in several countries as a suicide method [236–238], it is also associated with cognitive impairments [239,240]. NO_2 and NO_X produce the most apparent association with adverse MH, such as anxiety [241], schizophrenia [242,243], depression [28,242,244], and various neurodevelopment disorders [245–248] in urban areas [249]. NO_2 and NO_X are commonly associated with motor vehicle exhausts [250]. Future research should aim to fill these gaps and consider the combined effects of multiple pollutants to provide a more comprehensive understanding of how air quality influences mental health.

(5) Several studies did not adequately control for potential confounders, such as meteorological, SES, lifestyle factors, and pre-existing health conditions, which could influence the observed associations between air pollution and mental health [45,46]. It is well acknowledged that meteorological conditions affect PM concentration in the atmosphere [251–257]. Lower SES populations, including minorities [258], often reside in areas lacking green spaces and higher pollution levels due to proximity to industrial zones, heavy traffic, and other pollution sources, work in jobs involving harmful exposures, and are more exposed to extreme weather events [259]. Future studies should better incorporate comprehensive adjustments for these variables to isolate the effects of air pollution on mental health.

(6) The variability in air pollution measurement methods in the selected studies may present a challenge. While some studies used fixed monitoring stations or LUR models, others solely relied on portable sensors or governmental databases, leading to potential inconsistencies in exposure assessment. Standardizing or using a mixed-method approach (e.g., LUR model with databases or portable monitors) to compare results and air quality measurement approaches across studies could improve the findings.

(7) Due to the strict inclusion criteria, many studies, including those of vulnerable populations such as children and the elderly (>69), were excluded from the scoping review. While the review identified the gap in research on assessing air quality effects on mental health in working-age urban adult populations, vulnerable populations might experience different or more severe implications of air pollution on mental health due to heightened sensitivities. Including vulnerable groups, including those with pre-existing mental health conditions, in future research is crucial as it could provide a more detailed understanding of the health impacts of air pollution [11]. This could have been why little to no research was discovered on other continents, such as South America and Africa—the lack of South American and African studies represents a significant research gap. These regions face unique environmental challenges and socio-economic conditions that could influence the relationship between air pollution and mental health differently, especially in South America and Africa, compared to more industrialized areas [74]. In many South American and African countries, limited funding, lack of infrastructure for air quality monitoring, and insufficient public health research capacities hinder comprehensive studies on environmental health [51]. Furthermore, political and economic challenges often divert attention and resources from environmental health issues, exacerbating the research gap [74].

Addressing this gap is essential for comprehensively understanding global health impacts and informing policies in these underrepresented regions.

(8) Exploring the interactive effects of multiple pollutants and other environmental stressors (e.g., noise pollution, green space) on mental health could provide more understanding of these complex relationships [45]. Green spaces are widely viewed as a health-promoting characteristic of residential environments, which could be useful to include in studies to broaden the understanding of how mental health could be improved when exposed to air pollution [260]. Advanced statistical techniques, such as structural equation modeling and machine learning, could be employed to unravel these multifaceted interactions [56].

(9) To widen the literature search, it is advisable to complement multiple databases, such as Medline, Web of Science, Google Scholar, or discipline-specific databases. Utilizing multiple databases can help broaden your search scope, ensure comprehensive coverage, and minimize potential biases or omissions in the literature.

6. Conclusions

The detailed examination of methodologies used in the scoping review provides valuable insights into the methods used to collect data required to correlate outdoor air quality, mainly ambient $PM_{2.5}$, and mental health outcomes, specifically depression, stress, and anxiety, in specific regions and adult populations. The most preferred method in studies to analyze AQ and MH are quantitative methods: using AQ data from monitoring stations to assert AQ, which is required for other AQ analysis methods, such as LUR; for MH, it is questionnaires with psychological scales, which indicates a focus on quantifiable and standardized mental health measures. Statistical methods, particularly linear regression models, have been widely used to find the relationship between AQ and MH.

Future research must address the diverse demographics (e.g., ages, cultures, races, geographical regions, etc.) and socioeconomic statuses (e.g., income, education level), as well as consider other environmental factors (e.g., meteorological conditions, vegetation, noise, etc.) to develop effective global health policies and interventions. Expanding research to encompass various pollutants and underrepresented geographical areas such as South America and Africa and including vulnerable groups such as children and the elderly will provide a more inclusive understanding of the mental health impacts of air pollution. Furthermore, integrating qualitative methods alongside quantitative analyses can enhance our understanding of the complex interactions between environmental factors and mental health.

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References

1. World Health Organization (WHO). Ambient (Outdoor) Air Pollution. 2022. Available online: https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health (accessed on 10 July 2024).
2. American Lung Association. Health Impact of Pollution | State of the Air. 2024. Health Impact of Pollution | State of the Air. 2024. Available online: https://www.lung.org/research/sota/health-risks (accessed on 26 July 2024).
3. European Environment Association (EEA). How Air Pollution Affects Our Health. 2023. Available online: https://www.eea.europa.eu/en/topics/in-depth/air-pollution/eow-it-affects-our-health (accessed on 26 July 2024).
4. United States Environmental Protection Agency (US EPA). Research on Health Effects from Air Pollution. 2020. Available online: https://www.epa.gov/air-research/research-health-effects-air-pollution (accessed on 26 July 2024).
5. Pykett, J.; Campbell, N.; Fenton, S.-J.; Gagen, E.; Lavis, A.; Newbigging, K.; Parkin, V.; Williams, J. Urban precarity and youth mental health: An interpretive scoping review of emerging approaches. *Soc. Sci. Med.* **2023**, *320*, 115619. [CrossRef] [PubMed]
6. Neufeld, S.A.S. The burden of young people's mental health conditions in Europe: No cause for complacency. *Lancet Reg. Health-Eur.* **2022**, *16*, 100364. [CrossRef] [PubMed]
7. Appleton, R.; Barnett, P.; Chipp, B.; Clark, M.; Goldblatt, P.; Jeffreys, S.; Machin, K.; Needle, J.J.; Shah, P.; Thompson, G.; et al. Development of a conceptual framework to guide description and evaluation of social interventions for people with serious mental health conditions. *SSM-Ment. Health* **2023**, *4*, 100271. [CrossRef]
8. Chen, F.; Zhang, X.; Chen, Z. Air pollution and mental health: Evidence from China Health and Nutrition Survey. *J. Asian Econ.* **2023**, *86*, 101611. [CrossRef]
9. Schraufnagel, D.E. The health effects of ultrafine particles. *Exp. Mol. Med.* **2020**, *52*, 311–317. [CrossRef]
10. Hamanaka, R.B.; Mutlu, G.M. Particulate Matter Air Pollution: Effects on the Cardiovascular System. *Front Endocrinol.* **2018**, *9*. Available online: https://www.frontiersin.org/journals/endocrinology/articles/10.3389/fendo.2018.00680/full (accessed on 28 July 2024). [CrossRef] [PubMed]
11. Block, M.L.; Calderón-Garcidueñas, L. Air pollution: Mechanisms of neuroinflammation and CNS disease. *Trends Neurosci.* **2009**, *32*, 506–516. [CrossRef]
12. Pun, V.C.; Manjourides, J.; Suh, H. Association of Ambient Air Pollution with Depressive and Anxiety Symptoms in Older Adults: Results from the NSHAP Study. *Environ. Health Perspect.* **2017**, *125*, 342–348. [CrossRef] [PubMed]
13. Perera, F.P.; Wang, S.; Rauh, V.; Zhou, H.; Stigter, L.; Camann, D.; Jedrychowski, W.; Mroz, E.; Majewska, R. Prenatal Exposure to Air Pollution, Maternal Psychological Distress, and Child Behavior. *Pediatrics* **2013**, *132*, e1284–e1294. [CrossRef]
14. Fonken, L.K.; Xu, X.; Weil, Z.M.; Chen, G.; Sun, Q.; Rajagopalan, S.; Nelson, R.J. Air pollution impairs cognition, provokes depressive-like behaviors and alters hippocampal cytokine expression and morphology. *Mol. Psychiatry* **2011**, *16*, 987–995. [CrossRef]
15. Tran, N.Q.V.; Miyake, K. Neurodevelopmental Disorders and Environmental Toxicants: Epigenetics as an Underlying Mechanism. *Int. J. Genom.* **2017**, *2017*, 7526592. [CrossRef] [PubMed]
16. Bhatt, D.P.; Puig, K.L.; Gorr, M.W.; Wold, L.E.; Combs, C.K. A Pilot Study to Assess Effects of Long-Term Inhalation of Airborne Particulate Matter on Early Alzheimer-Like Changes in the Mouse Brain. *PLoS ONE* **2015**, *10*, e0127102. [CrossRef]
17. Kyi-Tha-Thu, C.; Fujitani, Y.; Hirano, S.; Win-Shwe, T.-T. Early-Life Exposure to Traffic-Related Air Pollutants Induced Anxiety-like Behaviors in Rats via Neurotransmitters and Neurotrophic Factors. *Int. J. Mol. Sci.* **2022**, *24*, 586. [CrossRef]
18. Zundel, C.G.; Ryan, P.; Brokamp, C.; Heeter, A.; Huang, Y.; Strawn, J.R.; Marusak, H.A. Air Pollution, Depressive and Anxiety Disorders, and Brain Effects: A Systematic Review. *Neurotoxicology* **2022**, *93*, 272–300. [CrossRef] [PubMed]
19. Zhu, J.; Lu, C. Air Quality, Pollution Perception, and Residents' Health: Evidence from China. *Toxics* **2023**, *11*, 591. [CrossRef] [PubMed]
20. Li, Z.-H.; Mao, Y.-C.; Li, Y.; Zhang, S.; Hu, H.-Y.; Liu, Z.-Y.; Liu, X.-J.; Zhao, J.-W.; Huang, K.; Chen, M.-L.; et al. Joint effects of prenatal exposure to air pollution and pregnancy-related anxiety on birth weight: A prospective birth cohort study in Ma'anshan, China. *Environ. Res.* **2023**, *238*, 117161. [CrossRef] [PubMed]
21. Kanner, J.; Pollack, A.Z.; Ranasinghe, S.; Stevens, D.R.; Nobles, C.; Rohn, M.C.H.; Sherman, S.; Mendola, P. Chronic exposure to air pollution and risk of mental health disorders complicating pregnancy. *Environ. Res.* **2021**, *196*, 110937. [CrossRef] [PubMed]
22. Li, J.; Huang, L.; Han, B.; Van Der Kuijp, T.J.; Xia, Y.; Chen, K. Exposure and perception of PM2.5 pollution on the mental stress of pregnant women. *Environ. Int.* **2021**, *156*, 106686. [CrossRef] [PubMed]
23. Ahmed, S.M.; Mishra, G.D.; Moss, K.M.; Yang, I.A.; Lycett, K.; Knibbs, L.D. Maternal and Childhood Ambient Air Pollution Exposure and Mental Health Symptoms and Psychomotor Development in Children: An Australian Population-Based Longitudinal Study. *Environ. Int.* **2022**, *158*, 107003. [CrossRef]
24. Iglesias-Vázquez, L.; Binter, A.-C.; Canals, J.; Hernández-Martínez, C.; Voltas, N.; Ambròs, A.; Fernández-Barrés, S.; Pérez-Crespo, L.; Guxens, M.; Arija, V. Maternal exposure to air pollution during pregnancy and child's cognitive, language, and motor function: ECLIPSES study. *Environ. Res.* **2022**, *212*, 113501. [CrossRef]
25. Zou, M.-L.; Jiang, C.-B.; Chen, Y.-H.; Wu, C.-D.; Candice Lung, S.-C.; Chien, L.-C.; Kallawicha, K.; Yang, Y.-T.; Lo, Y.-C.; Chao, H.J. Effects of air pollution, land-use type, and maternal mental health on child development in the first two years of life in the Greater Taipei area. *Environ. Res.* **2021**, *197*, 111168. [CrossRef] [PubMed]

