ASSESSMENT OF INDIVIDUAL-LEVEL EXPOSURE TO AIR POLLUTANTS USING PERSONAL MONITORING

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Doctoral Dissertation
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OCENA INDIVIDUALNE IZPOSTAVLJENOSTI ONESNAŽILOM IZ ZRAKA Z UPORABO OSEBNEGA MONITORINGA

Doktorska disertacija

Supervisor: Dr. David Kocman

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To the ones that matter most

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Abstract

A paradigm shift is occurring in the assessment of exposure to urban environmental stressors. Improved accuracy of personal monitors has enabled researchers to study exposure at the individual level. Monitoring stations are the primary reference point for air quality in urban environments, although there is a need to assess exposure in greater spatial and temporal detail. In this work, an evaluation of personal monitors is conducted in the context of assessing individual exposure to urban stressors, validating results, and using advanced exposure assessment methods. An initial overview of the field analysed a broader range of urban stressors and the use of personal monitors for exposure assessment. Poor air quality, particularly elevated particulate matter (PM) levels, were identified as of particular concern and were most commonly assessed using personal monitors. However, gaps were identified in data collection, dissemination of results, communication, assessment of exposure in different areas, participant involvement, etc. This work addresses several of these gaps and evaluates some approaches and tools to gain more information from personal monitor-based exposure assessments.

Within the community of users of personal monitors, a consensus has formed that validation is required before the device is deployed. In some cases, validation and calibration is also required during and after sampling. The results of this work have shown that simple collocation of the personal monitor with a research-grade reference sensor can be sufficient. The Personal PM Monitor (PPM) used in the ICARUS H2020 project (icarus2020.eu), which recorded PM exposure of 82 participants as part of the sampling campaign in Ljubljana, Slovenia, was found to be fit for purpose by collocation with a reference sensor. In addition, each participant was provided with an activity and biometric monitoring device, and required to complete an activity diary for each hour each day. Combining these datasets provided an extraordinary amount of detailed data on exposure, activities, movement, routines, and behaviours. On the other hand, the collection of these data also had shortcomings. Manual collection of activity data by participants was shown to be tedious and error-prone. Therefore, a machine learning approach was used to compensate for this shortcoming, and attempts were made to predict or recognize certain complex activities using only personal monitors. The results showed higher accuracy when a combination of personal monitors was used.

In this work, two assessments of performance and applicability of personal monitors were performed: (i) by comparing indoor and outdoor exposure during a high PM concentration event, i.e., an atmospheric thermal inversion, and (ii) using an agent-based model (ABM) to assess exposure and compare it with data from ICARUS. Although these are two different assessments and approaches, similar conclusions can be drawn. A personal monitor provides insight into indoor and outdoor exposure with high spatial and temporal granularity. The results show that while outdoor PM concentrations account for most of the exposure, indoor activities are a significant contributor. In addition, the ABM yielded results comparable to the ICARUS data, indicating that simulations informed by personal monitor data can assess exposure in various scenarios. Personal interactions in the model were shown to influence exposure and dose of particulate matter. These results could help decision makers develop data-driven and effective policies.

Dissemination and communication are critical in participatory projects, as indicated by the literature review and the ICARUS project. One aspect, a personalized report of participant data, was demonstrated in this work. The communication and visualization was based on participant feedback and multiple iterations. Data accuracy and validity considerations must be directly communicated not only in the report but also in the visualizations. An automated approach allowed for the compilation of over 600 individual reports. Overall, a well-structured report was shown to guide participants through the data and help them gain useful information.

Povzetek

Pri ocenjevanju izpostavljenosti stresorjem v urbanem okolju prihaja do spremembe paradigme. Izboljšana natančnost naprav za osebni monitoring raziskovalcem omogoča raziskovanje izpostavljenosti na individualni ravni. Merilne postaje še vedno predstavljajo glavno referenčno točko za kakovost zraka v urbanih okoljih. Vedno večji pomen pa pridobiva ocenjevanje izpostavljenosti z izboljšano prostorsko-časovno resolucijo. Doktorsko delo podaja oceno osebnega monitoringa v kontekstu ocenjevanja izpostavljenosti posameznika urbanim stresorjem, validacijo rezultatov in uporabo naprednih metod za ocenjevanje izpostavljenosti. V začetnem pregledu področja je bil analiziran širši spekter urbanih stresorjev in uporaba naprav pri ocenjevanju izpostavljenosti. Slaba kakovost zraka, zlasti povišane ravni trdnih delcev (PM), je bila opredeljena kot največja skrb in najpogosteje preučevana s tehnologijami osebnega monitoringa. Ugotovljene so bile vrzeli pri zbiranju podatkov, diseminaciji rezultatov, komunikaciji, ocenjevanju izpostavljenosti v različnih okoljih, vključevanju udeležencev itd. To delo obravnava več omenjenih vrzeli ter ocenjuje nekatere pristope in orodja za izboljšanje pridobivanja informacij iz ocen izpostavljenosti na podlagi osebnega monitoringa.

V znanstveni skupnosti, ki se ukvarja z uporabo osebnega monitoringa, se je oblikovalo soglasje, da je pred uporabo naprave potrebna validacija. V nekaterih primerih sta validacija in kalibracija potrebni tudi med in po vzorčenju. Rezultati v tem delu so pokazali, da je lahko kolokacija naprave z referenčnim senzorjem raziskovalnega razreda zadostna. Osebni monitor PM (PPM), uporabljen v projektu ICARUS H2020 (icarus2020.eu), ki je beležil izpostavljenost PM 82 udeležencev v okviru kampanje vzorčenja v Ljubljani, Slovenija, je bil ugotovljen kot primeren za namen, tako da je bil kolociran z referenčnim senzorjem. Vsakemu udeležencu je bil dodeljen še osebni monitor dejavnosti in biometrični monitor, udeleženci pa so morali vsak dan za vsako uro izpolniti dnevnik aktivnosti. Združevanje teh naborov podatkov je zagotovilo izjemno količino podrobnih podatkov o izpostavljenosti, dejavnostih, gibanju, rutinah in vedenju. Po drugi strani pa je zbiranje teh podatkov razkrilo pomanjkljivosti. Ročno zbiranje podatkov o dejavnostih udeležencev se je izkazalo za obremenjujoče in s pogostimi napakami. V ta namen je bil uporabljen pristop strojnega učenja, ki je kompenziral to pomanjkljivost in poskušal predvideti ali prepoznati specifične kompleksne dejavnosti z uporabo naprav za osebni monitoring. Rezultati so pokazali večjo natančnost pri uporabi kombinacije naprav.

V okviru tega dela sta bili izvedeni dve oceni delovanja in uporabnosti osebnih monitorjev: (i) primerjava izpostavljenosti v zaprtih prostorih in na prostem v času visokih koncentracij PM, tj. atmosferska toplotna inverzija, in (ii) z uporabo agentnega modela (ABM) za oceno izpostavljenosti in primerjavo z ICARUS podatki. Osebni monitor omogoča vpogled v notranjo in zunanjo izpostavljenost PM z visoko prostorsko-časovno resolucijo. Rezultati so pokazali, da medtem ko koncentracije delcev na prostem določajo večino izpostavljenosti, dejavnosti v zaprtih prostorih prispevajo precejšen delež. Poleg tega je ABM pokazal podobne rezultate kot ICARUS podatki, kar kaže, da lahko simulacije na podlagi podatkov osebnih monitorjev ocenjujejo izpostavljenost v različnih scenarijih.

Pokazalo se je, da osebne interakcije v modelu vplivajo na izpostavljenost in odmerek PM. Ti rezultati bi lahko potencialno pomagali odločevalcem pri oblikovanju bolj podatkovno usmerjenih in učinkovitih politik.

Komuniciranje je ključnega pomena pri participativnem projektu, kot je razvidno iz pregleda literature in projekta ICARUS. V tem delu je prikazan primer individualnega poročila za udeležence. Komunikacija in vizualizacija sta temeljili na povratnih informacijah udeležencev in večkratnih popravkih. Rezultati so pokazali, da je točnost podatkov treba sporočiti ne samo v poročilu, ampak tudi neposredno v vizualizacijah. Avtomatski pristop je omogočil sestavo več kot 600 posameznih poročil. Pravilno strukturirano poročilo udeležence vodi skozi podatke in jim pomaga pridobiti koristne informacije.

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Abbreviations

AQ ... Air Quality
EU EEA ... European Union European Environment Agency
US EPA ... United States Environmental Protection Agency
WHO ... World Health Organization
EC ... European Commission
QA/QC ... Quality Assurance/Quality Control
PM ... Particulate Matter
UFP ... Ultra-fine Particles
TVOC/VOCs ... Total (Volatile Organic Compounds)
PAHs ... Polycyclic Aromatic Hydrocarbons
TADs ... Time Activity Diaries
MET ... Metabolic Equivalent of Task
CS ... Citizen Science
DIY ... Do-It-Yourself
SAT ... Smart Activity Tracker
PPM ... Personal Particulate Matter (monitor)
IAQ ... Indoor Air Quality

Chapter 1

Introduction

Urban environmental stressors encompass a wide range of environmental conditions and factors that impact the physical and mental well-being of individuals residing in urban settings. Air pollution, noise and thermal stress are the three most common stressors associated with urban environments (European Environment Agency 2023a), as visualized with some of their sources in Figure 1. Additionally, degradation of the urban landscape (Hintz et al. 2018; Park and Evans 2016; Wetzstein 2017), inadequate access to green and blue spaces (Chen and Chang 2015), traffic congestion (Liang and Gong 2020), poor transport and access options, overcrowding (Park and Evans 2016), waste and unpleasant odours (Sucker, Both, and Winneke 2001), and others, can be considered as urban stressors. Air pollution, and more specifically inhalable particulate matter, stands out as a stressor of high concern due to its high negative impact on health and wellbeing, and prevalence in urban environments (Southerland et al. 2022). The European Environmental Agency (EEA) estimated that in 2020 around 90% of city dwellers in Europe were exposed to harmful levels of air pollution, with more than 285,000 premature deaths attributed to exposure to poor air quality (European Environment Agency 2022).

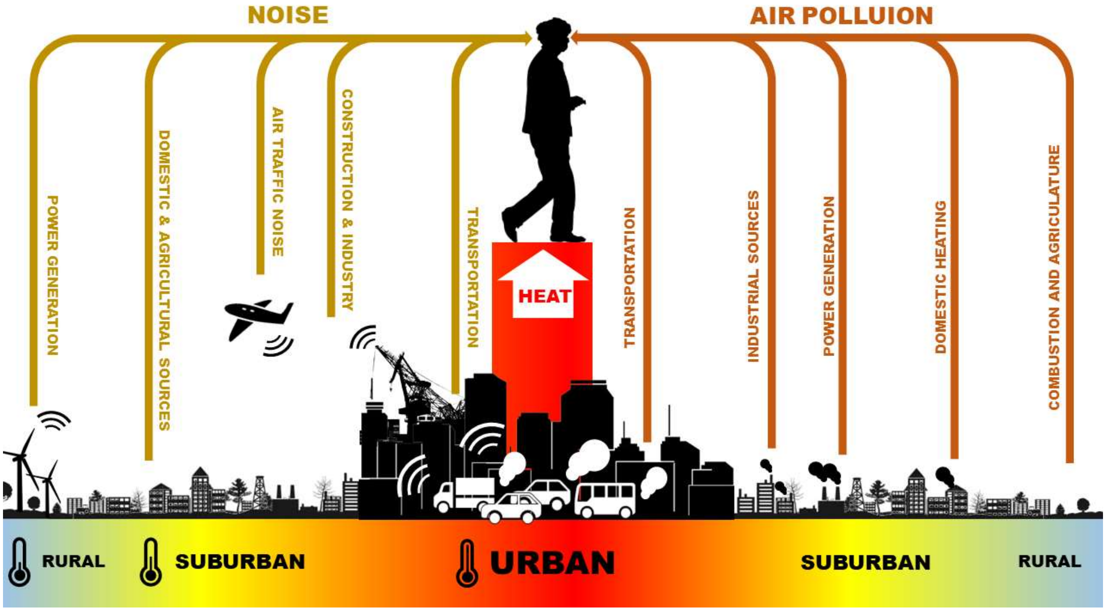

Figure 1: Some sources of the three main urban environmental stressors, i.e., air pollution, noise, and thermal/heat stress.

Air pollution in cities is traditionally measured by government-run stations, which are often sparse and associated with high costs. Data is collected and curated by agencies or departments that operate these stations and communicated to the public with delay, after validation. The accessibility of the data is dependent on the specific policy of the responsible governmental entity. Personal monitors, encompassing a variety of personal monitors and low-cost sensors, present a novel set of tools for assessing exposure to air pollutant and other urban stressors (Fanti et al. 2021). These technologies have often been associated with poor performance, frequent data gaps, inadequate QA/QC, data drifting, unreliability, and other issues regarding their use and the quality of the data they provide. However, recent developments show an improved performance and a narrative shift, as the devices become more reliable and accurate (Giordano et al. 2021; Morawska et al. 2018). Importantly, personal monitors enable greater participation of non-expert individuals in the research, e.g., exposure assessments. This work addressed various real-world applications of personal monitors in participatory-based exposure assessments. Applications of personal monitors for evaluating exposure to urban stressors are discussed in Section 3.1. Furthermore, Section 3.2 explores the validity and comparability of specific personal monitors, as a proof-of-concept, and uses this data in estimating the dose of particulate matter in two individuals.

Exposure assessments often rely on participants providing information on their activities during the sampling campaign. Manually recording activities for large groups is associated with poor precision and reliability, requiring more resources, and issues with recall bias, further elaborated in Section 3.3. This section discusses the use of machine learning as a tool to improve human activity recognition, in turn reducing or completely eliminating participant input in collecting activity data, and reducing errors in exposure studies.

Outdoor air quality, particularly in urban environments, has improved in recent decades, due to more rigorous standards and regulations (Zhang et al. 2022). Indoor air quality, on the other hand, in both private and public spaces, is less regulated, with standards being more difficult to enforce (Y. Xie et al. 2022). Individuals in industrialized nations spend 80-90% of their time in indoor environments (Klepeis et al. 2001; Schweizer et al. 2007). Information on indoor air quality is sparse, with individuals rarely having information about their personal exposure to air pollutants. Portability and low cost of personal monitors expand the scope of domains and microlocations where exposure can be assessed, including indoor environments. An extended assessment of exposure to PM2.5 in different microenvironments and during various activities is explored in Section 3.5. Additionally, this section discusses the use of a stochastic model, i.e., an agent-based model, for exposure assessment. Using personal monitors in the context of assessing exposure indoors and outdoors during high-exposure events, e.g., atmospheric thermal inversion, is discussed in Section 3.4.

Personal monitors, in general, provide data with high temporal granularity, i.e., minute-resolution, creating new challenges in terms of collecting, harmonizing and analysing large amounts of data. These issues, in combination with visualizing and reporting data to participants, are discussed in detail in Section 3.6.

The following sections consist of an explanation on the broader context of air pollution, a general outline of the main environmental stressor, i.e., particulate matter, analysed in this work, defining the terms associated with exposure and dose, an analysis of personal monitors, and an in-depth overview of the personal monitors used in this work. Moreover, the context of participatory approaches and Citizen Science is discussed, and a detailed description of the ICARUS project, as the main source of data, is provided.

