Universidade do Porto
Faculdade de Desporto

Structural pathways linking sociodemographic characteristics, air pollution exposure, 24-hour movement behaviours, and health-related outcomes in children: An exploratory study using network science.

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Dissertação apresentada à Faculdade de Desporto da Universidade do Porto para a obtenção do grau de Mestre em Atividade Física, Exercício e Saúde - contextos clínicos - nos termos do disposto no Decreto-Lei n.º 74/2006, de 24 de março, na redação atualmente em vigor.

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1. EXPOSIÇÃO A POLUENTES DO AR 2. COMPORTAMENTOS DE MOVIMENTO 24-HORAS 3. CIÊNCIA DE REDES 4. APTIDÃO CARDIORRESPIRATÓRIA 5. STRESS OXIDATIVO

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Resumo

Introdução: A exposição à poluição do ar é uma preocupação central de saúde pública, especialmente em crianças, pela sua suscetibilidade à inflamação sistémica e stress oxidativo. Embora a atividade física tenha benefícios para a saúde, a sua interação, aliada aos demais comportamentos de movimento (comportamento sedentário e sono) com a exposição a poluentes do ar no *continuum* das 24 horas é ainda pouco explorada. **Objetivo:** Este estudo utiliza ciência de redes para investigar as vias estruturais que associam caraterísticas sociodemográficas, exposição a poluentes do ar, comportamentos de movimento 24 horas e desfechos relacionados com a saúde em crianças portuguesas de 1º ciclo. **Metodologia:** Realizou-se um estudo piloto transversal e exploratório com 14 crianças (8–11 anos) de Valongo, Portugal. Os dados sociodemográficos e as características da habitação foram obtidos através de questionários. A exposição a poluentes individual ($PM_{2.5}$, PM_{10} e CO_2) foi medida com sensores portáteis durante 48h e os comportamentos de movimento por acelerometria durante 5 dias da semana. As variáveis de saúde incluíram: Aptidão Cardiorrespiratória, Índice de Massa Corporal, status oxidativo total e status antioxidante total. Utilizou-se um Modelo de Impacto Estrutural Estendido, baseado na Ciência de Redes, para a análise de dados no Python (3.14). **Resultados:** Os fatores sociodemográficos exerceram o maior impacto direto nos comportamentos de movimento (impacto = 0.96). Os comportamentos de movimento funcionaram como um *bottleneck* estrutural parcial, mediando o impacto da exposição ambiental nos indicadores relacionados à saúde (impacto indireto = 0,66). **Conclusão:** Os comportamentos de movimento de 24 horas apresentaram impacto mediador na relação entre poluentes do ar e indicadores relacionados à saúde nas crianças avaliadas.

Palavras-chave: Exposição a poluentes do ar; Comportamentos de movimento 24-horas; Ciência de redes; Aptidão Cardiorrespiratória; Stress Oxidativo.

Abstract

Introduction: Air pollution exposure is a major global health concern, particularly for children, given their susceptibility to systemic inflammation and oxidative stress. While physical activity is known to benefit health, its interaction with APE and other co-dependant behaviours within a 24-hour continuum remains understudied. **Objective:** This study utilizes network science to investigate the structural pathways linking sociodemographic characteristics, individual air pollution exposure, 24-hour movement behaviours, and health-related outcomes in Portuguese primary school children. **Methods:** A pilot cross-sectional exploratory study was conducted with 14 children (aged 8-11) from Valongo, Portugal. Sociodemographic data and household characteristics were assessed via questionnaire. Individual APE ($PM_{2.5}$, PM_{10}, and CO_2) was measured using portable sensors over 48 hours, while movement behaviours were assessed via accelerometry over five weekdays. Health outcomes included cardiorespiratory fitness, body mass index, total oxidant status, and total antioxidant status. An extended structural impact model was employed for data analysis in Python (3.14). **Results:** Sociodemographic factors exerted the strongest direct impact on movement behaviours (normalized impact = 0.96). Movement behaviours emerged as a partial structural bottleneck, mediating the impact of environmental exposure on health outcomes (indirect impact = 0.66) more significantly than the direct environmental-health pathway (impact = 0.43). **Conclusion:** 24-hour movement behaviours presented a mediating impact on the relationship between air pollutants and health-related outcomes in the evaluated children.

Keywords: Air pollution exposure; 24-hour movement behaviours, Network science, Cardiorespiratory fitness; Oxidative stress.

List of abbreviations

Tables 1 and 2 contain all abbreviations and acronyms used in this dissertation. Table A includes all of the document except for the literature review table, while Table B exclusively includes abbreviations and acronyms present in the literature review table.

Table 1 – Abbreviations, acronyms and symbols used in this dissertation.

Abbreviation	**Definition**
20-mSRT	20-m Shuttle Run Test
24-h movement behaviour	24-hour Movement Behaviour
AP	Air Pollution
APE	Air Pollution Exposure
BMI	Body Mass Index
CO_2	Carbon Dioxide
CPET	Cardiopulmonary Exercise Testing
CRF	Cardiorespiratory Fitness
CV	Cardiovascular
DGS	Direção Geral de Saúde
ENMO	Eucledian Norm Minus One
FEV1	Forced Expiratory Volume in One Second
FVC	Forced Vital Capacity
GDPR	European Union General Data Protection Regulation
G	Groups
I	Direct Impact
IAP	Indoor Air Pollution
ISPUP	Institute of Public Health, University of Porto
LDL	Low-Density Lipoprotein
MVPA	Moderate to Vigorous Physical Activity
NCD	Noncommunicable Diseases
OS	Oxidative Stress
PA	Physical Activity
PM	Particulate Matter
PM_{10}	Coarse Particles
$PM_{2.5}$	Fine Particles
PPM	Parts Per Million
ROS	Reactive Oxygen Species
R^2	Coefficient of Determination

Abbreviation	Definition
SES	Socioeconomic Status
SB	Sedentary Behaviour
T2DM	Type 2 Diabetes Mellitus
TAS	Total Antioxidant Status
TOS	Total Oxidant Status
UFP	Ultrafine Particles
VO_{2max}	Maximal Amount of Oxygen
WMS	Whole Mouth Saliva
WHO	World Health Organization
c^{bet}	Betweenness Centrality
c^{eig}	Eigenvector Centrality
c^{pr}	PageRank Centrality
C_i	Structural Centrality Score
ρ_{ij}	Spearman's Rank Correlation Coefficients
95%CI	95% Confidence Intervals
mg	Milligravitational Units

Note: Abbreviations are organized in alphabetical order, and symbols appear after them. Some symbols (e.g., c^{eig}, I and R^2) represent mathematical or statistical measures used in the analyses.

Table 2 - Abbreviations and acronyms used in the literature review table.

Abbreviation	Definition
3DPAR	3-Day Physical Activity Recall
8-OHdG	8-hydroxy-2'-deoxyguanosine
95% CI	95% Confidence Interval
ADI	Area Deprivation Index
APE	Air Pollution Exposure
AQI	Air Quality Index
ASQ-3	Ages and Stages Questionnaires, 3rd Edition
BAMSE	Barn (Children), Allergy, Milieu, Stockholm, Epidemiology (Swedish Birth Cohort)
BMI	Body Mass Index
BSID-III	Bayley Scales of Infant and Toddler Development, 3rd Edition
CARE	Children's Air pollution and Respiratory health (Study name)
CDI-SF	Children's Depression Inventory - Short Form

Abbreviation	**Definition**
CES-D	Center for Epidemiologic Studies Depression Scale
CHAP	China High Air Pollutants (dataset)
CO	Carbon Monoxide
COPD	Chronic Obstructive Pulmonary Disease
COX	Cyclooxygenase
CRF	Cardiorespiratory Fitness
CRP	C-Reactive Protein
CSHQ	Children's Sleep Habits Questionnaire
DBP	Diastolic Blood Pressure
DE	Diesel Exhaust
DNA	Deoxyribonucleic Acid
EHC-93	Ottawa Urban Dust (Standardized particulate matter sample)
ESCAPE	European Study of Cohorts for Air Pollution Effects
$FEF_{25–75}$	Forced Expiratory Flow at 25–75% of the pulmonary volume
FeNO	Fractional Exhaled Nitric Oxide
FEV_1	Forced Expiratory Volume in 1 second
FMD	Flow-Mediated Dilation
FVC	Forced Vital Capacity
GAD	Generalized Anxiety Disorder
GBD	Global Burden of Disease
GDP	Gross Domestic Product
GINIplus	German Infant Nutritional Intervention plus environmental and genetic influences on allergy development
GIS	Geographic Information System
GTx	Geographically weighted / Spatiotemporal model
HICs	High-Income Countries
HDL-C	High-Density Lipoprotein Cholesterol
HP	High-Pollution (School/Area)
HPD	High-Pollution District
HRV	Heart Rate Variability
ICD	International Classification of Diseases
IFN-γ	Interferon gamma
IL	Interleukin (e.g., IL-6. IL-8)
IPAQ-SF	International Physical Activity Questionnare
IQ	Intelligence Quotient
IQR	Interquartile Range
ISAAC	International Study of Asthma and Allergies in Children
LacCer	Lactosylceramide

Abbreviation	**Definition**
LC-MS/MS	Liquid Chromatography with Tandem Mass Spectrometry
LISAplus	Influence of Lifestyle factors on the development of the Immune System and Allergies in East and West Germany
LMICs	Low- and Middle-Income Countries
LOX	Lipoxygenase
LPD	Low-Pollution District
LUR	Land Use Regression
MAP	Mean Arterial Pressure
MCP-1	Monocyte Chemoattractant Protein-1
MET	Metabolic Equivalent of Task
MFT	Multistage Fitness Test (20m shuttle run)
MI	Myocardial Infarction
MPO	Myeloperoxidase
MSD	Meso Scale Discovery (Electro-chemiluminescence assay method)
MVPA	Moderate-to-Vigorous Physical Activity
NO_2	Nitrogen Dioxide
NOx	Nitrogen Oxides
O3	Ozone
ORs	Odds Ratios
PA	Physical Activity
PC	Phosphatidylcholine
PE	Phosphatidylethanolamine
PEF	Peak Expiratory Flow
PM	Particulate Matter
PM_1	Particulate Matter $\leq$ 1 µm
$PM_{2.5}$	Particulate Matter $\leq$ 2.5 µm
PM_{10}	Particulate Matter $\leq$ 10 µm
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROSPERO	International Prospective Register of Systematic Reviews
SB	Sedentary Behaviour
SBP	Systolic Blood Pressure
SCARED	Screen for Child Anxiety Related Disorders
Si	Silicon
SM	Sphingomyelin
SNPs	Single Nucleotide Polymorphisms
SO_2	Sulfur Dioxide
SP	Slightly Polluted (school/area)

Abbreviation	Definition
TC	Total Cholesterol
Ti	Titanium
TNF-α	Tumour Necrosis Factor alpha
TRAP	Traffic-Related Air Pollution
USA	United States of America
VEGF	Vascular Endothelial Growth Factor
VOCs	Volatile Organic Compounds
WBA	Whole Blood Assays

Note: Abbreviations are listed in alphabetical order and are specific to the literature review table of this dissertation. Symbols and units (e.g., $FEF_{25–75}$, VO_{2max}, $PM_{2.5}$) represent physiological or environmental measurements, while some abbreviations correspond to specific study names or datasets (e.g., BAMSE, CARE)

1 Introduction

Air pollution exposure (APE) is a major global health concern, responsible for over nine million deaths annually (Fuller et al., 2022). APE has also been shown to increase systemic inflammation and oxidative stress (Miller et al., 2024; Yoshida, 2024). These mechanisms are thought to underlie both local damage — such as impaired pulmonary immune response — and systemic effects, including increased risk of insulin resistance and type 2 diabetes mellitus (T2DM). (Thangavel et al., 2022). Chronic exposure to air pollution has been consistently associated with reduced forced expiratory volume in one second (FEV_1) and forced vital capacity (FVC), increased risk of asthma and chronic obstructive pulmonary disease (COPD) exacerbations, lung cancer, adverse cardiovascular events and epilepsy hospitalizations, as well as with sleep loss and decreases in happiness (Almetwally et al., 2020; Tsai et al., 2025).

Children are particularly vulnerable to the harmful effects of APE, as their developing immune system and increased inhalation rate (Holgate, 2017) enhance their susceptibility to pulmonary and systemic inflammation, increased oxidative stress (Gruzieva et al., 2017; Loxham et al., 2019), premature mortality and delayed cognitive development (Sunyer et al., 2015). A recent systematic review has also reported a global positive association between APE and obesity risk in children and adolescents (Zheng et al., 2024).

Physical activity (PA) is well recognized for its benefits on lung function, resistance to infection, cardiovascular health, and endothelial activity (Fuertes et al., 2018; Kunutsor et al., 2022; Nayor & Vasan, 2015; Soto-Rodríguez et al., 2024). According to the World Health Organization (WHO), nearly 1.8 billion adults worldwide do not meet PA guidelines (World Health Organization, 2024), increasing their risk of cardiovascular disease and several types of cancer (Friedenreich et al., 2021; Onagbiye et al., 2024). Insufficient PA also seems to mediate the development of noncommunicable diseases (NCD), by exacerbating intermediate risk factors such as hypertension, fasting plasma glucose and low-density lipoprotein (LDL) (Bourke et al., 2024).

Beyond PA, the analysis of other co-dependant movement behaviours, namely sleep and sedentary behaviour (SB), within a 24-hour continuum, provides relevant insights into health and developmental outcomes (Chaput et al., 2014). In children and adolescents, compliance with 24-hour movement behaviour (24-h movement behaviour) guidelines is associated with reduced obesity risk, greater physical fitness and improved cognitive function (Hossian et al., 2025). Nonetheless, prior studies have shown higher APE to be associated with lower levels of moderate to vigorous physical activity (MVPA) in the youth (Yu et al., 2017) and with lower odds of attending 24-hour movement behaviour guidelines in children (Lopez-Gil et al., 2022). This is particularly critical, as movement behaviours may act as prospective behaviours against the harmful effect of APE on the human body, especially during childhood, a key developmental window for establishing healthy and sustainable PA behaviours (Kohake et al., 2025). Nevertheless, exploratory studies should test this hypothesis. Therefore, this study investigates the structural pathways linking sociodemographic characteristics, APE, 24-hour movement behaviours, and health-related outcomes in children.

