The Exposome and Air Pollution: A Survey on PM2.5, Ozone, Black Carbon, and Their Interactions with Gut Microbiota

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Abstract

This survey paper explores the intricate interplay between environmental exposures, specifically air pollution components such as PM2.5, ozone, and black carbon, and their influence on health through interactions with the gut microbiota within the exposome framework. By integrating diverse datasets and advanced modeling techniques, the paper elucidates the complex mechanisms by which these pollutants induce oxidative stress, inflammation, and epigenetic modifications, thereby altering metabolic pathways and contributing to a range of health outcomes. The survey highlights significant epidemiological evidence linking long-term exposure to these pollutants with increased risks of cardiovascular, respiratory, and metabolic diseases. It emphasizes the importance of precise exposure assessment methodologies and the integration of spatial and temporal data to enhance the accuracy of health impact predictions. The paper also addresses the socio-economic and environmental justice implications of pollution exposure, advocating for targeted public health strategies and policy interventions to mitigate health disparities. Furthermore, it underscores the necessity for comprehensive research that combines environmental health studies with gut microbiome analyses to unravel the mechanisms through which pollutants influence health. By advancing our understanding of these interactions, the survey aims to inform effective public health strategies and interventions aimed at reducing the adverse health effects associated with air pollution. Future research directions include the development of innovative monitoring technologies, refinement of predictive models, and exploration of causal relationships to enhance our understanding of pollution-induced health risks.

1 Introduction

1.1 Concept of Exposome

The exposome encompasses all environmental exposures experienced by an individual throughout their life, integrating external and internal factors that influence health outcomes [1]. This framework goes beyond traditional epidemiological methods by incorporating extensive personal and environmental data, providing a holistic view of exposure interactions [2]. Air pollution, a crucial component of the exposome, has been linked to adverse health effects from chronic exposure, necessitating the integration of spatial and temporal data for accurate assessment. Advanced methodologies like Distance Adjusted Propensity Score Matching (DAPSm) enhance confounding adjustments by considering spatial proximity [3].

Adaptive learning models, such as those by Gyarmati and Szabo, are increasingly integrated into the exposome framework, enabling real-time parameter adjustments to improve classification performance in dynamic environments [4]. The 'DigitalExposome' initiative exemplifies this integration by utilizing multi-sensor data collection to quantify exposure effects, particularly in urban areas where environmental factors significantly impact individual well-being [5]. Furthermore, innovative

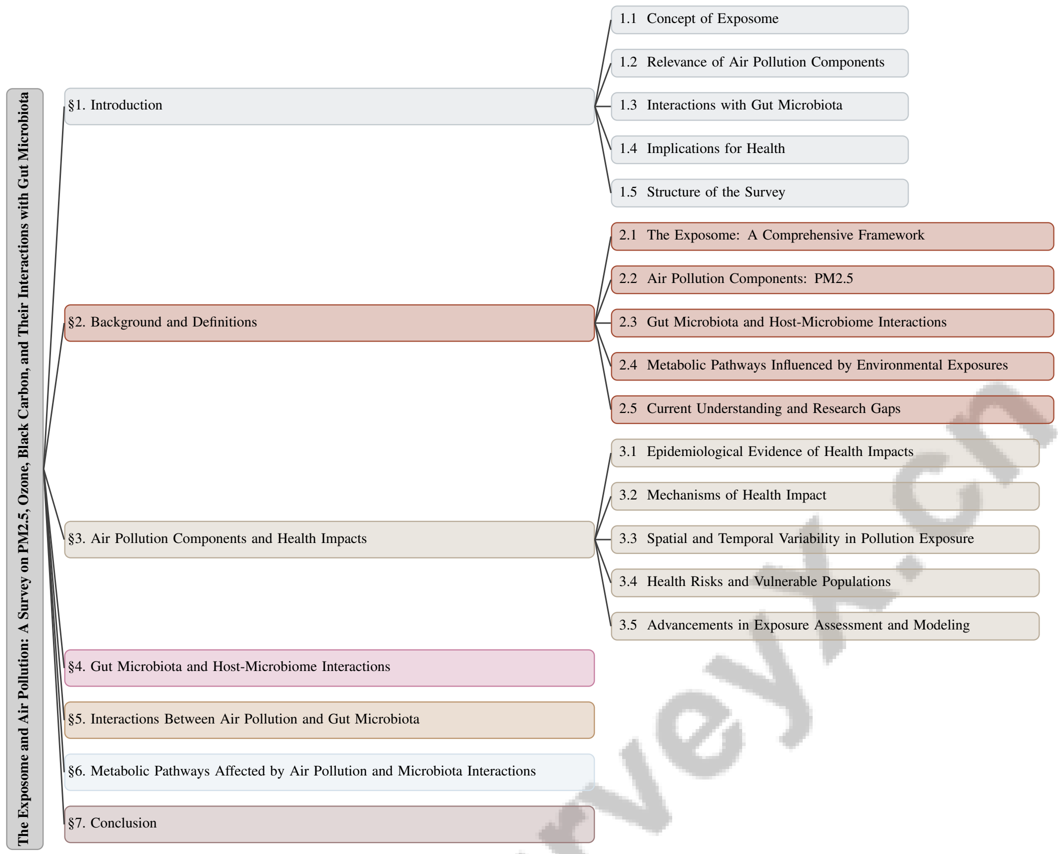

Figure 1: chapter structure

biotechnological approaches for air purification, as highlighted by Gonzalez et al., enhance the exposome framework by addressing air quality challenges [6]. Thus, the exposome offers critical insights into the interactions between environmental factors and health, emphasizing the need for robust data integration in environmental health research.

1.2 Relevance of Air Pollution Components

Air pollution is a key element of the exposome, with PM2.5, ozone, and black carbon being particularly concerning due to their prevalence and health impacts. PM2.5, a complex mixture of various pollutants, can penetrate the respiratory and circulatory systems, leading to respiratory and cardiovascular diseases [7]. Its adverse effects are evident even prenatally, correlating with negative birth and health outcomes [8], highlighting the need for precise exposure assessment methodologies [9].

Ozone, characterized by its interactions with other pollutants, complicates risk assessment and regulation, especially in urban areas where it poses significant health risks during outdoor activities [10]. Seasonal and diurnal variations in ozone levels require sophisticated modeling techniques for effective prediction and mitigation [11].

Black carbon, primarily from combustion processes, significantly contributes to air pollution and climate change [12]. Its association with respiratory and cardiovascular diseases underscores the necessity for interventions targeting major emission sources, such as traffic [13]. The intersection of black carbon with climate dynamics and public health considerations further emphasizes its relevance within the exposome [14].

Integrating PM2.5, ozone, and black carbon into the exposome framework is essential for understanding the complex relationships between environmental exposures and health outcomes. Advanced spatial machine learning models can generate interpretable measures of variable importance, enhancing comprehension of air pollution predictors [15]. This integrative approach is crucial for developing effective public health strategies and interventions aimed at mitigating air pollution's health impacts. Additionally, classifying nanoparticles by dimensionality, morphology, and composition further underscores their significance in environmental health [16].