1.1 Air quality and air pollution

Air quality is an environmental factor that can impact human health and well-being. It refers to the concentration and nature of various natural and man-made components suspended in the atmosphere, e.g., gases, particulate matter, and air toxics. Generally, when air quality is discussed, it is put in context of air pollution. The EC directive on ambient air quality and cleaner air for Europe does not specifically establish what air quality is, rather puts it in context with reducing air pollution to “levels which minimize harmful effects on human health, paying particular attention to sensitive populations, and the environment as a whole, to improve the monitoring and assessment of air quality including the deposition of pollutants and to provide information to the public” (European Commission 2008).

Principal air pollutants that influence air quality in outdoor environments are:

- Particulate Matter (PM): Particulate matter consists of various sizes of solid particles or liquid droplets suspended in the air. Sources of particulate matter include industrial emissions, vehicle exhaust, construction activities, and natural sources like dust and pollen. PM is discussed in depth in section 1.2.
- Gases: Air quality is influenced by various gases present in the atmosphere. These include nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), and volatile organic compounds (VOCs). These gases originate from a wide range of sources, including combustion processes in vehicles and industrial facilities, natural emissions such as volcanic activity, and chemical reactions occurring in the atmosphere. Ozone (O_3), nitrogen dioxide (NO_2), and sulphur dioxide (SO_2) have been linked to adverse health effects such as bronchial reactivity, inflammation, thrombotic responses, gastrointestinal disorders, blood vessel inflammation, and increased mortality, hospital admissions, and respiratory symptoms due to day-to-day variations in NO_2 concentration (Morakinyo, Mukhola, and Mokgobu 2020; Xu et al. 2022).
- Air Toxics: Hazardous air pollutants, commonly referred to as air toxics, are a subset of air pollutants that have known or suspected health effects even at low concentrations. These pollutants are typically distinguished by their toxicity and the fact that they can pose significant health risks even at very low concentrations. While some VOCs can be considered air toxins, the term "air toxins" is often used to refer to a specific list of pollutants regulated by environmental agencies due to their recognized harmful effects. Common examples of air toxins include:
    - Benzene, Formaldehyde, and Acetaldehyde, all VOCs and air toxics, classified as carcinogens or potential carcinogens.
    - Heavy metal air toxics, such as lead and mercury, pose health risks, including developmental delays, learning disabilities, behavioural problems, and nervous system damage, with exposure occurring through ingestion of lead-contaminated dust or soil and inhalation of lead particles, as well as the potential for mercury accumulation in aquatic ecosystems, leading to contamination of fish and seafood, which can serve as a source of human exposure.
    - Polycyclic Aromatic Hydrocarbons (PAHs) are a group of air toxics formed from the incomplete combustion of organic materials. They are often associated with combustion processes like those in vehicle exhaust and industrial emissions.

   - Other examples include dioxin, asbestos, toluene, and metals such as cadmium, chromium, and others.

Generally, more emphasis is put on assessing air quality outdoors in research and policymaking. While there is an increasing focus on indoor environments, there is still a need for further research. As individuals spend a significant portion of their time indoors it is necessary to assess air pollution indoors. Indoor air quality is influenced by specific pollutants, which can be traced back to various sources, as evident in Figure 2.

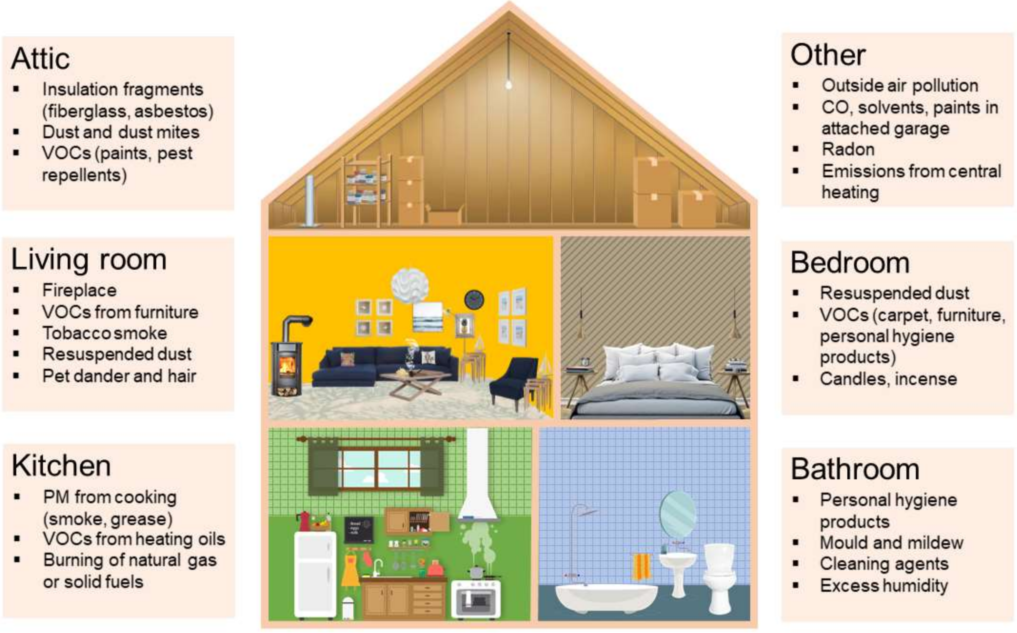

Figure 2: Infographic presenting a variety of indoor air pollution sources.

PM sources are separated into primary and secondary PM. Primary PM often originate from cooking, biomass heating, tobacco smoking, washing, cleaning, and other indoor activities, while secondary PM infiltrate from the outdoor environment or are generated due to chemical reactions between indoor and outdoor sources (Zhang et al. 2021). VOCs find their way indoors through sources like building materials, household products, and even outdoor air infiltration. The emission of VOCs from these sources depends on various factors. For example, elevated temperatures lead to increased initial acetaldehyde emissions and expedite the decline in subsequent emissions, while higher humidity levels are associated with greater emission factors (Jin et al. 2023; Suzuki et al. 2014). Indoor CO primarily originates from combustion sources such as cooking and heating appliances, while in developed countries, the main source of exposure is faulty, improperly installed, or poorly maintained fossil fuel-burning appliances, as well as outdoor air infiltration (Penney et al. 2010). NO_2, influenced by both indoor sources like poorly maintained fuel-burning appliances and outdoor factors, plays a significant role in indoor air quality, with potential for elevated occupational exposures in specific settings, such as accidents involving diesel- or propane-fuelled ice resurfacing machines and underground parking garages (Jarvis et al. 2010). Indoor environments are diverse and frequently changing, which makes the composition and nature of indoor air pollutants complex and challenging to measure and assess.

1.2 Airborne Particulate Matter

Airborne particulate matter (PM) is the main urban environmental stressor considered in this work. Estimates suggest that 96% of the urban population in the European Union is exposed to levels of fine particulate matter above the World Health Organization (WHO) guidelines (European Environment Agency 2023b). PM is regarded as a pollutant of high concern for two reasons: 1) being the pollutant with the largest impact on public health, and 2) ranking high among avoidable causes of non-communicable diseases (Harrison 2020). Particulate matter (PM) represents a broad group of airborne organic and inorganic particulates. Inhalable PM represents particles with a diameter <10 µm, and fine PM particles with a diameter of <2.5 µm, capable of reaching the alveoli in the lungs and penetrate into the blood circulation (Jakovljević et al. 2018). Exposure to elevated concentrations of PM is associated with an increased adverse effect on cardiovascular and respiratory diseases, and increased morbidity and mortality (Anderson, Thundiyil, and Stolbach 2012). Composition of the particles, and their impact on health, can vary based on their origin as summarized in Kim et al. (2015):

- $PM_{2.5}$ (fine particles), composed of sulphate, nitrate, ammonium, hydrogen ion, elemental carbon, organic compounds, PAH, metals, particle-bound water, and biogenic organics (Cheung et al. 2011), is emitted by combustion of fossil fuels, transformation of NOx, SO_2, and organics, high temperature processes (Srimuruganandam and Shiva Nagendra 2012), and biological contaminants (Vardoulakis et al. 2020). They can remain suspended for days or weeks (Cheung et al. 2011) and travel for up to 1000 kilometres (Srimuruganandam and Shiva Nagendra 2012).
- PM_{10} (coarse particles) are composed of resuspended soil and street dust, fly ash, metal oxides, sea salt, pollen, mould spores, and plant parts (Cheung et al. 2011). Sources include industrial dusts, (re)suspension, construction, fossil fuel combustion, and ocean spray (Srimuruganandam and Shiva Nagendra 2012). Due to their larger size, they have a lifetime of minutes or hours (Cheung et al. 2011), and can travel up to 10 kilometres (Srimuruganandam and Shiva Nagendra 2012).

Apart from particles with a diameter of 2.5-10 µm (PM_{10}) and 0.1-2.5 µm ($PM_{2.5}$), there is a group of particles with a diameter of <0.1 µm called ultrafine PM or UFP. These are produced via nucleation, condensation, and coagulation from compounds in the gas phase, and cause health concerns due to their ability to penetrate the pulmonary alveoli (Moreno-Ríos, Tejeda-Benítez, and Bustillo-Lecompte 2022). UFP are the least researched among the listed PM size groups in terms of their prevalence, sources, composition and toxicity (Moreno-Ríos et al. 2022). Due to the aforementioned lack of research and consensus, the WHO provides recommended ambient air quality guidelines only for PM_{10} (15 µg/m^3 annual, 45 µg/m^3 24-hour) and $PM_{2.5}$ (5 µg/m^3 annual, 15 µg/m^3 24-hour) (World Health Organization 2021). However, there are no separate WHO guidelines for PM in indoor environments as "there is no convincing evidence of a difference in the hazardous nature of particulate matter from indoor sources as compared with those from outdoors" (World Health Organization 2010). Recently, there have been more calls for countries to set up indoor air quality guidelines and find ways to measure and enforce them (Morawska, Marks, and Monty 2022; Winck et al. 2022). Stricter national guidelines for indoor air quality have proven successful and have lowered average concentrations of $PM_{2.5}$ in China (Q. Xie et al. 2022). On the other hand, measuring exposure to PM in indoor environments is challenging due to multiple factors, e.g., privacy issues, complex microenvironments and sources, and infrequent use of devices to measure AQ (Y. Xie et al. 2022). Individual-level measurements using personal monitors offer a novel approach to assessing exposure and health risks, as demonstrated in Sections 3.4 and 3.5.

1.2.1 Exposure and dose

Exposure, defined as “contact between an agent and a target, where contact takes place at an exposure surface over an exposure period”, measures the concentration of inhalable PM (agent) in the vicinity of a person (target). The official glossary for exposure sciences, developed by the International Society for Exposure Analysis, and expanded upon for the context of this work by the International Programme on Chemical Safety (IPCS), defines several terms used in this work, related to PM exposure (Inter-Organization Programme for the Sound Management of Chemicals and International Program on Chemical Safety 2004; Zartarian, Bahadori, and McKone 2005):

- Exposure assessment: The process of estimating or measuring the magnitude, frequency and duration of exposure to an agent, along with the number and characteristics of the population exposed. Ideally, it describes the sources, pathways, routes, and the uncertainties in the assessment.
- Dose: The amount of agent that enters a target after crossing an exposure surface. If the exposure surface is an absorption barrier, the dose is an absorbed dose/uptake dose; otherwise, it is an intake dose. In the case of a dose assessment of an inhaled agent, the exposure surface is defined as a “theoretical surface at the entrance to the mouth and nose during the exposure duration” (Inter-Organization Programme for the Sound Management of Chemicals and International Program on Chemical Safety 2004). If the estimate is limited only to crossing the exposure surface and not crossing and absorption barriers, e.g., lung surface, it is an example of an intake dose.
- Intake: The process by which an agent crosses an outer exposure surface of a target without passing an absorption barrier, i.e., through ingestion or inhalation. In the case of PM (in this work), the dose assessment only considers crossing an outer exposure surface, i.e., a theoretical surface over the nose and mouth. As referenced in the IPCS risk assessment terminology handbook (Inter-Organization Programme for the Sound Management of Chemicals and International Program on Chemical Safety 2004), it is necessary to make certain assumptions during actual field studies. Among others, that the air in the vicinity of a person’s nose/mouth is assumed to be well mixed, and that a measured concentration (made in the proximity of the person) is assumed to be the exposure at the person’s nose/mouth.
- Activity pattern data: Information on human activities used in exposure assessments. These may include a description of the activity, frequency of activity, duration spent performing the activity, and the microenvironment in which the activity occurs. In this work, activity pattern data was collected using questionnaires and time activity diaries (TADs).
- Exposure model: A conceptual or mathematical representation of the exposure process.

An exposure assessment does not necessarily take into account the amount of the pollutant that enters the human body through respiration. A calculated dose based on an inhalation rate can provide more information on the effect of activities, microlocations, indoor-outdoor exposure and personal characteristics (Faria et al. 2020; Novak et al. 2020; Q. Xie et al. 2022). Although there are differences between individuals, generally, as particle size decreases, the deeper it can penetrate into the human respiratory system.

Penetration and deposition are also contingent on the shape, density and type of the material. Deposition is governed based on four different mechanisms (Darquenne 2020):

- Interception, with particles physically touching the surface; larger particles, fibres.
- Impaction, particles "hitting" a surface at a bend in the airway system; >10 µm diameter, deposited in nose/throat.
- Sedimentation, depositing due to gravitational forces and air resistance; >0.5 µm diameter.
- Diffusion, based on random motions of fine PM, caused by their collisions with gas molecules; dominant form of deposition for <0.5 µm diameter.

Penetration, deposition, and uptake are important considerations in health impact assessments of specific PM sizes. This work does not include health impact assessments and instead uses the definition of dose or intake dose as stated, "amount of agent that enters a target after crossing an exposure surface" (Zartarian et al. 2005), with the agent being PM of different size classes, the target a human individual, and the exposure surface the surface above the nose/mouth. The volume of air crossing the exposure surface per minute is called "minute ventilation". The estimated dose of PM is a function of the concentration of PM and minute ventilation.

Estimating minute ventilation can be achieved using different proxies, e.g., heart rate, breath frequency, power expenditure of Metabolic Equivalent of Task (MET), physical activity types, or combination of methods (Dons et al. 2017). Minute ventilation models generally have a wide range of percent error, often based on a small number of subjects (Greenwald et al. 2019). Models for estimating minute ventilation and their applicability in personal monitor-based research are further explored in Section 3.2. Conceptually, PM dose and exposure are discussed in Section 3.5.

1.2.2 Composition and toxicity of airborne particulate matter

Mass concentrations of PM are not sufficient to provide a comprehensive health outcome assessment. Understanding the health effects of PM relies heavily on its chemical composition, with a focus on polycyclic aromatic hydrocarbons (PAHs) due to their carcinogenicity in many urban and industrial studies; however, recent research highlights the role of other chemical components, like polar organics, in causing cytotoxicity, genotoxicity, or DNA damage, emphasizing the need for further investigation into the chemical specifics of particulate matter (Alves et al. 2023). Ambient PM, with their varied sizes, shapes, surface properties, and chemical compositions from multiple sources, can result in diverse health effects. Research has shown that even PM with the same mass concentrations may have varying impacts on human health, emphasizing the complexity of assessing their effects and the need for enhanced understanding of exposure and health outcomes before specific source or component control strategies can be deemed more effective than targeting PM as a whole (Park et al. 2018). Specifically, research showed highest toxicity for diesel exhaust, followed by burning of biomass, gasoline, and coal, while acknowledging that even at the same mass concentration, the effects of PM on human health are variable (Park et al. 2018).

While taking into account the composition of particles would benefit health outcome assessments, it is difficult to achieve in mobile and diverse settings in indoor and outdoor environments. Moreover, assessments made based on samples taken throughout a longer period of time do not capture the fine-grained variations in a complex environment.