2 Literature review

2.1 Conceptual and Operational Definitions:

2.1.1 Air pollution

Air pollution (AP) can be defined as all destructive effects of any sources which contribute to the pollution of the atmosphere or the deterioration of ecosystems (Ghorani-Azam et al., 2016). It can be classified according to different parameters, namely source, origin, and size. Regarding size, AP can be classified as gaseous or particulate matter (PM) (Almetwally et al., 2020). PM are, in turn, defined as mixed organic and inorganic substances, and can be subclassified in coarse particles (PM_{10}), with a diameter of less than 10 µm, fine particles ($PM_{2.5}$), with a diameter of less than 2.5 µm, and ultrafine particles (UFP), with a diameter of less than 0.1 µm (Almetwally et al., 2020).

Air pollution exposure (APE) has traditionally been assessed through stationary monitoring stations (Snyder et al., 2013). More recently, individual assessments using portable monitoring sensors started to be implemented and are now considered as the gold standard approach for APE assessments (Larkin & Hystad, 2017). While monitoring stations gather large amounts of data, portable sensors capture individual changes, which have been shown to exist not only between people, but also between different microenvironments (Turner et al., 2024). Importantly, both these methods can be combined through mathematical models, such as Land-use regression models (LUR), leading to more precise long-term personal exposure predictions (Larkin & Hystad, 2017). The predictive performance and spatial resolution of LUR are inherently constrained by the density and quality of observational inputs (Ma et al., 2024), underscoring the critical role of individual monitors in providing the high-resolution data necessary to resolve micro-scale pollution dynamics and mitigate exposure misclassification. However, the absence of individualized exposure data has been described as a major limitation across multiple reviews examining diverse health-related outcomes (Almetwally et al., 2020; Maddren et al., 2024; Tainio et al., 2021; Zheng et al., 2024). Turner et al. (2024) measured the individual exposure to $PM_{2.5}$ and UFP in adolescents, and found substantial interindividual variability in pollutant levels, as well as variable correlations between to different pollutant types. Notably, pollutant concentrations varied greatly across microenvironments, with the highest $PM_{2.5}$ exposure occurring at home. Varaden et al. (2021) found, through similar individual assessments, that children who walked to and from school were exposed to higher pollutant levels especially when choosing main roads instead of secondary ones, showing how pollutants change greatly over small distances. While Turner et al. (2024)'s study was conducted during the COVID-19 pandemic, potentially increasing the time adolescents spent at home, other studies have shown that indoor air pollution (IAP) levels are roughly twice as high as outdoor environment levels, yet receive considerably less attention (González-Martín et al., 2021). In 2019, IAP accounted for 3.2 million premature deaths globally, including over 237,000 among children under 5 years old (Oloo et al., 2025). Moreover, school-aged children spend approximately 23 - 35% of their day in school, including morning hours, when ambient air pollution peaks (De Bont et al., 2019). These data are alarming and underscore the need for further investigation using individual sensors, which can capture the true cumulative pollutant dose inhaled across all daily microenvironments. This is particularly relevant in children, a population often underrepresented in studies with such methodological approach (Turner et al., 2024).

2.1.2 24-hour Movement Behaviours

The 24-hour movement behaviour (24-h movement behaviour) paradigm conceptualizes the daily cycle as a compositional continuum of co-dependent behaviours – including physical activity (PA) (light and moderate-to-vigorous), sedentary behaviour (SB), and sleep – recognizing that the time spent in any one behaviour necessarily displaces time from another, collectively influencing health outcomes across the lifespan (Rollo et al., 2020). The focus of previous research on individual associations between one of these components (PA, sleep or SB) and several health-related outcomes is now evolving towards this paradigm, which considers the collective influence of these behaviours across the 24 hours (Brown et al., 2024). Since the release of the Canadian 24-h Movement Guidelines for Children and Youth (Tremblay et al., 2016), new recommendations for different segments of the population became available and have been adopted by several countries globally (Brown et al., 2024).

In Portugal, official recommendations for children's Movement Behaviours are based on the World Health Organization (WHO) guidelines (Activity & Team, 2020), which have been formally translated and integrated into the Portuguese public health framework by the Direção Geral de Saúde (DGS) (Saúde, 2020). For children aged 9 to 11 (age distribution of this dissertation's sample), these recommendations advocate for at least 60 minutes of moderate-to-vigorous physical activity (MVPA), primarily aerobic, with vigorous-intensity and bone-strengthening activities incorporated at least three times per week. Furthermore, the guidelines advise limiting sedentary behaviour, specially restricting recreational screen time to no more than two hours daily, while ensuring a consistent sleep duration of 9 to 11 hours per night (Activity & Team, 2020). However, in research focusing on 24-h movement behaviour, international integrated frameworks are commonly adopted. In particular, the Canadian 24-h Movement Guidelines for Children and Youth (Tremblay et al., 2016) are the most frequently used globally, including in Portugal, as they integrate PA, SB and sleep (Hossian et al., 2025). A recent 2025 systematic review revealed the vast majority of research on 24-h movement behaviours is descriptive in nature, with 95% of studies investigating guideline compliance, whereas a mere 2% utilized an experimental design (Hossian et al., 2025). These findings underscore the imperative to invest in experimental research and to evolve from a reductionist 'compliance versus non-compliance' dichotomy toward a methodology focused on the characterization of integrated 24-h movement behaviour profiles.

The assessment of 24-h movement behaviours can be conducted using either subjective self-reported instruments or objective device-based methods (Rodrigues et al., 2025; Suc et al., 2024). While self-reported tools, such as questionnaires and time-used diaries, are often preferred in large-scale studies for their feasibility and low cost, they face significant limitations, including low-to-moderate validity and systematic errors, which may limit the accuracy of movement behaviour estimates, particularly at the individual level (Suc et al., 2024). Conversely, accelerometery provides a more precise alternative, allowing for the continuous and objective monitoring of movement intensity and duration throughout the entire 24-h cycle in free-living conditions (Rodrigues et al., 2025). To ensure the robustness of accelerometer-derived data, researchers must consider critical methodological parameters, such as device placement (e.g., wrist or hip), sampling frequency (Hertz), and the selection of epoch lengths – the time intervals used to aggregate raw acceleration data (Rodrigues et al., 2025). Furthermore, the adoption of standardized protocols and specific processing decisions, including non-wear time criteria, choice of cut-points, and application of valid sleep algorithms is essential to accurately capture the movement continuum and facilitate the analysis and comparison of results across different populations (Rodrigues et al., 2025).

2.1.3 Cardiorespiratory fitness

Cardiorespiratory fitness (CRF) is defined as the integrated capacity of the circulatory and respiratory systems to supply oxygen to skeletal muscle mitochondria for energy production (Raghuveer et al., 2020). Beyond its physiological basis, CRF is recognized as a powerful and independent marker of physical health, and is consistently associated with mental health, cognitive function, and academic achievement in youth (Raghuveer et al., 2020). High levels of CRF are strongly associated with a more favourable cardiovascular (CV) risk profile, whereas low CRF in childhood and adolescence has been shown to track into adulthood and is associated with an increased risk of future CV disease and all-cause mortality. (Raghuveer et al., 2020).

Hill and Lupton (1923) originally described CRF over 100 years ago as the maximal amount of oxygen (VO_2max) that can be consumed during strenuous exercise. Decades later, Shephard et al. (1968) demonstrated the physiological validity of VO_2max as a measure of aerobic capacity, classifying it as an international reference standard for quantifying CRF. In the contemporary scientific literature, VO_2max remains the established gold standard for quantifying CRF in both clinical and research settings (Harber et al., 2024). Despite the emergence of new technologies, the measurement of VO_2max through cardiopulmonary exercise testing (CPET) continues to be the criterion measure due to its unparalleled ability to integrate the limits of the pulmonary, CV and muscular systems (Harber et al., 2024). Furthermore, Harber et al. (2024) reaffirm VO_2max relevance as a clinical vital sign, essential for risk stratification and the prediction of chronic disease outcomes.

CRF can be measured both directly and indirectly. Direct assessment of CRF is obtained through ventilatory gas analysis during a graded exercise test at maximal exertion (CPET), providing a precise measure of VO_2max (Migliano et al., 2019). Indirect methods estimate VO_2max using maximal or submaximal exercise tests or non-exercise algorithms derived from performance outcomes, physiological variables, or self-reported characteristics (Migliano et al., 2019). The 20-m shuttle run is the most used filed test to estimate VO_2max in school settings (Migliano et al., 2019). Based on the prototype of Léger et al. (1984) it is a valid, feasible and reliable tool to assess CRF, showing moderate to high criterion validity when compared to direct assessments in children (Migliano et al., 2019; Tomkinson et al., 2019).

2.1.4 Saliva collection (TOS/TAS)

Human saliva is an exocrine secretion of the salivary glands, composed mainly of water (99%), but also containing electrolytes, proteins, lipids, and enzymes (Dongiovanni et al., 2023). Recent studies described human saliva as a valuable diagnostic tool to detect CV disease, local and systemic inflammation and metabolic disorders (Dongiovanni et al., 2023).

The assessment of salivary biomarkers is marked by considerable methodological heterogeneity, encompassing differences in collection procedures, pre-analytical handling, analytical assays, and technological platforms, all of which may influence biomarker concentrations and limit cross-study comparability (Dongiovanni et al., 2023). A recent systematic review found 22 different methods for saliva collection, with passive drooling, Salivette®, and spitting being the most widely used (Mortazavi et al., 2024). Moreover, the authors identified different types of saliva, with whole mouth saliva (WMS) being the most common type (Mortazavi et al., 2024). WMS is commonly collected during morning time, as it allows for a more equal contribution of different salivary glands (parotid, submandibular and sublingual glands), though ideal sampling periods may vary according to which components are needed (e.g., optimal detection of oral cancer metabolites has been suggested approximately between 14:00 and 20:00) (Mortazavi et al., 2024; Porcheri & Mitsiadis, 2019). While there is still no reference method for transportation and storage of salivary samples, centrifuging samples and storing them at -70°C to -80°C (T2) is the most utilized method, though analysing samples immediately after collection without centrifuging or storage seems to lead to more DNA quantity and quality (Mortazavi et al., 2024).

Oxidative stress (OS) is characterized by homeostatic disruption in which the generation of reactive oxygen species (ROS) overwhelms the available antioxidant defences (M. Chen et al., 2019). Due to the short half-life and high reactivity of ROS, oxidative stress is commonly assessed indirectly through oxidative damage byproducts and antioxidant-related parameters, as illustrated in experimental models of oxidative stress (M. Chen et al., 2019; Y. Chen et al., 2019). Since the measurement of oxidant molecules individually is not practical, the total oxidant status (TOS) can be used, as oxidant effects are known to be additive (Erel, 2005). TOS can be assessed through the colorimetric method developed by Erel (2005), which is based on the oxidation of the ferrous ion-o-dianisidine complex to ferric ions by oxidant molecules present in the sample (Kurt et al., 2021). The total antioxidant status (TAS) can also be assessed through a calorimetric assay, which is based in the ability of antioxidants in the sample to inhibit the oxidation of a substrate to its radical form with the resulting suppression of absorbance being proportional to antioxidant concentration (Rani & Mythili, 2014).

In this dissertation, we utilized the E-BC-K802-M kit for the assessment of TOS, which is based on the colorimetric method developed by Erel (2005), and the E-BC-K801-M kit for the determination of TAS. While the TAS assay is also based on a method originally developed and validated by Erel (2004), it employs different reagents and calibration standards according to the manufacturer’s protocol (Elabscience, USA).

2.2 State of the Art

2.2.1 Association between APE and 24-h movement behaviours

Although the benefits of PA are well established (Fuertes et al., 2018; Kunutsor et al., 2022; Nayor & Vasan, 2015; Soto-Rodríguez et al., 2024), its interaction with APE is not. Some studies suggest exercising in highly polluted environments may lead to adverse cardiovascular outcomes (Kim et al., 2021), whereas others report inverse associations between PA and cardiovascular-related mortality, independent of pollution levels (Andersen et al., 2015). A recent systematic review indicated that oxidative stress and inflammation induced by air pollutants may attenuate or even reverse the beneficial effects of PA (Gonzalez-Rojas et al., 2025). However, the authors emphasized the need for studies in specific populations, as most existing evidence focuses on young adults, and noted considerable heterogeneity in exposure assessment methods, underscoring the importance of further research.

A 2024 systematic review reported that evidence on the associations between APE and 24-hour movement behaviours in children remains limited for PA and sedentary behaviour. The only cited study regarding these variables (Yu & Zhang, 2023) was conducted in Chinese children aged 4 to 6 years and reported a negative association between APE and PA levels, as well as a positive association between APE sedentary behaviour. Evidence for sleep remains inconsistent, with studies reporting heterogeneous and often non-significant associations across different APE (Maddren et al., 2024). These inconsistencies motivate further research, specifically, to determine whether the deleterious effects of APE are due to the pollutants themselves or mediated, at least in some part, by children's suboptimal 24-h movement behaviour profiles. Furthermore, these uncertainties underscore the need for studies to move beyond binary guideline compliance and instead examine continuous dimensions of movement behaviours across the full 24-h spectrum. This shifts the binary approach for a full characterization of children's 24-h movement behaviour profiles. It also allows us to further understand whether more favourable profiles provide any degree of resilience against exposure to ambient air pollutants, a mechanism that is yet to be investigated (Martins et al., 2025).