1.3 Interactions with Gut Microbiota

The interactions between air pollution components and gut microbiota are a vital research area within the exposome framework, revealing the complex interplay between environmental exposures and human health. Air pollutants such as PM2.5, ozone, and black carbon can influence gut microbiota composition and function, impacting host health through various biological pathways. The gut microbiota, a diverse community of microorganisms in the gastrointestinal tract, is crucial for maintaining homeostasis and modulating immune responses [17]. Dysbiosis, or perturbations in this microbial ecosystem, has been linked to various health disorders, including inflammatory and metabolic diseases [18].

Emerging evidence indicates that exposure to air pollutants can alter gut microbiome diversity and specific bacterial taxa abundance. For instance, PM2.5 exposure correlates with changes in gut bacteria, potentially increasing intestinal barrier permeability and systemic inflammation [7]. Similarly, ozone exposure may modulate gut microbial communities, influencing metabolic and immune pathways essential for health [10].

Moreover, black carbon, due to its particulate nature and chemical composition, may induce oxidative stress and inflammatory responses, affecting gut microbiota dynamics and host-microbiome interactions [12]. Inhalation of such pollutants can lead to alterations in gut microbial metabolites, impacting metabolic pathways and potentially exacerbating disease processes [13].

The intricate interactions between air pollution and gut microbiota necessitate comprehensive studies integrating advanced exposure assessment techniques with microbiome analyses. Such research is essential for unraveling the mechanisms by which environmental factors influence gut microbiota and contribute to health outcomes, informing targeted interventions and public health strategies [15]. Understanding these interactions within the exposome framework provides valuable insights into the broader implications of environmental exposures on human health and disease [19].

1.4 Implications for Health

The interactions between air pollution components and gut microbiota have profound implications for human health, affecting a wide range of health outcomes from prenatal stages to adulthood. Maternal exposure to air pollution during pregnancy is linked to negative health outcomes in children, highlighting the need to protect vulnerable populations during critical developmental periods [20]. Socio-economic factors, such as maternal education, can mediate these health outcomes, serving as protective factors in varying environmental contexts [21].

The spatial variability of PM2.5 pollution, characterized by diverse sources and chemical compositions, necessitates localized public health interventions tailored to the unique characteristics of pollution sources and their interactions with local populations [22]. Developing spatial vulnerability indices is crucial for assessing population vulnerability to extreme environmental conditions, including air pollution, which significantly impacts health globally [23]. Additionally, considering mobility in exposure assessments leads to more accurate estimates of health effects, informing public health policy and intervention strategies [24].

Rainfall serves as a natural mitigator of air pollutant levels, positively influencing population health [25]. However, comprehensive exposure assessment requires integrating home and workplace data to fully understand exposure-related health risks [26]. This holistic approach is vital for capturing the extent of health risks associated with air pollution.

Targeted air quality policies, such as the mandatory shutdown of small-capacity coal power plants, have shown significant public health improvements, evidenced by reduced under-5 mortality rates in China [27]. These policies demonstrate the effectiveness of strategic interventions in mitigating air pollution's adverse health impacts. The disproportionate effects of freight truck emissions on communities of color highlight the environmental injustices inherent in air pollution exposure, necessitating targeted policy interventions to address these disparities [28].

The economic burden associated with pollution-related health issues further emphasizes the need for improved regulatory measures. The relationship between air pollution and rising health costs underscores the importance of policy decisions aimed at reducing health costs through enhanced air quality measures [29]. Furthermore, significant health risks and economic impacts related to poor indoor air quality, often exacerbated by modern building designs limiting ventilation, warrant regulatory attention [6].

In urban areas like Mexico City, advanced modeling techniques have improved ozone level predictions and respiratory health risk assessments, highlighting critical compliance areas for air quality standards during peak seasons [30]. The characterization of non-exhaust emissions, such as brake wear particles containing toxic metallic nanoparticles, further emphasizes the need for regulatory focus on reducing these pollution sources [13].

These interactions between air pollution and gut microbiota highlight the necessity for comprehensive strategies that integrate environmental health research with public health policy to effectively mitigate the health risks associated with air pollution [11].

1.5 Structure of the Survey

The survey is structured to provide a thorough exploration of the interactions between air pollution components and gut microbiota within the exposome framework. It begins with an introduction that establishes the foundational concept of the exposome and its relevance to environmental health research, emphasizing the significance of PM2.5, ozone, and black carbon. A detailed background section follows, defining key concepts such as the exposome, air pollution components, gut microbiota, and their interactions, alongside an examination of metabolic pathways influenced by environmental exposures.

Subsequent sections analyze the health impacts of air pollution, drawing on epidemiological evidence and exploring the biological mechanisms through which pollutants affect health. The variability in pollution exposure and its implications for vulnerable populations are discussed, alongside advancements in exposure assessment and modeling.

The survey transitions to an in-depth analysis of the gut microbiota's pivotal role in health and disease, specifically investigating the effects of air pollution on its composition and functionality. It further explores essential interactions between the host and microbiome regarding various environmental exposures, highlighting implications for autoimmune diseases and respiratory health [31, 32, 2]. The interactions between air pollution and gut microbiota are examined in detail, elucidating the mechanisms involved and their contributions to disease processes and health outcomes.

The penultimate section analyzes the metabolic pathways affected by these interactions, discussing their implications for health outcomes and potential interventions. The survey concludes by summarizing key findings, discussing implications for future research and public health policy, and emphasizing the importance of integrating exposome research with studies on air pollution and gut microbiota to effectively mitigate health risks.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 The Exposome: A Comprehensive Framework

The exposome framework encompasses all environmental exposures encountered by individuals throughout their lives, integrating personal and environmental data to elucidate health risk factors, including those related to asthma [2]. This approach surpasses traditional epidemiological methods by systematically addressing dynamic interactions between environmental factors and health outcomes. The DigitalExposome exemplifies this integration, employing mobile sensing technologies to quantitatively evaluate individual exposure to various urban environmental factors and their effects on well-being [5].

Air pollutants within the exposome are categorized by their sources—major, area, mobile, and natural—each contributing uniquely to public health outcomes [11]. This classification underscores the critical relationship between air quality and health, necessitating comprehensive assessments that include both indoor and outdoor environmental data. Such assessments are vital for identifying and mitigating the health impacts of over 400 chemical compounds and biological pollutants found in indoor environments [6].

The exposome's capacity to integrate diverse datasets allows for innovative methodologies, such as BNI-specific estimators, which evaluate subgroup-specific causal effects without predefined subgroup definitions, thereby enhancing understanding of environmental justice implications [33]. This integrative approach is crucial for advancing environmental health research and developing targeted interventions to reduce health disparities and improve public health outcomes.

2.2 Air Pollution Components: PM2.5, Ozone, and Black Carbon

Air pollution consists of a complex array of pollutants, with PM2.5, ozone, and black carbon being particularly concerning due to their prevalence and significant health impacts. PM2.5, particulate matter with a diameter less than 2.5 micrometers, penetrates deep into the lungs and enters the bloodstream, leading to severe cardiovascular and respiratory diseases [34]. Sources of PM2.5 include industrial emissions, vehicular exhaust, and natural events like wildfires, with vehicular emissions being a major contributor [16]. Accurate estimation of PM2.5 concentrations is essential for quantifying health benefits from emissions reductions; however, the inadequate placement of PM2.5 air quality sensors complicates effective monitoring due to spatial and temporal variability [35].