26. Reuben, A.; Arseneault, L.; Beddows, A.; Beevers, S.D.; Moffitt, T.E.; Ambler, A.; Latham, R.M.; Newbury, J.B.; Odgers, C.L.; Schaefer, J.D.; et al. Association of Air Pollution Exposure in Childhood and Adolescence with Psychopathology at the Transition to Adulthood. *JAMA Netw. Open* **2021**, *4*, e217508. [CrossRef] [PubMed]
27. World Health Organization (WHO). More than 90% of the World's Children Breathe Toxic Air Every Day. 2018. Available online: https://www.who.int/news/item/29-10-2018-more-than-90-of-the-worlds-children-breathe-toxic-air-every-day (accessed on 23 June 2024).
28. Roberts, S.; Arseneault, L.; Barratt, B.; Beevers, S.; Danese, A.; Odgers, C.L.; Moffitt, T.E.; Reuben, A.; Kelly, F.J.; Fisher, H.L. Exploration of NO2 and PM2.5 air pollution and mental health problems using high-resolution data in London-based children from a UK longitudinal cohort study. *Psychiatry Res.* **2019**, *272*, 8–17. [CrossRef] [PubMed]
29. Campbell, C.E.; Cotter, D.L.; Bottenhorn, K.L.; Burnor, E.; Ahmadi, H.; Gauderman, W.J.; Cardenas-Iniguez, C.; Hackman, D.; McConnell, R.; Berhane, K.; et al. Air pollution and age-dependent changes in emotional behavior across early adolescence in the U.S. *Environ. Res.* **2024**, *240*, 117390. [CrossRef] [PubMed]
30. Kelly, F.J.; Fussell, J.C. Size, source and chemical composition as determinants of toxicity attributable to ambient particulate matter. *Atmos. Environ.* **2012**, *60*, 504–526. [CrossRef]
31. Yun, G.; Yang, C.; Ge, S. Understanding Anthropogenic PM2.5 Concentrations and Their Drivers in China during 1998–2016. *Int. J. Environ. Res. Public Health* **2022**, *20*, 695. [CrossRef] [PubMed]
32. European Environment Association (EEA). Premature Deaths Due to Air Pollution Continue to Fall in the EU, More Efforts Needed to Deliver a Toxic-Free Environment. 2022. Available online: https://www.eea.europa.eu/en/newsroom/news/premature-deaths-due-air-pollution (accessed on 28 July 2024).
33. Arksey, H.; O'Malley, L. Scoping studies: Towards a methodological framework. *Int. J. Soc. Res. Methodol.* **2005**, *8*, 19–32. [CrossRef]
34. Baker, E.; Barlow, C.F.; Daniel, L.; Morey, C.; Bentley, R.; Taylor, M.P. Mental health impacts of environmental exposures: A scoping review of evaluative instruments. *Sci. Total Environ.* **2024**, *912*, 169063. [CrossRef] [PubMed]
35. Mazumder, H.; Rimu, F.H.; Shimul, M.H.; Das, J.; Gain, E.P.; Liaw, W.; Hossain, M.M. Maternal health outcomes associated with ambient air pollution: An umbrella review of systematic reviews and meta-analyses. *Sci. Total Environ.* **2024**, *914*, 169792. [CrossRef]
36. Theron, L.C.; Abreu-Villaça, Y.; Augusto-Oliveira, M.; Brennan, C.; Crespo-Lopez, M.E.; de Paula Arrifano, G.; Glazer, L.; Gwata, N.; Lin, L.; Mareschal, I.; et al. A systematic review of the mental health risks and resilience among pollution-exposed adolescents. *J. Psychiatr. Res.* **2022**, *146*, 55–66. [CrossRef]
37. Lu, J.G. Air pollution: A systematic review of its psychological, economic, and social effects. *Curr. Opin. Psychol.* **2020**, *32*, 52–65. [CrossRef] [PubMed]
38. Buoli, M.; Grassi, S.; Caldiroli, A.; Carnevali, G.S.; Mucci, F.; Iodice, S.; Cantone, L.; Pergoli, L.; Bollati, V. Is there a link between air pollution and mental disorders? *Environ. Int.* **2018**, *118*, 154–168. [CrossRef] [PubMed]
39. Embase. 2024. Available online: https://www.embase.com/search/quick?phase=continueToApp (accessed on 10 February 2024).
40. PubMed. 2024. Available online: https://pubmed.ncbi.nlm.nih.gov/ (accessed on 10 February 2024).
41. Ponsoni, A.; Branco, L.D.; Cotrena, C.; Shansis, F.M.; Grassi-Oliveira, R.; Fonseca, R.P. Self-reported inhibition predicts history of suicide attempts in bipolar disorder and major depression. *Compr. Psychiatry* **2018**, *82*, 89–94. [CrossRef] [PubMed]
42. Chesney, E.; Goodwin, G.M.; Fazel, S. Risks of all-cause and suicide mortality in mental disorders: A meta-review. *World Psychiatry* **2014**, *13*, 153–160. [CrossRef] [PubMed]
43. Miyazaki, H.; Hino, K.; Ito, T.; Abe, T.; Nomoto, M.; Furuno, T.; Takeuchi, I.; Hishimoto, A. Relationship of emergency department visits for suicide attempts with meteorological and air pollution conditions. *J. Affect. Disord.* **2023**, *333*, 154–160. [CrossRef] [PubMed]
44. Mouly, T.A.; Mishra, G.D.; Hystad, P.; Nieuwenhuijsen, M.; Knibbs, L.D. Residential greenspace and anxiety symptoms among Australian women living in major cities: A longitudinal analysis. *Environ. Int.* **2023**, *179*, 108110. [CrossRef] [PubMed]
45. Huang, J.; Kwan, M.-P.; Tse, L.A.; He, S.Y. How People's COVID-19 Induced-Worries and Multiple Environmental Exposures Are Associated with Their Depression, Anxiety, and Stress during the Pandemic. *Int. J. Environ. Res. Public Health* **2023**, *20*, 6620. [CrossRef] [PubMed]
46. Kandola, A.; Hayes, J.F. Real-time air pollution and bipolar disorder symptoms: Remote-monitored cross-sectional study. *BJPsych Open* **2023**, *9*, e107. [CrossRef] [PubMed]
47. Yang, T.; Wang, J.; Huang, J.; Kelly, F.J.; Li, G. Long-term Exposure to Multiple Ambient Air Pollutants and Association with Incident Depression and Anxiety. *JAMA Psychiatry* **2023**, *80*, 305–313. [CrossRef]
48. Roberts, H.; Helbich, M. Multiple environmental exposures along daily mobility paths and depressive symptoms: A smartphone-based tracking study. *Environ. Int.* **2021**, *156*, 106635. [CrossRef]
49. Lan, Y.; Roberts, H.; Kwan, M.-P.; Helbich, M. Daily space-time activities, multiple environmental exposures, and anxiety symptoms: A cross-sectional mobile phone-based sensing study. *Sci. Total Environ.* **2022**, *834*, 155276. [CrossRef] [PubMed]
50. Ji, Y.; Liu, B.; Song, J.; Cheng, J.; Wang, H.; Su, H. Association between traffic-related air pollution and anxiety hospitalizations in a coastal Chinese city: Are there potentially susceptible groups? *Environ. Res.* **2022**, *209*, 112832. [CrossRef] [PubMed]