2.2.2 Association between APE and CRF

As synthesised in Table 3, studies regarding APE and CRF are lacking. Recent systematic reviews have evaluated cardiopulmonary health rather than specifically evaluating CRF (Gonzalez-Rojas et al., 2025; Madureira et al., 2019). While the assessed variables include FEV_1 and FVC measurements, none of the included studies have assessed VO_2max (Gonzalez-Rojas et al., 2025; Madureira et al., 2019). This is worth noting, as CRF is a known indicator of current and future health among school-aged children, independently of PA levels (Lang et al., 2018). A 2004 study assessing maximal oxygen consumption in children aged 8 to 12 years concluded that greater exposure to air pollutants appears to be negatively associated with VO_2max (Ignatius et al., 2004). Furthermore, habitual physical exercise was not associated with improvements in VO_2max among children exposed to high levels of pollutants, while a positive association was observed among those with lower exposure (Ignatius et al., 2004). In contrast, another study involving children aged 7 to 12 found no significant differences in CRF between those exposed to higher versus lower concentrations of air pollutants (Ramirez et al., 2012). These contrasting results in conjunction with the lack of other studies evaluating the relationship between APE and CRF in children lead to a relevant gap in the literature.

2.2.3 Association between APE and Obesity

Obesity is the leading cause of preventable death worldwide, and mechanisms such as metabolic dysfunction via increased oxidative stress and adipose tissue inflammation may link it to APE (An et al., 2018). A recent systematic review reported a global positive association between APE and obesity risk in children and adolescents (Zheng et al., 2024). Interestingly, sub-analyses of specific population sources revealed that studies using predictive exposure models – capable of capturing more comprehensive data – reported higher risk estimates compared with those relying on stationary monitoring stations. These findings highlight the need for individualized APE assessments in future research (Zheng et al., 2024). Moreover, expanding research in age-specific populations is critical, as associations between APE and obesity risk are known to vary by age (i.e., children versus adults) (An et al., 2018).

2.2.4 Sociodemographic characteristics

Environmental and behavioural patterns are unlikely to occur in isolation and may be shaped by the child's sociodemographic context. Sociodemographic characteristics have been proposed as contextual factors that may influence daily activity patterns. However, empirical evidence regarding whether these proposed mechanisms translate into measurable differences in children's behaviours and health remains mixed and primarily focused on variables such as socioeconomical status (SES) (Gresham & Karatekin, 2025; Xing et al., 2025). Moreover, existing literature has primarily examined these sociodemographic variables as covariates or confounders, rather than explicitly exploring their potential interrelationships with environmental and behavioural domains (Gresham & Karatekin, 2025). As a result, the extent to which sociodemographic, environmental, and behavioural factors co-occur or cluster in ways that may influence health-related outcomes remains insufficiently understood.

Overall, the current body of evidence is limited by a predominant reliance on stationary pollution monitoring, incapable of capturing true cumulative personal APE, and by the scarcity of research integrating objective and continuous 24-hour movement behaviour profiles, rather than binary guideline compliance. Additionally, the modulation of these dynamics by upstream sociodemographic determinants remains underexplored. Crucially, it also remains unclear whether optimal behavioural profiles can confer resilience against deleterious effects triggered by pollutants. To address these gaps and overcome methodological limitations, the present study applies an Extended Structural Impact Modelling framework, which integrates both bivariate associations and the topological relevance of each variable within the broader network. This framework allows the simultaneous examination of direct and mediated pathways, offering a more integrated and mechanistic understanding of how sociodemographic, environmental and behavioural factors interact to influence child health – an advantage not captured by traditional analytical methods.

To facilitate the synthesis and critical appraisal of the existing evidence, Table 3 summarises the main characteristics and findings of studies related to the above-mentioned topics. Although not all studies included in the table are explicitly cited in the literature review, they were incorporated due to their relevance and contribution to a more comprehensive understanding of the current scientific landscape. Studies were organized according to themes: APE and combined health outcomes include 1 systematic review (Rackow et al., 2025), 5 narrative or non-systematic reviews (Fuller et al., 2022) (Thangavel et al., 2022) (Tainio et al., 2021) (Almetwally et al., 2020) (Ghorani-Azam et al., 2016), and 2 observational studies (Liu et al., 2025; Zundel et al., 2025). APE and inflammatory markers include 3 observational studies (Miller et al., 2024) (Gruzieva et al., 2017) (Klumper et al., 2015). APE and oxidative stress include 1 narrative review (Yoshida, 2024). APE and CRF include 2 systematic reviews (Gonzalez-Rojas et al., 2025) (Madureira et al., 2019) and 3 observational studies, with 1 prospective cohort (Tsai et al., 2025), and 2 cross-sectional studies (Ramirez et al., 2012) (Ignatius et al., 2004). APE and movement behaviours include 1 systematic review (Maddren et al., 2024), and 5 observational studies, with 2 cross-sectional (Yuan et al., 2024) (Lopez-Gil et al., 2022), 1 longitudinal (Yu & Zhang, 2023), and 2 cohort studies (Cai et al., 2023) (Yu et al., 2017). APE and obesity includes 2 systematic reviews (Zheng et al., 2024) (An et al., 2018). Individual APE variability include 1 narrative/conceptual review (Larkin & Hystad, 2017), and an observational personal monitoring panel study (Turner et al., 2024). Inside each group studies are presented in reverse chronological order, from most recent to the earliest publications.

Table 3 - Summary of the main characteristics, key findings and limitations of studies regarding air pollution exposure, inflammatory markers, oxidative stress, cardiorespiratory fitness, 24-hour movement behaviours, and obesity.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
(Rackow et al., 2025) APE and combined health outcomes	The interaction between air pollution, weather conditions, and health risks: a systematic review	Systematic review (PRISMA/PROSPERO).	APE and combined health outcomes	n = 62 studies (2010–2024) including time-series (n=31), case-crossover (n=16), cohort (n=10), and ecological designs. General populations in High-Income Countries (HICs) restricted to Europe and North America (USA, Canada, Mexico). Includes subgroups: children (<18 years), elderly (>65 years), and sex-stratified analyses.	**APE:** Heterogeneous methods: fixed-site monitoring stations, dispersion models, LUR, and satellite-derived data. Predominance of broad area averaging for exposure estimation. **Other variables:** Administrative health records (ICD codes) for all-cause and cause-specific mortality, hospitalizations, and emergency department visits. Lifestyle variables (PA, BMI, sleep quality) were notably absent or unadjusted.	**Synergistic Effects:** Strong evidence that $PM_{2.5}$, PM_{10}, and O_3 interact with high temperatures to amplify all-cause mortality. **Cardiovascular/Respiratory:** Interaction between PM_{10}/high temperatures exacerbates cardiovascular risks; $PM_{2.5}$/high temperatures increase respiratory hospitalizations. Mixed evidence regarding temperature interactions with $PM_{2.5}$ on asthma/respiratory symptoms. **Mental Health:** Emerging evidence of NO_2 and O_3 synergy with extreme heat for mental health disorders and suicide.	High methodological heterogeneity preventing meta-analysis; geographic restriction (Europe/North America); exposure misclassification due to broad-area averaging (lack of individual APE assessments); risk of bias from uncontrolled individual confounders (PA, BMI, smoking); insufficient data on non-temperature meteorological variables (humidity, wind, precipitation).
(Zundel et al., 2025) APE and combined health outcomes	Outdoor air pollution and psychiatric symptoms in adolescents: a study of peripheral inflammatory marker associations	Exploratory, observational, cross-sectional analysis.	APE and combined health outcomes	n=78 adolescents (10 – 17 years; 48.7% female) from the Detroit metropolitan area, USA. Community-based recruitment.	**APE:** Modeled residential $PM_{2.5}$ using a generalized random forest model (past-month average). No personal monitoring/wearable sensors were utilized. **Other**	$PM_{2.5}$ exposure was positively associated with increased lipid mediators. $PM_{2.5}$ associated with increased IL-6 and higher anxiety scores (total, GAD, and Social AD) exclusively in females; males showed an inverse IL-6 relationship. IL-8	Cross-sectional design (single timepoint) prevents temporal/dynamic assessment; modeled residential exposure ignores daily mobility and micro-environments (lack of personal APE data); psychiatric outcomes based on self-reports

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
					variables: Biochemical: Plasma lipid mediators (COX and LOX pathways via LC-MS/MS); Proinflammatory cytokines (IL-6, IL-8, TNF-α) and CRP (U-PLEX assay). Psychiatric: Self-reported anxiety (SCARED) and depressive symptoms (CDI-SF). Covariates: BMI, age, sex, Area Deprivation Index (ADI), and parental smoking.	associated with higher depressive symptoms; TNF-α associated with anxiety symptoms in females only. No direct association between $PM_{2.5}$ and CRP or TNF-α.	rather than clinical diagnoses; limited geographic generalizability.
(Liu et al., 2025) APE and combined health outcomes	Air pollution and hypertension in rural versus urban children: Lipidomic insights into $PM_{2.5}$ impacts	Prospective cohort study (Chongqing Children's Health Cohort) with a nested case-control analysis for lipidomic assessment.	APE and combined health outcomes	n = 4,433 children (n_{urban} = 2,239; n_{rural} = 2,194), aged 6–17 years, from Chongqing, Guizhou, and Sichuan, China. School-based recruitment.	**APE:** Residential $PM_{2.5}$ estimated via satellite-derived data and machine learning (1 km resolution); cumulative monthly and annual averages (2000–2023). **Other variables:** Hemodynamic variables: SBP, DBP, and MAP (electronic sphygmomanometer); paediatric hypertension diagnosis (>95th	**Lipid Profile:** Cumulative $PM_{2.5}$ exposure associated with decreased HDL-C and increased non-HDL-C. Lipid markers partially mediated the $PM_{2.5}$ -hypertension relationship. **Metabolic Pathways:** Urban children showed mediation via LacCer, SM, and PC species. Rural children showed mediation via phosphatidylethanolamines (PE). **Area-Specific Effects:** Distinct lipidomic patterns suggest mechanisms dependent on	Findings restricted to paediatric populations; lack of multi-omic integration (transcriptomics/proteomics); reliance on modeled residential exposure (no personal monitoring); potential for misclassification due to 1 km spatial resolution.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
					percentile). Biochemical: Conventional lipid profile (TC, HDL-C, non-HDL-C); High-resolution lipidomics (LC-MS/MS). Covariates: BMI, waist circumference, pubertal status, second-hand smoke, and dietary patterns.	$PM_{2.5}$ sources (urban traffic/industrial vs. rural biomass/dust).	
(Fuller et al., 2022) APE and combined health outcomes	Pollution and health: a progress update	Global progress update and narrative review utilizing Global Burden of Disease (GBD 2019) data and literature synthesis.	APE and combined health outcomes	Global scope with specific focus on vulnerable groups: children (lead exposure and IQ impacts), pregnant women, and occupational workers. Analysis of trends across LMICs and high-income regions.	**APE:** Population-level estimates derived from predictive models. Analysis includes ambient $PM_{2.5}$, household air pollution, lead, and chemical pollutants. PM data were log transformed for analysis.	Pollution accounts for over 9 million annual deaths, with air pollution (ambient and household) responsible for approximately 6.7 million. Since 2000, deaths from "modern" pollution (ambient $PM_{2.5}$, lead, and chemicals) have increased, while "traditional" pollution deaths (water, biomass) have declined. Lead exposure contributes to 0.9 million deaths and significant paediatric IQ loss. Findings highlight substantial pollution-related economic losses as a percentage of GDP.	Significant underestimation of chemical burden due to toxicological data gaps; critical lack of ground-level monitoring stations in specific regions (e.g., Africa); lack of integration between individual-level exposure (sensors/biomarkers) and population-level health data; fragmented global policies and chronic underfunding.
(Thangavel et al., 2022)	Recent Insights into Particulate Matter (PM(2.5))-Mediated	Narrative review with a systematized search strategy (PubMed and ScienceDirect, 2010–2022) and	APE and combined health outcomes	Heterogeneous synthesis of epidemiological cohorts (general and clinical populations)	**APE:** Predominantly aggregate data from ambient monitoring stations; limited evidence from individualized	**Systemic Impact:** Consistent evidence of $PM_{2.5}$ toxicity across respiratory, cardiovascular, reproductive, metabolic,	Geographical bias (focus on high-pollution regions); methodological heterogeneity (ambient vs. individual monitoring); presence of