Ozone, a secondary pollutant formed through photochemical reactions involving nitrogen oxides (NO2) and volatile organic compounds (VOCs), exacerbates asthma and contributes to cardiovascular diseases [10]. Understanding the relationship between ozone and its precursors is vital for air quality management, necessitating robust predictive models to mitigate impacts. Evaluating control strategies for extreme ozone events remains challenging due to computational costs and the absence of uncertainty measures in existing modeling approaches [36].

Black carbon, a byproduct of incomplete combustion from diesel engines and biomass burning, significantly affects air pollution and climate change. Its inhalation is linked to adverse health outcomes, including respiratory and cardiovascular diseases, underscoring the need to control emissions from primary sources like traffic and maritime activities [13]. The dual role of black carbon as both a climate forcer and a health risk emphasizes its critical position in the air pollution framework.

Integrating PM2.5, ozone, and black carbon into the exposome framework is essential for a comprehensive understanding of their health impacts. Advanced modeling techniques yield high-resolution estimates of pollutant concentrations, facilitating effective exposure assessments and intervention strategies [12]. Addressing the challenges posed by these pollutants requires a multifaceted approach, particularly in urban areas where minimizing exposure is crucial for public health [37]. The long-term variation of population exposure to PM2.5, especially in regions like Eastern China, further underscores the necessity for city-level data to inform public health strategies [38].

2.3 Gut Microbiota and Host-Microbiome Interactions

The gut microbiota, a complex ecosystem of microorganisms in the gastrointestinal tract, is vital for host health, influencing metabolic processes, immune system support, and protection against pathogens [31, 32]. This microbial community plays a key role in digesting complex carbohydrates, synthesizing vitamins, and modulating immune responses, thereby contributing to metabolic and immune homeostasis. The composition and functionality of the gut microbiota are influenced by factors such as diet, genetics, and environmental exposures, emphasizing its relevance within the exposome framework.

Host-microbiome interactions are essential for physiological balance and disease prevention, involving signaling pathways that regulate immune function, energy metabolism, and gut barrier integrity. Dysbiosis, or microbial imbalance, is linked to various health conditions, including inflammatory bowel disease, obesity, and metabolic syndrome. Microbial metabolites, particularly short-chain fatty acids, facilitate bidirectional communication between the host and microbiota, affecting metabolic processes and immune function, thereby highlighting the intricate relationship between the microbiome and overall health [39, 31, 32, 40].

Environmental factors, notably air pollution, can significantly impact gut microbiota composition and function, thereby influencing host-microbiome interactions. Exposure to pollutants like PM2.5

and ozone has been shown to affect microbial diversity and the abundance of specific bacterial taxa, potentially increasing intestinal permeability and systemic inflammation. Investigating how environmental exposures, particularly air pollution, influence gut microbiota is crucial for understanding the development and exacerbation of autoimmune diseases and other health conditions, including asthma and multiple sclerosis [31, 18, 2].

The integration of citizen science and community engagement in environmental monitoring, as illustrated by Hsu et al., underscores the importance of participatory design and data visualization in understanding environmental impacts on gut microbiota [41]. Engaging communities in data collection and analysis provides valuable insights into local environmental conditions and their health effects, informing targeted interventions and public health strategies.

Studying gut microbiota and host-microbiome interactions within the exposome framework reveals complex relationships between environmental exposures—such as air pollution and toxic sites—and health outcomes, particularly in vulnerable populations. By integrating personal and environmental data, this research demonstrates how daily mobility patterns contribute to exposure risks, indicating that individuals may experience significant health impacts from environmental hazards even in seemingly safe areas. This comprehensive approach highlights the necessity of considering both personal habits and environmental factors to address health disparities linked to environmental exposures [31, 19, 2]. Such insights are crucial for developing effective interventions to mitigate the adverse health effects associated with environmental pollutants.

2.4 Metabolic Pathways Influenced by Environmental Exposures

Environmental exposures, especially to air pollutants like PM2.5, ozone, and black carbon, significantly impact metabolic pathways, influencing various health outcomes. These pollutants can induce oxidative stress and inflammation, critical factors in altering metabolic processes. The integration of spatial statistics with dimension reduction techniques, as shown by Jandarov et al., provides a novel means of extracting principal components that predict the impact of these exposures at unmeasured locations, enhancing our understanding of their metabolic effects [42].

Oxidative stress from pollutants like PM2.5 disrupts mitochondrial function, altering energy metabolism and producing reactive oxygen species (ROS), which damage cellular components and contribute to diseases such as cardiovascular disorders and metabolic syndrome. Ozone exposure exacerbates health outcomes by generating secondary pollutants and oxidative agents that disrupt lipid metabolism and activate inflammatory pathways, increasing the risk of respiratory and cardiovascular diseases, even at concentrations below current regulatory standards [43, 44, 45, 46].

Black carbon, due to its particulate nature and ability to adsorb organic compounds, affects metabolic pathways by interacting with gut microbiota, influencing the production of microbial metabolites like short-chain fatty acids that are crucial for host energy homeostasis and immune regulation. Environmental exposures, such as air pollution, can trigger systemic inflammation and metabolic dysregulation, underscoring the complex interplay between these factors and overall metabolic health. Research indicates that fine particulate matter (PM2.5) and other pollutants significantly contribute to chronic diseases, including autoimmune disorders and cardiovascular issues, emphasizing the urgent need for public health interventions to mitigate these risks [31, 45, 2].

Employing advanced methodologies, such as those proposed by Jandarov et al., enhances the ability to capture the spatial variability and intricate interactions between environmental exposures and metabolic pathways, which is essential for understanding health effects in air pollution cohort studies. This approach improves predictive accuracy and uncovers underlying mechanisms that inform public health interventions [15, 47]. Understanding these metabolic disruptions within the exposome framework is vital for advancing environmental health research and informing public health strategies aimed at reducing pollution-related disease burdens.

2.5 Current Understanding and Research Gaps

Research on the health impacts of air pollution reveals critical gaps and challenges that impede a comprehensive understanding and effective intervention strategies. Despite advancements in epidemiological studies, exposure assessment methodologies often fall short in capturing the complexities of pollution mixtures and their health effects [11]. Traditional approaches frequently focus on individual

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pollutants, neglecting the joint distribution of exposures, which can bias effect size estimates [34]. This limitation is exacerbated by the static nature of conventional methods, overlooking variability introduced by individual mobility patterns [48].

A significant challenge in current research is residual confounding, particularly in time-series studies examining environmental exposures and health outcomes [49]. Existing methods often fail to account for unmeasured or mismeasured confounders, leading to biased effect estimates [49]. Moreover, the sparse distribution of air quality monitoring systems, which typically rely on residential locations for exposure assessment, complicates health effect estimation by not considering individual mobility and daily activities [24]. This underrepresentation of affected populations contributes to inaccurate health impact assessments [50].

The limited availability of comprehensive datasets that encompass a wide range of exposure levels and study characteristics further exacerbates these challenges, potentially leading to biases in effect size estimates [34]. Additionally, unanswered questions remain regarding the long-term health effects of chronic exposure to nanoparticles and the mechanisms of their toxicity [16]. The global perspective on air quality inequality highlights rising levels primarily driven by international disparities, underscoring the need for inclusive environmental justice research and policy [37].