51. Li, C.; Managi, S. Spatial Variability of the Relationship between Air Pollution and Well-being. *Sustain. Cities Soc.* **2022**, *76*, 103447. [CrossRef]
52. Lohmann, P.M.; Gsottbauer, E.; You, J.; Kontoleon, A. Air pollution and anti-social behaviour: Evidence from a randomised lab-in-the-field experiment. *Soc. Sci. Med.* **2023**, *320*, 115617. [CrossRef] [PubMed]
53. Huang, D.; Tian, M.; Yuan, L. Do objective and subjective traffic-related pollution, physical activity and nature exposure affect mental wellbeing? Evidence from Shenzhen, China. *Sci. Total Environ.* **2023**, *869*, 161819. [CrossRef] [PubMed]
54. Feng, J.; Cai, M.; Qian, Z. (Min); Zhang, S.; Yang, Y.; McMillin, S.E.; Chen, G.; Hua, J.; Tabet, M.; Wang, C.; et al. The effects of long-term exposure to air pollution on incident mental disorders among patients with prediabetes and diabetes: Findings from a large prospective cohort. *Sci. Total Environ.* **2023**, *897*, 165235. [CrossRef] [PubMed]
55. Zu, D.; Zhai, K.; Qiu, Y.; Pei, P.; Zhu, X.; Han, D. The Impacts of Air Pollution on Mental Health: Evidence from the Chinese University Students. *Int. J. Environ. Res. Public Health* **2020**, *17*, 6734. [CrossRef] [PubMed]
56. Tao, Y.; Kou, L.; Chai, Y.; Kwan, M.-P. Associations of co-exposures to air pollution and noise with psychological stress in space and time: A case study in Beijing, China. *Environ. Res.* **2021**, *196*, 110399. [CrossRef]
57. Kim, H.-J.; Kim, H.-S.; Kim, S.; Hwang, J.; Lee, H.; Park, B.; Kim, B. Effects of vitamin D on associations between air pollution and mental health outcomes in Korean adults: Results from the Korea National Health and Nutrition Examination Survey (KNHANES). *J. Affect. Disord.* **2023**, *320*, 390–396. [CrossRef]
58. Kim, H.-J.; Min, J.; Seo, Y.-S.; Min, K. Relationship between chronic exposure to ambient air pollution and mental health in Korean adult cancer survivors and the general population. *BMC Cancer* **2021**, *21*, 1298. [CrossRef]
59. Sakhvidi, M.J.Z.; Lafontaine, A.; Lequy, E.; Berr, C.; de Hoogh, K.; Vienneau, D.; Goldberg, M.; Zins, M.; Lemogne, C.; Jacquemin, B. Ambient air pollution exposure and depressive symptoms: Findings from the French CONSTANCES cohort. *Environ. Int.* **2022**, *170*, 107622. [CrossRef] [PubMed]
60. Hao, G.; Zuo, L.; Xiong, P.; Chen, L.; Liang, X.; Jing, C. Associations of $PM_{2.5}$ and road traffic noise with mental health: Evidence from UK Biobank. *Environ. Res.* **2022**, *207*, 112221. [CrossRef] [PubMed]
61. Zhang, H.; Xia, Y.; Cao, L.; Chang, Q.; Zhao, Y. Associations between long term exposures to outdoor air pollution and indoor solid fuel use and depression in China. *J. Environ. Manag.* **2022**, *302*, 113982. [CrossRef] [PubMed]
62. Chen, B.; Ma, W.; Pan, Y.; Guo, W.; Chen, Y. $PM_{2.5}$ exposure and anxiety in China: Evidence from the prefectures. *BMC Public Health* **2021**, *21*, 429. [CrossRef] [PubMed]
63. Díaz, J.; López-Bueno, J.A.; López-Ossorio, J.J.; Gónzález, J.L.; Sánchez, F.; Linares, C. Short-term effects of traffic noise on suicides and emergency hospital admissions due to anxiety and depression in Madrid (Spain). *Sci. Total Environ.* **2020**, *710*, 136315. [CrossRef]
64. Wang, R.; Xue, D.; Liu, Y.; Liu, P.; Chen, H. The Relationship between Air Pollution and Depression in China: Is Neighbourhood Social Capital Protective? *Int. J. Environ. Res. Public Health* **2018**, *15*, 1160. [CrossRef] [PubMed]
65. Shin, J.; Park, J.Y.; Choi, J. Long-term exposure to ambient air pollutants and mental health status: A nationwide population-based cross-sectional study. *PLoS ONE* **2018**, *13*, e0195607. [CrossRef]
66. Wan, S.; Rojas-Rueda, D.; Pretty, J.; Roscoe, C.; James, P.; Ji, J.S. Greenspace and mortality in the U.K. Biobank: Longitudinal cohort analysis of socio-economic, environmental, and biomarker pathways. *SSM-Popul. Health* **2022**, *19*, 101194. [CrossRef]
67. Rahman, M.M.; Lorenzo, M.; Ban-Weiss, G.; Hasan, Z.; Azzouz, M.; Eckel, S.P.; Conti, D.V.; Lurmann, F.; Schlaerth, H.; Johnston, J.; et al. Ambient temperature and air pollution associations with suicide and homicide mortality in California: A statewide case-crossover study. *Sci. Total Environ.* **2023**, *874*, 162462. [CrossRef]
68. Carroll, M.; Gao, C.X.; Campbell, T.C.H.; Smith, C.L.; Dimitriadis, C.; Berger, E.; Maybery, D.; Ikin, J.; Abramson, M.J.; Sim, M.R.; et al. Impacts of coal mine fire-related $PM_{2.5}$ on the utilisation of ambulance and hospital services for mental health conditions. *Atmos. Pollut. Res.* **2022**, *13*, 101415. [CrossRef]
69. Zhang, W.; Peng, S.; Fu, J.; Xu, K.; Wang, H.; Jin, Y.; Yang, T.; Cottrell, R.R. Urban Air Pollution and Mental Stress: A Nationwide Study of University Students in China. *Front. Public Health* **2021**, *9*, 685431. [CrossRef] [PubMed]
70. Helbich, M.; Browning, M.H.E.M.; Huss, A. Outdoor light at night, air pollution and depressive symptoms: A cross-sectional study in the Netherlands. *Sci. Total Environ.* **2020**, *744*, 140914. [CrossRef] [PubMed]
71. Generaal, E.; Timmermans, E.J.; Dekkers, J.E.C.; Smit, J.H.; Penninx, B.W.J.H. Not urbanization level but socioeconomic, physical and social neighbourhood characteristics are associated with presence and severity of depressive and anxiety disorders. *Psychol. Med.* **2019**, *49*, 149–161. [CrossRef] [PubMed]
72. Radua, J.; De Prisco, M.; Oliva, V.; Fico, G.; Vieta, E.; Fusar-Poli, P. Impact of air pollution and climate change on mental health outcomes: An umbrella review of global evidence. *World Psychiatry* **2024**, *23*, 244–256. [CrossRef]
73. Bhui, K.; Newbury, J.B.; Latham, R.M.; Ucci, M.; Nasir, Z.A.; Turner, B.; O'Leary, C.; Fisher, H.L.; Marczylo, E.; Douglas, P.; et al. Air quality and mental health: Evidence, challenges and future directions. *BJPsych Open* **2023**, *9*, e120. [CrossRef] [PubMed]
74. Braithwaite, I.; Zhang, S.; Kirkbride, J.B.; Osborn, D.P.J.; Hayes, J.F. Air Pollution (Particulate Matter) Exposure and Associations with Depression, Anxiety, Bipolar, Psychosis and Suicide Risk: A Systematic Review and Meta-Analysis. *Environ. Health Perspect.* **2019**, *127*, 126002. [CrossRef] [PubMed]
75. Chen, C.; Liu, C.; Chen, R.; Wang, W.; Li, W.; Kan, H.; Fu, C. Ambient air pollution and daily hospital admissions for mental disorders in Shanghai, China. *Sci. Total Environ.* **2018**, *613–614*, 324–330. [CrossRef]
76. Rentschler, J.; Leonova, N. Global air pollution exposure and poverty. *Nat. Commun.* **2023**, *14*, 4432. [CrossRef] [PubMed]