1.3 Personal Monitors

Personal monitors encompass a wide range of devices, referring to low-cost devices/sensors/monitors with one or more of the following characteristics: miniaturized, wearable, portable, carriable, personal, or individual (Fanti et al. 2021). As discussed in Fanti et al. (2021), the term “low-cost sensor” is not clearly defined and unanimously agreed upon in the scientific community. While the name itself provides some information, it can be understood differently based on the financial resources of the entity (researcher, research group, institute, organisation) discussing the devices. Monitoring devices could be grouped based on their cost in three categories: reference-grade, research-grade, and low-cost. A simplistic look would be to define low-cost devices with a price tag of 1- to 3-figure values (in EUR or USD), research-grade with 4- to 5-figure values, and reference-grade with ≥5-figure values. These three categories with some basic characteristics are shown in Figure 3. This work uses the working definition of “low-cost” as having a considerably lower cost than reference-grade, and lower cost than research-grade, and that a single unit does not impact the monitoring budget considerably (Ruiter et al. 2020).

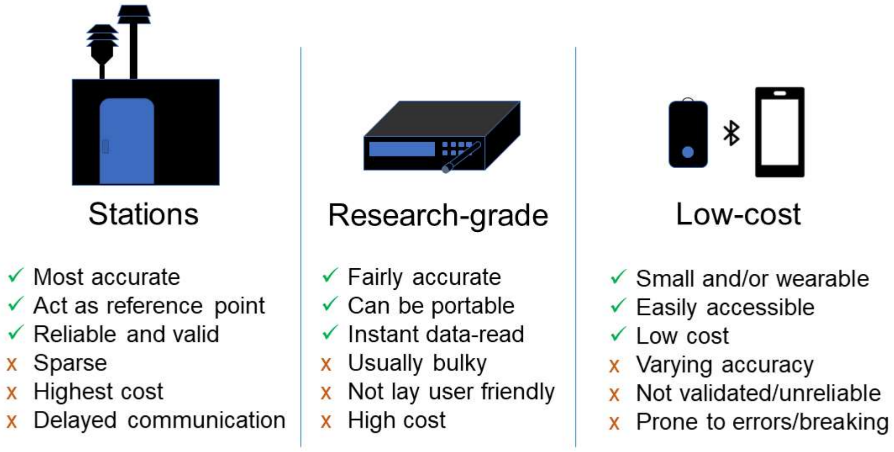

Figure 3: Monitoring devices, grouped based on their cost. Basic strong points and deficiencies are listed for each group, based on the research described in this work.

Personal monitors equipped with low-cost sensors have become useful tools for assessing exposure to a wide range of pollutants, including particulate matter, and gaseous pollutants, e.g., NO_2, CO, O_3, and VOCs. Personal monitors measuring gaseous pollutants typically employ various measuring mechanisms such as electrochemical sensors, metal oxide sensors, or semiconductor sensors. Electrochemical sensors, for instance, are commonly used for detecting gases like CO and NO_2. These sensors function by measuring changes in electrical current when gases come into contact with specific electrodes. Research has shown that they are generally suitable for typical air analysis but are sensitive to humidity extremes, prone to drying out in low humidity or bursting in high humidity, and their signal outputs are influenced by various external factors beyond the specific compound of interest (Cämmerer et al. 2020). Metal oxide sensors are effective in detecting VOCs and work based on changes in the electrical resistance of a metal oxide layer when exposed to target gases. Their limitations include high limits of detection as well as poor sensitivity and selectivity (Isaac, Pikaar, and Biskos 2022). Semiconductor sensors are employed for various gases, including O_3 and NO_2, and rely on changes in electrical conductivity in the presence of specific gases. While these low-cost sensors may have limitations in terms of accuracy compared to reference-grade instruments, they offer a practical means of monitoring personal exposure to gaseous pollutants in real-time.

To enable the use of low-cost devices in broad applications, their performance and accuracy have to be evaluated. Different methods have been developed, which can be tailored based on the proposed use of a specific device, e.g., static comparison with reference instruments, controlled chamber test, and mobility tests (Languille et al. 2020). A common approach is to compare the results obtained from the low-cost device with a reference instrument. Ideally, the two devices should be in the same location or co-located. Moreover, the period for consistent calibration of sensors varies by type, and is influenced by factors like environmental settings, cross-sensitivities, reference instruments, and the final analysis or modelling (Kang et al. 2022). The most effective calibration periods encompass diverse environmental conditions, potentially achieving accurate calibration in as little as one week, emphasizing the importance of strategic selection and monitoring to minimize co-location time (Levy Zamora et al. 2023). Controlled chamber tests offer the option to set specific environmental and meteorological conditions, and known concentrations of pollutants, and observe the response from low-cost devices. Evaluation chambers have been developed specifically for testing low-cost and miniaturized sensors in controlled environments (Omidvarborna, Kumar, and Tiwari 2020; Papapostolou et al. 2017). Low-cost personal monitors are often designed to be mobile, being attached to a moving object or worn/carried by an individual. The varying conditions in air flow and movement can impact the performance of the sensors and the outputs. Testing in mobile conditions offers an insight into how the sensors are affected. This process frequently involves comparing the results obtained during movement with near-by reference monitoring stations (Chen et al. 2022; Hassani et al. 2023)

Using personal monitors to provide accurate enough, fit-for-purpose PM exposure assessments is a recently developed approach. While such devices were available in the 1990s and 2000s, recently they have seen considerable improvements in their accuracy, reliability and a decrease in cost. This has led to a transformation from their use for few specialized applications, to a broadly applied tool used to assess PM exposure in a variety of environments and applications. A shifting paradigm from measuring air pollution (and exposure) solely with governmental reference stations to assessments incorporating low-cost devices has been recognized by the U.S. EPA and EU EEA in the past decade (Borrego et al. 2015; Morawska et al. 2018; Snyder et al. 2013).In general, low-cost PM sensors operate by utilizing the light-scattering principle – light intensity of the infrared/red light reaching the phototransistor is modulated by the presence of particles in the light path (Giordano et al. 2021). The components and design of the device impact the intensity of the modulation, influencing the performance of different sensor models. Commercially available sensors often employ a laser or LED source and photodiode to estimate particle concentrations using algorithms to convert scattered light into particle concentrations (Kaur and Kelly 2023). This method, when used in miniaturized low-cost sensors, can lead to erroneous data. However, biases and calibration dependencies can be corrected using meteorology, sensor age, aerosol source, particle composition, refractive index, and others (Giordano et al. 2021). While several possibilities exist to calibrate and validate sensors, this is not frequently exercised in projects/research (Chojer et al. 2020). A method of validating a low-cost sensor is described in Section 3.2, based on co-locating the device with a research-grade monitor. Personal monitors can serve a variety of purposes, taking into account the drawbacks of the devices and incorporating validation and calibration techniques.

1.3.1 Personal monitors in citizen science

The nature of their low cost and small size makes personal monitors more accessible to be used in large participant-based studies, including citizen science (CS). Although the strict definition of CS is not uniformly defined, in a broad sense it can encompass different approaches of engaging the general public in scientific tasks (Haklay et al. 2021; Vohland et al. 2021). It is often interchangeably used with numerous other terms. However, as referenced in Robinson (2022), there is a wider consensus forming on the nomenclature used in this kind of research. Haklay (2013) proposed a four-tiered system of describing research with non-expert volunteers: 1) crowdsourcing, where participants passively collect data, 2) distributed intelligence, with participants having some input in interpretation, 3) participatory science, with participants contributing to defining problems, and 4) extreme CS, where participants are involved in all aspects of research design, implementation, and analysis. While the overarching term "Citizen Science" is used to describe a range of approaches, specific projects and research should be appropriately labelled based on the level of participant involvement.

When instruments are handled by numerous lay individuals in CS projects, there is a high risk of unintentional damage to the device and/or components, user errors, reduced functionality, etc. A lower cost, with incorporated redundancies, makes them easily replaceable. Moreover, several options exist to construct the devices with a do-it-yourself (DIY) approach, enabling repair and upgrades of the device at different stages of the research. These aspects make personal monitors uniquely suited for engaging young children, i.e., primary school pupils, in CS projects (Kocman et al. 2020), raising their awareness of air pollution and encouraging them to adopt positive behaviour changes [45]. Connecting pupils at an early stage in their education with monitoring and sensing devices for urban stressors can equip them with the necessary tools and knowledge to be more involved in CS projects in the future.

CS, concerning air pollution and exposure to PM, often uses personal monitors with integrated low-cost PM sensors. In such cases, user perspectives should be considered. Research shows successful data harvesting as an important aspect of user involvement and motivation, though it frequently fails when using personal monitors (Robinson et al. 2018). A co-creative approach to designing and operating personal monitor-based exposure research should incorporate user-experience and user input when designing research protocols. Moreover, when personal monitors are applied in community-based CS, the community itself should be involved at all stages, limitations and benefits have to be clearly communicated, and study challenges addressed promptly (Commodore et al. 2017). The integrated assessment of personal monitor applications for evaluating exposure to urban stressors in Section 3.1 explores these approaches in depth and provides recommendations.

1.4 Data Collection and the ICARUS Project

Assessing PM dose models in Section 3.2, building classification models in 3.3, evaluating the importance of indoor and outdoor AQ in exposure assessments in 3.4, comparing real-world data with agent-based model results in 3.5, and demonstrating the harmonization and visualization protocols for large-scale projects in 3.6 was based on a large quantity of data. The majority of data used in these sections had been collected in the scope of the ICARUS (Integrated Climate forcing and Air pollution Reduction in Urban Systems) Horizon 2020 project, active from May 2016 to October 2020. Additional information is available on the project website https://icarus2020.eu/, including the following general description: "*The project applied integrated tools and strategies for urban impact* *assessment in support of air quality and climate change governance in EU Member States leading to the design and implementation of appropriate abatement strategies to improve the air quality and reduce the carbon footprint in European cities"* (ICARUS2020 2020). In the scope of the project, participants collected data, gave feedback on their experience, took part in a focus group, and collaborated in designing the result reports for participants. According to Robinson (2022), and based on Haklay's hierarchy, the listed activities place ICARUS on Level 3 – Participatory science. One phase of the project included two seasonal data collection campaigns that took place in 7 European cities (Athens, Basel, Brno, Ljubljana, Madrid, Milan, Thessaloniki) (Kocman et al. 2022; Sarigiannis and Karakitsios 2018). Ethical approval for the ICARUS project in Slovenia was obtained from the National Medical Ethics Committee of the Republic of Slovenia (approval No. 0120-388/2018/6 on 22 August 2018) and informed consent was obtained from all subjects involved in the study. As referenced in Kocman et al. (2022), where a detailed description of the methodology is available, the ICARUS campaigns had three specific objectives:

- i) collect data on external environmental exposure and exposure determinants by combining location, activity and air pollution data in different micro-environments,
- ii) demonstrate feasibility of using new sensor and mobile technologies in collecting exposure data, and
- iii) analyse and compare exposure data in several different European cities.

Each campaign had up to 100 participants collecting data with low-cost wearable and stationary devices. Sensors selected for the ICARUS campaign had to fulfil several criteria: 1) AQ sensors had to collect ancillary data, e.g., temperature, humidity, location, 2) the devices had to be portable and reliable, 3) performance of the device had to be previously independently evaluated and reported, 4) the device had to be low-cost, according to the project budget, 5) high-resolution data collection, and reliable storing and transmission was required, 6) it had to be unobtrusive to the wearer and robust, and 7) user-friendly for non-scientifically trained individuals (Kocman et al. 2022).

Additionally, each individual (and household) filled out an extensive questionnaire about their lifestyle and living environment, and reported data on their daily activities by filling out one Time Activity Diary (TAD) per day. Personal demographics, living habits, health and socio-economic information were collected in the scope of the questionnaire for individuals. The household questionnaire concerned the dwelling type and other specifications, e.g., ventilation, heating. Information on the immediate surroundings of their household and the local area were also collected, e.g., traffic, noise, possible sources of pollution. The TAD allowed inputs with hourly resolution for four categories:

- microlocations: indoors home, office or other, and outdoors home, office or other;
- in transit: bus, car, motorbike, bicycle, foot, other;
- activities: indoor resting, sleep, playing, sports, cooking, smoking, cleaning, and outdoor running and sports;
- house conditions: burning candle, lit fireplace, open windows or turned-on AC/fan.

1.4.1 The Ljubljana ICARUS campaign

Sections 3.2, 3.3, 3.4, 3.5, and 3.6 are based on data collected in the city of Ljubljana, Slovenia, in the scope of the ICARUS sampling campaigns. Sampling in Ljubljana took place between February 2019 and May 2019. The first campaign, labelled as winter/heating, was held in February and March, while the second campaign, labelled as summer/non-heating, took place in May and June. Two distinct periods were selected to capture seasonal variation.

The city of Ljubljana, situated in a subalpine basin, is affected by a combination of local and remote influences. Complex surrounding topography and the associated drag, extended periods of anticyclonic conditions, and a unique concave shape, result in calm meteorological conditions during colder months with persistent temperature inversions, resulting in a build-up of locally sourced emissions (Kikaj, Vaupotič, and Chambers 2019). This phenomenon is further described in Section 3.4. A distinct winter/non-heating campaign in Ljubljana was necessary to assess exposure/dose under the aforementioned conditions. There were 82 participants involved in the Ljubljana campaign, with 75 participants (49 households) in the winter/heating campaign, and 78 (46 households) in the summer/non-heating campaign. A heatmap of the geographic distribution of all the participants in the Ljubljana ICARUS campaigns is shown in Figure 4. The discrepancy in the number of participants and households is due to (1) some participants from the first campaign opting out of the second campaign, and (2) family members of the participants already involved in the winter campaign joining the summer sampling campaign. Kocman et al. (2022) list several reasons stated by participants for leaving the campaign: limited number of devices, lack of time, and unsatisfactory user experience. Additional information on the campaign in Ljubljana can be found in Robinson (2022).

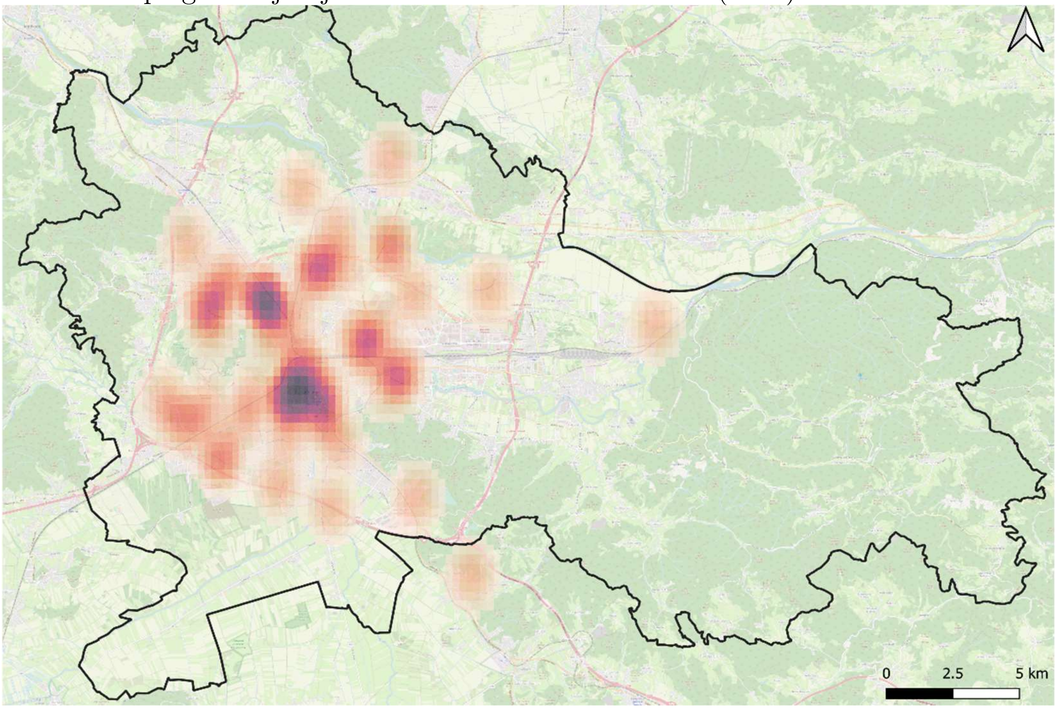

Figure 4: Heatmap of the geographical distribution of households of participants in the ICARUS campaign in the Municipality of Ljubljana (black line).