Another significant gap is the inadequate consideration of spatial autocorrelation and misalignment in estimating pollution-health relationships, which can bias causal estimates [51]. The assumption of unbiased site selection in existing statistical methods for analyzing air quality data often results in inaccurate health impact assessments [38]. Furthermore, disparities in PM2.5 exposure by race/ethnicity and socioeconomic status (SES) have persisted for over three decades, highlighting a critical gap in understanding inequities in data collection [35].

Addressing these research gaps necessitates a multidisciplinary approach that integrates advanced modeling techniques, comprehensive monitoring, and innovative research methodologies. Such efforts are essential for enhancing our understanding of the complex interactions between air pollution and health, ultimately informing more effective public health strategies and policy interventions [52].

The intricate relationships between air pollution components and their associated health impacts necessitate a thorough understanding of the underlying mechanisms. To elucidate this complexity, Figure 2 illustrates the hierarchical categorization of air pollution components alongside their health impacts. This figure details epidemiological evidence, mechanisms of health impact, spatial and temporal variability, and health risks for vulnerable populations. Additionally, it highlights advancements in exposure assessment and modeling. Each primary category is meticulously divided into specific subcategories and detailed points, thereby providing a comprehensive overview of the multifaceted factors contributing to the health effects of air pollution. Such a structured representation not only enhances our understanding but also emphasizes the urgency of addressing these critical public health challenges.

3 Air Pollution Components and Health Impacts

3.1 Epidemiological Evidence of Health Impacts

Epidemiological studies robustly link air pollution, particularly PM2.5, ozone, and black carbon, to significant health impacts. Long-term PM2.5 exposure is associated with increased premature mortality, as reinforced by meta-analyses evaluating all-cause and cause-specific mortality [34]. The absence of a safe threshold for PM2.5 exposure highlights the need for stringent air quality management [34]. Beyond mortality, PM2.5 is linked to respiratory diseases and potential neurodegenerative conditions [16]. The global health and economic burdens of air pollution, with varying exposure levels across regions, necessitate targeted interventions for vulnerable populations [37].

Ozone exacerbates respiratory conditions such as asthma and contributes to cardiovascular diseases [11]. Controlling mobile-source emissions is critical for managing ozone levels and mitigating health impacts [11]. The correlation between air pollution from forest fires and increased COVID-19 cases and mortality underscores the broader public health implications of air quality [14].

This relationship is further illustrated in Figure 3, which categorizes the health impacts of air pollution, highlighting the effects of PM2.5 and ozone, as well as the connection between air quality and COVID-

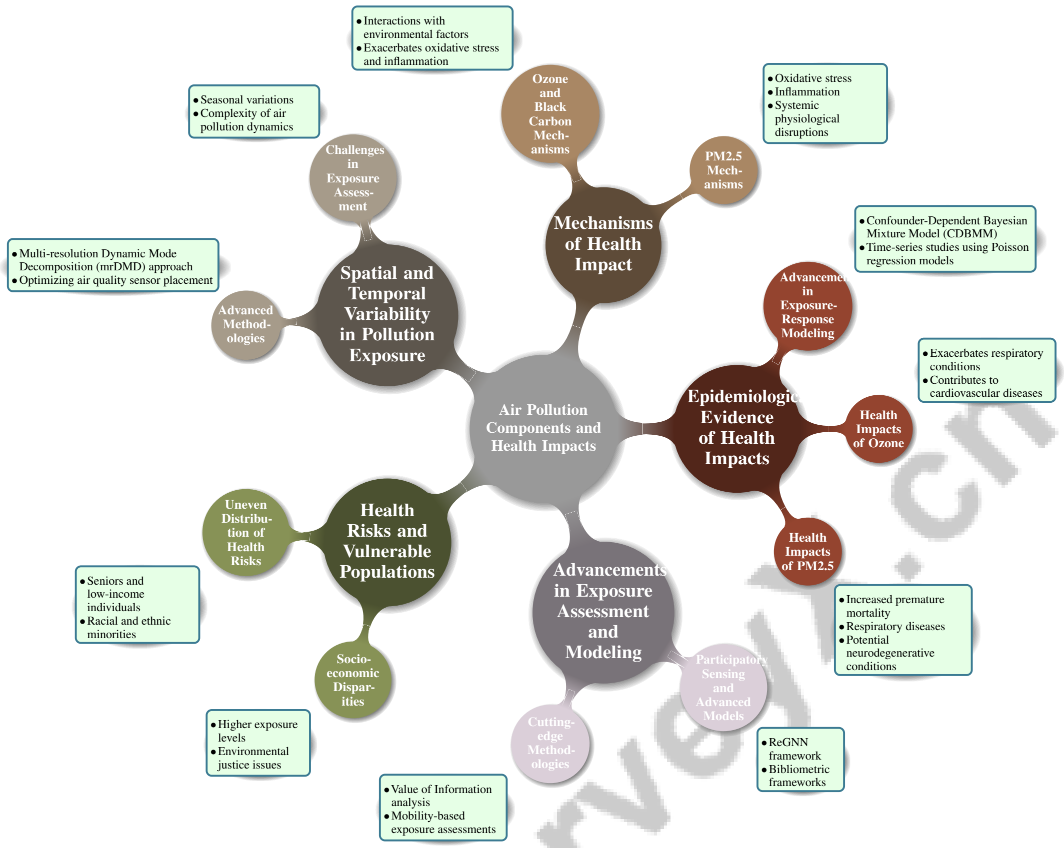

Figure 2: This figure illustrates the hierarchical categorization of air pollution components and their health impacts, detailing epidemiological evidence, mechanisms of health impact, spatial and temporal variability, health risks for vulnerable populations, and advancements in exposure assessment and modeling. Each primary category is further divided into specific subcategories and detailed points, providing a comprehensive overview of the complex relationships and factors contributing to air pollution's health effects.

19. The figure synthesizes significant findings from various studies, reinforcing the urgent need for public health interventions.

Advancements in exposure-response modeling, such as the Confounder-Dependent Bayesian Mixture Model (CDBMM), have refined our understanding of PM2.5's heterogeneous causal effects, enabling targeted interventions for vulnerable groups [36]. Time-series studies using Poisson regression models further elucidate air pollution's health impacts, highlighting the need for improved exposure assessment methodologies [49].

Biases in public health assessments due to preferential sampling in monitoring networks, like the SOCAB network, can inflate pollution level estimates [38]. Addressing these biases is crucial for accurate health impact assessments and effective strategies. Integrating advanced exposure assessment methodologies with robust epidemiological evidence is vital for formulating comprehensive interventions to reduce air pollution's adverse health effects.

3.2 Mechanisms of Health Impact

The health impacts of PM2.5, ozone, and black carbon involve complex biological mechanisms, primarily oxidative stress, inflammation, and systemic physiological disruptions. PM2.5's small size allows deep penetration into the respiratory system and bloodstream, exacerbating systemic inflammation and contributing to cardiovascular and respiratory disorders [34]. Meta-regression techniques reveal significant associations between PM2.5 exposure and mortality, with effect size variations influenced by exposure levels and study design [34].