77. Ju, K.; Lu, L.; Wang, W.; Chen, T.; Yang, C.; Zhang, E.; Xu, Z.; Li, S.; Song, J.; Pan, J.; et al. Causal effects of air pollution on mental health among Adults—An exploration of susceptible populations and the role of physical activity based on a longitudinal nationwide cohort in China. *Environ. Res.* **2023**, *217*, 114761. [CrossRef]
78. Chen, H.; Quick, M.; Kaufman, J.S.; Chen, C.; Kwong, J.C.; Van Donkelaar, A.; Meng, J.; Martin, R.V.; Kim, J.; Lavigne, E.; et al. Impact of lowering fine particulate matter from major emission sources on mortality in Canada: A nationwide causal analysis. *Proc. Natl. Acad. Sci. USA* **2022**, *119*, e2209490119. [CrossRef]
79. Zeng, J.; Bao, R.; McFarland, M. Clean energy substitution: The effect of transitioning from coal to gas on air pollution. *Energy Econ.* **2022**, *107*, 105816. [CrossRef]
80. Cai, W.; Zhang, C.; Suen, H.P.; Ai, S.; Bai, Y.; Bao, J.; Chen, B.; Cheng, L.; Cui, X.; Dai, H.; et al. The 2020 China report of the *Lancet* Countdown on health and climate change. *Lancet Public Health* **2021**, *6*, e64–e81. [CrossRef] [PubMed]
81. Wang, S.; Su, H.; Chen, C.; Tao, W.; Streets, D.G.; Lu, Z.; Zheng, B.; Carmichael, G.R.; Lelieveld, J.; Pöschl, U.; et al. Natural gas shortages during the "coal-to-gas" transition in China have caused a large redistribution of air pollution in winter 2017. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 31018–31025. [CrossRef] [PubMed]
82. Yang, T.; Wu, D.; Zhang, W.; Cottrell, R.R.; Rockett, I.R.H. Comparative Stress Levels among Residents in Three Chinese Provincial Capitals, 2001 and 2008. *PLoS ONE* **2012**, *7*, e48971. [CrossRef] [PubMed]
83. Fuller, R.; Landrigan, P.J.; Balakrishnan, K.; Bathan, G.; Bose-O'Reilly, S.; Brauer, M.; Caravanos, J.; Chiles, T.; Cohen, A.; Corra, L.; et al. Pollution and health: A progress update. *Lancet Planet. Health* **2022**, *6*, e535–e547. [CrossRef] [PubMed]
84. Ji, H.; Wang, J.; Meng, B.; Cao, Z.; Yang, T.; Zhi, G.; Chen, S.; Wang, S.; Zhang, J. Research on adaption to air pollution in Chinese cities: Evidence from social media-based health sensing. *Environ. Res.* **2022**, *210*, 112762. [CrossRef]
85. AQLI. China. 2024. Available online: https://aqli.epic.uchicago.edu/country-spotlight/china/?lang=zh-hans (accessed on 26 July 2024).
86. Xu, Q.; Li, H.; Zhu, D. Socioeconomic status, personality, and major mental disorders: A bidirectional Mendelian randomization study. *Schizophrenia* **2024**, *10*, 49. [CrossRef] [PubMed]
87. Yang, J.; Shi, B.; Shi, Y.; Marvin, S.; Zheng, Y.; Xia, G. Air pollution dispersal in high density urban areas: Research on the triadic relation of wind, air pollution, and urban form. *Sustain. Cities Soc.* **2020**, *54*, 101941. [CrossRef]
88. Rockey, S. Considering Sex as a Biological Variable in Research—Your Input is Requested—NIH Extramural Nexus. 2014. Available online: https://nexus.od.nih.gov/all/2014/09/11/considering-sex-as-a-biological-variable-in-research-your-input-is-requested/ (accessed on 16 July 2024).
89. Qiu, X.; Danesh-Yazdi, M.; Wei, Y.; Di, Q.; Just, A.; Zanobetti, A.; Weisskopf, M.; Dominici, F.; Schwartz, J. Associations of short-term exposure to air pollution and increased ambient temperature with psychiatric hospital admissions in older adults in the USA: A case–crossover study. *Lancet Planet. Health* **2022**, *6*, e331–e341. [CrossRef]
90. Liu, G.; Sun, B.; Yu, L.; Chen, J.; Han, B.; Li, Y.; Chen, J. The Gender-Based Differences in Vulnerability to Ambient Air Pollution and Cerebrovascular Disease Mortality: Evidences Based on 26781 Deaths. *Glob. Heart* **2020**, *15*, 46. [CrossRef]
91. Kim, H.; Noh, J.; Noh, Y.; Oh, S.S.; Koh, S.-B.; Kim, C. Gender Difference in the Effects of Outdoor Air Pollution on Cognitive Function Among Elderly in Korea. *Front. Public Health* **2019**, *7*, 375. [CrossRef] [PubMed]
92. Szyszkowicz, M.; Kousha, T.; Kingsbury, M.; Colman, I. Air Pollution and Emergency Department Visits for Depression: A Multicity Case-Crossover Study. *Environ. Health Insights* **2016**, *10*, 155–161. [CrossRef] [PubMed]
93. Lødrup Carlsen, K.C.; Løvik, M.; Granum, B.; Mowinckel, P.; Carlsen, K.H. Soluble CD14 at 2 yr of age: Gender-related effects of tobacco smoke exposure, recurrent infections and atopic diseases. *Pediatr. Allergy Immunol.* **2006**, *17*, 304–312. [CrossRef] [PubMed]
94. Luginaah, I.N.; Fung, K.Y.; Gorey, K.M.; Webster, G.; Wills, C. Association of Ambient Air Pollution with Respiratory Hospitalization in a Government-Designated "Area of Concern": The Case of Windsor, Ontario. *Environ. Health Perspect.* **2005**, *113*, 290–296. [CrossRef] [PubMed]
95. Franklin, M.; Zeka, A.; Schwartz, J. Association between PM2.5 and all-cause and specific-cause mortality in 27 US communities. *J. Expo. Sci. Environ. Epidemiol.* **2007**, *17*, 279–287. [CrossRef] [PubMed]
96. Vollmer, W.M.; Enright, P.L.; Pedula, K.L.; Speizer, F.; Kuller, L.H.; Kiley, J.; Weinmann, G.G. Race and Gender Differences in the Effects of Smoking on Lung Function. *Chest* **2000**, *117*, 764–772. [CrossRef] [PubMed]
97. Yunginger, J.W.; Reed, C.E.; O'Connell, E.J.; Melton, L.J.; O'Fallon, W.M.; Silverstein, M.D. A Community-based Study of the Epidemiology of Asthma: Incidence Rates, 1964–1983. *Am. Rev. Respir. Dis.* **1992**, *146*, 888–894. [CrossRef] [PubMed]
98. Lin, J.; Zou, L.; Lin, W.; Becker, B.; Yeung, A.; Cuijpers, P.; Li, H. Does gender role explain a high risk of depression? A meta-analytic review of 40 years of evidence. *J. Affect. Disord.* **2021**, *294*, 261–278. [CrossRef] [PubMed]
99. Verma, R.; Balhara, Y.S.; Gupta, C. Gender differences in stress response: Role of developmental and biological determinants. *Ind. Psychiatry J.* **2011**, *20*, 4. [CrossRef]
100. Clougherty, J.E. A Growing Role for Gender Analysis in Air Pollution Epidemiology. *Environ. Health Perspect.* **2010**, *118*, 167–176. [CrossRef]
101. Wang, J.-X.; Liu, X.-Q. Climate change, ambient air pollution, and students' mental health. *World J. Psychiatry* **2024**, *14*, 204–209. [CrossRef] [PubMed]
102. Cao, Z.; Zhou, J.; Li, M.; Huang, J.; Dou, D. Urbanites' mental health undermined by air pollution. *Nat. Sustain.* **2023**, *6*, 470–478. [CrossRef]

103. Zhang, X.; Chen, X.; Zhang, X. The impact of exposure to air pollution on cognitive performance. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 9193–9197. [CrossRef] [PubMed]
104. Lin, G.-Z.; Li, L.; Song, Y.-F.; Zhou, Y.-X.; Shen, S.-Q.; Ou, C.-Q. The impact of ambient air pollution on suicide mortality: A case-crossover study in Guangzhou, China. *Environ. Health* **2016**, *15*, 90. [CrossRef]
105. Li, H.; Li, M.; Zhang, S.; Qian, Z. (Min); Zhang, Z.; Zhang, K.; Wang, C.; Arnold, L.D.; McMillin, S.E.; Wu, S.; et al. Interactive effects of cold spell and air pollution on outpatient visits for anxiety in three subtropical Chinese cities. *Sci. Total Environ.* **2022**, *817*, 152789. [CrossRef] [PubMed]
106. Vongruang, P.; Pimonsree, S. Biomass burning sources and their contributions to PM_{10} concentrations over countries in mainland Southeast Asia during a smog episode. *Atmos. Environ.* **2020**, *228*, 117414. [CrossRef]
107. United States Environmental Protection Agency (US EPA). *Best Practices for Review and Validation of Ambient Air Monitoring Data*; Report No.: EPA-454/B-21-007; U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Air Quality Assessment Division: Washington, DC, USA, 2021.
108. Department for Environment, Food & Rural Affairs (DEFRA). *Quality Assurance and Quality Control (QA/QC) Procedures for UK Air Quality Monitoring under the Air Quality Standards Regulations*; Department for Environment, Food and Rural Affairs: London, UK, 2023.
109. European Commission (EC). *Guide to the Demonstration of Equivalence of Ambient Air Monitoring Methods*; Working Group on Guidance for the Demonstration of Equivalence: EU; European Commission (EC): Brussels, Belgium, 2010; Volume 92.
110. European Environment Agency (EEA). Air Quality in Europe—2020 Report—European Environment Agency. Europe: European Environment Agency. 2020. Report No.: 9/2020. Available online: https://www.eea.europa.eu/publications/air-quality-in-europe-2020-report (accessed on 22 June 2024).
111. Mooney, P. *Connecting Data and Environmental Research at the Environmental Protection Agency*; Report No.: 192; Environmental Protection Agency (EPA): Wexford, Ireland, 2016.
112. Gupta, P.; Christopher, S.A.; Wang, J.; Gehrig, R.; Lee, Y.; Kumar, N. Satellite remote sensing of particulate matter and air quality assessment over global cities. *Atmos. Environ.* **2006**, *40*, 5880–5892. [CrossRef]
113. Zhang, Y.; Li, Z.; Bai, K.; Wei, Y.; Xie, Y.; Zhang, Y.; Ou, Y.; Cohen, J.; Zhang, Y.; Peng, Z.; et al. Satellite remote sensing of atmospheric particulate matter mass concentration: Advances, challenges, and perspectives. *Fundam. Res.* **2021**, *1*, 240–258. [CrossRef]
114. Geddes, J.A.; Martin, R.V.; Boys, B.L.; Van Donkelaar, A. Long-Term Trends Worldwide in Ambient NO_2 Concentrations Inferred from Satellite Observations. *Environ. Health Perspect.* **2016**, *124*, 281–289. [CrossRef]
115. Wang, Z.; Chen, L.; Tao, J.; Zhang, Y.; Su, L. Satellite-based estimation of regional particulate matter (PM) in Beijing using vertical-and-RH correcting method. *Remote Sens. Environ.* **2010**, *114*, 50–63. [CrossRef]
116. Mukonza, S.S.; Chiang, J.-L. Meta-Analysis of Satellite Observations for United Nations Sustainable Development Goals: Exploring the Potential of Machine Learning for Water Quality Monitoring. *Environments* **2023**, *10*, 170. [CrossRef]
117. White, A.R. Human expertise in the interpretation of remote sensing data: A cognitive task analysis of forest disturbance attribution. *Int. J. Appl. Earth Obs. Geoinf.* **2019**, *74*, 37–44. [CrossRef]
118. Cheung, Y.; Pang, M.; Lin, H.; Lee, C.K.J. Enable Spatial Thinking Using GIS and Satellite Remote Sensing—A Teacher-Friendly Approach. *Procedia-Soc. Behav. Sci.* **2011**, *21*, 130–138. [CrossRef]
119. van Donkelaar, A.; Martin, R.V.; Brauer, M.; Kahn, R.; Levy, R.; Verduzco, C.; Villeneuve, P.J. Global Estimates of Ambient Fine Particulate Matter Concentrations from Satellite-Based Aerosol Optical Depth: Development and Application. *Environ. Health Perspect.* **2010**, *118*, 847–855. [CrossRef]
120. Duncan, B.N.; Yoshida, Y.; Damon, M.R.; Douglass, A.R.; Witte, J.C. Temperature dependence of factors controlling isoprene emissions. *Geophys. Res. Lett.* **2009**, *36*, 2008GL037090. [CrossRef]
121. United States Environmental Protection Agency (US EPA). Frequent Questions About Air Sensors. 2020. Available online: https://19january2021snapshot.epa.gov/air-sensor-toolbox/frequent-questions-about-air-sensors (accessed on 10 July 2024).
122. Ferguson-Moore, J. Can Emerging Air Monitoring Solutions Overcome Current Measurement Limitations? 2023. Available online: https://www.awe.international/article/1851688?utm_source=website&utm_medium=social (accessed on 2 August 2024).
123. Sokhi, R.S.; Moussiopoulos, N.; Baklanov, A.; Bartzis, J.; Coll, I.; Finardi, S.; Friedrich, R.; Geels, C.; Grönholm, T.; Halenka, T.; et al. Advances in air quality research—Current and emerging challenges. *Atmos. Chem. Phys.* **2022**, *22*, 4615–4703. [CrossRef]
124. Su, L.; Gao, C.; Ren, X.; Zhang, F.; Cao, S.; Zhang, S.; Chen, T.; Liu, M.; Ni, B.; Liu, M. Understanding the spatial representativeness of air quality monitoring network and its application to $PM_{2.5}$ in the mainland China. *Geosci. Front.* **2022**, *13*, 101370. [CrossRef]
125. Ippolito, A.R. Toxicities That Matter: Slow Bureaucracy and Polluting Temporalities in a Southern Italian City. Environment and Planning C: Politics and Space. 2022. Available online: https://journals.sagepub.com/doi/full/10.1177/23996544221107517 (accessed on 4 August 2024).
126. Li, Z. Bureaucratic response to performance information: How mandatory information disclosure affects environmental inspections. *Public Adm. Rev.* **2023**, *83*, 750–762. [CrossRef]
127. McCarron, A.; Semple, S.; Braban, C.F.; Swanson, V.; Gillespie, C.; Price, H.D. Public engagement with air quality data: Using health behaviour change theory to support exposure-minimising behaviours. *J. Expo. Sci. Environ. Epidemiol.* **2023**, *33*, 321–331. [CrossRef]