1.4.2 Personal monitors used

Three low-cost devices were selected based on the ICARUS criteria. Two wearable personal monitors were used, a wrist-worn Garmin Vivosmart 3 Smart Activity Tracker (SAT), and a project-built portable Arduino-based low-cost personal monitor (built by IoTech Telecommunications, Thessaloniki, Greece), labelled as the PPM (Personal PM monitor). One stationary device was set up in each household, the uHoo Indoor Air Quality monitoring station (IAQ). An overview of the functionality and build of the devices used is available in Table 1.

Table 1: Details on the functionality and build of the ICARUS WP4 personal monitors.

Device	**SAT**	**PPM**	**IAQ**
Mobility	Wrist-worn/Wearable	Portable	Stationary
Placement	Personal/individual	Personal/individual	Household
Temporal resolution	1 minute (at full minute)	1 minute (approximately every 60 seconds)	1 minute (at full minute)
Provided data	Heart rate, MET, sleep level, activity type, intensity, steps, distance, kcal, stress	PM_1, $PM_{2.5}$, PM_{10}, temperature, relative humidity, location coordinates, speed, altitude	CO, CO_2, VOCs, $PM_{2.5}$, O_3, NO_2, temperature, relative humidity, air pressure
Data storage	Internal storage for 14 days on device; Garmin cloud storage	Internal SD card, IoTech cloud storage	uHoo cloud storage
Access to data	Via ICARUS portal	Via IoTech cloud and ICARUS portal	Via uHoo cloud
Connection protocol	Bluetooth	GSM	Wi-Fi
Water/dust resistant	Fully waterproof	Non-resistant	Non-resistant
Battery	Up to 5 days on one charge	Up to 8 hours on one charge	No battery/plugged in electricity at all times
Charging	2 hours	6-7 hours	/

1.4.2.1 The Smart Activity Tracker

The Garmin Smart Activity Tracker (SAT) was used for collecting biometric data, e.g., heart rate, movement. Per the specifications of the Garmin Vivosmart 3, the device is equipped with four sensors: a “Garmin Elevate” wrist heart rate monitor, barometric altimeter, accelerometer, and ambient light sensor.

Two main datapoints collected by the SAT have been used extensively in this work – heart rate, and movement (steps, MET). The SAT measures heart rate by using the photoplethysmography (PPG) optical measurement method, which uses a light source and a photodetector at the surface of the skin to measure volumetric variations of blood circulation (Castaneda et al. 2018). Typically, an infrared light emitting diode or a green LED are used as the light source, the SAT using the latter. A green LED penetrates deeper into the tissue and can provide more accurate measurements. While the wrist is not the only location on the human body where a PPG sensor can be placed, it has become the most common, due to it being inexpensive, highly portable, and convenient to wear (Castaneda et al. 2018). While the use of PPG-based sensors has been extensively analysed and validated, they frequently show contrasting results, often resulting from methodological shortcomings of the applied validation techniques (Sartor et al. 2018). Some suggested improvements for accuracy include accounting for skin tone, obesity, age, gender, physiology, and external factors (Fine et al. 2021), positioning the sensor on the ulnar and radial arteries (Lee et al. 2011) or on the forearm (Shimazaki et al. 2018), and integrating inertial sensors (Hnoohom, Mekruksavanich, and Jitpattanakul 2023; Thomas et al. 2016). Motion artifacts are disturbances in signal acquisition based on movements of the individual wearing the PPG-based device. They can be considered as micro-motions (tapping with finger) or macro-motions (walking), both causing significant fluctuations to the signal (Fine et al. 2021). Tightness of the strap influences the accuracy of the collected signal from the PPG, and accounting for the contact force is necessary to reduce errors (Sim, Ahn, and Doh 2018).

The heart rate sensor is located at the back of the Garmin Vivosmart 3 SAT, facing the wearers skin. Garmin's proprietary software uses data on heart rate (and heart rate variability) to estimate the intensity of physical activity, stress tracking, collecting sleep tracking metrics, respiration rate, calories burned, and other insights. While the heart rate data is collected in per-second intervals, the reported data in the ICARUS campaign is the average heart rate per minute (Lee et al. 2013).

Movement in wrist-worn devices is most commonly detected using a multi-axes accelerometer. Micromachined microelectromechanical systems accelerometers have become ubiquitous in smart activity trackers, sensing the gravitational force on multiple axes. Results from numerous validation experiments have shown that consumer-grade wrist-worn devices with accelerometers produce fairly accurate data, under certain circumstances (Lin et al. 2018). Crucially, slow walking speed can produce less reliable data, more prevalent among older adults (Svarre et al. 2020; Tedesco et al. 2019a). Clinical application of these devices should be more thoroughly assessed based on the aims of the specific study (Lai et al. 2020; Tedesco et al. 2019b). In non-clinical applications, such as the ICARUS sampling campaign, this issue can be considered less relevant, as it does not specifically focus on older individuals. Moreover, the winter and summer sampling campaigns in Ljubljana included 3 and 4 older adults (age >65 years), respectively.

Validation studies have shown that the Garmin Vivosmart series devices record, in general, accurate fit-for-purpose data (Dorn et al. 2019; MONTES et al. 2020; Wahl et al. 2017), even in physical activity estimates in older adults (Briggs et al. 2021; Chow and Yang 2020). Some caution is advised when considering energy expenditure data (Passler et al. 2019; Reddy et al. 2018), and during constant high vigorous activity (athlete) (Pasadyn et al. 2019).

Each participant in the ICARUS sampling campaigns received one SAT, selected from two size classes based on their gender and age. They were instructed to strap the device on their dominant hand and fasten it as tight as possible, while still comfortable. Prior to the first visit when the participants received the devices, their personal data (gender, age, height, weight) was acquired and input in the SAT. Participants were given a charger for the SAT and instructed on how to charge the device in case the battery drained before the end of their data collection period. The SAT had approximately 5 days of battery life. All the data the participants collected was stored on the device, and at the end of the collection period uploaded to the Garmin server by a field worker/researcher. Data transfer to the server was possible via a USB charging cable or a Bluetooth connection to a smartphone with an installed Garmin Connect application. Participants had no access to their data during the data collection period, and did not have the Garmin Connect application installed on their smartphones.

Several issues with the SAT were discovered during the data collection campaigns. While the participants were instructed to tightly strap the device, in some cases this was not strictly followed. In such cases the SAT was not able to collect heart rate data, as the sensor was not close enough to the skin. The movement data was recorded. Moreover, as the device only stored data locally, the researcher team did not have information if the device is functioning correctly and collecting data, until it was connected to the server. Without this information field workers/researchers were not able to intervene if the devices malfunctioned or were not used correctly.

1.4.2.2 The Personal Particulate Matter monitor

The Personal Particulate Matter monitor (PPM) was primarily used to collect geographical location and PM concentration data. Additionally, ambient temperature and relative humidity data was collected. This project-built device comprised multiple components and was based on the Arduino platform.

The main component was a Plantower pms5003 sensing unit, produced by the Nanchang Panteng Technology Co., Beijing, China, shown in Figure 5. This sensor is a nephelometer, using the light scattering principle, as described in Section 1.3, to estimate particle size and mass concentration in real time. Generally, low-cost optical sensors follow a similar concept, where a fan draws particles into a beam of light illuminating particles as they pass through, with scattered light being recorded on a photodetector and converted into an electrical signal. Sensors using this principle to assess PM concentrations are collectively referred to as optical particle sensors. The pms5003 collects the data from the photodetector and counts the number of particles based on a bin or particle size class, e.g., aerodynamic diameters between 2.5 µm and 10 µm. The particle mass for each size class is estimated after particle numbers are collected for all the bins. All optical particle sensors have to make certain assumptions, such as the size and composition of the particle, which can make them less accurate and more dependent on frequent calibrations.

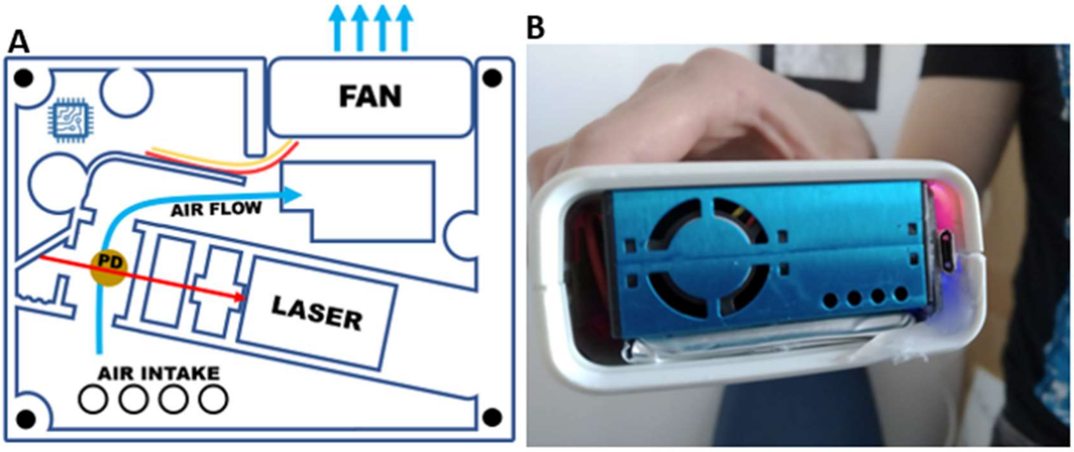

Figure 5: (A) A schematic representation of the pms5003 sensor. The image shows the airflow through the device, passing through the sensor, where the photodiode (PD) detects particles, and exiting the device via the fan. (B) Photograph of the pms5003 placed in the PPM. The four holes on the right bottom side od the sensor represent the air intake. The micro-USB port on the right side of the PPM is used for charging the battery.

The pms5003 has been repeatedly used in wearable/portable and stationary AQ measuring devices. Inputting the search term “pms5003” in Scopus produced 83 hits (4 May 2023), with papers spanning from 2017 to 2023. Although this does not capture all research using the pms5003 sensors, as papers in some cases describe the sensor as “the Plantower PM sensor”. The most widely used commercial personal monitors with an integrated pms5003 sensor is the PurpleAir Classic outdoor Air Quality monitor, with thousands of devices placed in various locations around the world contributing to a real-time map, available online (PurpleAir 2023). When the term “PurpleAir” is added to the search terms, 95 results come up, though newer iterations of the device use next generations of Plantower sensors. As the sensors have been extensively used and deployed, there is a large body of research evaluating their use and validating the data accuracy.

The pms5003 has shown fairly accurate results in short-term and long-term laboratory and field evaluations. Field tests have repeatedly shown pms5003 sensors having moderate to high correlation with reference instruments, and high inter-sensor correlation (Bulot et al. 2019; Cowell et al. 2022; Masic et al. 2020). Results from long-term evaluations are somewhat conflicting, showing little to no drift (Connolly et al. 2022; Masic et al. 2020), and others recommending bimonthly calibration to account for drift in conditions with high average humidity (Cowell et al. 2022). Moreover, all field evaluations demonstrate the influence of high relative humidity on the results of the sensor. Indoor and laboratory evaluations come to similar conclusions, with the pms5003 having a moderate to high correlation with reference instruments. Some exceptions are noted for high relative humidity (Suriano and Prato 2023), smaller particles (<0.3 µm) (Singer and Delp 2018), larger particles (>2 µm) (Molina Rueda et al. 2023), and for PM concentrations of >100 µg/m^3 (Park et al. 2023). Measuring the accuracy under controlled conditions in a clean room, and exposed to cigarette smoke, showed good agreement with reference instruments and between sensors, and an improvement when results from different models of sensors were combined (Bulot et al. 2020). Research has demonstrated that the pms5003 can be used for purposes beyond measuring PM concentrations, i.e., for bioaerosol monitoring (Priyamvada et al. 2021).

Due to the sensor’s low cost, small size, extensive use in research, and accurate data, it has been deployed in various community and participatory-based projects and research. A common use of the sensor is to integrate it into Do-It-Yourself (DIY) stationary devices capable of continuous measurements of PM concentrations. These devices are mounted on urban furniture or other infrastructure and used to collect PM concentration data in the local environment. The lower cost makes them more accessible to developing countries and can provide useful information to local communities and decision makers (Gryech et al. 2020; Lassman et al. 2020). Moreover, the use of these devices has been demonstrated in CS applications to improve estimates of air quality based on satellite data (Ford et al. 2019) and improve sensor accuracy with community-maintained sensors (Connolly et al. 2022).

The PPM, with an integrated pms5003 sensor, was provided for each participant in the ICARUS campaign for the duration of their sampling period. A micro-USB charger was provided to each participant. In a smaller repeat sampling campaign, described in Section 3.3, an additional battery (power bank) was provided. The device functioned between 6 and 8 hours and needed 3-4 hours to charge to full capacity. Participants were instructed to charge the device whenever possible, i.e., the participant must be close to the device at all times and have an electrical outlet or USB port nearby. During movement from room to room, indoor and outdoor, and when commuting, the participants affixed the PPM on their clothes or other personal item, e.g., backpack or handbag. All the collected data was stored on the internal SD card and simultaneously uploaded to a server via GSM network. This offered a real-time status check of each device. After the data collection campaign ended, the PPM was collected from the participants and the data from the SD card uploaded to a local device. In this case, same as with the SAT, the participants did not have access to the data in real-time. However, all participants received an extensive personal report, based on the data they collected, described in detail in Section 3.6. A detailed description of the PPM design, testing, and deployment was provided by Chapizanis (2019).

A DIY approach provided numerous customization options to design the PPM based on the goal of the project. However, it was not feasible to go through extensive testing, regarding repeated use, user- and researcher-friendliness, and other related features. Some devices frequently stopped working, consequently producing numerous data gaps. Researchers and field workers were frequently tasked with informing participants when the device malfunctioned, prompting them to reset the device or find a better GSM signal. This inconvenienced the participants and required more time and effort from the researchers. Further reading on these aspects is available in Robinson (2022). A relatively short battery life required frequent charging. When participants forgot to charge the PPM, it led to more data gaps. The pms5003, which also had an integrated temperature and relative humidity sensor, was affixed on the battery. Charging caused the battery to heat up, which led to some anomalies in the recorded data during the first few minutes. This issue if further elaborated in Section 3.2. Moreover, intense movements, e.g., during running, sometimes caused the device to stop working. Due to its size, it was also somewhat obtrusive to the wearer and difficult to attach securely during sporting activities. Inconsistent time stamps required rounding to the nearest minute to harmonize with the other collected data.

1.4.2.3 The uHoo Indoor Air Quality monitoring station (IAQ)

The uHoo Indoor Air Quality (IAQ) station was a multi-sensor stationary device, placed in each participating household in the ICARUS campaign, to assess indoor air quality. It measured ambient temperature and relative humidity, air pressure, and concentrations of $PM_{2.5}$ and various gases (CO_2, NO_2, CO, TVOC, and O_3). This work utilizes the data collected with the IAQ in Section 3.6, where it was included in the individual reports to participants. While the IAQ data was not used as extensively as the SAT and PPM data, a brief overview of the functionalities, accuracy, and drawbacks of the device is included in this section.