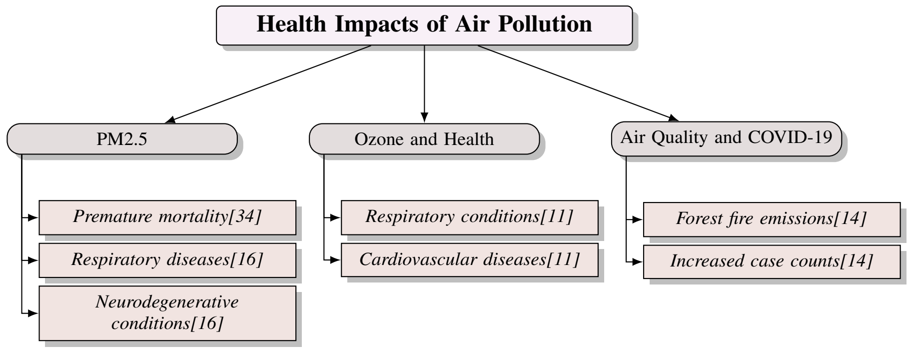

Figure 3: This figure illustrates the health impacts of air pollution, categorizing the effects of PM2.5, ozone, and the relationship between air quality and COVID-19, highlighting significant findings from various studies.

Ozone's health risks are compounded by interactions with environmental factors, such as temperature, which are often non-linear and nonadditive, complicating health impact assessments [49]. Temporal relationships between ozone exposure and health outcomes can enhance causal effect estimates by incorporating future exposure indicators into regression models [49].

Black carbon, a byproduct of incomplete combustion, exacerbates oxidative stress and inflammation, affecting metabolic pathways and increasing the risk of diseases like diabetes. Rising global air quality inequality, driven by inter-country disparities, necessitates targeted interventions [37].

Developing advanced statistical models and methodologies is essential for accurately capturing pollutant exposure intricacies and their health impacts. Detecting preferential sampling in air quality monitoring networks enhances understanding of pollution levels and their health effects [38]. Integrating high-resolution data and machine learning frameworks allows for precise exposure assessments and informs effective public health strategies.

3.3 Spatial and Temporal Variability in Pollution Exposure

Spatial and temporal variability in pollution exposure poses challenges for accurately assessing health impacts from pollutants like PM2.5, ozone, and black carbon. Seasonal variations modulate pollution levels, affecting exposure assessments and necessitating effective mitigation strategies [53]. The relationship between PM2.5 concentrations and meteorological factors, such as temperature and humidity, varies by region and season, particularly in China, underscoring the complexity of air pollution dynamics and the need for region-specific management strategies [54].

Advanced methodologies, like the multi-resolution Dynamic Mode Decomposition (mrDMD) approach, capture spatial and temporal variability in PM2.5 concentrations, optimizing air quality sensor placement to enhance exposure assessment accuracy and inform public health interventions [55]. Incorporating advanced analytical techniques provides deeper insights into the complexities of air pollution dynamics and their significant health repercussions. This understanding aids in identifying vulnerable populations and specific exposure risks, facilitating the development of targeted policies and interventions to mitigate air pollution exposure and improve public health outcomes. These efforts yield substantial environmental and health co-benefits, as outlined in strategic guidelines for stakeholders, including citizens, enterprises, and public authorities [52, 56, 57, 58].

3.4 Health Risks and Vulnerable Populations

Health risks associated with air pollution exposure are unevenly distributed, with certain demographic groups facing disproportionately higher risks. Seniors, particularly those aged 81-85 with low income and individuals over 85, are especially vulnerable to PM2.5 exposure [58]. The interplay between heat waves and air pollution episodes exacerbates these risks, particularly in urban areas where these events compound public health challenges [59].

Socio-economic factors further compound disparities in pollution exposure and health impacts. Racial and ethnic minorities, along with lower-income and marginalized populations, experience higher exposure levels and associated health risks, highlighting persistent environmental justice issues [60]. For instance, Beijing residents face increased risks due to elevated PM2.5 concentrations, underscoring the need for targeted interventions in high-pollution areas [61].

Workplace environments significantly influence health outcomes, necessitating a nuanced understanding of how occupational exposures contribute to overall pollution-related health risks [26]. Identifying subgroups most affected by air pollution is crucial, particularly regarding mortality rates [62]. Addressing these disparities requires a comprehensive approach considering treatment effect heterogeneity, as significant health benefits from emissions reductions have been observed in high-poverty and high-smoking communities [33].

These findings emphasize the need for tailored public health strategies and interventions addressing vulnerable populations' unique challenges. Prioritizing equitable access to clean air aims to mitigate air pollution's disproportionate health impacts, particularly for low-income communities and communities of color, who often experience higher exposure levels due to mobility patterns and proximity to pollution sources. Integrating comprehensive data on population mobility and pollution emissions enhances understanding of these disparities, informing effective measures to promote environmental justice and improve community health outcomes [35, 26, 63, 28, 52].

3.5 Advancements in Exposure Assessment and Modeling

Benchmark	Size	Domain	Task Format	Metric
AQI-PM[64]	38,277	Air Quality Monitoring	Regression	RMSE, R2
APMH[65]	12,615	Mental Health	Mental Illness Assessment	K6 Score, Probability of Severe Mental Illness
TAP[66]	7,300,000	Air Quality	Time Series Analysis	R2, RMSE
cosSquareFormer[67]	35,596	Air Quality	Pollutant Level Estimation	RMSE, MAPE
PM2.5-Monitor-Benchmark[68]	1,000,000	Indoor Air Quality	Pm2.5 Monitoring	Accuracy, RMSE
PM2.5-Wildfire[69]	19,850	Environmental Health	Exposure Assessment	Mean Bias, RMSD
PMBM[70]	120	Air Quality	Sensor Evaluation	PM2.5 Accuracy, PM10 Accuracy
WF-AQ[71]	6,000,000	Air Quality	Pollutant Measurement	CO, PM2.5

Table 1: This table presents a comprehensive overview of various benchmarks used in air quality and environmental health research. It details the size, domain, task format, and evaluation metrics for each benchmark, highlighting the diversity in approaches to air pollution monitoring and assessment. The benchmarks span multiple domains, including air quality monitoring, mental health assessment, and pollutant measurement, underscoring the interdisciplinary nature of exposure assessment advancements.

Recent advancements in exposure assessment and modeling have significantly enhanced our understanding and prediction of air pollution exposure, particularly concerning pollutants like PM2.5, ozone, and black carbon. These advancements utilize cutting-edge methodologies and technologies, including Value of Information analysis, mobility-based exposure assessments, and multi-sensor data fusion, to address traditional health impact modeling limitations. By integrating real-time environmental data with individual physiological responses, these approaches yield more accurate exposure and health impact estimates, quantifying uncertainties in health outcome predictions and capturing human mobility effects on environmental hazard exposure [72, 19, 5, 73]. Table 1 provides a detailed overview of representative benchmarks utilized in these recent advancements, illustrating the diverse methodologies employed to enhance our understanding of air pollution exposure and its health impacts.

Participatory sensing has emerged as a promising strategy to expand air quality monitoring's spatial coverage, enhancing community involvement in environmental health initiatives [74]. By integrating citizen science with traditional monitoring networks, participatory sensing enriches the understanding of air pollution dynamics and their health impacts.