128. Jiao, W.; Hagler, G.; Williams, R.; Sharpe, R.; Brown, R.; Garver, D.; Judge, R.; Caudill, M.; Rickard, J.; Davis, M.; et al. Community Air Sensor Network (CAIRSENSE) project: Evaluation of low-costsensor performance in a suburban environment in the southeastern United States. *Atmos. Meas. Tech.* **2016**, *9*, 5281–5292. [CrossRef]
129. Snyder, E.G.; Watkins, T.H.; Solomon, P.A.; Thoma, E.D.; Williams, R.W.; Hagler, G.S.W.; Shelow, D.; Hindin, D.A.; Kilaru, V.J.; Preuss, P.W. The Changing Paradigm of Air Pollution Monitoring. *Environ. Sci. Technol.* **2013**, *47*, 11369–11377. [CrossRef] [PubMed]
130. Clements, A.; Duvall, R.; Greene, D.; Dye, T. The Enhanced Air Sensor Guidebook. U.S. Environmental Protection Agency. 2022. Available online: https://cfpub.epa.gov/si/si_public_record_report.cfm?Lab=CEMM&dirEntryId=356426 (accessed on 20 March 2024).
131. De Nazelle, A.; Bode, O.; Orjuela, J.P. Comparison of air pollution exposures in active vs. passive travel modes in European cities: A quantitative review. *Environ. Int.* **2017**, *99*, 151–160. [CrossRef]
132. Holstius, D.M.; Pillarisetti, A.; Smith, K.R.; Seto, E. Field calibrations of a low-cost aerosol sensor at a regulatory monitoring site in California. *Atmos. Meas. Tech.* **2014**, *7*, 1121–1131. [CrossRef]
133. Badura, M.; Batog, P.; Drzeniecka-Osiadacz, A.; Modzel, P. Evaluation of Low-Cost Sensors for Ambient $PM_{2.5}$ Monitoring. *J. Sens.* **2018**, *2018*, 5096540. [CrossRef]
134. Amegah, A.K.; Agyei-Mensah, S. Urban air pollution in Sub-Saharan Africa: Time for action. *Environ. Pollut.* **2017**, *220*, 738–743. [CrossRef]
135. Sousan, S.; Koehler, K.; Hallett, L.; Peters, T.M. Evaluation of the Alphasense Optical Particle Counter (OPC-N2) and the Grimm Portable Aerosol Spectrometer (PAS-1.108). *Aerosol Sci. Technol. J. Am. Assoc. Aerosol Res.* **2016**, *50*, 1352–1365. [CrossRef] [PubMed]
136. Jerrett, M.; Donaire-Gonzalez, D.; Popoola, O.; Jones, R.; Cohen, R.C.; Almanza, E.; de Nazelle, A.; Mead, I.; Carrasco-Turigas, G.; Cole-Hunter, T.; et al. Validating novel air pollution sensors to improve exposure estimates for epidemiological analyses and citizen science. *Environ. Res.* **2017**, *158*, 286–294. [CrossRef]
137. Castell, N.; Dauge, F.R.; Schneider, P.; Vogt, M.; Lerner, U.; Fishbain, B.; Broday, D.; Bartonova, A. Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? *Environ. Int.* **2017**, *99*, 293–302. [CrossRef]
138. Larkin, A.; Geddes, J.A.; Martin, R.V.; Xiao, Q.; Liu, Y.; Marshall, J.D.; Brauer, M.; Hystad, P. Global Land Use Regression Model for Nitrogen Dioxide Air Pollution. *Environ. Sci. Technol.* **2017**, *51*, 6957–6964. [CrossRef] [PubMed]
139. Hoek, G.; Beelen, R.; de Hoogh, K.; Vienneau, D.; Gulliver, J.; Fischer, P.; Briggs, D. A review of land-use regression models to assess spatial variation of outdoor air pollution. *Atmos. Environ.* **2008**, *42*, 7561–7578. [CrossRef]
140. Ryan, P.H.; LeMasters, G.K. A Review of Land-use Regression Models for Characterizing Intraurban Air Pollution Exposure. *Inhal. Toxicol.* **2007**, *19*, 127–133. [CrossRef] [PubMed]
141. Jerrett, M.; Arain, A.; Kanaroglou, P.; Beckerman, B.; Potoglou, D.; Sahsuvaroglu, T.; Morrison, J.; Giovis, C. A review and evaluation of intraurban air pollution exposure models. *J. Expo. Sci. Environ. Epidemiol.* **2005**, *15*, 185–204. [CrossRef] [PubMed]
142. De Hoogh, K.; Chen, J.; Gulliver, J.; Hoffmann, B.; Hertel, O.; Ketzel, M.; Bauwelinck, M.; Van Donkelaar, A.; Hvidtfeldt, U.A.; Katsouyanni, K.; et al. Spatial $PM_{2.5}$, NO_2, O_3 and BC models for Western Europe—Evaluation of spatiotemporal stability. *Environ. Int.* **2018**, *120*, 81–92. [CrossRef] [PubMed]
143. Beelen, R.; Hoek, G.; Pebesma, E.; Vienneau, D.; De Hoogh, K.; Briggs, D.J. Mapping of background air pollution at a fine spatial scale across the European Union. *Sci. Total Environ.* **2009**, *407*, 1852–1867. [CrossRef] [PubMed]
144. Gulliver, J.; Briggs, D.J. Time–space modeling of journey-time exposure to traffic-related air pollution using GIS. *Environ. Res.* **2005**, *97*, 10–25. [CrossRef] [PubMed]
145. Beelen, R.; Hoek, G.; Vienneau, D.; Eeftens, M.; Dimakopoulou, K.; Pedeli, X.; Tsai, M.-Y.; Künzli, N.; Schikowski, T.; Marcon, A.; et al. Development of NO_2 and NO_x land use regression models for estimating air pollution exposure in 36 study areas in Europe—The ESCAPE project. *Atmos. Environ.* **2013**, *72*, 10–23. [CrossRef]
146. Mays, N. Qualitative research in health care: Assessing quality in qualitative research. *BMJ* **2000**, *320*, 50–52. [CrossRef] [PubMed]
147. Tenny, S.; Brannan, J.M.; Brannan, G.D. Qualitative Study. In *StatPearls*; StatPearls Publishing: Treasure Island, FL, USA, 2024. Available online: http://www.ncbi.nlm.nih.gov/books/NBK470395/ (accessed on 23 June 2024).
148. McCusker, K.; Gunaydin, S. Research using qualitative, quantitative or mixed methods and choice based on the research. *Perfusion* **2015**, *30*, 537–542. [CrossRef] [PubMed]
149. Denzin, N.K.; Lincoln, Y.S. *The SAGE Handbook of Qualitative Research*, 4th ed.; SAGE Publications: Thousand Oaks, CA, USA, 2011.
150. Robins, C.S.; Ware, N.C.; dosReis, S.; Willging, C.E.; Chung, J.Y.; Lewis-Fernández, R. Dialogues on Mixed-Methods and Mental Health Services Research: Anticipating Challenges, Building Solutions. *Psychiatr. Serv.* **2008**, *59*, 727–731. [CrossRef]
151. Barbour, R.S. Checklists for improving rigour in qualitative research: A case of the tail wagging the dog? *BMJ* **2001**, *322*, 1115–1117. [CrossRef]
152. Pope, C. Qualitative research in health care: Analysing qualitative data. *BMJ* **2000**, *320*, 114–116. [CrossRef]
153. LaMarre, A.; Chamberlain, K. Innovating qualitative research methods: Proposals and possibilities. *Methods Psychol.* **2022**, *6*, 100083. [CrossRef]