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
APE and combined health outcomes	Toxicity in Humans: An Overview	defined inclusion/exclusion criteria.		and experimental models.	exposure monitoring. **Other variables:** Epidemiological: Mortality, hospital admissions, clinical diagnoses (asthma, COPD, MI), and lung function. Experimental: Biochemical markers (cytokines, ROS, gene expression), histological analysis, and high-throughput omics.	and central nervous systems. **Mechanisms:** Oxidative stress and chronic inflammation as primary drivers of local and systemic damage. **Clinical Highlights:** Increased asthma/COPD exacerbations; impaired lung development in children; associations with MI, hypertension, atherosclerosis, and reduced HRV; DNA damage and epigenetic alterations (carcinogenesis); increased susceptibility to viral infections (e.g., COVID-19).	intrinsic/extrinsic confounders; poor external validation of laboratory models; lack of multi-layer mechanistic studies (integrating epidemiology and omics); insufficient data on cumulative/combined pollutant effects. Lack of personal APE assessments. This article is not formally identified as a systematic review
(Tainio et al., 2021) APE and combined health outcomes	Air pollution, physical activity and health: A mapping review of the evidence.	Non-systematic mapping review of evidence (published up to 2019).	APE and combined health outcomes	Predominantly healthy adults in High-Income Countries (HICs) and China. Significant scarcity of data on vulnerable groups (children, elderly, pregnant women) and clinical populations. Focus primarily on active transport domains.	**APE:** Multi-level monitoring: fixed-site stations (ambient/AQI), residential modelling, and individual monitoring via portable/wearable sensors (NO_2, PM_{10}, $PM_{2.5}$, UFP, CO, and VOCs). **Physical Activity (PA):** Measured via self-report (MET-hours) and objective tools (accelerometry, pedometry, heart	**Behavioural:** High pollution levels reduce outdoor PA probability and shift choices toward motorized transport. **Dose:** Active commuters often face higher inhaled doses than motorized users due to increased minute ventilation, despite varying ambient concentrations. **Health Effects:** Chronic PA benefits generally outweigh pollution risks in low-to-moderate exposure settings. However, acute benefits (blood pressure,	Lack of systematic quality assessment; insufficient individual-level objective data (simultaneous monitoring of PA and exposure); limited research on non-transport domains (e.g., indoor exercise, gyms); lack of longitudinal data for sensitive sub-populations, such as children.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
					rate, and VO2max tests). **Inhaled Dose:** Estimated (in some studies) by combining pollutant concentrations with ventilation rates/respiratory deposition models.	lung function, HRV) may be attenuated by TRAP. Modelling suggests net positive outcomes for active travel except in extreme pollution scenarios.	
((Almetwally et al., 2020) APE and combined health outcomes	Ambient air pollution and its influence on human health and welfare: an overview	Comprehensive narrative review synthesizing evidence from over 170 published studies.	APE and combined health outcomes	Global synthesis covering diverse demographic groups (children, adolescents, and adults) across various geographical and occupational settings.	**APE:** Summary of methodologies: predominantly fixed-site ambient monitoring stations and spatial modelling (e.g., Land Use Regression - LUR). Limited evidence from high-resolution individual/portable sensors. **Other variables:** Multiple clinical and behavioural outcomes, including respiratory function (FEV_1/FVC), cardiovascular events, metabolic risk (T2D), neurological conditions (epilepsy), and behavioural factors (sleep, productivity, and well-being).	**Respiratory:** Strong associations of $PM_{2.5}$, NO_2, and SO_2 with asthma exacerbations, hospitalizations, and lung cancer mortality. **Cardiovascular:** Increased risk of events, mortality, and blood pressure changes with APE. **Metabolic/Neurological:** Emerging links to Type 2 Diabetes and epilepsy-related admissions. **Social/Behavioural:** Consistent evidence that $PM_{2.5}$, and NO_2 reduce sleep quality, cognitive performance, and general well-being/happiness.	Predominance of ecological/time-series designs relying on aggregate data (fixed stations) rather than individual exposure; scarcity of studies directly linking air pollution to physical activity behaviour changes; incomplete understanding of biological mechanisms (oxidative stress/inflammation); heterogeneity in methodology across studies.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
(Ghorani-Azam et al., 2016) APE and combined health outcomes	Effects of air pollution on human health and practical measures for prevention in Iran	Descriptive narrative review.	APE and combined health outcomes	Synthesis of diverse populations across various study designs (cohort, cross-sectional, and experimental), including children, adults, and fetal development stages. This review focused only in studies from Iran.	**APE:** Predominantly aggregate data from fixed monitoring stations and biological markers (biomarkers) in occupational settings. Lack of individual-level monitoring (portable sensors). **Other variables:** Mortality and morbidity (Respiratory and Cardiovascular); Lung function; Birth weight; Systemic inflammation and oxidative stress markers; Neurodegenerative and dermatological/ocular indicators.	Significant association between PM exposure and increased respiratory/cardiovascular morbidity and mortality; chronic exposure linked to reduced lung function and adverse fetal development (low birth weight). Plausible mechanistic links via oxidative stress and systemic inflammation; increasing evidence for neuroinflammation and neurodegeneration. Significant economic/sanitary impacts; underscores the need for regulatory interventions (fuel standardization, public transport, and continuous monitoring).	Methodological nature of the review (non-systematic/non-meta-analytical); lack of formal quality assessment of included studies; lack of standardized pollutant measurement methods and outcome-specific data within the Iranian context. Absence of data outside the Iranian context, limiting generability.
(Miller et al., 2024) APE and inflammatory markers	Ambient $PM_{2.5}$ and specific sources increase inflammatory cytokine responses to stimulators and reduce sensitivity to inhibitors	Longitudinal observational study with two assessment points (baseline and 2-year follow-up).	APE and inflammatory markers	n = 272 children at baseline (13.9 ± 0.5 years; 63.6% female) from Chicago, USA. Longitudinal analysis included 253 participants. Multi-ethnic sample (39.0% White, 38.2% Black, 32.4% Hispanic/Latinx, 9.6% Asian/other).	**APE:** Annual $PM_{2.5}$ mass and 15 constituents estimated via machine learning (hyperlocal 50m and neighbourhood levels). Source apportionment identified 5 factors: motor vehicles, soil/crustal dust, industrial, metal/agriculture,	Cross-sectional: Higher $PM_{2.5}$ (notably motor vehicles and soil) associated with increased stimulated cytokine responses. Longitudinal: Higher $PM_{2.5}$ (notably motor vehicles and biomass) associated with reduced sensitivity to anti-inflammatory inhibitors over 2 years. No robust associations found for circulating biomarkers.	Observational design (no causality); exposure misclassification (residential-only modelling); imprecise $PM_{2.5}$ mass estimation; high interdependence between stimulation/inhibition composites; localized healthy sample with low circulating biomarker variability.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
					and biomass combustion. **Outcome measures:** Ex-vivo cytokine responsiveness (stimulation and inhibition composites) via Whole Blood Assays (WBA). Fasting circulating inflammatory biomarkers. Morning blood collection (08:00–10:00).		
(Gruzieva et al., 2017) APE and inflammatory markers	Exposure to Traffic-Related Air Pollution and Serum Inflammatory Cytokines in Children	Prospective birth cohort study (BAMSE). Cross-sectional analysis of biomarkers (age 8) and gene expression (age 16) using linear regression models.	APE and inflammatory markers	n = 670 children (8.3 ± 0.5 years; 45.2% female) from Stockholm County. Sub-sample (n=238) at age 16. Sample enriched for physician-diagnosed asthma (n=237) to assess effect modification.	**APE:** Time-weighted NO_2 and PM_{10} concentrations (Airviro dispersion modelling) at residential, daycare, and school addresses. Assessment periods: early-life (1st year of life) and current exposure (12 months prior to age 8). **Outcome measures:** 10 serum cytokines (IFN-γ, IL-1β, IL-2, IL-4, IL-6, IL-8, IL-10, IL-12p70, IL-13, TNF-α) via electro-chemiluminescence (MSD). Genotyping (IL6 SNPs) via	Early-life NO_2 exposure associated with a 13.6% increase (95% CI: 0.8–28.1) in IL-6 at age 8 per 10 μg/m³ increment. In children with asthma, early-life NO_2 associated with a 27.8% increase (95% CI: 4.6–56.2) in IL-10. Strongest associations observed for early-life window.	High collinearity between NO_2 and PM_{10}; potential APE misclassification (outdoor modelling vs. personal intake); limited inflammatory biomarker panel.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
					Illumina Human610-Quad BeadChip.		
(Klumper et al., 2015) APE and inflammatory markers	Air pollution and cytokine responsiveness in asthmatic and non-asthmatic children	Nested epidemiological study within the GINIplus and LISAplus birth cohorts. Observational analysis using a random sub-sample enriched with asthmatic cases.	APE and inflammatory markers	n = 86 children (6 years old; 33.3% female in asthmatic and 39.0% female in non-asthmatic groups) from Wesel, Germany. Sub-samples include 27 physician-confirmed asthmatic cases and 59 non-asthmatic controls.	**APE:** Long-term residential exposure to traffic-related air pollution (TRAP) (NO_2, NOx, PM_{10}, and $PM_{2.5}$) estimated via Land-Use Regression (LUR) models developed by the ESCAPE project. **Outcome measures:** Cytokine responsiveness (IL-6, IL-8, IL-10, IL-12p70, MCP-1, TNF-α, IFN-γ) via ex-vivo Whole Blood Assays (WBA) stimulated with urban dust (EHC-93), measured by flow cytometry. Responsiveness defined as the ratio of stimulated to spontaneous concentrations.	Significant effect modification by asthma status. In asthmatic children, TRAP exposure (especially NO_2 and NOx) was associated with increased IL-6, IL-8, and TNF-α responsiveness. No significant associations were observed in non-asthmatic children or the total sample.	Use of a non-local, high-dose stimulus (EHC-93) for WBA; temporal gap between exposure modelling (2008–2009) and blood sampling (2002–2005); potential APE misclassification (lack of personal intake).
(Yoshida, 2024)	Oxidative Stress Induced by Air Pollution	Narrative literature review (non-systematic).	APE and oxidative stress	Not specified (encompasses general urban populations, occupational groups,	**APE:** Multiple sources - due to different study methodologies - including TRAP,	Consistent links PM and TRAP to oxidative stress and systemic inflammation. Nanomaterials increase	Mass-based regulations fail to capture regional toxicity; mechanistic gaps in systemic PM effects; limited translation from

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
APE and oxidative stress				and experimental in vitro/in vivo models).	indoor $PM_{2.5}$, road-deposited dust, and occupational nanomaterials (urinary Si and Ti concentrations). **Outcome measures:** Oxidative stress biomarkers (e.g., 8-OHdG, ROS), inflammatory markers, metabolomic/plasma profiles, and clinical outcomes (e.g., low birth weight, mitochondrial stress).	oxidative biomarkers. PM toxicity varies by regional composition, independent of mass concentration. High BMI/obesity exacerbates susceptibility and impairs compensatory responses. Algae-derived compounds show potential protective effects against PM-induced damage.	experimental models to humans; lack of integrated individual-level exposure monitoring.
(Gonzalez-Rojas et al., 2025) APE and CRF	Air Pollution and Endurance Exercise: A Systematic Review of the Potential Effects on Cardiopulmonary Health	Systematic review (PRISMA) of 24 articles (up to August 2024).	APE and CRF	Aggregated sample of 559 participants (18–65 years). Gender distribution: 45% male, 20% female, and 35% not specified. Small sample sizes per study (n = 7 to 53).	**APE:** Heterogeneous assessment including real-world urban routing (direct/personal monitoring of NO_2, NOx, PM_{10}, $PM_{2.5}$) and controlled chamber exposures (e.g., Diesel Exhaust - DE). $PM_{2.5}$ (42%)and PM_{10} (27%) were the most frequent pollutants. **Outcome measures:** Cardiopulmonary health markers: lung function (FEV_1, FVC, PEF), inflammatory/oxidati	Endurance exercise in high-pollution environments may impair cardiopulmonary health, evidenced by increased inflammation and oxidative stress, reduced lung function, and altered hemodynamics. Findings are inconsistent across studies, with some reporting significant declines in FEV_1 and FMD, while others found no acute effects.	High methodological heterogeneity (exercise intensity/duration, exposure levels); predominance of small sample sizes; lack of longitudinal evidence; under-representation of vulnerable populations; inconsistent control of climatic factors; unknown chronic adaptation mechanisms; lack of CRF assessments.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
					ve stress biomarkers (IL-6, VEGF), and hemodynamic/vascular variables (SBP, DBP, HRV, FMD).		
(Tsai et al., 2025) APE and CRF	Long-term $PM_{2.5}$ exposure impairs lung growth and increases airway inflammation in Taiwanese school children	Community-based prospective cohort study (CARE study) with a 2-year follow-up (2016–2018).	APE and CRF	n = 5,364 children from Changhua County, Taiwan. Baseline age: 9.7 years; Follow-up age: 11.4 years (IQR: 7.8–13.8). Gender distribution: 47.7% female.	**APE:** Individual-level $PM_{2.5}$ exposure estimated via Land-Use Regression (LUR) and GTx models, integrated with school and home addresses (8h school / 16h home). **Outcome measures:** Lung function (FEV_1, FVC, FEF_{25-75}) via spirometry. Airway inflammation via Fractional Exhaled Nitric Oxide (FeNO). Respiratory symptoms and asthma diagnosis via validated ISAAC questionnaires.	Long-term $PM_{2.5}$ exposure was significantly associated with impaired lung growth and increased airway inflammation. Impact was higher in children with new-onset wheezing.	Potential exposure misclassification (modeled vs. personal monitoring); lack of bronchodilator reversibility testing; geographical specificity limiting generalizability; lack of CRF assessments.
(Madureira et al., 2019) APE and CRF	Cardio-respiratory health effects of exposure to traffic-related air pollutants while exercising	Systematic review (PRISMA) of 13 human studies (2000–2018).	APE and CRF	Heterogeneous samples across 13 studies, including healthy adults (18–60 years), susceptible groups (asthma, COPD), and elderly with coronary artery disease.	**APE:** Comparison of high-traffic vs. low-traffic environments (e.g., urban streets vs. parks). Exposure characterized via fixed-site stations or personal PM monitors. High-	Significant FEV_1 and FVC declines post-exercise in high-traffic areas for susceptible populations (asthma, COPD), but inconsistent results in healthy adults. TRAP exposure associated with increased sputum	Significant methodological heterogeneity (varying exercise intensity/duration); diverse populations limiting generalizability; potential environmental confounding (noise, meteorology); lack of

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
	outdoors: A systematic review				exposure sites typically 2–10× higher in $PM_{2.5}$ and NO_2. **Outcome measures:** Lung function (FEV_1, FVC, $FEF_{25–75}$) measured pre- and post-exercise. Airway inflammation biomarkers (FeNO, sputum neutrophils, myeloperoxidase, IL-8).	inflammatory markers (neutrophils, IL-8, MPO). $PM_{2.5}$ and ultrafine particles showed more severe respiratory impacts than coarse particles or NO_2.	personal APE assessments; lack of CRF assessments
(Ramirez et al., 2012) APE and CRF	Should they play outside? Cardiorespiratory fitness and air pollution among schoolchildren in Bogota	Cross-sectional observational study.	APE and CRF	n = 1,045 children (9.8 ± 1.5 years; 48.8% female) from 4 public schools in Bogotá, Colombia (altitude 2,640 m). Schools categorized by traffic proximity: 3 High-Pollution (HP) and 1 Slightly Polluted (SP).	**APE:** School-level PM_{10} monitoring (gravimetric sampling) for 4 weeks (07:00–15:00). **Outcome measures:** CRF (VO2max) estimated via 20m shuttle run test (Leger). Lung function (spirometry) in a sub-sample (n=434). Habitual PA (3DPAR questionnaire) and BMI.	No significant difference in VO2max between HP and SP schools after adjustment. Overweight/obese children showed significantly lower VO2max. In the sub-sample, girls with FEV_1/FVC < 80 exhibited slightly lower VO2max.	Cross-sectional design; ecological exposure assessment (school-level, short-term) without personal monitoring; unequal response rates between districts (SP 64.3% vs. HP 95.4%); exclusion of other pollutants (e.g., $PM_{2.5}$, NO_2).
(Ignatius et al., 2004) APE and CRF	Impact of air pollution on cardiopulmonary fitness in schoolchildren	Cross-sectional observational study comparing two school populations in districts with distinct pollution levels.	APE and CRF	n = 821 children (8–12 years) from Hong Kong. Low-pollution district (LPD): n=555, 9.19 ± 0.88 years, 51.4% female. High-pollution district	**APE:** Annual mean concentrations of SO_2, NO_2, and PM_{10} from fixed-site monitoring stations (12 months prior). Ecological/area-level	HPD children had significantly lower adjusted VO2max compared to LPD. PA was associated with higher VO2max in the LPD, but this benefit was attenuated	Cross-sectional design (no causality); ecological exposure assessment (no personal monitoring); lack of local MFT validation; potential selection bias