Advanced statistical models, such as the ReGNN framework, improve traditional regression models by incorporating neural networks to create summary variables that moderate environmental hazards' effects on health outcomes [75]. This approach facilitates a nuanced understanding of how different populations are affected by pollution, enabling targeted interventions.

Bibliometric frameworks have provided valuable insights into existing PM2.5 exposure research, identifying trends and influential works, informing policy and research priorities, and highlighting gaps for future investigation [57].

In air quality modeling, the multi-resolution Dynamic Mode Decomposition (mrDMD) algorithm is employed to identify optimal sensor locations, enhancing pollution exposure assessment accuracy by strategically positioning monitoring networks to effectively capture spatial variability [55]. This ensures optimal placement of air quality sensors for accurate pollution dynamics monitoring.

The potential outcome approach offers a robust framework for distinguishing between design and analysis phases in modeling, ensuring consistent results across different outcomes and enhancing causal interpretation [76]. This method strengthens the robustness of causal inferences drawn from pollution exposure data.

Integrating machine learning techniques with traditional statistical models has improved prediction accuracy. For instance, the airpred method via the H2O platform enhances scalability and accuracy in predicting pollution levels in areas lacking monitoring stations [77]. These advancements underscore the critical role of innovative modeling techniques in addressing pollution exposure complexities and their health impacts.

Furthermore, regression-based time series analyses and moving median analyses have demonstrated significant improvements in estimating health impacts, particularly in the presence of unmeasured confounders. Integrating variable importance measures in spatial machine learning models has enhanced model interpretability, aiding model selection and improving air pollution exposure assessment [15].

Collectively, these advancements enhance our understanding of air pollution exposure by providing detailed insights into specific emission sources and their health impacts across demographics, ultimately informing the development of targeted public health strategies and interventions to effectively mitigate air pollution's adverse health effects [52, 57, 58].

4 Gut Microbiota and Host-Microbiome Interactions

The intricate relationship between gut microbiota and host-microbiome interactions is shaped by various environmental factors, notably air pollution, and individual health conditions, impacting health outcomes and disease susceptibility [32, 2, 31, 78, 62]. Understanding the contributions of gut microbiota to health and disease requires analyzing its interactions with environmental influences, particularly air pollution, affecting host responses.

4.1 Role of Gut Microbiota in Health and Disease

The gut microbiota, a diverse microbial community in the gastrointestinal tract, is crucial for maintaining health and influencing disease processes. It plays a key role in physiological functions like breaking down complex carbohydrates, vitamin production, and immune regulation, significantly affecting overall health [32, 2, 31, 52, 79]. The balance and composition of gut microbiota are essential for metabolic homeostasis and immune system function.

Exposure to air pollutants, such as PM2.5, significantly affects gut microbiota composition and function, altering DNA methylation profiles crucial for understanding the interplay between environmental factors and gut microbiota [79]. These epigenetic changes can disrupt microbial balance, leading to dysbiosis linked to inflammatory and metabolic diseases.

Maternal health and environmental exposures during critical developmental periods are particularly influential on health outcomes. Maternal education moderates the relationship between environmental exposures and birth outcomes, highlighting socio-economic factors in modulating environmental stressor effects on health [21]. Maternal exposure to PM2.5 is associated with adverse health outcomes in children, emphasizing the need for protective measures during pregnancy [80].

The gut microbiota's role extends to its interactions with environmental pollutants, which can disrupt normal microbial functions and lead to systemic health effects. Advanced statistical models like the Cox model enhance understanding of the complex relationships between environmental exposures and health outcomes by accounting for measurement errors and unknown changepoints [81]. These insights inform targeted interventions and public health strategies.

The gut microbiota is crucial for overall health and the development of various diseases, as its composition and function are significantly influenced by environmental factors like air pollution, which is linked to increased risks of autoimmune diseases and chronic conditions such as cardiovascular disease [31, 45, 2]. Understanding these interactions within the exposome framework is essential for developing effective interventions to mitigate adverse health effects associated with environmental pollutants.

4.2 Influence of Air Pollution on Gut Microbiota

Research into the influence of air pollution on gut microbiota composition and function reveals the intersection of environmental exposures and microbiome dynamics. Air pollutants such as PM2.5, ozone, and black carbon alter gut microbiota, impacting host health through various biological pathways. The DigitalExposome framework elucidates how these pollutants influence physiological responses, enhancing our understanding of gut microbiota interactions [5].

The complex effects of air pollution on gut microbiota necessitate advanced analytical techniques to accurately capture these interactions. Integrating high-resolution data and uncertainty measures through models like DIMAQ is critical for effective health impact assessments [82]. These models provide nuanced insights into the relationship between air pollution and gut microbiota, emphasizing the need for precise exposure assessments.

Dynamic human activities and their relationship with air pollutant exposure further complicate these interactions. Methods proposed by Fan et al. offer a more nuanced understanding of environmental justice issues, particularly in urban settings where vulnerable populations are disproportionately affected [63]. This understanding is vital for addressing the broader implications of air pollution on gut microbiota and health.

Urban planning and curbside management strategies, which influence traffic-related air quality, have been shown to alter gut microbiota composition and function [83]. This underscores the importance of integrating urban planning with environmental health initiatives to mitigate the adverse effects of air pollution on gut microbiota. Additionally, employing integrated systems that combine air quality sensors and Bluetooth Low Energy (BLE) beacons enables real-time monitoring of indoor air conditions and human movements, providing valuable data on how indoor air quality influences gut microbiota [84].

Despite advancements, challenges such as selective reporting and inadequate treatment of confounding variables can introduce biases in reported outcomes. Innovative statistical methods, including Bayesian hierarchical models, allow for simultaneous estimation of causal effects and identification of relevant confounders, enhancing the reliability of findings related to air pollution and gut microbiota interactions [85]. Current studies often overlook the long-term effects of indoor air pollutants and the comprehensive evaluation of biotechnological methods in real-world applications [6].

The interactions between air pollution and gut microbiota are multifaceted, involving various environmental factors and biological mechanisms. As illustrated in Figure 4, the key factors influencing this relationship include the impact of specific pollutants, the role of advanced analytical techniques, and the importance of urban planning strategies. Addressing current research methodologies' challenges and leveraging advanced analytical techniques are crucial for deepening our understanding of these interactions and their implications for human health [32].

4.3 Host-Microbiome Interactions and Environmental Exposures

Host-microbiome interactions are significantly influenced by environmental exposures, modulating health outcomes through complex biological pathways. These interactions are essential for maintaining physiological balance and are mediated by factors such as microbial metabolites and immune signaling pathways. The integration of advanced statistical methodologies, like the ReGNN framework, provides a robust approach to uncover hidden interactions among predictors, enhancing our understanding of health risks associated with environmental hazards [75].