154. Pilar, M.; Jost, E.; Walsh-Bailey, C.; Powell, B.J.; Mazzucca, S.; Eyler, A.; Purtle, J.; Allen, P.; Brownson, R.C. Quantitative measures used in empirical evaluations of mental health policy implementation: A systematic review. *Implement. Res. Pract.* **2022**, *3*, 26334895221141116. [CrossRef]
155. Johnson, R.B.; Onwuegbuzie, A.J. Mixed Methods Research: A Research Paradigm Whose Time Has Come. *Educ. Res.* **2004**, *33*, 14–26. [CrossRef]
156. Elmer, T.; Fernández, A.; Stadel, M.; Kas, M.; Langener, A. Bidirectional Associations Between Smartphone Usage and Momentary Well-being in Young Adults: Tackling Methodological Challenges by Combining Experience Sampling Methods with Passive Smartphone Data. *PsyArXiv*, 2023. [CrossRef]
157. Krohne, N.; Gomboc, V.; Lavrič, M.; Podlogar, T.; Poštuvan, V.; Šedivy, N.Z.; De Leo, D. Slovenian Validation of the Mental Health Literacy Scale (S-MHLS) on the General Population: A Four-Factor Model. *INQUIRY* **2022**, *59*, 004695802110471. [CrossRef]
158. Johnson, S.; Dalton-Locke, C.; Vera San Juan, N.; Foye, U.; Oram, S.; Papamichail, A.; Landau, S.; Rowan Olive, R.; Jeynes, T.; Shah, P.; et al. Impact on mental health care and on mental health service users of the COVID-19 pandemic: A mixed methods survey of UK mental health care staff. *Soc. Psychiatry Psychiatr. Epidemiol.* **2021**, *56*, 25–37. [CrossRef] [PubMed]
159. Chiang, J.J.; Lam, P.H. Commentary: Ecology momentary assessment as a tool for understanding dynamic patterns in child and adolescent health and development—Reflections on Russell and Gajos (2020). *J. Child Psychol. Psychiatry* **2020**, *61*, 395–398. [CrossRef] [PubMed]
160. Vaingankar, J.A.; Chong, S.A.; Abdin, E.; Siva Kumar, F.D.; Chua, B.Y.; Sambasivam, R.; Shafie, S.; Jeyagurunathan, A.; Seow, E.; Subramaniam, M. Understanding the relationships between mental disorders, self-reported health outcomes and positive mental health: Findings from a national survey. *Health Qual. Life Outcomes* **2020**, *18*, 55. [CrossRef] [PubMed]
161. Wei, Y.; McGrath, P.J.; Hayden, J.; Kutcher, S. Mental health literacy measures evaluating knowledge, attitudes and help-seeking: A scoping review. *BMC Psychiatry* **2015**, *15*, 291. [CrossRef]
162. Shiffman, S.; Stone, A.A.; Hufford, M.R. Ecological Momentary Assessment. *Annu. Rev. Clin. Psychol.* **2008**, *4*, 1–32. [CrossRef]
163. Schmidt-Stiedenroth, K.; Mambrey, V.; Dreher, A.; Loerbroks, A. Psychosocial working conditions and mental health among medical assistants in Germany: A scoping review. *BMC Public Health* **2024**, *24*, 716. [CrossRef] [PubMed]
164. Lauwers, L.; Trabelsi, S.; Pelgrims, I.; Bastiaens, H.; De Clercq, E.; Guilbert, A.; Guyot, M.; Leone, M.; Nawrot, T.; Van Nieuwenhuyse, A.; et al. Urban environment and mental health: The NAMED project, protocol for a mixed-method study. *BMJ Open* **2020**, *10*, e031963. [CrossRef] [PubMed]
165. Clark, C.; Myron, R.; Stansfeld, S.; Candy, B. A systematic review of the evidence on the effect of the built and physical environment on mental health. *J. Public Ment. Health* **2007**, *6*, 14–27. [CrossRef]
166. Heavens, D.; Hodgekins, J.; Lower, R.; Spauls, J.; Carroll, B.; Gee, B.; Clarke, T.; Wilson, J. Service user experience of the Norfolk youth service. *Ment. Health Rev. J.* **2020**, *25*, 85–98. [CrossRef]
167. Khoo, J.; Hasan, H.; Eagar, K. Utilisation patterns of privately funded mental health services in Australia. *J. Health Organ. Manag.* **2019**, *33*, 5–17. [CrossRef] [PubMed]
168. Roberts, L.R.; Sadan, V.; Siva, R.; Sathiyaseelan, M.; Rosalind, S.E.; Suresh, P.; Montgomery, S.B. Factors Predicting Mental Health Among Women in Low-Income Communities of a Changing Society: A Mixed-Methods Study. *Int. J. Womens Health* **2023**, *15*, 381–394. [CrossRef] [PubMed]
169. Wen, J.; Fang, Y.; Su, Z.; Cai, J.; Chen, Z. Mental health and its influencing factors of maintenance hemodialysis patients: A semi-structured interview study. *BMC Psychol.* **2023**, *11*, 84. [CrossRef] [PubMed]
170. Alderman, A.K.; Salem, B. Survey Research. *Plast. Reconstr. Surg.* **2010**, *126*, 1381–1389. [CrossRef]
171. Beck, A.T.; Steer, R.A.; Brown, G. Beck Depression Inventory–II. 1996. Available online: https://doi.apa.org/doi/10.1037/t00742-000 (accessed on 22 June 2024).
172. Creswell, J.W. *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, 4th ed.; SAGE Publications: Thousand Oaks, CA, USA, 2014.
173. Spitzer, R.L.; Kroenke, K.; Williams, J.B.W.; Löwe, B. A Brief Measure for Assessing Generalized Anxiety Disorder: The GAD-7. *Arch. Intern. Med.* **2006**, *166*, 1092. [CrossRef]
174. Kroenke, K.; Spitzer, R.L.; Williams, J.B.W. The PHQ-9. *J. Gen. Intern. Med.* **2001**, *16*, 606–613. [CrossRef]
175. Guest, G.; Bunce, A.; Johnson, L. How Many Interviews Are Enough?: An Experiment with Data Saturation and Variability. *Field Methods* **2006**, *18*, 59–82. [CrossRef]
176. Boyatzis, R.E. *Transforming Qualitative Information: Thematic Analysis and Code Development*; Sage Publications, Inc.: Thousand Oaks, CA, USA, 1998.
177. Singh, S.; Sagar, R. A critical look at online survey or questionnaire-based research studies during COVID-19. *Asian J. Psychiatry* **2021**, *65*, 102850. [CrossRef] [PubMed]
178. van Ballegooijen, W.; Riper, H.; Klein, B.; Ebert, D.D.; Kramer, J.; Meulenbeek, P.; Cuijpers, P. An Internet-Based Guided Self-Help Intervention for Panic Symptoms: Randomized Controlled Trial. *J. Med. Internet Res.* **2013**, *15*, e154. [CrossRef] [PubMed]
179. Kocalevent, R.-D.; Hinz, A.; Brähler, E. Standardization of the depression screener Patient Health Questionnaire (PHQ-9) in the general population. *Gen. Hosp. Psychiatry* **2013**, *35*, 551–555. [CrossRef] [PubMed]
180. Mays, N.; Pope, C. Qualitative Research: Rigour and qualitative research. *BMJ* **1995**, *311*, 109–112. [CrossRef] [PubMed]
181. Andrade, C. The Limitations of Online Surveys. *Indian J. Psychol. Med.* **2020**, *42*, 575–576. [CrossRef] [PubMed]