A frequently cited report of a field evaluation of the IAQ was conducted by the Air Quality Sensor Performance Evaluation Centre in CA, USA, in 2017 (Air Quality Sensor Performance Evaluation Center 2017), approximately 1 year after the commercial deployment. These results showed poor performance of the $PM_{2.5}$ and CO sensors, and fair-to-good performance of the O_3 sensor. Our own rudimentary validation experiments for $PM_{2.5}$ in 2019 produced similar results. Future software updates claim to have improved the sensor accuracy. Importantly, as with most other commercial personal monitors, the uHoo was not designed to be used as a research-grade reference monitor for indoor air quality. A recent evaluation of the uHoo by Baldelli (2021) showed an improved performance and good-to-excellent correlation with reference devices for all measured AQ parameters in a laboratory environment (R^2 of 0.98, 0.97, 0.99, 0.96, 0.99, and 0.82 and r_s of 0.98, 0.99, 0.90, 0.92, 0.98 and 0.57 for $PM_{2.5}$, CO_2, CO, NO_2, TVOC (ethylene), and O_3 respectively). The same experiment showed good correlation (uHoo to reference instrument) of $PM_{2.5}$, CO_2, and O_3 in a real indoor place, although lower than in laboratory conditions. On the other hand, other experiments have shown poor performance of the IAQ in terms of measuring $PM_{2.5}$ concentrations, specifically for low concentrations of $PM_{2.5}$ (<10 µg/m^3) and smaller sized particles (Demanega et al. 2021). The PM sensor used in the IAQ (Shinyei Kaisha PPD42-60) has shown inconsistent performance in field tests (Johnson et al. 2018). Two key differences between the Shinyei and Plantower sensors are the light source and air flow function. As described in Section 1.4.2.2, the pms5003 uses a red laser diode and a fan that draws the air in the sensor. On the other hand, the PPD42 uses a “classical” light emitting diode and a power resistor that heats the surrounding air generating air flow (Canu et al. 2018). These simplified functionalities lower the cost of the PPD42 (10 to 15 USD), compared to the pms5003 (30 to 40 USD).

The uHoo IAQ has not been as extensively utilized in research as the SAT and PPM. A home telemedicine system for continuous respiratory monitoring was developed that integrated the uHoo device (Angelucci, Kuller, and Aliverti 2021). It was used to continuously measure indoor AQ in the homes of chronic respiratory patients. An application of the uHoo to measure AQ in a gastrointestinal endoscopy unit in a hospital setting has reportedly shown promising results for health-related protective strategies (Bang et al. 2020). Moreover, it had been used to detect poor indoor AQ in warehouses (AlKheder et al. 2022) and estimate exposure to airborne allergens from mice and rats (Baldelli et al. 2020). A MSc thesis on the topic of the influence of indoor AQ on students' academic performance utilized the uHoo and showed a positive relationship between indoor AQ and perceived quality of learning (de Boer 2022). On the other hand, the author acknowledged that the $PM_{2.5}$ did not correlate with other PM measuring equipment and that TVOC values were constant and did not change "no matter what happened around it" (de Boer 2022). While these examples are few, spread out through different applications, and were conducted in different years, they show that the IAQ can be used for certain fit-for-purpose indoor AQ monitoring applications.

Each household in the ICARUS campaign was assigned one IAQ, which was installed by a field worker during the first visit. Prior to the installation, one of the participants from the household had to confirm that there was an available Wi-Fi network. The participants could communicate the password to the field worker or input it themselves, if they did not wish to share it. Participants and the field worker together decided on the room where the device should be placed. The selected room had to be one which all the household members use and was most frequently used. This was often a living room or an open space combining a living room, dinning rom, and kitchen. After the device was installed, the data stream to the uHoo server was checked. The participants were instructed not to interact with the device in any way, unless instructed by the research team. When the sampling period was finished, the device was unplugged and removed from the household. The data was downloaded from the uHoo server to a local device and harmonized with all the other data, as described in 3.6.

Users described the IAQ device as "unnoticeable, non-disturbing, unobtrusive, and something that is plugged in and forgotten" (Robinson 2022). Moreover, the installation was quick and straightforward, the data was easily accessible, and a real-time status check possible in the smartphone app for the research team. Additional options were available to set notifications if the device recorded elevated concentrations or stopped working. On the other hand, the device required a constant connection to the Wi-Fi network that was assigned during installation. When the Wi-Fi connection failed, no data was recorded. Similarly, the IAQ did not record data when there was no electrical power. An improvement to the device would be a small battery (as the device uses little power) and an internal data storage. During a week-long sampling campaign, the IAQ produced around 10 MB of data. A small data storage could store a considerable amount of data, which would be uploaded once the connection is restored. These issues produced numerous data gaps.

Chapter 2

Hypothesis and Aims

The purpose of this dissertation is to:

(a) assess the overall usefulness and applicability of personal monitoring devices and technologies in individual-level exposure assessments in urban environments,
(b) evaluate their accuracy by comparing their performance with the reference research-grade monitors and assess their output in real-world applications,
(c) develop and implement automated procedures and tools for fusion, harmonization and visualization of data coming from diverse data streams,
(d) determine the applicability and accuracy of advanced data analysis techniques, e.g., machine learning methods, in exposure assessments, and
(e) compile a comprehensive assessment of individual-level exposure to indoor air pollutants and assess relative contributions of various activities and time spent in specific microlocations, using personal monitors with participants under real-world conditions.

The outcomes of this research offer a comprehensive overview of the feasibility of individual-level exposure assessments and a roadmap to conduct this process, while considering advantages and the drawbacks of these technologies. These results provide insights into the applications of personal monitors in urban environments, and additionally how communication is customized and adapted to different stakeholders involved.

2.1 Aims

- Select, test, collocate and validate the appropriate personal monitors for urban stressor exposure and airborne particulate matter intake dose assessments.
- Deploy personal monitors in a proof-of-concept exposure assessment campaign, including collecting and harmonizing the data coming from multiple data streams.
- Determine the feasibility of machine-learning-supported data analysis in exposure assessments.
- Develop a method for an integrated personal monitor-based multi-sensor urban stressor exposure and airborne particulate matter intake dose assessment.

2.2 Hypothesis

Hypotheses tested as part of this dissertation, based on data collected by personal monitors for the assessment of individual-level exposure to air pollutant and other urban stressors:

1) Personal monitors offer adequate accuracy compared to research-grade reference instruments and are fit for exposure and intake dose assessments on an individual level.
2) Machine learning can be used to accurately classify manually logged activity and micro-location self-assessment data.
3) In real-world conditions, increased exposure to air pollutants is dominated by relative contributions resulting from a few specific activities and microlocations only.
4) Higher-resolution temporal and spatial data provides an improved and more detailed assessment of an individual's exposure to air pollutants.
5) Intake dose of airborne particulate matter is dependent on physical activity and the environment of the individual.

Chapter 3

Scientific Publications

This work consists of six manuscripts of scientific publications. The publications are presented in the order following the development and execution of the dissertation. An extensive scoping literature review is presented in the first publication (Section 3.1), detailing the current state-of-the-art in the field of assessing exposure to urban stressors, using personal monitors. This publication serves as a detailed introduction into the concepts of exposure assessments in urban environments, urban stressors as a risk to human health and wellbeing, types and applications of personal monitors, and engagement with stakeholders and participants. An evaluation of specific personal monitors and a comparison of particulate matter intake dose models are reported in the second publication (Section 3.2). Based on the results reported in this publication and other conclusions from the completed ICARUS sampling campaigns, a machine-learning-based approach for complex human activity recognition is presented as part of the third publication (Section 3.3). The demonstrated approach could improve exposure assessments using personal monitors in terms of accuracy, deployment, data collected, and other aspects. The fourth (Section 3.4) and fifth (Section 3.5) publication report the development and demonstration of different personal monitor-based exposure and dose assessment to particulate matter. Specifically, the fourth publication reports on comparing indoor and outdoor exposure during high-exposure events, i.e., atmospheric thermal inversion. The fifth publication demonstrates a comparison between two approaches to a PM exposure assessment: a stochastic, i.e., agent-based model (ABM), and an approach using environmental, biometric and activity data, collected with personal monitors. Moreover, the fifth publication contains a description of an experiment based on a simplified virtual simulated society. The sixth publication (Section 3.6) focuses on data harmonization, fusion, and visualization used in the compilation of the final participants' report.

3.1 Manuscript 1: Integrated Assessment of Personal Monitor Applications for Evaluating Exposure to Urban Stressors: A Scoping Review

Section 3.1 consists of a scientific review article published in Environmental Research in 2023, authored by Rok Novak, Johanna A. Robinson, Christos Frantzidis, Iliriana Sejdullahu, Marco Giovanni Persico, Davor Kontić, Dimosthenis Sarigiannis, and David Kocman.

This scoping review provides an overview of the current state of research, and gaps and needs in personal monitor applications evaluating exposure to urban stressors. Moreover, recommendations are provided for more integrated, inclusive, and robust approaches in future research. The review explores various approaches of utilizing personal monitors through four evaluation criteria: 1) scope of exposure assessment, 2) stakeholder engagement, 3) involvement of participants, and 4) ethical considerations. The compiled results were analysed by using a waterfall methodology, delineating projects into distinct phases. This approach allowed a systematic identification of gaps and needs in each project/research phase. A graphical representation of the review process and some general results are shown in Figure 6.

The results and conclusions of the review serve as an introduction to the overall topic of using personal monitors for exposure assessments. Specifically, the contents of the review deal with, among others, the types of personal monitors used in research, data collection and harmonization protocols, time-activity profiling, domains of interest, and integration of external data sources. These insights provide a contextual framework for the following sections of the thesis.

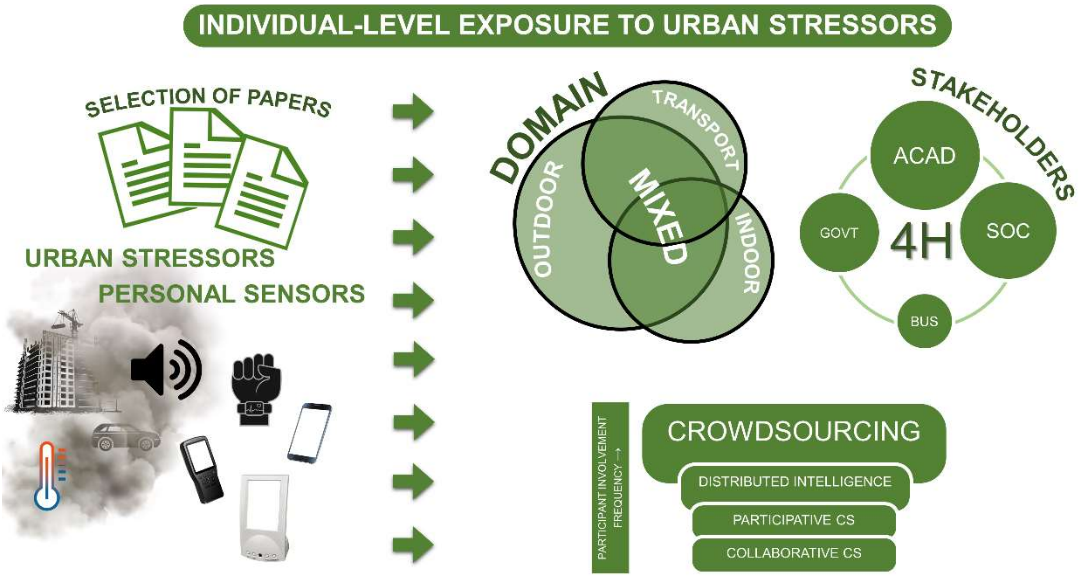

Figure 6: Schematic representation of the review process and general results.

I contributed to the conceptualization of the review, methodological design, the formal analysis and selection of papers, data curation and investigation, design of visualization, writing the original draft, and being involved in the review and editing.

The article was written in the scope of the URBANOME project, specifically based on Deliverable 1.1, entitled: Methodological review paper on the type and use of sensor-based technologies available for personal exposure assessment including which sensors are going to be employed in URBANOME.

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Review article

Integrated assessment of personal monitor applications for evaluating exposure to urban stressors: A scoping review

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ABSTRACT

Urban stressors pose a health risk, and individual-level assessments provide necessary and fine-grained insight into exposure. An ever-increasing amount of research literature on individual-level exposure to urban stressors using data collected with personal monitors, has called for an integrated assessment approach to identify trends, gaps and needs, and provide recommendations for future research. To this end, a scoping review of the respective literature was performed, as part of the H2020 URBANOME project. Moreover, three specific aims were identified: (i) determine current state of research, (ii) analyse literature according with a waterfall methodological framework and identify gaps and needs, and (iii) provide recommendations for more integrated, inclusive and robust approaches. Knowledge and gaps were extracted based on a systematic approach, e.g., data extraction questionnaires, as well as through the expertise of the researchers performing the review. The findings were assessed through a waterfall methodology of delineating projects into four phases. Studies described in the papers vary in their scope, with most assessing exposure in a single macro domain, though a trend of moving towards multi-domain assessment is evident. Simultaneous measurements of multiple stressors are not common, and papers predominantly assess exposure to air pollution. As urban environments become more diverse, stakeholders from different groups are included in the study designs. Most frequently (per the quadruple helix model), civil society/NGO groups are involved, followed by government and policymakers, while business or private sector stakeholders are less frequently represented. Participants in general function as data collectors and are rarely involved in other phases of the research. While more active involvement is not necessary, more collaborative approaches show higher engagement and motivation of participants to alter their lifestyles based on the research results. The identified trends, gaps and needs can aid future exposure research and provide recommendations on addressing different urban communities and stakeholders.

1. Introduction

Poor air quality (hereafter AQ), noise, heatwaves and other environmental urban stressors are associated with 13% of deaths in the EU, air pollution being foremost among these with over 400 000 premature deaths, followed by 12 000 associated with environmental noise

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(European Environment Agency, 2021). In this review, the three environmental urban stressors primarily assessed are air pollution, noise and thermal burdens (causing stress). Dense urban areas are more likely to experience multiple challenges in terms of exposure to urban stressors, from increasing levels of traffic and therefore associated air and noise pollution (Liang and Gong, 2020; Zhang and Batterman, 2013), accommodating tourism and other services with residential use (Wetzstein, 2017), balancing space for efficient transportation and greenspace (Chen and Chang, 2015), developing systems and techniques to tackle the consequences of more frequent heatwaves (Hintz et al., 2018), etc.

Increased concentrations of air pollutants can have detrimental effects on human health, ranging from respiratory and cardiovascular diseases, neuropsychiatric complications, eye irritation, and skin diseases to long-term chronic diseases such as cancer (Ghorani-Azam et al., 2016; Manisalidis et al., 2020). Long-term exposure to particulate matter is related to cardiovascular diseases (Hamanaka and Mutlu, 2018), infant mortality (Manisalidis et al., 2020), and an increased risk of hospital admission for cardiovascular and respiratory diseases (Dominici et al., 2006).

Noise pollution can lead to several negative health effects, such as increased blood pressure and cardiovascular diseases (Münzel et al., 2017), higher levels of stress, and an increased risk for stroke (Münzel et al., 2020). Vulnerable groups, such as children, are more impacted by cognitive effects of noise, and evidence shows that noise exposure in schools can lead to reading and memory issues in children (Kamp and Davies, 2013; Stansfeld and Clark, 2015).