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
				(HPD): n=266, 9.92 ± 0.82 years, 49.3% female.	exposure assignment based on school and residential district. **Outcome measures:** CRF (VO2max) estimated via 20m Multistage Fitness Test (MFT). Lung function (FEV_1, FVC) via spirometry. Habitual physical activity (PA) and respiratory history via parental questionnaires.	and non-significant in the HPD.	(participants had better lung function/PA levels).
(Maddren et al., 2024) APE and Movement behaviours	Associations Between Postnatal Pollution Exposures, 24-h Movement Behaviours, and Motor Development Outcomes Among Children (0–12 Years Old): A Systematic Review.	Systematic review (PROSPERO protocol) of 18 studies (narrative synthesis; meta-analysis not performed due to high heterogeneity).	APE and Movement behaviours	Aggregated sample of 167,309 children (0–12 years; study sizes n = 144 to 115,023). Predominantly from high-income countries (n=13 studies). Both sexes included (gender-stratified effects reported in specific subgroups).	**APE:** Area-based estimation via GIS, LUR, satellite modelling, and fixed monitoring stations. Biological markers (blood, hair, nails) for heavy metals. Parental reports for indoor pollutants and noise. Research-grade personal sensors were rarely utilized. **Outcome measures:** Motor development (e.g., ASQ-3, BSID-III, Denver II). 24-h movement behaviours: sleep (CSHQ, actigraphy) and physical activity/sedentary	Evidence is limited and inconsistent. 12 studies reported associations between pollution and motor delays; 5 studies linked exposure to sleep disturbances. A key study (Yu & Zhang) found that an increase in $PM_{2.5}$ was associated with reduced MVPA and increased SB. Mixed results for sleep, with noise and PM associated with poorer outcomes in specific sub-populations.	Significant methodological heterogeneity in exposure and outcome tools (7 different motor scales); lack of data from low-income countries; scarcity of evidence regarding 24-h movement behaviours; lack of individual-level exposure monitoring; insufficient adjustment for meteorological confounders.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
					behaviour (accelerometery).		
(Yuan et al., 2024) APE and Movement behaviours	Sufficient sleep and physical activity can relieve the effects of long-term exposure to particulate matter on depressive symptoms among 0.31 million children and adolescents from 103 counties in China	School-based cross-sectional observational study (surveillance data from 2019–2022).	APE and Movement behaviours	n = 312,390 children and adolescents (10–25 years; mean age 15.36 years) from 103 counties in China. Gender distribution: 51.1% female.	**APE:** Long-term (3-year mean) exposure to PM_1, $PM_{2.5}$, and PM_{10} estimated via the China High Air Pollutants (CHAP) dataset. Exposure attributed via school-level geocoding. Models adjusted for meteorological factors (temperature, humidity, wind, and precipitation). **Outcome measures:** Depressive symptoms (CES-D). Self-reported sleep duration (weighted average) and physical activity (IPAQ-SF). Guideline compliance based on age-specific Chinese guidelines.	Significant positive association between long-term PM exposure and depressive symptoms. Sufficient sleep, MVPA, and outdoor activity significantly mitigated these associations (lower ORs). Females and participants aged 10–18 years showed higher susceptibility. A dose-response relationship was observed even at levels below international air quality standards.	Cross-sectional design precludes causal inference; exposure misclassification due to school-level geocoding (lack of residential/individual monitoring); recall/measurement bias from self-reported data; lack of data on household pollution and academic pressure.
(Yu & Zhang, 2023)	Impact of ambient air pollution on physical activity and sedentary	Longitudinal observational study using individual fixed-effects panel regression analysis.	APE and Movement behaviours	n = 206 children (4.55 ± 1.03 years) from Hebei Province, China. Gender distribution: 52.4% female.	**APE:** Daily 24h concentrations of AQI,PM_{10}, and $PM_{2.5}$, obtained from the nearest municipal	Increased pollution levels were significantly associated with reduced PA and increased SB, with a dose-response relationship. For every 10-	No distinction between indoor/outdoor activity; ecological exposure assessment (station-based); lack of lag-effect analysis; convenience

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
APE and Movement behaviours	behaviour in children				monitoring station to the school site. **Outcome measures:** Movement behaviours via triaxial accelerometery (ActiGraph wGT3X-BT; 8 consecutive days). MVPA, light PA, step count, and Sedentary Behaviour (SB) were included as variables. BMI as a covariate.	unit increase in AQI: MVPA -5.94 min/day and SB +15.7 min/day. Girls showed more pronounced declines in MVPA and steps.	sampling; exclusion of parental socioeconomic status.
(Cai et al., 2023) APE and Movement behaviours	Early-Life Exposure to $PM_{2.5}$ and Sleep Disturbances in Preschoolers from 551 Cities of China	Cohort study (cross-sectional analysis of the Chinese National Cohort of Motor Development - CNCMD).	APE and Movement behaviours	n = 115,023 children (4.5 ± 0.9 years) recruited from 551 cities in China. Gender: 47.0% female.	**APE:** Individual $PM_{2.5}$ exposure estimated via satellite-based geospatial model (1Km X 1Km resolution). Assessment windows: Pre-natal (gestational trimesters) and post-natal (0–18, 18–36, and 0–36 months). **Outcome measures:** Sleep quality assessed via the Children's Sleep Habits Questionnaire (CSHQ). Sleep disturbance defined as total score > 41. Specific sub-scales: Sleep-disordered	Both pre- and post-natal $PM_{2.5}$ were associated with higher CSHQ scores (worse sleep quality). Post-natal exposure (0–36 months) showed a stronger effect (+0.46 per IQR) compared to pre-natal exposure (+0.22 per IQR). Significant risk for sleep disturbance was found only for post-natal exposure (OR 1.10; 95% CI: 1.04–1.15), with 0–18 months identified as the critical window. SDB and daytime sleepiness were the most affected domains.	Potential recall/reporting bias (parental questionnaire); lack of objective sleep measures (accelerometer); absence of indoor pollution, second-hand smoke, noise, or nocturnal light data; potential residual confounding. Lack of personal APE assessments.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
					breathing (SDB) and daytime sleepiness.		
(Lopez-Gil et al., 2022) APE and Movement behaviours	Association between air pollution and 24-h movement behaviours in a representative sample of Spanish youth	Cross-sectional analysis of secondary data from the Spanish National Health Survey (ENSE 2017).	APE and Movement behaviours	n=4,398 children and adolescents (2–14 years) from a representative national sample in Spain. Gender distribution: 49.2% female.	**APE:** Regional mean $PM_{2.5}$ concentrations based on official governmental reports, categorized into tertiles (low, medium, and high pollution levels). **Outcome measures:** Adherence to 24-h movement guidelines (PA, screen time, and sleep duration) via parental-reported questionnaires. BMI z-scores calculated from proxy-reported weight and height.	Significant inverse association between $PM_{2.5}$ levels and adherence to the triple 24-h guidelines. Prevalence of meeting all three recommendations was lower in high-pollution tertiles (7.6%) compared to low-pollution tertiles (14.%; $p < 0.001$). No significant association was found for sleep duration alone. Higher $PM_{2.5}$ tertiles were associated with a higher prevalence of overweight/obesity.	Cross-sectional design precludes causal inference; potential recall and social desirability bias from parental reports; ecological exposure assessment (regional averages), lack of personal APE assessments; lack of adjustment for urban-level confounders (e.g., green spaces, traffic density).
(Yu et al., 2017) APE and Movement behaviours	The association between ambient fine particulate air pollution and physical activity: a cohort study of university	Prospective longitudinal cohort study with repeated measures (4 waves).	APE and Movement behaviours	n=3,445 university freshmen (close to 11,000 longitudinal observations) from Beijing, China (Mean age: 18.18 ± 0.85 years). Gender distribution: 32.3% female.	**APE:** Weekly average ambient $PM_{2.5}$ concentrations (city-level) obtained from the U.S. Department of State monitoring program. Adjusted for meteorological factors (temperature,	Significant inverse association between $PM_{2.5}$ and PA. A 1 SD increase in $PM_{2.5}$ was associated with a reduction of 32.45 min/week in MVPA and -226.14 MET-min/week. Reductions were driven primarily by vigorous PA (-22.32 min/week).	Self-reported PA, lack of objetive measures; city-level aggregate exposure assessment, lack of personal exposure assessments; convenience sample from a single university; potential confounding by typical

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
	students living in Beijing				wind, and precipitation). **Outcome measures:** Physical activity levels via the IPAQ-short (vigorous, moderate, walking, MVPA, and MET-min/week). Covariates included self-reported BMI and physical/mental health status.	Walking showed no significant association. Impact on moderate PA was significant in males only.	freshman-year PA decline trends.
(Zheng et al., 2024) APE and Obesity	Association of air pollution exposure with overweight or obesity in children and adolescents: A systematic review and meta-analysis	Systematic review and meta-analysis (PRISMA/PROSPERO).	APE and Obesity	n = 17 studies. Participants stratified into children (<10 years) and adolescents (10–19 years). Global distribution: Asia (n=11), Europe (n=7), and Americas (n=9). Sample sizes ranging from ≈ 400 - 400,000. Some but not all studies stratified results by sex.	**APE:** Predictive modelling (LUR, machine learning, hybrid models (n=20) and fixed monitoring stations (n=7). Pollutants assessed were: PM_1, $PM_{2.5}$, PM_{10}, NO_x, O_3, SO_2, CO. No personal/wearable sensors utilized in the included studies. **Other variables:** Overweight/obesity risk (OR), defined by WHO or national standards. BMI increments (kg/m^2). Covariates: Physical Activity (PA), diet, socioeconomic status, and sleep duration.	**Risk Association:** Global positive association between pollutants and overweight/obesity. Risk per +10μ/m^3: PM_1 (OR 1.23), $PM_{2.5}$ (OR 1.18), PM_{10} (OR 1.11). **BMI:** Statistically significant BMI increments associated with PM_1, $PM_{2.5}$, PM_{10}, and NO_x. **Stratification:** Stronger effects observed in Asia, developing countries, and for long-term exposure (>1 year).	High heterogeneity across studies; exposure assessments (models/stations) do not capture individual pollutants exposure; limited evidence linking personal exposure to biomarkers; causal inference restricted by the inclusion of cross-sectional designs.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
(An et al., 2018) APE and Obesity	Impact of ambient air pollution on obesity: a systematic review	Systematic review of observational studies (longitudinal cohorts and cross-sectional designs) published until September 2017.	APE and Obesity	n = 16 studies. Paediatric (0–17 years) and adult (>18 years) populations across 7 countries (predominantly USA, n=9). Sample sizes ranging from 100 - 400,000 participants. Most studies included both genders. Gender distribution (when reported): 54% female.	**APE:** Spatially attributed air pollution levels based on regional monitoring stations or dispersion modelling. **Other variables:** Adiposity: BMI, obesity status, waist circumference, and body fat percentage. Behavioural/Functional: Physical Activity (PA) and Cardiorespiratory Fitness (CRF). Methods included objective anthropometry and self-reported data.	**General Synthesis:** Inconclusive evidence; 44% of reported effects showed a positive association between APE and weight, 44% were null, and 12% were negative. **Proposed Mechanisms:** 1) Systemic inflammation and oxidative stress in adipose tissue; 2) Mediation via chronic comorbidities (e.g., asthma, CVD); 3) Environmental barriers reducing PA and increasing sedentary behaviour, leading to a positive energy balance.	Significant methodological heterogeneity (precluding meta-analysis); risk of bias from self-reported anthropometrics; lack of power analyses; insufficient longitudinal follow-up to detect adiposity changes in 50% of studies; limited robust testing of biological or behavioural mediators. Lack of objectively measured CRF. Monitoring stations data for APE (lack of personal data).
(Turner et al., 2024) Individual APE variability	Variability in personal exposure to ultrafine and fine particles by microenvironment among adolescents in Cincinnati	Observational panel study with 7-day continuous personal monitoring.	Individual APE variability	n = 25 asthmatic adolescents and young adults (13–22 years; mean 18.1 ± 2.6). Cincinnati, USA. High socioeconomic status (SES) convenience sample.	**APE:** Direct Personal Monitoring: UFP (PNC via Partector 2; 10–300 nm) and $PM_{2.5}$ (MicroPEM; gravimetrically corrected mass). Microenvironments (MEs) were classified through a GPS-based algorithm - Home, School, Transit, Other, Unknown.	**High Variability:** Personal exposure varied significantly between and within subjects across MEs. "Transit" ME showed the highest UFP means and a disproportionate exposure-time ratio of 1.91 (only 3% of time). **Time Dominance:** "Home" was the primary ME (70% of time) with an exposure ratio of 1.0. **Pollutant Correlation:** Low-to-moderate correlation between UFP and $PM_{2.5}$ (≈	Potential sensor drift (lack of field intercomparison); activity patterns influenced by COVID-19 (increased time at home); GPS signal loss (20% unknown data); non-representative sample (high SES/Caucasian); inability to distinguish specific transit modes.