182. Snowden, L.R. Bias in Mental Health Assessment and Intervention: Theory and Evidence. *Am. J. Public Health* **2003**, *93*, 239–243. [CrossRef] [PubMed]
183. Andrews, G.; Slade, T.; Peters, L. Classification in psychiatry: ICD–10 *versus* DSM–IV. *Br. J. Psychiatry* **1999**, *174*, 3–5. [CrossRef] [PubMed]
184. Czeisler, M.É.; Wiley, J.F.; Czeisler, C.A.; Rajaratnam, S.M.W.; Howard, M.E. Uncovering survivorship bias in longitudinal mental health surveys during the COVID-19 pandemic. *Epidemiol. Psychiatr. Sci.* **2021**, *30*, e45. [CrossRef]
185. DeJonckheere, M.; Vaughn, L.M. Semistructured interviewing in primary care research: A balance of relationship and rigour. *Fam. Med. Community Health* **2019**, *7*, e000057. [CrossRef]
186. Smith, J.A.; Osborn, M. Interpretative phenomenological analysis as a useful methodology for research on the lived experience of pain. *Br. J. Pain* **2015**, *9*, 41–42. [CrossRef] [PubMed]
187. Chartrand, T.L.; Maddux, W.W.; Lakin, J.L. Beyond the Perception-Behavior Link: The Ubiquitous Utility and Motivational Moderators of Nonconscious Mimicry. In *The New Unconscious*; Hassin, R.R., Uleman, J.S., Bargh, J.A., Eds.; Oxford University Press: Oxford, UK, 2012; pp. 334–361. ISBN 978-0-19-530769-6.
188. Renjith, V.; Yesodharan, R.; Noronha, J.A.; Ladd, E.; George, A. Qualitative Methods in Health Care Research. *Int. J. Prev. Med.* **2021**, *12*, 20. [CrossRef] [PubMed]
189. Horsfall, M.; Eikelenboom, M.; Draisma, S.; Smit, J.H. The Effect of Rapport on Data Quality in Face-to-Face Interviews: Beneficial or Detrimental? *Int. J. Environ. Res. Public. Health* **2021**, *18*, 10858. [CrossRef] [PubMed]
190. Newby, D.; Taylor, N.; Joyce, D.W.; Winchester, L.M. Optimising the use of electronic medical records for large scale research in psychiatry. *Transl. Psychiatry* **2024**, *14*, 232. [CrossRef] [PubMed]
191. Hecht, J. The future of electronic health records. *Nature* **2019**, *573*, S114–S116. [CrossRef] [PubMed]
192. Russ, T.C.; Woelbert, E.; Davis, K.A.S.; Hafferty, J.D.; Ibrahim, Z.; Inkster, B.; John, A.; Lee, W.; Maxwell, M.; McIntosh, A.M.; et al. How data science can advance mental health research. *Nat. Hum. Behav.* **2018**, *3*, 24–32. [CrossRef] [PubMed]
193. Hjollund, N.H.I.; Valderas, J.M.; Kyte, D.; Calvert, M.J. Health Data Processes: A Framework for Analyzing and Discussing Efficient Use and Reuse of Health Data with a Focus on Patient-Reported Outcome Measures. *J. Med. Internet Res.* **2019**, *21*, e12412. [CrossRef]
194. Lowe, H.J.; Ferris, T.A.; Hernandez, P.M.; Weber, S.C. STRIDE—An Integrated Standards-Based Translational Research Informatics Platform. *AMIA. Annu. Symp. Proc.* **2009**, *2009*, 391–395. [PubMed]
195. Casey, J.A.; Schwartz, B.S.; Stewart, W.F.; Adler, N.E. Using Electronic Health Records for Population Health Research: A Review of Methods and Applications. *Annu. Rev. Public Health* **2016**, *37*, 61–81. [CrossRef]
196. Smit, J.-A.; van der Graaf, R.; Mostert, M.; Vaartjes, I.; Zuidgeest, M.; Grobbee, D.; van Delden, J.J.M. Overcoming ethical and legal obstacles to data linkage in health research: Stakeholder perspectives. *Int. J. Popul. Data Sci.* **2023**, *8*, 2151. [CrossRef]
197. Gehrmann, J.; Herczog, E.; Decker, S.; Beyan, O. What prevents us from reusing medical real-world data in research. *Sci. Data* **2023**, *10*, 459. [CrossRef] [PubMed]
198. Kass, N.E.; Natowicz, M.R.; Hull, S.C.; Faden, R.R.; Plantinga, L.; Gostin, L.O.; Slutsman, J. The Use of Medical Records in Research: What Do Patients Want? *J. Law Med. Ethics J. Am. Soc. Law Med. Ethics* **2003**, *31*, 429–433. [CrossRef] [PubMed]
199. Crawley, M.J. *The R Book*, 1st ed.; Wiley: Hoboken, NJ, USA, 2012. Available online: https://onlinelibrary.wiley.com/doi/book/10.1002/9781118448908 (accessed on 8 July 2024).
200. Muñoz-Pichardo, J.M.; Pino-Mejías, R.; García-Heras, J.; Ruiz-Muñoz, F.; Luz González-Regalado, M. A multivariate Poisson regression model for count data. *J. Appl. Stat.* **2021**, *48*, 2525–2541. [CrossRef]
201. Hidalgo, B.; Goodman, M. Multivariate or Multivariable Regression? *Am. J. Public Health* **2013**, *103*, 39–40. [CrossRef] [PubMed]
202. Gelman, A.; Hill, J. *Data Analysis Using Regression and Multilevel/Hierarchical Models*, 1st ed.; Cambridge University Press: Cambridge, UK, 2006. Available online: https://www.cambridge.org/core/product/identifier/9780511790942/type/book (accessed on 4 July 2024).
203. Raudenbush, S.W.; Bryk, A.S. *Hierarchical Linear Models: Applications and Data Analysis Methods*; SAGE: Thousand Oaks, CA, USA, 2002.
204. Peng, C.-Y.J.; Lee, K.L.; Ingersoll, G.M. An Introduction to Logistic Regression Analysis and Reporting. *J. Educ. Res.* **2002**, *96*, 3–14. [CrossRef]
205. Koletsi, D.; Pandis, N. Conditional logistic regression. *Am. J. Orthod. Dentofac. Orthop.* **2017**, *151*, 1191–1192. [CrossRef] [PubMed]
206. van der Net, J.B.; Janssens, A.C.J.W.; Eijkemans, M.J.C.; Kastelein, J.J.P.; Sijbrands, E.J.G.; Steyerberg, E.W. Cox proportional hazards models have more statistical power than logistic regression models in cross-sectional genetic association studies. *Eur. J. Hum. Genet.* **2008**, *16*, 1111–1116. [CrossRef] [PubMed]
207. Yang, S.; Berdine, G. The Negative Binomial regression. *Southwest Respir. Crit. Care Chron.* **2015**, *3*, 50–54.
208. Lu, B. Propensity Score Matching with Time-Dependent Covariates. *Biometrics* **2005**, *61*, 721–728. [CrossRef]
209. Wang, M. Generalized Estimating Equations in Longitudinal Data Analysis: A Review and Recent Developments. *Adv. Stat.* **2014**, 303728. [CrossRef]
210. Thurman, S.L. Ethical considerations in longitudinal studies of human infants. *Infant Behav. Dev.* **2015**, *38*, 116–125. [CrossRef] [PubMed]
211. Hedeker, D.; Gibbons, R.D. *Longitudinal Data Analysis | Wiley Series in Probability and Statistics*; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2006. Available online: https://onlinelibrary.wiley.com/doi/book/10.1002/0470036486 (accessed on 22 June 2024).

212. Singer, J.D.; Willett, J.B. *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*; Oxford University Press: Oxford, UK, 2003. Available online: https://academic.oup.com/book/41753 (accessed on 23 June 2024).
213. Diggle, P.J.; Heagerty, P.; Liang, K.Y.; Zeger, S.L. *The Analysis of Longitudinal Data*, 2nd ed.; Oxford University Press: Oxford, UK, 2002.
214. Campbell, C.E.; Cotter, D.L.; Bottenhorn, K.L.; Burnor, E.; Ahmadi, H.; Gauderman, W.J.; Cardenas-Iniguez, C.; Hackman, D.; McConnell, R.; Berhane, K.; et al. Air pollution and emotional behavior in adolescents across the U.S. *medRxiv* 2023, *preprint*. [CrossRef]
215. Bishop, K.; Ketcham, J.; Kuminoff, N. *Hazed and Confused: The Effect of Air Pollution on Dementia*; National Bureau of Economic Research: Cambridge, MA, USA, 2018. Available online: http://www.nber.org/papers/w24970.pdf (accessed on 26 July 2024).
216. Yeung, J.; CNN. Chinese People Are Living Two Years Longer Thanks to 'War on Pollution', Report Says. 2023. Available online: https://www.cnn.com/2023/08/30/asia/air-pollution-report-china-south-asia-intl-hnk-scn/index.html (accessed on 27 July 2024).
217. Mead, M.I.; Okello, G.; Mbandi, A.M.; Pope, F.D. Spotlight on air pollution in Africa. *Nat. Geosci.* **2023**, *16*, 930–931. [CrossRef]
218. Husaini, D.C.; Reneau, K.; Balam, D. Air pollution and public health in Latin America and the Caribbean (LAC): A systematic review with meta-analysis. *Beni-Suef Univ. J. Basic Appl. Sci.* **2022**, *11*, 122. [CrossRef] [PubMed]
219. Fuller, C.H.; Amegah, A.K. Limited Air Pollution Research on the African Continent: Time to Fill the Gap. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6359. [CrossRef]
220. La Colla, N.S.; Botté, S.E.; Marcovecchio, J.E. Atmospheric particulate pollution in South American megacities. *Environ. Rev.* **2021**, *29*, 415–429. [CrossRef]
221. Gómez Peláez, L.M.; Santos, J.M.; de Almeida Albuquerque, T.T.; Reis, N.C.; Andreão, W.L.; de Fátima Andrade, M. Air quality status and trends over large cities in South America. *Environ. Sci. Policy* **2020**, *114*, 422–435. [CrossRef]
222. Rössler, W. The stigma of mental disorders: A millennia-long history of social exclusion and prejudices. *EMBO Rep.* **2016**, *17*, 1250–1253. [CrossRef]
223. Clavo, B.; Cánovas-Molina, A.; Díaz-Garrido, J.A.; Cañas, S.; Ramallo-Fariña, Y.; Laffite, H.; Federico, M.; Rodríguez-Abreu, D.; Galván, S.; García-Lourve, C.; et al. Effects of ozone therapy on anxiety and depression in patients with refractory symptoms of severe diseases: A pilot study. *Front. Psychol.* **2023**, *14*, 1176204. [CrossRef]
224. Manczak, E.M.; Miller, J.G.; Gotlib, I.H. Census tract ambient ozone predicts trajectories of depressive symptoms in adolescents. *Dev. Psychol.* **2022**, *58*, 485–492. [CrossRef]
225. Gładka, A.; Rymaszewska, J.; Zatoński, T. Impact of air pollution on depression and suicide. *Int. J. Occup. Med. Environ. Health* **2018**, *31*, 711–721. [CrossRef] [PubMed]
226. Kioumourtzoglou, M.-A.; Power, M.C.; Hart, J.E.; Okereke, O.I.; Coull, B.A.; Laden, F.; Weisskopf, M.G. The Association Between Air Pollution and Onset of Depression Among Middle-Aged and Older Women. *Am. J. Epidemiol.* **2017**, *185*, 801–809. [CrossRef] [PubMed]
227. Zhuang, Y.; Li, L.; Zhang, Y.; Dai, F. Associations of exposure to volatile organic compounds with sleep health and potential mediators: Analysis of NHANES data. *Front. Public Health* **2024**, *12*, 1423771. [CrossRef] [PubMed]
228. Tang, L.; Liu, M.; Tian, J. Volatile organic compounds exposure associated with depression among U.S. adults: Results from NHANES 2011–2020. *Chemosphere* **2024**, *349*, 140690. [CrossRef] [PubMed]
229. Fiedler, N.; Laumbach, R.; Kelly-McNeil, K.; Lioy, P.; Fan, Z.-H.; Zhang, J.; Ottenweller, J.; Ohman-Strickland, P.; Kipen, H. Health Effects of a Mixture of Indoor Air Volatile Organics, Their Ozone Oxidation Products, and Stress. *Environ. Health Perspect.* **2005**, *113*, 1542–1548. [CrossRef] [PubMed]
230. Tota, M.; Karska, J.; Kowalski, S.; Piątek, N.; Pszczołowska, M.; Mazur, K.; Piotrowski, P. Environmental pollution and extreme weather conditions: Insights into the effect on mental health. *Front. Psychiatry* **2024**, *15*, 1389051. [CrossRef] [PubMed]
231. Szyszkowicz, M.; Rowe, B.H. Ambient Air Pollution and Depressive Symptoms. 2014. Available online: https://peerj.com/preprints/757v1 (accessed on 3 August 2024).
232. Yang, A.C.; Tsai, S.-J.; Huang, N.E. Decomposing the association of completed suicide with air pollution, weather, and unemployment data at different time scales. *J. Affect. Disord.* **2011**, *129*, 275–281. [CrossRef]
233. Szyszkowicz, M.; Rowe, B.; Colman, I. Air pollution and daily emergency department visits for depression. *Int. J. Occup. Med. Environ. Health* **2009**, *22*, 355–362. [CrossRef] [PubMed]
234. Szyszkowicz, M.; Willey, J.B.; Grafstein, E.; Rowe, B.H.; Colman, I. Air Pollution and Emergency Department Visits for Suicide Attempts in Vancouver, Canada. *Environ. Health Insights* **2010**, *4*, EHI.S5662. [CrossRef]
235. Hopkins, R.O.; Woon, F.L.M. Neuroimaging, Cognitive, and Neurobehavioral Outcomes Following Carbon Monoxide Poisoning. *Behav. Cogn. Neurosci. Rev.* **2006**, *5*, 141–155. [CrossRef]
236. Pan, Y.-J.; Liao, S.-C.; Lee, M.-B. Suicide by charcoal burning in Taiwan, 1995–2006. *J. Affect. Disord.* **2010**, *120*, 254–257. [CrossRef]
237. Lee, E.; Leung, C.-M. Clinical predictors of psychiatric and medical morbidities of charcoal-burning suicide attempt in Hong Kong. *Gen. Hosp. Psychiatry* **2008**, *30*, 561–563. [CrossRef]
238. Liu, K.Y.; Beautrais, A.; Caine, E.; Chan, K.; Chao, A.; Conwell, Y.; Law, C.; Lee, D.; Li, P.; Yip, P. Charcoal burning suicides in Hong Kong and urban Taiwan: An illustration of the impact of a novel suicide method on overall regional rates. *J. Epidemiol. Community Health* **2007**, *61*, 248–253. [CrossRef]