Extreme temperatures can lead to overheating, causing cardiopulmonary problems and increased cardiovascular mortality, disrupted sleep, impaired cognitive performance, and increased risk of suicide and hospital admission for mental illness (Khosla et al., 2021).

Urban stressors are interconnected. For example, due to higher temperatures, ozone levels can rise, increasing cardiorespiratory mortality and morbidity (Tong et al., 2021).

As research on exposure to urban stressors takes place in complex urban environments, it often involves multiple stakeholders and can provide opportunities for stakeholder-based initiatives (Soma et al., 2018). To provide a simplified and more manageable overview, the quadruple helix model is frequently applied (Bellandi et al., 2021). It presents an upgraded version of the triple helix model, as it includes civil society (Roman and Fellnhofer, 2022). The quadruple helix model thus divides stakeholders into four groups – academia and research, civil society and NGOs, businesses and the private sector, as well as government and policymakers (Arnkil et al., 2010). Such an approach provides several options to review the motivations and engagement of each group as well as their interactions.

Recent technological developments have enabled low-cost portable sensors to offer novel insight into exposure to urban stressors on a granular, individual level in multiple domains, which is not achievable with monitoring station networks. Though low-cost AQ sensors have often been subject to poor performance, erroneous data, and other issues, the narrative has been changing in the past few years as the devices become more reliable and accurate (Lewis and Edwards, 2016; Morawska et al., 2018; Giordano et al., 2021). These devices have been widely used in the past decade and provide researchers with affordable and highly customizable tools to collect the data needed for exposure assessment (Chatzitheochari et al., 2018; Leaffer et al., 2019). Their wearability, portability, and generally small size provide the opportunity to collect data in various domains or environments, e.g., indoor (Sá et al., 2022), outdoor (Chatzidiakou et al., 2019), traffic (Motlagh et al., 2021), and greenspace (Mueller et al., 2022). As smartphones have become ubiquitous, researchers often use them as low-cost sensors for noise measurements (Bocher et al., 2017), and they have been shown to provide accurate fit-for-purpose data (Aumond et al., 2017).

When participants use and host the devices that collect the data for exposure assessments and provide additional feedback, the approach begins to verge on citizen science (Oyola et al., 2022). Participants can become even more involved by co-creating research and collaborating in its dissemination. Depending on the level of participation, citizen science projects can be split into four levels: crowdsourcing, distributed intelligence, participative citizen science, and collaborative citizen science (Haklay et al., 2013). With participants becoming more involved and making significant contributions to research, issues of intellectual property and data privacy can emerge (Scassa and Chung, 2021).

The purpose of this scoping review was to identify good practices and concepts in low-cost sensor-based exposure to urban stressors research and to identify gaps (Munn et al., 2018). Therefore, three specific aims were identified for this review:

i) Determine the current state of exposure research, based on individual-level measurements using personal monitors (low-cost sensors and wearables), by using data extraction questionnaires and expertise of the researchers performing the review.
ii) Analyse research with a waterfall methodology, delineating projects into distinct phases. Using this data, gaps and needs will be identified for each specific phase and overall project/research design.
iii) Provide recommendations for developing more integrated, inclusive and robust approaches in utilizing personal monitors to aid exposure assessment, connecting stakeholders and engaging participants in urban areas.

A qualitative and quantitative review was conducted, with papers evaluated based on four general aspects: a) scope of exposure assessment, b) engagement of stakeholders, c) inclusion of citizen science principles, and d) consideration of ethical and intellectual property aspects. This review provides an overview of the current state of research in using personal monitoring devices for providing inputs for exposure assessment to urban stressors.

2. Materials and methods

This section explains the process in selecting the papers for this review, including the specific keywords. Exclusion criteria are listed in section 2.2, which were further employed to select the papers pertinent to the review topic. A PRISMA flowchart is added for a visual aid to the selection process. Section 2.3 describes data extraction, which was conducted with an online questionnaire. The queries were based on four general aspects: scope of exposure assessment, stakeholder engagement, involvement of participants, and ethical considerations.

2.1. *Identification: Selection of papers*

A review of currently available research on the topic of assessing individual-level exposure to urban stressors by using low-cost or next-generation sensors and monitors was conducted. Papers published between January 1, 2004 and August 17, 2021 and collected from Scopus (473) and Web of Science (308) were considered in the first round of reviews. The search queries, delimited by the "AND" Boolean in four building blocks, were as follows:

- observed urban stressors or measured parameters: ("particulate matter" OR "heart rate" OR "movement" OR "activity" OR "GPS" OR "gas*" OR "air*" OR "pollut*" OR "PM" OR "NO2" OR "CO") AND
- mode of data collection, focused on low-cost and wearable devices: ("exposure sens*" OR "mobile sensor node*" OR "low-cost sensor" OR "wrist-worn" OR "wearable sens*" OR "portable sens*" OR "sensor network" OR "crowd sensing" OR "participatory sensing") AND
- centred around exposure and urban health: ("exposome" OR "agent-based model" OR "intake dose" OR "exposure*" OR "urban health" OR "wellbeing" OR "liveability" OR "health concerns") AND
- an urban environment: ("urban*" OR "city" OR "municipality")

2.2. Screening: Titles, abstracts, and whole papers

After the initial title screening, 288 papers remained. Further title and abstract screenings were performed by two reviewers. The exclusion criteria were the following:

- no use of low-cost personal/individual-level or household sensors/ devices or smartphones
- no mention of any urban environmental stressors: gaseous pollutants, e.g., NO_2, CO; particulate matter (hereafter PM) pollution – all sizes from ultrafine particles (hereafter UFP) to PM_{10} or dust; noise; temperature; in relation to green and blue spaces; activity/heart rate connection; etc.
- the study was not applied in an urban setting
- if the focus of the paper was only on occupational health exposures related to an industry sector e.g., agriculture, mining, or manufacturing, and so not in an urban setting
- the use of devices/methods applied only at specific high-exposure events, e.g., music festivals/concerts/dust storms
- description of a device, a design, calibration, etc., without any application, implementation, or use in an urban environment

This step yielded 100 papers. After text screening, an additional 8 review papers and 6 papers not relevant to the topic were removed. In the end, 86 were included in the review , and one paper, describing a specific use of data, was replaced by a paper describing the same project ("Sniffer Bike" (Wesseling et al., 2021)) in greater detail.

The identification of studies is summarized as a PRISMA flowchart (Fig. 1).

In addition to the outcomes resulting from the literature reviewed, several review papers on the topics of sensor technologies, measuring exposure and urban stressors, as well as citizen science and other participatory approaches were considered (see section 4).

2.3. Evaluation and data extraction

The best practices in using low-cost sensors and monitors for exposure assessments were considered. A quantitative and qualitative data extraction was performed using an online questionnaire (Appendix 1). Specific queries were extracted from four evaluation criteria:

- Scope of exposure assessment was reviewed, based on methodological approaches, including the number and type of devices used (Helbig et al., 2021), data collection and harmonization protocols, time–activity profiling, domains of interest (Leung, 2015; Khan et al., 2018) (outdoor, indoor, traffic, etc.), and the integration of external data sources, e.g., earth observation (hereafter EO), monitoring/weather stations. In addition, the involvement and number of participants and geographical and temporal extent were considered.

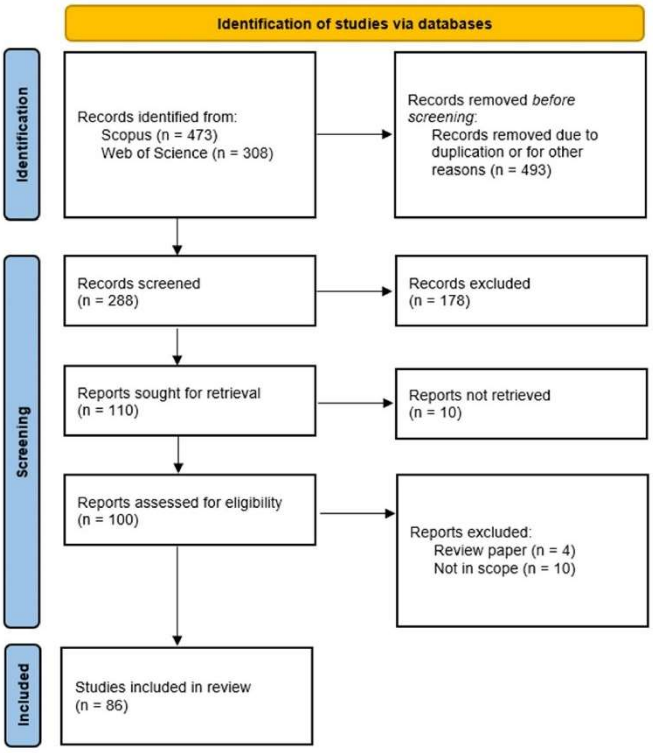


Fig. 1. PRISMA flowchart of paper identification, screening, and inclusion in review (Stansfeld and Clark, 2015).

- Stakeholder engagement was assessed based on the quadruple helix model of stakeholders (Arnkil et al., 2010): (i) academia/research, (ii) society/NGOs, (ii) businesses, and (iv) government/policy-makers. Each paper was assessed on the role and involvement of these groups.
- Involvement of participants was assessed according to four general levels (Haklay et al., 2013): (i) crowdsourcing, (ii) distributed intelligence, (iii) participative citizen science, and (iv) collaborative citizen science. Context on participant engagement and communication was included.
- Ethical considerations were evaluated based on the inclusion of ethics boards, data and privacy protection protocols, and intellectual property aspects (Resnik et al., 2015).

3. Results

This section is comprised of five subsections and details the results of the data extraction and review process. Initially, some general characteristics of the papers are provided, followed by subsection 3.2 exploring the results based on the first evaluation criteria – scope of exposure assessment. Several aspects are analysed, including the devices and methods used, number of participants included and their involvement, domains used in the assessment and data collection and stressors. Subsection 3.3 details the results on stakeholder engagement, based on the quadruple helix model, including the type of stakeholder(s) engaged, their involvement, and any tangible outcomes produced by the project. In subsection 3.4, the results of the review of citizen science and other participatory approaches are presented. These are separated based on four levels of participant inclusion, spanning from a crowdsourcing approach to collaborative citizen science. The last subsection, 3.5, shows different aspects of ethics, privacy, data protection, and intellectual property issues and challenges.

3.1. General characteristics and geographic distribution

Fig. 2 shows the number of included papers by the year the research was conducted (for those that provided this information) and the stressors they addressed, indicating a gradual year-to-year increase of respective studies.

Most of the reviewed studies were conducted in Europe, North America or Asia, as is evident in Fig. 3. This is a trend observed in other reviews and is a consequence of funding and prioritization for urban stressors in Europe and North America, as well as higher degrees of urbanization compared to other regions.

3.2. Scope of exposure assessment and applicability

Within the scope of applicability of exposure assessment approaches, the review focused on 1) the method used for exposure assessments, 2) participants in the study, 3) domains of interest, 4) stressors assessed per domain, 5) any activity data collection, and 6) ancillary data considered.

3.2.1. Method of exposure assessments

The exposure assessment method was determined by the number and type of devices used, by ancillary data (e.g., activity logs, AQ monitoring stations), and by addressed health outcomes.

All papers were evaluated based on the complexity of the exposure assessment and assigned to one of two categories:

- Targeted approach: in general, papers included in this category use a single low-cost device or system, which can include multiple sensors, and calculated exposure to various stressors. The approach can include using smartphones as data collecting devices.
- Extensive approach: employing multiple devices and monitors in combination with activity, microlocation, or other external data sources (e.g., earth observation, near real-time traffic data, AQ data) and measuring environmental and physiological/biometric parameters, such as heart rate, body temperature, movement, and/or others. This level of complexity can include estimates of the intake dose of various pollutants, complex movement-based exposure, etc.

More than half the papers were assigned to the category of targeted approach. The main stressor analysed was air pollution (predominantly PM) due to the severity of the negative effects it has on human health (Varaden et al., 2021; Mousavi and Wu, 2021; Wesseling et al., 2021; Chen et al., 2020; Agrawaal et al., 2020; Brzozowski et al., 2020), as a result of concerns voiced by participants through citizen science approaches (da Schio, 2020), or as a main source of air pollution, e.g., combustion of solid fuels or traffic (Johnston et al., 2019; Coffey et al., 2019). PM measurements were often accompanied with NO_2, CO, CO_2, VOC, and other pollutants (Tan and Smith, 2021; Frederickson et al., 2020; Hanoune et al., 2019; Dam et al., 2017; Valle et al., 2017; Ali et al., 2015; Sm et al., 2019) or with temperature and humidity measurements (Tan et al., 2020; ChewThornburgJackSmithYang, 2019; Boso et al., 2020). Noise was primarily assessed using smartphone apps, observing general and long-term trends (Ghosh et al., 2019; Lefevre and Issarny, 2018), singular events (Zipf et al., 2020), or comparing indoor and outdoor exposure near busy roadways (Leao et al., 2014).

In terms of tools employed to measure the (environmental) burden of urban stressors, the low-cost sensors used most frequently were portable and wearable. Portable PM, gaseous air pollutants, and noise measuring sensors were generally carried in either backpacks or suitcases (Varaden et al., 2021; Tan and Smith, 2021; Frederickson et al., 2020; Tan et al., 2020; Soares et al., 2020; Johnston et al., 2019; Ghosh et al., 2019; Lefevre and Issarny, 2018; Valle et al., 2017; Dalla Valle et al., 2017; Liu et al., 2015; Leao et al., 2014; Hofman et al., 2021; Liu et al., 2020).

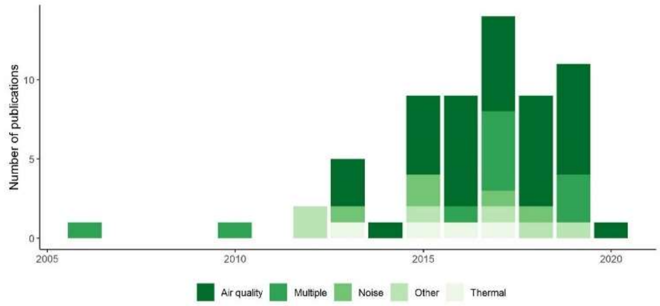


Fig. 2. Number of publications by year of publication and evaluated stressors.

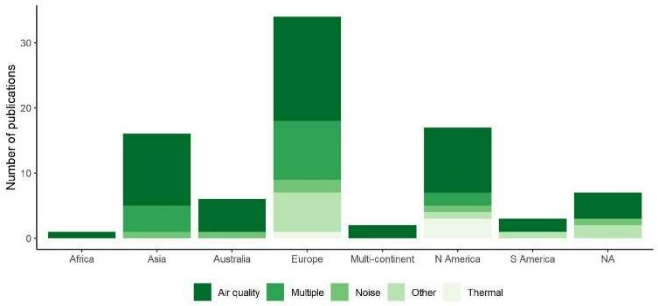


Fig. 3. Number of publications by region and evaluated stressors.

Although personal monitors are becoming smaller and more versatile, there remains the issue of incorporating ancillary components, which can bulk up the measuring equipment, making it less attractive for use. Fewer papers describe using wearable sensors, worn on a wrist, an arm, a belt, or on another part of the body/clothes (da Schio, 2020; Pigliautile et al., 2020; Chen et al., 2020; Zhang et al., 2019; Dam et al., 2017; Dons et al., 2017; Sugg et al., 2018; ChewThornburgJackSmithYang, 2019; Agrawaal et al., 2020; Puhakka et al., 2020). Those least used were stationary sensors (Perelló et al., 2021; Mousavi and Wu, 2021; Pigliautile et al., 2020; Coffey et al., 2019; Haynes et al., 2019; Alsina-Pagès et al., 2016; Uejio et al., 2016; Boso et al., 2020; Brzozowski et al., 2020) as they were not explicitly included in the search query for this review.