Authors/Year/ Theme	Title	Study Design	Main Theme	Study Population	Data Assessments	Maind findings	Limitations and Gaps
						0.47), reaching its minimum in "Transit" (≈ 0.24).	
(Larkin & Hystad, 2017) APE assessments variability	Towards Personal Exposures: How Technology Is Changing Air Pollution and Health Research	Narrative review and conceptual framework for personal exposure assessment, integrating the PURE-Air project as a case study.	APE assessments variability	Global scoping review of general APE assessments. Case study of the PURE-Air cohort: n = 225,000 adults (35–70 years) in 25 countries; personal monitoring sub-sample: n = 1,200 individuals.	**APE:** Personal Monitoring: Low-cost wearable sensors (e.g., UPAS, AirBeam) for $PM_{2.5}$ and NO_2. Mobility: Smartphone GPS for time-activity patterns. Modelling: Integration of "big data" (Satellite 1 X 1 km and LUR 100 m resolution) through machine-learning algorithms.	**Methodological Integration:** Synergetic use of wearables and big data improves long-term personal exposure prediction. **Variability:** High intra-community exposure variation identified via GPS-based mobility data. **Model Performance:** Global LUR models explained 54% of NO_2 variation across diverse settings.	Sensor calibration and accuracy issues; high complexity in multi-level data integration; ethical/privacy risks regarding high-resolution GPS; selection bias favouring high-SES populations with tech access.

Note: APE, air pollution exposure; TRAP, traffic-related air pollution; PM_1/$PM_{2.5}$/PM_{10}, particulate matter ≤ 1/2.5/10 µm; CRF, cardiorespiratory fitness; MVPA, moderate-to-vigorous physical activity; FeNO, fractional exhaled nitric oxide; HRV, heart rate variability; LUR, land-use regression; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses. Additional abbreviations are defined in the Abbreviations list.

3 **Methods**

This dissertation is based in a scientific article submitted for publication, in which the methodology is described in detail. Therefore, this section presents only a brief overview of the methodology described in the article.

This cross-sectional study was conducted in 2 Portuguese primary schools located in Valongo, a city around the periphery of Porto. Participants included typically developing children aged 8-11 years, whose legal guardians provided informed consent. Ethical approval was obtained in accordance with the Helsinki Declaration (World Medical Association, 2013).

Children's APE ($PM_{2.5}$, PM_{10} and carbon dioxide (CO_2)) was individually measured using portable monitoring devices over two weekdays, while 24-h movement behaviours (PA, SB, and sleep) were assessed via accelerometry over 5 weekdays. Health-related outcomes included TOS, TAS, CRF and body mass index (BMI). Sociodemographic variables (Sex, Dwelling Type , Household Size, Mode of Transport, and Allergies) were assessed via questionnaire.

Data were analysed using an Extended Structural Impact Model, complemented by regression analyses, to evaluate the direct and indirect pathways linking sociodemographic characteristics, APE, movement behaviours, and health-related outcomes. This dual approach allows for the identification of both structural influence and statistical predictability within the system.

This study aimed to investigate the structural pathways linking sociodemographic characteristics, APE, 24-hour movement behaviours, and health-related outcomes in children, using a complex system framework.

4 **Results**

The Results section is presented in article format, and follows the guidelines of the American Journal of Human Biology.

Structural pathways linking sociodemographic characteristics, air pollution exposure, 24-hour movement behaviours, and health-related outcomes in children**: An exploratory study using network science.**

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Conflict of interests statement

The Authors declare no conflict of interests

Abstract

Introduction: Air pollution exposure is a major global health concern, particularly for children, given their susceptibility to systemic inflammation and oxidative stress. While physical activity is known to benefit health, its interaction with APE and other co-dependant behaviours within a 24-hour continuum remains understudied. **Objective:** This study utilizes network science to investigate the structural pathways linking sociodemographic characteristics, individual air pollution exposure, 24-hour movement behaviours, and health-related outcomes in Portuguese primary school children. **Methods:** A pilot cross-sectional exploratory study was conducted with 14 children (aged 8-11) from Valongo, Portugal. Sociodemographic data and household characteristics were assessed via questionnaire. Individual APE ($PM_{2.5}$, PM_{10}, and CO_2) was measured using portable sensors over 48 hours, while movement behaviours were assessed via accelerometry over five weekdays. Health outcomes included cardiorespiratory fitness, body mass index, total oxidant status, and total antioxidant status. An extended structural impact model was employed for data analysis in Python (3.14). **Results:** Sociodemographic factors exerted the strongest impact on movement behaviours (normalized impact = 0.96). Movement behaviours emerged as a partial structural bottleneck, mediating the impact of environmental exposure on health outcomes (indirect impact = 0.66) more significantly than the direct environmental-health pathway (impact

= 0.43). **Conclusion:** 24-hour movement behaviours presented a mediating impact on the relationship between air pollutants and health-related outcomes in the evaluated children.

Keywords: Air pollution exposure; 24-hour movement behaviours, Network science, Cardiorespiratory fitness; Oxidative stress.

Introduction

Air pollution exposure (APE) constitutes a major global health challenge and is currently estimated to account for more than 9 million deaths worldwide each year (Fuller et al., 2022). A growing body of evidence indicates that exposure to air pollutants triggers systemic inflammation and oxidative stress (Miller et al., 2024; Yoshida, 2024), biological pathways that contribute to both localized pulmonary injury and widespread systemic dysfunction, including elevated cardiometabolic risk (Thangavel et al., 2022). Children represent a particularly vulnerable population to the harmful effects of APE, due to their ongoing immune system development and increased inhalation rate (Holgate, 2017). This enhances their susceptibility to pulmonary and systemic inflammation, increased oxidative stress (Gruzieva et al., 2017; Loxham et al., 2019), premature mortality and delayed cognitive development (Sunyer et al., 2015). A recent systematic also review reported a global positive association between APE and obesity risk in children and adolescents, with effect estimates varying according to the exposure assessment method (Zheng et al., 2024).

Physical activity (PA) is well recognized for its benefits on lung function, resistance to infection, cardiovascular health, and endothelial activity (Fuertes et al., 2018; Kunutsor et al., 2022; Nayor & Vasan, 2015; Soto-Rodríguez et al., 2024). Although the benefits of PA are well established, its interaction with APE is not. A recent systematic review indicated that oxidative stress and inflammation induced by air pollutants may attenuate or even reverse the beneficial effects of PA (Gonzalez-Rojas et al., 2025). However, the authors emphasized the need for studies in specific populations, as most existing evidence focuses on young adults, and noted considerable heterogeneity in exposure assessment methods, underscoring the importance of further research.

Beyond PA, the analysis of other co-dependant movement behaviours, namely sleep and sedentary behaviour (SB), within a 24-hour continuum, provides relevant insights into health and developmental outcomes (Chaput et al., 2014). A 2024 systematic review reported that evidence on the associations between APE and 24-hour movement behaviours in children remains limited for PA and SB – as only one study examined these outcomes - and inconsistent for sleep, with studies reporting heterogeneous and often non-significant associations across different APE (Maddren et al., 2024). These inconsistencies motivate further research to clarify whether the adverse effects of APE are attributable to pollutant exposure itself or are partly mediated by suboptimal 24-hour movement behaviour profiles in children, while highlighting the need to move beyond binary guideline compliance toward continuous assessments across the full 24-hour movement spectrum. This allows for a full characterization of children's 24-hour movement behaviour profiles, and for further understanding of whether more favourable profiles provide any degree of resilience against exposure to ambient air pollutants, a mechanism that is yet to be investigated (Martins et al., 2025).

APE has traditionally been assessed through stationary monitoring stations, which limit data collection, accessibility and individual specificity (Snyder et al., 2013). The absence of individualized exposure data has been described as a major limitation across multiple reviews examining diverse health-related outcomes (Almetwally et al., 2020; Maddren et al., 2024; Tainio et al., 2021; Zheng et al., 2024). This is a problem, as individual exposure assessments through portable monitoring sensors are considered the gold standard approach (Larkin & Hystad, 2017), and APE varies substantially between individuals and across different microenvironments (Turner et al., 2024; Varaden et al., 2021). Moreover, children are a population often underrepresented in studies with such methodological approach (Turner et al., 2024). Importantly, these environmental and behavioural patterns are unlikely to occur in isolation and may be shaped by the child's sociodemographic context. However, empirical evidence regarding whether sociodemographic context shapes children's behaviours and health remains mixed and primarily focused on variables such as socioeconomical status (SES) (Gresham & Karatekin, 2025; Xing et al., 2025). Moreover, existing literature has examined sociodemographic variables primarily as covariates or confounders, rather than explicitly exploring their potential interrelationships with environmental and behavioural domains

(Gresham & Karatekin, 2025). As a result, the extent to which sociodemographic, environmental, and behavioural factors co-occur or cluster in ways that may influence health-related outcomes remains insufficiently understood.

Overall, the current body of evidence is limited by a predominant reliance on stationary pollution monitoring, incapable of capturing true cumulative personal APE, and by the scarcity of research integrating objective and continuous 24-hour movement behaviour profiles, rather than binary guideline compliance. Additionally, the modulation of these dynamics by upstream sociodemographic determinants remains underexplored. Crucially, it also remains unclear whether optimal behavioural profiles can confer resilience against deleterious effects triggered by pollutants. To address these gaps and overcome methodological limitations, the present study applies an Extended Structural Impact Modelling framework, which integrates both bivariate associations and the topological relevance of each variable within the broader network. This framework allows the simultaneous examination of direct and mediated pathways, offering a more integrated and mechanistic understanding of how sociodemographic, environmental, and behavioural factors interact to influence child health – an advantage not captured by traditional analytical methods.

Therefore, this study investigates the structural pathways linking sociodemographic background, real-time individually measured APE, 24-hour movement behaviours, and health-related outcomes – including total oxidant status (TOS), total antioxidant status (TAS), CRF and BMI - in Portuguese primary school children, using a complex system framework. In particular, we aim to determine the moderating role of 24-hour movement behaviours on the associations between individual APE and health-related outcomes across children with diverse sociodemographic profiles.

Material and Methods

This study constitutes a secondary analysis of data from the Move Air project, which methodological framework has been previously detailed (Martins et al., 2025). All the Helsinki Declarations' ethical aspects were followed (World Medical Association, 2013). The evaluation methods and procedures were approved by the Data Protection office of the Public Health Institute of University of Porto - approval number was

CEFADE 32-2023. The main methodological procedures relevant to the present study are summarized below.

Setting and Participants

The present cross-sectional study was conducted in two primary schools in Valongo, a city located around the periphery of Porto, Portugal. The schools were selected based on convenience sampling and were both public institutions situated in rural areas. Data collection took place between April and May 2024, during the third school period.

Participants included typical neuro-developed children, aged 8-11 (in 3rd and 4th grades), who agreed to participate, and whose legal guardians gave consent. A total of 19 children participated in the assessments, with 5 not accepting to use the individual sensors for air pollution exposure or the accelerometer, resulting in a total of 14 participants. Demographic information collected included age and sex. The mean age of participants was 8.57 ± 0.646, and 64.3% were female.

The study complies with the European Union General Data Protection Regulation (GDPR) and was conducted under the supervision of Data Protection Office of the Institute of Public Health, University of Porto (ISPUP) Written informed consent was obtained from the parents or legal guardians, and age-appropriate assent was obtained from the children prior to data collection. Participation was voluntary and all procedures followed ethical standards for research involving human participants and vulnerable populations.

Assessments

All participating children underwent a comprehensive set of assessments encompassing exposure variables, health-related outcomes, movement behaviours and sociodemographic factors. The assessments for each of these variables are explained below in a more detailed manner.

Exposure variables

Children's exposure to PM and carbon dioxide (CO_2) was assessed using a portable monitoring system composed of an optical dispersion sensor (NOVA SDS011) for $PM_{2.5}$ and PM_{10} (Bozilov et al., 2022) and a non-dispersive infrared sensor (MH-Z19B) for CO_2 (Fayos-Jordan et al., 2021). Each child wore the monitoring system continuously for a 48-hour period, corresponding to two typical weekdays (Monday-Wednesday), chosen to minimise atypical weekly variability in environmental exposure.

The system, named MIDAS, was programmed to record data every minute for PM ($\mu g/m^3$) and CO_2 (parts per million (ppm)). For PM, a 30-second running average of particle counts calculated by the SDS011 sensor was used, to reduce short-term variability due to individual breaths or abrupt movements (Bozilov et al., 2022). Although the system includes a GPS module (NEO6MV2) for geolocation, for the purpose of the present study, data were processed to derive the total personal exposure profile. This approach captures cumulative exposure experience by the child across all visited environments (e.g., home, school, transport), providing a comprehensive measure of the individualized inhaled dose, regardless of the specific setting.

All sensors were positioned in a dedicated holder attached to the front strap of the child's backpack. This placement was chosen to ensure that the sensors were located close to the breathing zone, while minimising interference during daily activities. The monitoring system was continuously powered using a commercially available external power bank (BI-B61) placed inside the backpack. Research staff verified device functioning at the beginning and end of each 48-hour period, and children were instructed not to remove the backpack except when sleeping or during activities where backpacks were not permitted (e.g., swimming class). In cases where the backpacks could not be worn, children were instructed to place them at the boundary of the activity area, as close to them as possible.

Salivary biomarkers

Saliva samples were collected individually using Salivette® Cortisol tubes (SARS51.1534, SARSTEDT, DE) during the morning (between 8:00 and 10:00), ensuring at least 60 minutes had elapsed since food or liquid intake or toothbrushing. Children placed a sterile cotton swab in their mouth for approximately 1-2 minutes, while the research staff assured the swab was fully saturated. Children were also advised not to purposefully increase saliva production. Samples were immediately kept under cold conditions and transported to the Biochemistry lab at the Faculty of Sport. Upon arrival (within 30-60 minutes), samples were centrifuged to separate saliva from the swab. After centrifugation, supernatant saliva was aliquoted in microtubes and stored at −80 °C until analysis.