239. Lo, C.-P.; Chen, S.-Y.; Lee, K.-W.; Chen, W.-L.; Chen, C.-Y.; Hsueh, C.-J.; Huang, G.-S. Brain Injury After Acute Carbon Monoxide Poisoning: Early and Late Complications. *Am. J. Roentgenol.* **2007**, *189*, W205–W211. [CrossRef] [PubMed]
240. Ho, R.C.M.; Cheng, W.; Chua, A.N.C.; Mak, A. Neuropsychiatric aspects of carbon monoxide poisoning: Diagnosis and management. *Adv. Psychiatr. Treat.* **2012**, *18*, 94–101. [CrossRef]
241. Hautekiet, P.; Saenen, N.D.; Demarest, S.; Keune, H.; Pelgrims, I.; Van der Heyden, J.; De Clercq, E.M.; Nawrot, T.S. Air pollution in association with mental and self-rated health and the mediating effect of physical activity. *Environ. Health* **2022**, *21*, 29. [CrossRef] [PubMed]
242. Nobile, F.; Forastiere, A.; Michelozzi, P.; Forastiere, F.; Stafoggia, M. Long-term exposure to air pollution and incidence of mental disorders. A large longitudinal cohort study of adults within an urban area. *Environ. Int.* **2023**, *181*, 108302. [CrossRef] [PubMed]
243. Bai, L.; Zhang, X.; Zhang, Y.; Cheng, Q.; Duan, J.; Gao, J.; Xu, Z.; Zhang, H.; Wang, S.; Su, H. Ambient concentrations of NO_2 and hospital admissions for schizophrenia. *Occup. Environ. Med.* **2019**, *76*, 125–131. [CrossRef] [PubMed]
244. Vert, C.; Sánchez-Benavides, G.; Martínez, D.; Gotsens, X.; Gramunt, N.; Cirach, M.; Molinuevo, J.L.; Sunyer, J.; Nieuwenhuijsen, M.J.; Crous-Bou, M.; et al. Effect of long-term exposure to air pollution on anxiety and depression in adults: A cross-sectional study. *Int. J. Hyg. Environ. Health* **2017**, *220*, 1074–1080. [CrossRef]
245. Gignac, F.; Righi, V.; Toran, R.; Paz Errandonea, L.; Ortiz, R.; Mijling, B.; Naranjo, A.; Nieuwenhuijsen, M.; Creus, J.; Basagaña, X. Short-term NO_2 exposure and cognitive and mental health: A panel study based on a citizen science project in Barcelona, Spain. *Environ. Int.* **2022**, *164*, 107284. [CrossRef]
246. Yan, W.; Yue, H.; Ji, X.; Li, G.; Sang, N. Prenatal NO_2 exposure and neurodevelopmental disorders in offspring mice: Transcriptomics reveals sex-dependent changes in cerebral gene expression. *Environ. Int.* **2020**, *138*, 105659. [CrossRef] [PubMed]
247. Shang, L.; Yang, L.; Yang, W.; Huang, L.; Qi, C.; Yang, Z.; Fu, Z.; Chung, M.C. Effects of prenatal exposure to NO_2 on children's neurodevelopment: A systematic review and meta-analysis. *Environ. Sci. Pollut. Res. Int.* **2020**, *27*, 24786–24798. [CrossRef] [PubMed]
248. Min, J.; Min, K. Exposure to ambient PM_{10} and NO_2 and the incidence of attention-deficit hyperactivity disorder in childhood. *Environ. Int.* **2017**, *99*, 221–227. [CrossRef] [PubMed]
249. Bakolis, I.; Hammoud, R.; Stewart, R.; Beevers, S.; Dajnak, D.; MacCrimmon, S.; Broadbent, M.; Pritchard, M.; Shiode, N.; Fecht, D.; et al. Mental health consequences of urban air pollution: Prospective population-based longitudinal survey. *Soc. Psychiatry Psychiatr. Epidemiol.* **2021**, *56*, 1587–1599. [CrossRef] [PubMed]
250. World Health Organization (WHO). *Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease*; World Health Organization: Geneva, Switzerland, 2016. Available online: https://iris.who.int/handle/10665/250141 (accessed on 26 July 2024).
251. Pope, C.A.; Dockery, D.W. Health Effects of Fine Particulate Air Pollution: Lines that Connect. *J. Air Waste Manag. Assoc.* **2006**, *56*, 709–742. [CrossRef] [PubMed]
252. Nguyen, G.T.H.; La, L.T.; Hoang-Cong, H.; Le, A.H. An exploration of meteorological effects on $PM_{2.5}$ air quality in several provinces and cities in Vietnam. *J. Environ. Sci.* **2024**, *145*, 139–151. [CrossRef] [PubMed]
253. Chen, Z.; Chen, D.; Zhao, C.; Kwan, M.; Cai, J.; Zhuang, Y.; Zhao, B.; Wang, X.; Chen, B.; Yang, J.; et al. Influence of meteorological conditions on $PM_{2.5}$ concentrations across China: A review of methodology and mechanism. *Environ. Int.* **2020**, *139*, 105558. [CrossRef]
254. Dung, N.A.; Son, D.H.; Hanh, N.T.D.; Tri, D.Q. Effect of Meteorological Factors on PM_{10} Concentration in Hanoi, Vietnam. *J. Geosci. Environ. Prot.* **2019**, *7*, 138–150. [CrossRef]
255. Usman, F.; Zeb, B.; Alam, K.; Valipour, M.; Ditta, A.; Sorooshian, A.; Roy, R.; Ahmad, I.; Iqbal, R. Exploring the Mass Concentration of Particulate Matter and Its Relationship with Meteorological Parameters in the Hindu-Kush Range. *Atmosphere* **2022**, *13*, 1628. [CrossRef]
256. Banks, A.; Kooperman, G.J.; Xu, Y. Meteorological Influences on Anthropogenic $PM_{2.5}$ in Future Climates: Species Level Analysis in the Community Earth System Model v2. *Earths Future* **2022**, *10*, e2021EF002298. [CrossRef]
257. Zeb, B.; Ditta, A.; Alam, K.; Sorooshian, A.; Din, B.U.; Iqbal, R.; Habib ur Rahman, M.; Raza, A.; Alwahibi, M.S.; Elshikh, M.S. Wintertime investigation of PM_{10} concentrations, sources, and relationship with different meteorological parameters. *Sci. Rep.* **2024**, *14*, 154. [CrossRef] [PubMed]
258. Reuben, A.; Manczak, E.M.; Cabrera, L.Y.; Alegria, M.; Bucher, M.L.; Freeman, E.C.; Miller, G.W.; Solomon, G.M.; Perry, M.J. The Interplay of Environmental Exposures and Mental Health: Setting an Agenda. *Environ. Health Perspect.* **2022**, *130*, 025001. [CrossRef] [PubMed]
259. Rataj, E.; Kunzweiler, K.; Garthus-Niegel, S. Extreme weather events in developing countries and related injuries and mental health disorders—A systematic review. *BMC Public Health* **2016**, *16*, 1020. [CrossRef] [PubMed]
260. Beyer, K.M.M.; Kaltenbach, A.; Szabo, A.; Bogar, S.; Nieto, F.J.; Malecki, K.M. Exposure to Neighborhood Green Space and Mental Health: Evidence from the Survey of the Health of Wisconsin. *Int. J. Environ. Res. Public Health* **2014**, *11*, 3453–3472. [CrossRef]

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