Spatial and temporal variability in environmental exposures, particularly from air pollutants, necessitates sophisticated modeling techniques for accurate impact assessments on host-microbiome interactions. The reduced-rank spatiotemporal modeling approach enhances computational efficiency and robustness in predictions, especially with large datasets, improving our understanding of how

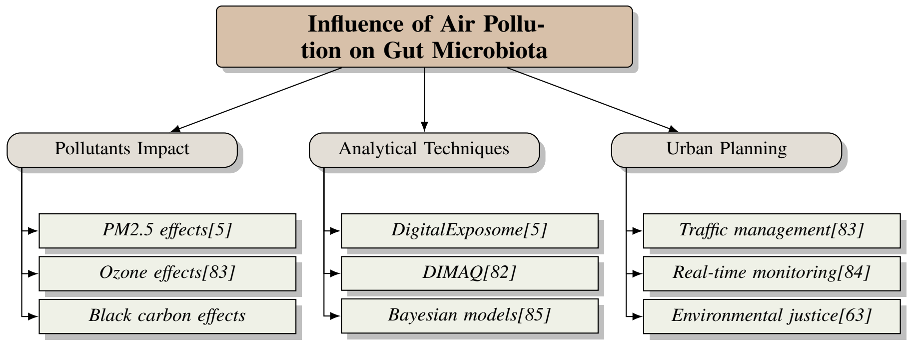

Figure 4: This figure illustrates the key factors influencing the relationship between air pollution and gut microbiota, highlighting the impact of specific pollutants, the role of advanced analytical techniques, and the importance of urban planning strategies.

these exposures influence microbiome dynamics [86]. Additionally, propensity score-based methods adapted from social network research can effectively handle interference in causal analysis, allowing for more accurate assessments of environmental impacts on host-microbiome interactions [87].

Current research often encounters challenges in addressing spatial autocorrelation within machine learning models, potentially leading to inaccuracies in predicting how environmental exposures affect host-microbiome interactions [88]. However, the leave-one-out approach to variable importance provides clearer comparisons across spatial machine learning models, enhancing our understanding of these interactions in the context of environmental exposures [15]. This approach is crucial for developing targeted interventions to mitigate the adverse effects of environmental pollutants on health.

Future research could benefit from exploring data across clustered regions or addressing nonlinear relationships in confounders to enhance the analytical power related to host-microbiome interactions and environmental exposures [89]. By leveraging real-time data analysis, methodologies proposed by Gyarmati and Szabo can adapt to changing conditions, maintaining high accuracy where traditional methods may falter [4]. These advancements highlight the importance of integrating cutting-edge analytical techniques to deepen our understanding of the complex interplay between environmental exposures and host-microbiome interactions.

5 Interactions Between Air Pollution and Gut Microbiota

5.1 Mechanisms of Interaction Between Air Pollutants and Gut Microbiota

Air pollutants, including PM2.5, ozone, and black carbon, interact with gut microbiota through oxidative stress, inflammation, and epigenetic modifications, altering microbiome composition and function. These pollutants induce systemic health effects, such as those caused by brake wear nanoparticles, which affect the gut microbiota via respiratory pathways [13]. Advanced modeling techniques, such as the scalable penalized land-use regression method LURK-Vecchia, improve exposure assessments by incorporating spatiotemporal correlations, enhancing our understanding of pollutant-microbiota interactions [90]. Integrating real-time health data with public pollution datasets further personalizes exposure assessments, revealing the dynamic nature of these interactions [10].

Spatial and temporal variations in pollutant exposure are critical for understanding these interactions. Systematic analyses using multilevel models account for spatial variability, providing insights into pollution exposure implications [35]. The generalized propensity score method, which incorporates spatial dependence into causal effect estimation, offers a more accurate understanding of how air pollution impacts gut microbiota [36]. The concept of 'air quality poverty' highlights global disparities in PM2.5 exposure, emphasizing the need to consider multiple pollutants to understand their collective impact on gut microbiota [37].

The interplay of chemical compositions, biological responses, and environmental conditions underscores the complex nature of interactions between air pollutants and gut microbiota, with potential health implications, including autoimmune diseases [52, 31, 78, 2]. By leveraging advanced statistical models and novel data sources, researchers can gain deeper insights into these interactions, informing targeted interventions and public health strategies aimed at mitigating air pollution's adverse health effects.

5.2 Disease Processes and Health Outcomes

Air pollution components like PM2.5, ozone, and black carbon interact with gut microbiota, contributing to disease processes and health outcomes through oxidative stress, inflammation, and epigenetic modifications. These interactions are particularly impactful in regions with high exposure burdens, such as Northern India, Bangladesh, Pakistan, and Eastern China [37]. Advanced modeling techniques, such as the Bayesian Localised Conditional Autoregressive (LCAR) model, enhance health effect estimations by capturing localized spatial correlations, providing insights into disease processes linked to air pollution [91].

As illustrated in Figure 5, key factors influencing disease processes and health outcomes related to air pollution are categorized into components of air pollution, socio-economic factors, and seasonal variations. Each category highlights specific elements that play a crucial role in understanding the health impacts of air pollution. Socio-economic factors, including social deprivation, exacerbate the health impacts of air pollution. Spatial profile regression highlights the intricate relationships between air pollution and socio-economic disparities, underscoring the need for public health policies addressing environmental justice [92]. The MedMatch method improves causal effect estimations by addressing unmeasured confounding and data sparsity, enhancing our understanding of health outcomes related to air pollution [93].

Seasonal and diurnal variations in pollutant concentrations, particularly ozone, significantly influence health outcomes. Models incorporating both spatial and temporal dependencies enhance the accuracy of ozone level predictions, leading to more precise risk assessments [30]. Individual responses to PM2.5 exposure vary significantly, indicating complex and personalized interactions between air pollution and health outcomes [94].

Unanswered questions remain regarding the long-term health impacts of low-level exposure to various pollutants and the effectiveness of different intervention strategies [11]. Prenatal exposure to PM2.5 during critical developmental windows has been associated with adverse outcomes, such as impaired cognitive function, indicating potential pathways for disease processes and health outcomes [8].

The complex relationship between air pollution and gut microbiota necessitates a comprehensive strategy integrating environmental, socio-economic, and biological considerations. Effective mitigation of air pollution is crucial for improving public health and environmental quality. This approach should involve tailored guidelines for various stakeholders, addressing diverse emission sources such as transportation, industry, and agriculture, to ensure a holistic reduction in pollution-related health risks [2, 31, 56, 52, 78]. This comprehensive perspective is essential for developing effective interventions aimed at mitigating the adverse health effects associated with air pollution.

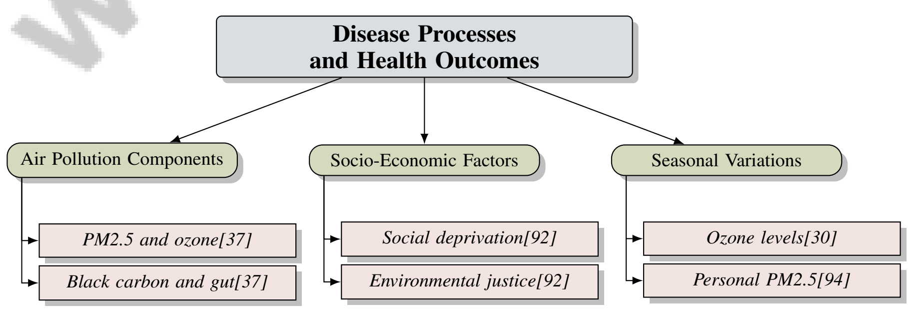

Figure 5: This figure illustrates the key factors influencing disease processes and health outcomes related to air pollution, categorized into components of air pollution, socio-economic factors, and seasonal variations. Each category highlights specific elements that play a crucial role in understanding the health impacts of air pollution.