Total antioxidant status (TAS) and total oxidant status (TOS) were assessed using commercially available colorimetric kits (E- BC- K801- M and E- BC- K802- M, respectively; Elabscience, USA). Children with visible periodontal disease or marked dental plaque were excluded from biomarker assessment to minimise contamination bias (Isola et al., 2021). TOS was expressed as μmol H_2O_2 equivalent/L, while TAS was expressed as mmol Trolox equivalent/L.

Cardiorespiratory fitness

Cardiorespiratory fitness (CRF) was assessed through the 20-m Shuttle Run Test (20-mSRT), a valid, feasible and reliable tool to estimate children's maximum oxygen uptake - VO2max; mL/ kg/min (Tomkinson et al., 2019) – based on the prototype of Léger et al. (1984). The test took place on a marked 20-meter distance either in the school gymnasium or outdoor, depending on weather conditions and available school facilities. Before the test, children received a demonstration, and were instructed to run between the markers, synchronizing their pace with an audible beep. Initial speed was 8.5 Km/h, and in increased by 0.25 Km/h every minute. Research staff ran the first laps with the children to avoid disproportionate pacing, and then positioned themselves at both ends, to observe compliance, record test criteria and monitor safety. The test ended when the child: (1) was unable to continue or voluntarily stopped due to fatigue or discomfort, (2) failed to reach the line on three consecutive beeps. Only the complete laps where the child reached the line before the beep were considered. For the comparison between children, the number of laps completed was used.

Movement behaviours

Children wore a tri-axial ActiGraph wGT3x accelerometer in the left hip for 24-hous over 5 consecutive days. Devices were attached using an elastic belt, and participants were instructed to keep them on at all times expect during prolonged water exposure (e.g., swimming or showering). Parents received written instructions, as well as an accelerometer diary to record wear days, sleep and wake times, whether the accelerometer was worn during sleep, and school attendance. A daily SMS was also sent to the parents to encourage compliance with device usage and diary completion.

Accelerometers were set to collect raw triaxial acceleration at 90 Hz. After retrieval, data were downloaded using the ActiLife Software (V.13.4), and analysis were conducted using the GGIR package (V.2.8-2) in R. Files with insufficient recording duration –

defined by detection of non-wear periods based on sustained intervals of near-zero acceleration – were identified and excluded. Raw data was converted into Eucledian Norm Minus One (ENMO) - an omnidirectional measure of body acceleration expressed in milligravitational units (mg) (Van Hees et al., 2013) - and after averaged into 1-s epoch values over the 5 monitored days. A monitored day was considered valid when it contained at least 16 hours of wear time, and participants were required to have a minimum of 3 valid weekdays. Movement behaviours were classified using the child-specific hip ENMO cut-points of 48 mg, 201 mg and 707 mg (Hildebrand et al., 2014; Hurter et al., 2018), which allowed for the estimation of the upper threshold of sedentary time, and the lower threshold for light PA (LPA), moderate PA (MPA) and vigorous PA (VPA), respectively. Total PA was also derived from the vector magnitude of the acceleration signal. Sleep duration was estimated through a children-validated accelerometer-based algorithm suitable for hip worn devices (Smith et al., 2020). This algorithm identifies sleep periods by detecting sustained episodes of low movement combined with minimal variation in the z-axis angle (which is the axis positioned perpendicular to the skin surface).

Sociodemographic status

Because all participants were on the same age-group, age wasn't included as a variable in the present analysis. Instead, we selected sociodemographic factors which could potentially influence children's APE and 24-hour movement behaviours. The included sociodemographics were Sex – boy or girl; Dwelling type – house or apartment ; Mode of transport to school – Car, Bus, Motorcycle, or Walking; Allergies – yes or no; and Household size.

Data processing and statistical analysis

Data analysis was conducted using a multi-stage approach, integrating descriptive statistics, structural impact modelling, and complementary regression analysis to unravel the complex pathways linking sociodemographic data, air pollution, movement behaviours, and health outcomes.

Extended Structural Impact Model

To test the study's conceptual framework, we employed an extended structural impact model, a graph-theory-based approach designed to quantify both direct and indirect casual flows across four distinct variable groups (G):

- G_1 (Sociodemographics): Sex, residence, transport mode, allergies, and household size.
- G_2 (Environmental exposure): $PM_{2.5}$, PM_{10}, and CO_2 average concentrations.
- G_3 (Movement behaviours): LPA, MPA, VPA, MVPA, SB and sleep duration.
- G_4 (Health outcomes): TOS, TAS, CRF, and BMI

The casual architecture was defined sequentially as $G_1 \rightarrow G_2 \rightarrow G_3 \rightarrow G_4$, allowing for the assessment of how upstream factors (sociodemographic factors and pollution) propagate through behavioural mediators to influence downstream health outcomes. This directional structure reflects the study's conceptual model; however, it is not used to infer econometric causality. Instead, the structural impact model quantifies directional influence patterns that align with the predefined framework.

Structural weighting and centrality

For each pair of variables between blocks (e.g., a variable X_1 in G_1 and a variable Y_2 in G_2), Spearman's rank correlation coefficients (ρ_{ij}) were calculated. However, to account for the topological importance of each variable within the system, we modelled each block as a weighted graph using a k-nearest neighbour strategy ($k = 4$) based on internal correlations. Three centrality metrics were computed for each variable within its block: Eigenvector centrality (c^{eig}), Betweenness centrality (c^{bet}), and PageRank (c^{pr}). A composite structural centrality score (C_i) was derived as the mean of these normalized centralities. This composite measure was used to weight the pairwise associations between variables belonging to different blocks. The Direct Impact (I) between variables was found by calculating the weighting scheme, computed using Equation 1. In this weighting scheme, 60% of the Direct Impact (I) derives from the raw Spearman correlation (ρ_{ij}), while the remaining 40% reflects the structural relevance of the originating variable through its composite centrality score (C_i).

$$I_{\{a \rightarrow b\}}^{\{(i,j)\}} = \rho_{\{ij\}[\,(1-\alpha)+\,\alpha C_i]}$$

Equation 1 - In this formulation, α = 0.4 and represents the weighting factor, ρ_ij represents the Spearman correlation between variables i and j, whereas C_i denotes the composite structural centrality score. I represents the final Direct Impact.

The purpose of the weighting procedure is not to replace the statistical association between variables, but rather to adjust it according to the structural importance of each variable within its own subsystem. For this reason, Spearman's correlation was retained as the primary determinant of I.

These weighting values are arbitrary, as no formal rule exists to define them. The threshold above 50% was chosen to filter out non-discriminative associations, whereas assigning 40% to centrality aimed to avoid the loss of relevant information in indirect relationships.

In practical terms, this approach results in a slight predominance of Spearman's correlation, thereby preserving statistical relationships to a greater extent while still incorporating structural information.

Pathways Analysis: Direct and Indirect Effects

Impact matrices were constructed to quantify the flow of influence through the system.

- Direct Impacts: Matrices representing immediate connections between sequential blocks (e.g., $I_{G2 \rightarrow G3}$) and direct transversal connections (e.g., $I_{G1 \rightarrow G3}$, bypassing pollution (G_2)).
- Indirect Impacts: Mediated effects were computed via matrix multiplication of the direct impact matrices. As an example, Equation 2 shows how the impact of pollution (G_2) on health-related outcomes (G_4) mediated by movement behaviours (G_3) was calculated:

$$I^{\{ind\}}_{\{G_2 \rightarrow G_4\}} = I_{\{G_2 \rightarrow G_3\}} \cdot I_{\{G_3 \rightarrow G_4\}}$$

Equation 2 - Indirect impact assessment

This allowed for the estimation of the Full Route impact ($G_1 \rightarrow G_2 \rightarrow G_3 \rightarrow G_4$), capturing how sociodemographic context, environmental exposure and movement behaviours jointly contribute to children's health, including both direct pathways and behaviourally mediated effects.

Complementary Regression and Inference

To validate the structural findings and estimate the proportion of variance explained, linear regression models were fitted for each outcome variable against predictors from preceding blocks. The coefficient of determination (R^2) was calculated to assess model fit.

To ensure statistical robustness and account for non-normal distribution typical of environmental and biological data, a bootstrap resampling procedure was applied. We performed B = 1000 iterations of resampling with replacement to generate empirical distributions for both the R^2 values and the regression coefficients. Significance was determined based on 95% confidence intervals (95%CI). Paths where the 95%CI did not include zero were considered statistically significant.

This dual approach – combining structural impact magnitude (network topology) with explained variance (R^2) – allowed for the identification of both strong structural influence (high impact) and statistical predictability (high R^2), providing complementary perspectives on system dynamics.

Results

The results are presented within the Extended Structural Impact Model framework, analysing the directional flows between four distinct predefined groups: Sociodemographics (G1), Environmental Exposure (G2), Movement Behaviours (G3), and Health-related Outcomes (G4). The analysis integrates normalized block-to-block impacts scores, nodal centrality metrics, and the decomposition of dominant topological pathways. All reported impact coefficients represent normalized structural impact scores, reflecting relative influence strength within the system, rather than effect sizes or causal estimates. To facilitate interpretation of the system-level dynamics, the main structural outputs are illustrated in Figures 1-3 (see below).

Global Structural Impact and Inter-Block Dynamics

The structural analysis revealed distinct patterns of influence governing the system. Among all direct inter-block connections, the strongest normalized impact was observed from sociodemographics to movement behaviours ($G_1 \rightarrow G_3$; impact = 0.96), indicating that sociodemographic characteristics were structurally dominant determinants of behavioural patterns within the network. The global organization of structural impacts across the four blocks is summarized in Figure 1 (consult figure 1 below).

When environmental exposure was introduced as an intermediate block, the indirect pathway linking sociodemographics to movement behaviours through APE ($G_1 \rightarrow G_2 \rightarrow G_3$) reached the maximum normalized impact value (1.00). This pattern indicates that sociodemographic factors were strongly associated with the environmental exposure profile, which in turn exhibited a substantial structural linkage with children's movement behaviour patterns.

Regarding downstream transmission to health-related outcomes, movement behaviours (G_3) emerged as the dominant structural mediation block, concentrating a large proportion of upstream influence before transmission to health-related outcomes. The direct structural impact from movement behaviours on health ($G_3 \rightarrow G_4$) was notably stronger (impact = 0.66) than the corresponding direct impact from environmental exposure to health outcomes, ($G_2 \rightarrow G_4$; impact = 0.43). This configuration indicates that a considerable proportion of the pollution-related influence on health outcomes was structurally channelled through behavioural patterns rather than acting exclusively through direct environmental – health linkages.

In addition to mediated pathways, a substantial direct structural connection was observed between sociodemographics and health-related outcomes ($G_1 \rightarrow G_4$; impact = 0.71). This finding suggests that sociodemographic factors were associated with health outcomes through pathways not fully captured by the environmental exposure or movement behaviour blocks included in the present model.

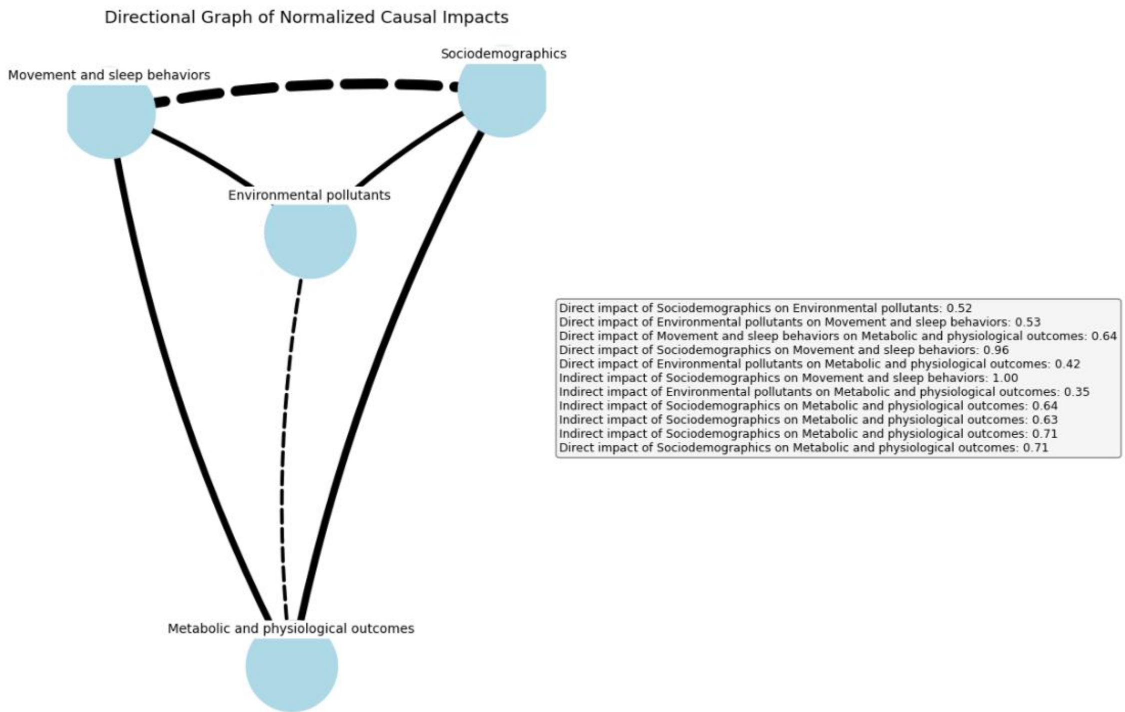

Figure 1. Global structural impact matrix illustrating normalized direct and indirect block-to-block influence scores among sociodemographics (G1), environmental exposure (G2), movement behaviours (G3), and health-related outcomes (G4).

Nodal Centrality and Hub Identification

To characterize the internal organization of each block, composite nodal centrality scores – derived from eigenvector centrality, betweenness centrality, and PageRank – were examined, identifying variables acting as structural hubs. This internal organization and the identification of structurally dominant variables are illustrated in Figure 2 (consult figure 2 below).