Smartphones have been shown to be convenient for use as portable measuring devices as they have multiple imbedded sensors and are used widely by urban populations. The integrated sensors (and modules that can be used as sensors) include a barometer, a gyroscope, an accelerometer, a camera, location/GPS tracking, and a microphone. As such, they can serve as a tool to collect data on movement or activity (location/GPS) and for assessing greenspace, urban nature/greenery, scenicness (Zhang et al., 2021; Juntti et al., 2021; Ferrara et al., 2018; Seresinhe et al., 2019), and exposure to sunlight (Guo et al., 2015). They are also utilized to log measured data or subjective opinions on AQ (Ueberham et al., 2019; Grossberndt et al., 2020).

Several papers include smartphones as noise measuring devices (Zipf et al., 2020; Ghosh et al., 2019; Lefevre and Issarny, 2018; Zhang et al., 2017; Leao et al., 2014); however, for more accurate noise measurements, an external microphone is often connected with the smartphone (Herranz-Pascual et al., 2019; Ueberham et al., 2019; Roe et al., 2020).

Papers assigned to extensive approach category include:

- data on the burden of urban stressors
- activity or microlocation logging, in combination with personal monitors or smartphones
- integrating physiological/biometric parameters, such as heart rate, forced vital capacity, and movement into the exposure assessment
- providing real-time insights of the results during data collection
- integrating collected data with external data sources

Stationary sensors were usually used in exposure assessments to determine outdoor AQ in the immediate vicinity of the participant's residence (Barkjohn et al., 2020; Sinaga et al., 2020), measure concentrations of PM in different rooms at once (Hegde et al., 2020), or provide indoor AQ measurements in classrooms (Sharma et al., 2017). AQ monitoring and meteorological stations can be used to provide background data (Dekoninck et al., 2015; MacKerron and Mourato, 2013) and how they relate to health outcomes (Bui et al., 2020) and to inform models based on personal monitors (Mead et al., 2013). An integrated approach can also include other sources of data inputs, e.g., consideration of social and discomfort factors (Schnell et al., 2012), emotional wellbeing in connection with AQ (Lal et al., 2020), and health databases (Pala et al., 2019).

Heart rate and movement/activity data (or their metabolic equivalents) can be recorded by wearable activity trackers, and the data can be used to estimate the inhalation rate or intake dose of a specific pollutant (Hu et al., 2014a); however, this can also be estimated using respiratory rates for specific age groups (deSouza et al., 2021). Activities like sleep, working indoors, eating, and general home activities will usually lead to a lower inhaled dose, while walking and working out will result in a higher inhaled dose (Hu et al., 2014a). Heart rate monitors can also be used to analyse whether urban green environments reduce stress in individuals (Roe et al., 2020) or how the positive effects of physical activity are negated by the negative effects of air pollution (Laeremans et al., 2018).

More than a third of the papers consider health outcomes to a certain degree, generally in relation to exposure to air pollutants. They often assess the influence of AQ on human health by using health questionnaires and personal AQ monitors (e.g., Zhang et al., 2017; Valle et al., 2017; Schnell et al., 2012; Sarmiento et al., 2020). Medical health assessments provide researchers with objective data and allow them to identify relations between AQ and (respiratory, cardiovascular, etc.) health (Laeremans et al., 2018). Several papers focus on respiratory health, more specifically on asthma in children (Perelló et al., 2021; Bui et al., 2020) and the wider population, in regard to how it relates to exposure to traffic (Dons et al., 2017).

Papers often seek connections between urban stressors and perceived psychological stress or discomfort (Ma et al., 2021; Marquart et al., 2021b; Zhang et al., 2014; Roe et al., 2020) and how inhabitants perceive their environments (Herranz-Pascual et al., 2019).

3.2.2. *Study participants*

For each of the reviewed papers, the number and characteristics of the study participants were extracted. The papers were categorized based on the number of participants they included. Most of the reviewed studies recruited less than 1000 participants. Given the fact that large population cohorts produce results with higher statistical significance, they offer a smaller level of complexity; therefore, the studies with >1000 participants were primarily assigned to the targeted approach category (refer to section 3.2.1). Most relied on smartphone apps and the data they generate, e.g., participants assessing their surroundings (Ferrara et al., 2018; Lefevre and Issarny, 2018; MacKerron and Mourato, 2013) or apps tracking their movement and activity (Fallah-Shorshani et al., 2018; Puhakka et al., 2020), or did not use personal monitors but instead deployed passive static NO_2 samplers (Perelló et al., 2021). One paper in the >1000 participants group presents results from a personal exposure campaign using low-cost wearable sensors, which was part of a larger cohort study (Arku et al., 2018). Approximately one-fourth of the papers did not specify the number of participants (Fig. 4).

In terms of the characteristics of the study participants, the majority of papers do not report any details about the groups of people recruited, or studies simply recruited participants based on their residence within the study area (Fig. 5).

Urban stressors can have the most detrimental effects on vulnerable groups, e.g., children or adolescents (Mahajan et al., 2021; Chen et al., 2020; Johnston et al., 2019; Fallah-Shorshani et al., 2018; Schnell et al., 2012) (and their families (Varaden et al., 2021; Perelló et al., 2021)), including children with asthma (Barkjohn et al., 2020; Bui et al., 2020), the elderly (Chatzidiakou et al., 2020; Roe et al., 2020), adults with self-reported common mental health problems (McEwan et al., 2020), people receiving emergency care (Uejio et al., 2016), and those with movement disabilities (Mora et al., 2017); therefore, these groups are represented in the studies to a large extent. Additionally, as research is predominantly conducted at universities and research institutes, it often relies on students, employees, and their families to be participants (Zhang et al., 2021; Marquart et al., 2021b; Zipf et al., 2020; Gelb and Apparicio, 2020; Liu et al., 2020; Hanoune et al., 2019; Mallires et al., 2019; Sharma et al., 2017; Sugg et al., 2018) or on the researchers conducting the study themselves (Tan and Smith, 2021, deSouza et al., 2021). Studies also involved participants based on specific conditions that could result in high exposure levels, frequently pertaining to appliances or devices (e.g., a wood-burning stove (Boso et al., 2020)), or a Purple Air device (Coffey et al., 2019) used to account for the possible impact on the AQ in their residence.

Smartphone and portable/wearable devices allow researchers to recruit participants that move around and cover large areas, e.g., cyclists (Wesseling et al., 2021; Ueberham et al., 2019; Dekoninck et al., 2015; Chew et al., 2019), drivers (Frederickson et al., 2020), or subway passengers (Zhang et al., 2017).

3.2.3. *Domains of interest*

Concerning the domains of interest, these were categorized as follows. Approximately half the papers cover only indoor spaces or in combination with outdoor spaces, as shown in Fig. 6. Recent studies have shifted their interest to the cumulative effect of outdoor and indoor pollution by adopting dynamic exposure models, as people spend most of their time indoors. Comfort and wellbeing in indoor spaces are correlated with higher productivity and better performance (Wyon, 2004). In the thermal stress domain, prototype devices were deployed in real-life environments to assess the thermal comfort of, for example, office workers, and simultaneously to offer options to reduce energy usage (Nanni et al., 2017), develop a system to measure asthma symptom triggers (Mallires et al., 2019), assess exposure to urban greenery (Zhang et al., 2021), or correlate indoor AQ in classrooms with occupancy rates (Hanoune et al., 2019; Sharma et al., 2017). The majority of the studies focused on the outdoor environment (or in combination with the indoor environment), while a minority specifically focused on green spaces.

3.2.4. *Main stressors addressed per domain*

Stressors addressed in each domain (as described in section 3.2.3) were analysed. The most frequent stressor addressed in almost all domains was air pollution, which was also the sole stressor measured in most cases. Thermal stressors were analysed within the indoor (Uejio et al., 2016) and outdoor (Ueberham et al., 2019; Sugg et al., 2018) domain or in indoor–outdoor combination (Fekih et al., 2021; Rebeiro-Hargrave et al., 2020; Hass and Ellis, 2019; Schnell et al., 2012). Noise was an important stressor in relation to the outdoor environment (Ghosh et al., 2019; Herranz-Pascual et al., 2019; Lefevre and Issarny, 2018) or transport domain (Marquart et al., 2021a; Zipf et al., 2020; Gelb and Apparicio, 2020; Ueberham et al., 2019; Dekoninck et al., 2015; Roe et al., 2020) and, to a lesser degree, within the indoor domain (Ma et al., 2020; Soares et al., 2020; Leao et al., 2014), although the latter were a part of campaigns that included the measurements of multiple environmental stressors. Within all the domains (apart from transport) other health stress parameters such as temperature, humidity, light, metabolic markers, mood/emotional markers, mobility patterns, and the presence greenspace were also included.

3.2.5. *Activity data collection*

Activity data can provide additional context to exposure assessments, and the technologies used, e.g., smartphone apps, questionnaires, and activity sensors, are also considered in this review. Most of the studies did not employ a technology for recording activity. For the ones that did, a smartphone app was the most common tool. Smartphone apps, used in outdoor domain-based papers, can prompt participants to identify their current activity (Seresinhe et al., 2019) or what they were doing in a past time interval, as determined by the users' movements (Lal et al., 2020), if they cycled to work (Chew et al., 2019), and why they took a specific cycling route (Ueberham et al., 2019). Studies involving the indoor domain are less reliable in terms of GPS, though there are options to use data from cell towers and Wi-Fi to improve location tracking (Glasgow et al., 2016). Another option is radio frequency identification which does not use energy and is less expensive and more transparent (Mora et al., 2017). Smartphones also collected activity data to accompany AQ data during specific activities (da Schio, 2020; Hu et al., 2014a) and employed gamification in assessments to provide context for medical conditions, e.g., asthma (Bui et al., 2020). Smartwatches and other wearable activity trackers were used to log data about activities predetermined on the device (da Schio, 2020; Hu et al., 2014a; Sugg et al., 2018; Puhakka et al., 2020), and several studies

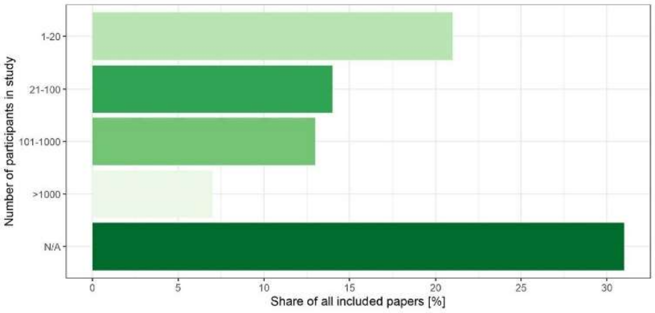


Fig. 4. Share of all papers based on categorization of the included studies according to the number of participants enrolled.

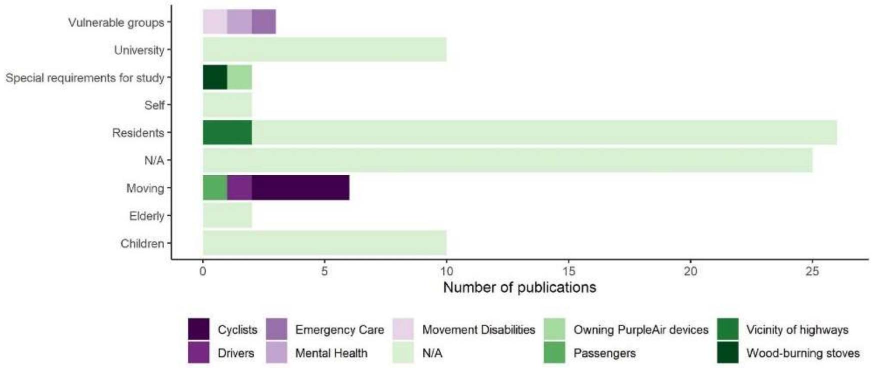


Fig. 5. Participant target groups as percentages of all considered papers and specific criteria required for inclusion.

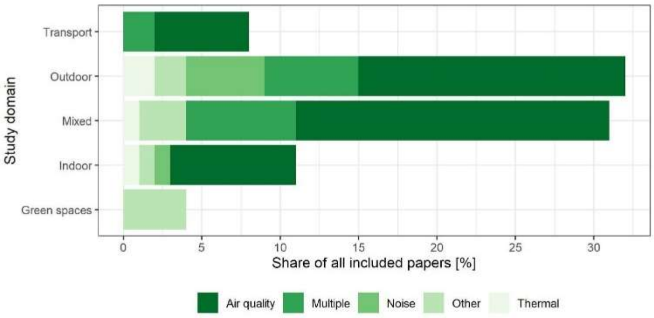


Fig. 6. Share of papers covering different domains and stressors. Categorization of the studies in the following domains: a) outdoors, b) combination of outdoor and indoor domains, c) indoors, d) transport, e) green spaces, and f) a combination.

included some kind of questionnaire or activity data diary in a digital/online format (Ma et al., 2020, 2021; Barkjohn et al., 2020; Sinaga et al., 2020; Hegde et al., 2020; Sarmiento et al., 2020).

3.2.6. Usage of external data sources

Exposure studies can include auxiliary data collected from various other sources to complement data from low-cost and wearable/portable devices. Land-cover and land-use data were used to determine green spaces in urban environments (Herranz-Pascual et al., 2019; Puhakka et al., 2020), whether these areas correlated with how participants observed and classified them (Seresinhe et al., 2019), and how built-up environments influenced exposure to urban heat stress (Sugg et al., 2018). Frequently, studies used near-by environmental and AQ monitoring stations to validate/calibrate devices, platforms, or models (Mousavi and Wu, 2021, deSouza et al., 2021; Wesseling et al., 2021; Fekih et al., 2021; Chen et al., 2020; Hass and Ellis, 2019; Hu et al., 2016) and to compare with results obtained from portable low-cost devices deployed in the field (Chatzidiakou et al., 2020; Mead et al., 2013). Data from AQ monitoring stations and EO were used in combination with location data, with overlaid GPS tracks to aid participant exposure assessment (Rebeiro-Hargrave et al., 2020), or with data on how participants perceived AQ in their environment (Grossberndt et al., 2020). Using EO and meteorological data can provide context for health and medical assessments and for determining environmental asthma triggers (Uejio et al., 2016; Bui et al., 2020) and the influence of environmental factors on the frequency of emergency calls.