6 Metabolic Pathways Affected by Air Pollution and Microbiota Interactions

6.1 Metabolic Pathways and Health Outcomes

The interaction between air pollution, including PM2.5, ozone, and black carbon, and gut microbiota significantly influences metabolic pathways, leading to various health outcomes. These pollutants trigger oxidative stress and inflammation, key mechanisms affecting metabolic processes. Dynamic Principal Component Analysis (DPCA) is instrumental in analyzing time-dependent data, providing insights into the temporal disruptions in metabolism due to environmental exposures [95]. Air pollution's role in the global increase in diabetes underscores the need to explore additional exacerbating factors. The Function-on-Function Regression (FFR) method demonstrates that prenatal PM2.5 exposure impacts metabolic pathways through DNA methylation, linking these epigenetic changes to adverse health outcomes [79].

To visualize these complex interactions, Figure 6 illustrates the relationship between air pollution and metabolic pathways, highlighting key effects, modeling techniques, and health impacts. Advanced modeling techniques generate high-resolution NO2 and PM2.5 estimates, facilitating precise assessments of pollution's effects on metabolic pathways by accounting for spatial and temporal dynamics [90]. Such estimates are crucial for understanding how exposure influences metabolic health across regions. The RC-GPS method corrects measurement errors in continuous exposures, enhancing insights into pollution-related metabolic pathways [9]. Evaluating health impacts under various curbside pickup strategies reveals traffic-related air pollutants' effects on metabolic pathways, highlighting urban planning's role in mitigating adverse effects. Metrics assessing health impacts from nanoparticle exposure, such as brake wear, further illustrate the intricate connections between air pollution and metabolic health [13].

Integrating advanced modeling techniques and high-resolution data is essential for elucidating the complex interactions between air pollution and metabolic pathways. This understanding is critical for developing targeted interventions and public health strategies to mitigate the adverse health effects associated with environmental exposures. Estimating both direct and spill-over effects while accounting for spatial dependencies provides a comprehensive framework for understanding the broader implications of air pollution on metabolic pathways [36].

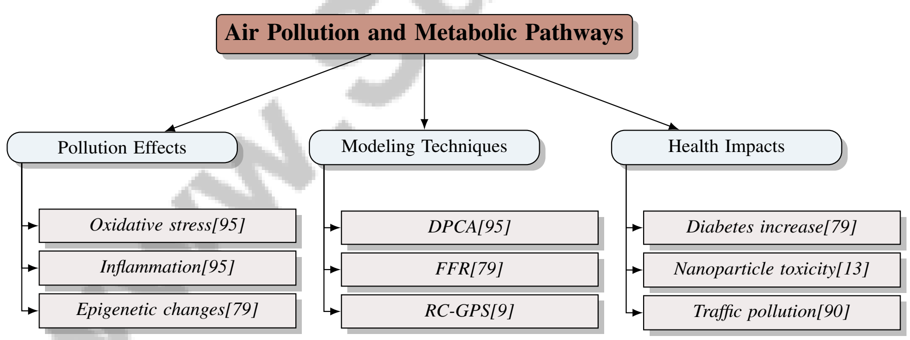

Figure 6: This figure illustrates the relationship between air pollution and metabolic pathways, highlighting key effects, modeling techniques, and health impacts.

6.2 Potential Interventions and Policy Implications

Effective interventions and policy measures are crucial for mitigating health risks associated with air pollution and its interactions with gut microbiota. Low-cost sensors significantly enhance real-time air quality monitoring, especially during wildfire seasons, where personal monitoring is vital for public health strategies. Enhanced calibration methods improve air quality assessments, ensuring accurate data collection and analysis. The method proposed by Nag et al. aids users in selecting healthier outdoor routes based on pollution levels, suggesting potential interventions to reduce health risks [10].

Advanced modeling techniques, such as multivariate spectral downscaling of PM2.5, enable more precise exposure assessments by allowing mean parameters to vary spatially, capturing nonstationarity in pollution data. Future research should refine these models to incorporate additional data sources and covariates, enhancing PM2.5 prediction accuracy and informing targeted interventions [38]. The ability to quantitatively assess sampling bias, as demonstrated by Jones et al., is crucial for accurate interpretations of air quality data, informing policy development.

Urgent policy interventions are needed to address specific pollution sources, such as fireworks, which significantly elevate PM2.5 levels and pose health risks due to certain elemental concentrations exceeding EPA risk-based levels. Integrating air pollution control strategies with public health initiatives is essential for addressing the complex interactions between environmental exposures and health outcomes. Developing integrated systems that combine physical-chemical and biotechnological methods for indoor air purification represents a promising avenue for future research, potentially mitigating health risks associated with poor indoor air quality [16].

The application of instrumental variables frameworks can unite diverse data sources, enhancing the robustness of causal inferences related to air pollution and health outcomes [49]. Future research should explore the sensitivity of results to different modeling choices and extend these frameworks to address discontinuous spatial patterns in confounders. Moreover, models that retain information from individual predictors while accounting for collinearity and spatial correlation can yield more informative results, supporting effective policy interventions [37].

These interventions and policy implications emphasize the necessity of a multifaceted approach to air quality management. By incorporating additional pollutants, refining statistical models, and integrating more environmental variables, future research can better inform policy decisions and enhance air quality management. Investigating additional covariates and refining models to improve predictive accuracy will address limitations and enhance real-time air quality monitoring [12].

7 Conclusion

7.1 Implications for Public Health and Future Research

Addressing the intricate interactions between air pollution and gut microbiota is critical for developing effective public health strategies. The economic impact of pollution-related health issues, including mental health disorders, highlights the necessity for targeted interventions. Future research should focus on advancing monitoring technologies and therapeutic strategies, particularly for vulnerable groups, while refining regulatory frameworks to address the complex relationships between pollutants and health outcomes.

Improving methodologies such as the Health Hazard Index (HHI) is vital for assessing health impacts in various indoor environments, thereby elucidating the effects of indoor air quality on health. Longitudinal studies are needed to establish causal links and examine underlying mechanisms, especially in relation to autoimmune diseases. Expanding datasets and exploring additional emission sources can enhance our understanding of air pollution dynamics, leading to more effective public health interventions.

Advancing predictive methodologies, including predictive Principal Component Analysis (PCA), should integrate health and geographic data to enhance accuracy across diverse epidemiological settings. Incorporating weekend scenarios into exposure minimization algorithms and exploring further optimization techniques can improve pollution exposure assessments.

The impact of anthropogenic climate change on wildfire management is a critical area for future research, necessitating proactive measures to mitigate its effects on public health. Moreover, refining methods for estimating the effects of environmental exposure mixtures and investigating causal relationships can significantly influence public health and inform future research directions.

Developing multivariate versions of the Peak Over Threshold (POT) modeling approach, which incorporate spatial dimensions to account for proximity to pollution sources, is essential for advancing air pollution research. Future studies should also aim to integrate more detailed health data and examine additional pollution thresholds to improve model applicability and precision.

Incorporating real-time monitoring of indoor air quality is crucial for effective asthma management and public health interventions. Enhancing model accuracy for pollutants and diverse contexts will further inform policy decisions and public health strategies. These research directions underscore the importance of integrating advanced methodologies with public health initiatives to effectively address the health impacts of air pollution and guide policy decisions aimed at improving population health outcomes.

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