Environmental Exposure

Within the environmental exposure block (G_2), CO_2 concentrations exhibited the highest composite centrality score, indicating a dominant role in structuring the internal connectivity of this block and its link to downstream movement behaviours. PM_{10} functioned as a secondary node, while $PM_{2.5}$ occupied a more peripheral position within the environmental network topology.

Movement Behaviours

Within the movement behaviours block (G_3), MVPA emerged as the primary hub, concentrating and transmitting influence toward health-related outcomes. In contrast, sedentary behaviour functioned as a distinct specific hub, showing a strong structural linkage with TOS.

Health-Related Outcomes

Within the health-related outcomes block (G_4), CRF acted as the primary sink node, receiving the strongest cumulative inputs from upstream blocks, particularly from MVPA. TOS exhibited a more selective structural profile, being predominantly linked to sedentary behaviour. BMI and TAS showed comparatively lower topological capture within the network.

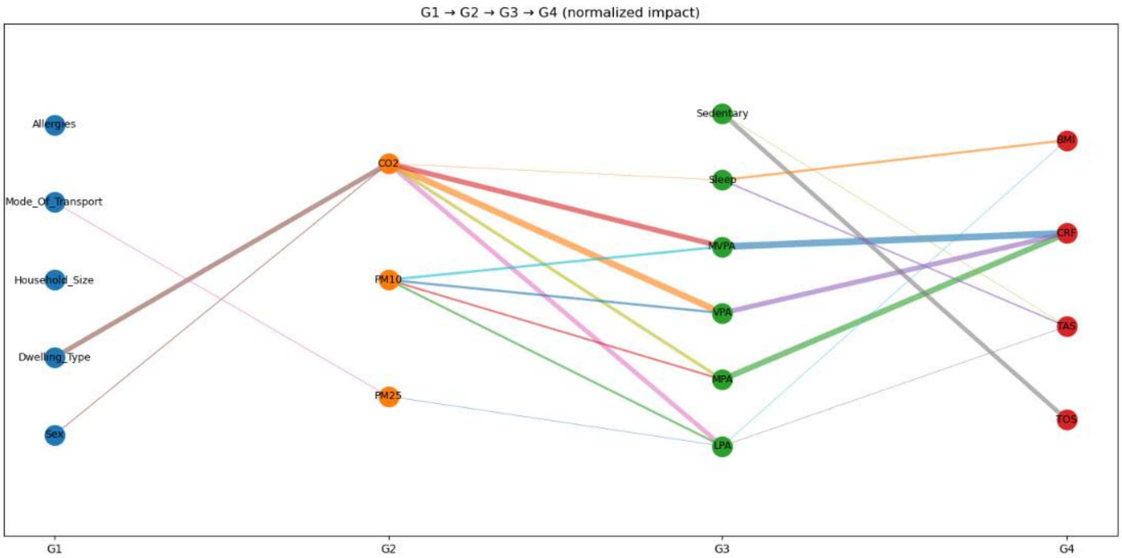

Figure 2. Nodal centrality maps for each variable block, displaying composite centrality scores based on eigenvector centrality, betweenness centrality, and PageRank. Node size reflects relative structural importance within each block.

Topological Pathway Analysis

Decomposition of the network into full structural routes linking all groups ($G_1 \rightarrow G_2 \rightarrow G_3 \rightarrow G_4$) highlighted several dominant trajectories of influence. These full structural routes are presented in Figure 3 (consult figure 3 below).

Dwelling-Type → CO_2 → MVPA → CRF

The strongest comprehensive pathway identified in the system followed the sequence: dwelling-type → CO_2 → MVPA → CRF. Within this route, CO_2 exposure was structurally associated with increased sedentary behaviour, which exhibited a strong specific linkage with elevated TOS.

Dwelling-Type/Allergies → CO_2 →Sedentary Behaviour → TOS

A secondary pathway was identified linking dwelling type and allergies to oxidative stress: dwelling-type/allergies → CO_2 →sedentary behaviour → TOS. In this chain, CO_2 exposure appears to reinforce sedentary behaviour, which creates a specific strong link to increase TOS.

Direct Pathways

In addition to behaviourally mediated routes, the model identified direct structural pathways connecting sociodemographic variables – particularly dwelling type and allergies – to BMI and CRF. Although the cumulative normalized impact of behaviour-mediated pathways (total impact = 7.87) exceeded that of direct sociodemographic – health pathways (total impact = 2.40), the presence of these direct connections indicates that sociodemographic characteristics were structurally associated with health-related outcomes independently of the environmental and behavioural profiles captured in this model.

Direct social impacts on health: The analysis also confirmed significant pathways connecting allergies and dwelling type directly to BMI and CRF. While the behaviour-mediated routes are dominant (cumulative impact of 7.87), a direct link still exists (impact: 2.40).

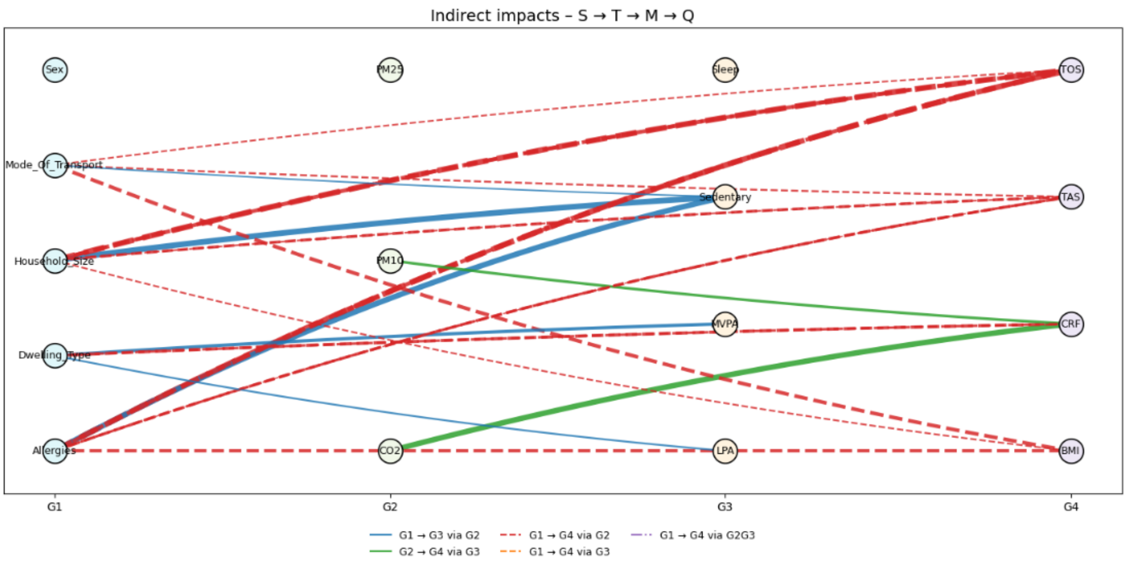

Figure 3. Topological pathway decomposition illustrating dominant full routes linking all groups (G1 →G2 → G3 → G4). Path thickness represents cumulative normalized structural impact.

Discussion

This cross-sectional study provides novel insights into the structural organisation linking sociodemographic factors, APE, 24-hour movement behaviours and health-related outcomes within a complex system framework. Overall, the findings indicate that movement behaviours constitute the principal mediating group through which upstream sociodemographic and environmental influences are predominantly transmitted to health-related outcomes. Moreover, sociodemographic variables showed the highest upstream structural influence of the system on movement behaviours.

The global causal architecture indicated that sociodemographic variables exert the strongest upstream structural influence on movement behaviours (Direct impact $_{G1 \rightarrow G3}$ = 0.96). Direct evidence linking non-traditional sociodemographic indicators to children's movement behaviours remains limited. Most existing literature is mixed and primarily focused on socio-economic status, while also assessing sociodemographics as confounders or covariates (Gresham & Karatekin, 2025; Xing et al., 2025). In this context, the present finding should be interpreted as exploratory, suggesting that everyday contextual characteristics may structurally condition behavioural patterns before the introduction of APE, contributing to a more nuanced understanding of sociodemographic-behaviour pathways.

Drawing upon the topological framework established by Yu et al. (2007), a structural bottleneck refers to a network component with high betweenness centrality, functioning as a critical bridge or tunnel through which a significant proportion of shortest pathways must traverse to connect distinct parts of a system. In the present analysis, while upstream factors converge strongly upon movement behaviours – evidenced by the maximum normalized impact of the $G_1 \rightarrow G_2 \rightarrow G_3$ pathway (I = 1.00), downstream transmission to health-related outcomes (G_4) reveals a crucial topological role. The influence of environmental exposure on health was not primarily direct ($G_2 \rightarrow G_4$ impact = 0.43), but instead structurally channelled through behavioural patterns ($G_2 \rightarrow G_3 \rightarrow G_4$ impact = 0.66). Although betweenness centrality was not independently quantified, this topological configuration indicates that 24-h movement behaviours function as a partial structural bottleneck, concentrating upstream influences before mediating their transmission to health-related outcomes. This reflects a topological property of the system rather than a directional or signed causal effect, highlighting the organizational relevance of 24-h movement behaviours in structuring exposure-health relationships. In the context of complex systems, topological properties capture the pattern of connections among components – i.e., the wiring diagram – rather than merely their physical positions or simple counts of links (Barabasi et al., 2011). Topology therefore describes how elements are organized and interconnected, a perspective that goes beyond summing linear metrics (Strogatz, 2001). As Strogatz (2001) notes, 'Because structure always affects function,', analysing these structural characteristics is critical for understanding system behaviour (Strogatz, 2001).

The mediating role of individual movement behaviours in associations between APE and health outcomes has been previously reported. Sleep quality has been shown to partially mediate the associations between APE and type 2 diabetes mellitus (Lin et al., 2025), while PA has been identified as a mediator of APE associations with generalized anxiety disorder and self-rated health (Hautekiet et al., 2022). However, sleep, sedentary behaviour and PA are perfectly collinear and interdependent, and should therefore be considered as a unified behavioural system (Chen et al., 2024; Pedišić, 2014). Although the mediating role of integral 24-h movement behaviours in the APE-health relationship had not yet been examined (Martins et al., 2025), evidence from other health contexts supports their relevance as an interdependent system mediating influence on health outcomes (Chen et al., 2024).

Taken together, considering that the mediating potential of movement behaviours has been demonstrated across other health outcomes, and that individual components of these behaviours have been shown to mediate associations between APE and health, the present findings are particularly relevant. Importantly, the present analysis was not intended to estimate causal effects , but to characterize the structural organisation of a complex system and identify components that concentrate and transmit influences across variable groups. This approach is therefore hypothesis-generating, highlighting system-relevant pathways that warrant targeted causal of longitudinal investigation.

This study presents several methodological strengths. The combination of individual-level, real-time APE assessments with objective 24-hour movement behaviour measurements via accelerometry provides a more accurate characterization of children's daily exposure-behaviour profiles than approaches based on area-level estimates or self-reported data. In addition, the adoption of an extended structural impact model within a complex-systems framework allowed the identification of key structural pathways and nodes, offering insights beyond traditional linear or single-mediator analyses. The inclusion of multiple health-related outcomes further enabled a more integrative assessment of children's health.

Some limitations should be acknowledged. The network-based approach does not establish temporal or causal directionality, and identified pathways should therefore be interpreted as hypothesis-generating. Exposure and movement behaviours were measured over relatively short periods of time and restricted to weekdays, which may not reflect longer-term or seasonal patterns. Generalisability is limited by the recruitment of participants from two schools within a single municipality. Finally, biological markers were assessed at a single time point and represented a limited panel, constraining the evaluation of dynamic biological responses over time.

Longitudinal and intervention studies are needed to test causal relevance of the pathways identified and to determine whether optimising 24-h movement behaviours can mitigate the health effects of APE. Broader and longer exposure monitoring, combined with more diverse, multi-site samples, would strengthen exposure assessments and external validity. Further validation of the complex-systems modelling framework an the inclusion of repeated and expanded biomarker assessments may help clarify underlying mechanisms and improve interpretability.

Conclusion

This study provides novel evidence supporting a possible mediating role of 24-hour movement behaviours in the association between personal APE and health-related outcomes.

Although causal inference is limited by the cross-sectional design, these findings support the integration of movement behaviours into environmental health research and emphasise the need for longitudinal and intervention studies to clarify causal mechanisms and inform public health strategies. Moreover, it encourages future research to move away from single linear associations, integrating system-based approaches to better understand latent patterns.

5 Final considerations

The present dissertation aimed to explore the complex interplay between sociodemographic characteristics, environmental exposure, movement behaviours and health-related outcomes in primary school children using a network science approach. To the best of our knowledge, this is the first study to map these variables using a systemic network rather than through single linear associative models.

The findings derived from this exploratory analysis allow for the following conclusions:

- Systemic interdependence over linear causality: The network analysis revealed that the relationship between APE and health-related outcomes is not merely direct but seems to be mediated by the 24-hour movement behaviours. This challenges the traditional reductionist view and supports a paradigm shift towards a holistic, systems-based approach in environmental epidemiology.
- Methodological feasibility and innovation: This work successfully demonstrated the feasibility of applying network science methodologies to a small sample, moving away from traditional linear regressions, which are not sensitive to some latent patterns, particularly in the context of biological complexity. Furthermore, this research introduces a significant technological milestone through the inaugural deployment of customized individual air pollutant sensors, specifically engineered by the Faculty of Engineering of the University of Porto (FEUP), allowing for high-resolution, real-time personal exposure monitoring. By overcoming several limitations of traditional research, this study serves as a first "proof-of-concept" for future research in the field.
- Implications for future research: While the sample size limits the generalization, the study establishes a crucial methodological baseline. Future investigations should prioritize longitudinal designs to assess the stability of this network topology over time. Furthermore, the integration of network science with standard epidemiological tools is highly recommended to better understand the non-linear pathways through which environmental inequality affects paediatric health.

In summary, this dissertation contributes to the literature not by providing definitive clinical thresholds, but by offering a novel methodological and analytical lens. It highlights that to protect children’s health in polluted environments, we should look beyond single linear associations, and address the intricate web of variables, including co-dependent movement behaviours, that may help shape both daily exposure and its consequences in health.

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