3.3. Stakeholder inclusion

3.3.1. Types of stakeholders and their interaction

This section deals with the involvement of various types of stakeholders in the papers. Following the quadruple helix model (Schütz et al., 2019), which describes university–industry–government–public–environment interactions within a knowledge economy, the four general stakeholder groups are considered:

- *Academia/Research*: institutions of higher education and research
- *Government/Policymakers*: system or group of people governing an organized community, including those responsible for or involved in formulating policies
- *Society/NGOs*: various groups of individuals not professionally involved in research activities, including non-governmental organizations
- *Businesses*: entities engaged in commercial activities

The number of papers with various combinations of stakeholders involved, as well as respective topics addressed, is shown in Fig. 7. Involvement of stakeholders from academia and research dominated,

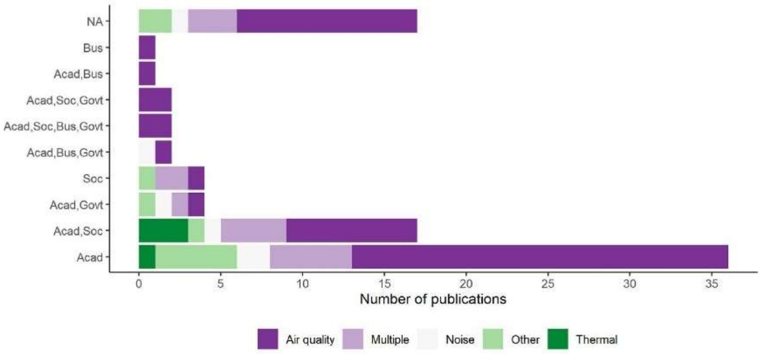


Fig. 7. Number of studies and their topics per combination of stakeholders involved and evaluated stressors. The quadruple helix stakeholders are abbreviated as Bus for business and private sector, Acad for academic and research, Soc for civil society and NGOs, and Govt for government and policymakers.

followed by society and NGOs, while governmental inclusion as well as that from the business sector were rare. In most cases, studies seemed strictly research-oriented. In case more than one stakeholder type was involved, this was related to the inclusion of non-professionals, either organized in groups, including NGOs, or individuals. In the society/NGO group, the multiple domain approach stood out.

3.3.2. *Inclusion levels*

The role of individual stakeholder inclusion was further analysed, considering the following possible options with increasing levels of inclusion:

- Stage 1: inclusion in the initial research design phase and/or provision of research findings
- Stage 2: in addition to first stage, inclusion in the data collection phase
- Stage 3: in addition to the first two phases, inclusion in data analyses and/or the communication/dissemination phase

Else, their role was limited to the recruitment of participants, financing, outside consultant, or another role.

The above-mentioned roles reported in the papers are summarized in Fig. 8 according to type of stakeholder group. With rare exceptions, research stakeholders were involved in all research phases. NGOs and similar stakeholders usually participated in the volunteer recruitment

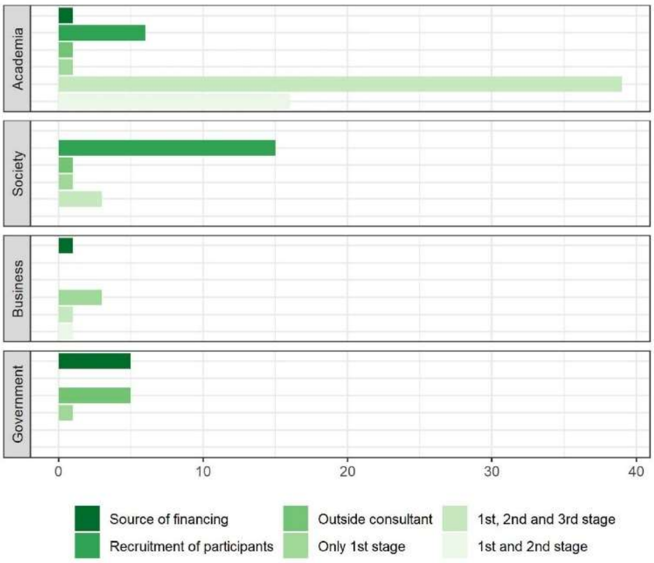


Fig. 8. Number of studies according to stakeholder group and type of involvement.

phase. Such examples were studies dealing with various approaches for individual-level exposure assessment and collaborating either in conducting measurement or in the testing of sensing technologies (Coffey et al., 2019; Herranz-Pascual et al., 2019; Ueberham et al., 2019; Pala et al., 2019; Glasgow et al., 2016; Mead et al., 2013; Sugg et al., 2018; Chew et al., 2019; Bui et al., 2020; Roe et al., 2020; Puhakka et al., 2020). On the other hand, governmental institutions usually participated as a funder or as an external consultant (Varaden et al., 2021; Perelló et al., 2021; Laurino et al., 2021; Mahajan et al., 2021; Gelb and Apparicio, 2020; Leao et al., 2014; Sarmiento et al., 2020). Where this was the case, the provision of meaningful information (i.e., on exposure) to policymakers and authorities was one of the main drivers and applications (Mahajan et al., 2021; Leao et al., 2014; Sarmiento et al., 2020). Similarly, the private sector functioned as financier and provider of equipment/infrastructure and other means for conducting the measurements. Some specific examples thereof comprise of company involvement in the design of the monitoring backpacks on loan and free of charge (Varaden et al., 2021), provision of an open data portal (Mousavi and Wu, 2021), and app development (Arku et al., 2018).

The motives for the involvement of different stakeholders varied. In the case of stakeholders from research and academia, their motivation was usually straightforward and comprised the generation of new scientific knowledge regarding exposure to urban stressors in various contexts, improvements in modelling tools to obtain finer spatio-temporal insights in respective exposures, or similar developments in other tools to be used as part of exposure assessment. Also, their motivation was to empower vulnerable populations and influence decision-makers. In the case of the general public and NGOs, motivation was driven by their desire to take part and contribute in new knowledge generation, direct improvements in specific living environments (Varaden et al., 2021; Roe et al., 2020; Sarmiento et al., 2020), but also involvement in the co-design and co-creation of the research process (Perelló et al., 2021; da Schio, 2020). In the case of governmental institutions, most were included in order to obtain support for their decision-making processes and access to concrete products and solutions that might improve overall quality of life in the city (e.g., Perelló et al., 2021; Mahajan et al., 2021; Lefevre and Issarny, 2018; Sarmiento et al., 2020; Hofman et al., 2021). In the case of stakeholders from business circles, their motivation stems all the way from altruistic cases of research support (Varaden et al., 2021; Mousavi and Wu, 2021; Mahajan et al., 2021) to interest in the innovative aspects of the tools developed and new business opportunities (Lefevre and Issarny, 2018; Hofman et al., 2021).

3.3.3. *Tangible outcomes or products*

Overall, more than a third of the papers report a tangible outcome or product resulting from the study. Of these, half are related to developing or deploying various monitoring systems (Fekih et al., 2021; Rebeiro-Hargrave et al., 2020; Soares et al., 2020; Hanoune et al., 2019; Mallires et al., 2019; Coffey et al., 2019; Haynes et al., 2019; Mora et al., 2017; Dam et al., 2017; Zhang et al., 2017; Arvind et al., 2016; Ali et al., 2015; Hu et al., 2014a; Bui et al., 2020; Agrawaal et al., 2020), followed by smartphone applications (Ferrara et al., 2018; Fallah-Shorshani et al., 2018; Lefevre and Issarny, 2018; Glasgow et al., 2016; Guo et al., 2015; Hu et al., 2014a; Leao et al., 2014; Hu et al., 2014b) and environmental models (Perelló et al., 2021; Mahajan et al., 2021; Chatzidiakou et al., 2020; Zipf et al., 2020; Dekoninck et al., 2015; Chew et al., 2019; Hofman et al., 2021). In two cases, pollution reduction is also identified as a tangible outcome (Barkjohn et al., 2020; Soares et al., 2020) (Fig. 9).

Outcomes in the form of monitoring systems comprised specific sensing devices, methodological frameworks, as well as tools for real-time data collection and interaction with subjects. Models dealt mostly with AQ issues, taking advantage of new sensing technologies to improve their resolution (Perelló et al., 2021; Chatzidiakou et al., 2020; Hofman et al., 2021), with one example of a holistic framework that embedded the social dimension in a technology-centric AQ sensing system (Mahajan et al., 2021). Models for exposure assessment as decision-support tools for policy makers were also present (Chatzidiakou et al., 2020; Dekoninck et al., 2015).

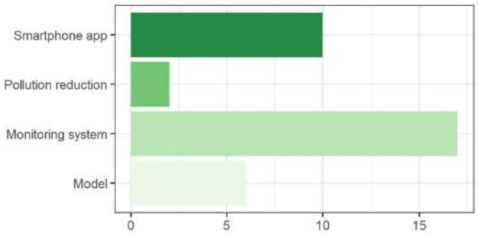


Fig. 9. Number of papers base on general categories of tangible outcomes or products.

3.4. *Citizen science and other participatory approaches*

Public participation in scientific research an take various forms (Shirk et al., 2012). In this section the level of participation is reviewed, that is, to what extent they were involved and how the data they collected were communicated back to them. Papers were classified according to four levels of involvement (Haklay et al., 2013):

- level 1 – crowdsourcing: people generated information passively, e.g., were invited to wear a sensor or have a sensor placed in their household/workplace (returned to the organizers)
- level 2 – distributed intelligence: people received some kind of training, provided information through observations, or interpreted existing information, e.g., by validating observations made by others
- level 3 – participative citizen science: the community defined the problem; it may be derived from previous projects (previous levels), thinking up new questions, etc.
- level 4 – collaborative citizen science: people participate at all levels, thinking up new questions, (co)designing the methods for data collection, and analysis

The urban stressors studied are variably present in different levels of engagement. AQ prevailed in all levels of involvement. However, noise measurements stood out for level 2, where participants provided their observations. Thermal stressors were studied only at level 1, where data were collected passively from participants. (see Fig. 10)

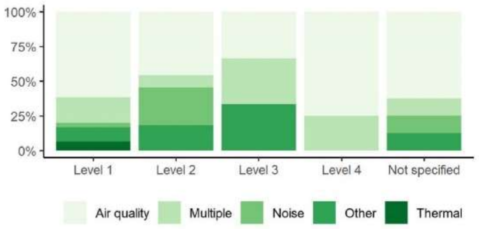


Fig. 10. Urban stressors and level of participant engagement in the reviewed papers.

For several papers, the level of participant involvement was not classified. In these cases, the papers do not provide any specific information on participant involvement and are more focused on technical development of the monitoring/sampling system.

3.4.1. Crowdsourcing

The majority of the papers were classified as level 1 – crowdsourcing, where participants carried a portable sensor unit on them or on their bike or vehicle or hosted them passively at their home, school, or workplace. Generally, these studies did not include information about feedback to the participants during or after the measuring campaign. In certain cases where participants used smartphone apps, they were shown real-time AQ data and visualizations (Rebeiro-Hargrave et al., 2020; Ghosh et al., 2019; Zhang et al., 2019; Guo et al., 2015; Leao et al., 2014; Seresinhe et al., 2019), though it was not necessary that the participants be in direct contact with the researchers (Mousavi and Wu, 2021). When participants received results after data collection had ended, it was in the form of a log in the app they used (Glasgow et al., 2016) or a comprehensive report with all the data they collected, with context from other participants, plots and other visualization, explanations, and recommendations (Rebeiro-Hargrave et al., 2020; Zhang et al., 2017). Involving participants more, e.g., by showing them real-time data on noise pollution with input options and providing comprehensive reports, showed that almost half of them were planning to use their smartphone to measure noise in the future (Zipf et al., 2020).

3.4.2. Distributed intelligence

In papers labelled level 2 – distributed intelligence, participants were more involved, going beyond hosting a device or inputting data on a smartphone. In some cases, participants hosted an AQ device but were more actively engaged, e.g., by providing objective measurements or participating in focus group discussion (Sinaga et al., 2020; Ueberham et al., 2019; Boso et al., 2020). A large proportion of papers report that the participants could see real-time data, and in two-thirds the participants actively inputted the data. About a third of the papers do not discuss reporting data to the participants, and two-thirds report that the participants did not see data after the measurement campaigns. Studies employed different ways to engage the participants, for example by allowing them more freedom in adjusting settings in the app they were using (Glasgow et al., 2016), allowing them to keep the app (Lefevre and Issarny, 2018), or having them actively input data on how they perceived green spaces (McEwan et al., 2020), the urban soundscape (Herranz-Pascual et al., 2019), or their exposure to various urban stressors (Ueberham et al., 2019). Using personal monitors was combined with multi-choice questionnaires, time–activity diaries (Mazaheri et al., 2018), or a web-based game to monitor perceived levels of pollution (Sîrbu et al., 2015). In Juntti et al. (2021), urban environmental quality and wellbeing were studied where participants took pictures with a smartphone app and were subsequently interviewed. On the other hand, Boso et al. (2020) employed a strategy where half the time the participants did not see any data and half the time they received instant feedback on indoor AQ; the authors showed that when participants were more engaged (had access to air pollution values), they had higher motivation and greater confidence in the information they had on their environment.

3.4.3. Participative citizen science

Papers classified as participative citizen science (level 3) also involved actively inputting data or hosting/wearing a device but included further involvement. Sarmiento et al. (2020) employed a citizen science model. In addition to wearable activity trackers and portable low-cost AQ sensor devices, a mobile app enabled residents to document neighbourhood features through geo-coded photographs, audio narratives, and GPS-tracked walking routes. Meetings were also conducted with the participants, one for each intervention and control area.

3.4.4. Collaborative citizen science

Four papers were assigned to collaborative citizen science (level 4), which, in addition to their actively inputting data, involved the participants in the design of aspects of the project. A key difference with previous levels is that in some cases the participants were involved in designing research questions and study protocols (da Schio, 2020). They received a comprehensive report and the final products of the data they collected and were offered a platform to connect with policymakers (Perelló et al., 2021). A more collaborative approach also included connecting participants with sensor designers/developers to co-create devices and engage in specific citizen-led campaigns (Mahajan et al., 2021; da Schio, 2020; Haynes et al., 2019).

3.4.5. Participant involvement via smartphones

Smartphones allow easy involvement of a high number of participants and instant delivery of results in real time. While low-cost sensor devices also allow large-scale deployment (Perelló et al., 2021), researchers usually have a limited number of devices and other resources available. In addition to participants already owning a smartphone, smartphone apps also allow flexibility in terms of level of participation. Participants can use them either passively to collect data or be more involved by inserting data and observations or by responding to surveys. They allow participants the option to adjust and regulate their involvement level, e.g., in the case of GPS privacy settings. The majority of the papers described a crowdsourcing approach.

Direct involvement can enhance learning and environmental awareness, and the use of focus groups and surveys can increase the level of participation as well as valuable feedback to scientists (Sîrbu et al., 2015).

3.5. Ethical and intellectual property issues

3.5.1. Ethics boards

Ethics boards and their mandatory approval are a key development in modern research that, at least in theory, provide protection to participants in research. This process is often criticized, with many calling for a more collaborative approach (McAreavey and Muir, 2011). Journals often require a statement on the approval of an ethics committee to be included in a submitted manuscript if the research dealt directly with participants. A fifth of the papers address these aspects. Although most of the papers deal with personal sensors for data collection, and some specifically address health status and related topics, in most cases ethical considerations are not mentioned. This lack of reporting can also be attributed to the discrepancy of ethics reporting rules in different countries and years.

A select few papers mention an independent external board or commission comprised of experts from appropriate fields that approved the study. Some studies involved an internal board or committee within the organization conducting/proposing the research.

3.5.2. Data protection and privacy

This section explores data protection and privacy issues in regard to EU and international regulations, e.g., referencing the General Data Protection Regulation.

A third of the papers discuss or mention data protection and privacy. Several options to obtain informed consent from the participants are referenced, e.g., participants provided their consent online (via web (Zhang et al., 2014) or app (McEwan et al., 2020)) prior to the start of the study or immediately after scheduling a meeting or were mailed a hard copy of the form. Regarding privacy policy, one protection measure was to ensure that access to databases was limited to a specific group of people, e.g., medical researchers administering the project (Laurino et al., 2021). Several papers discuss the privacy issues related to GPS data, which can be replaced with time–activity logs (Barkjohn et al., 2020), anonymized and aggregated into larger spatial cell units (Leao et al., 2014; Uejio et al., 2016), or actively recorded only when a person is in or near a specific space (Mears et al., 2021). Similarly, AQ data and/or activity data stored on a data server were not made visible publicly (Hu et al., 2014a), or participants could decide which information could be shared (Zhang et al., 2021). To provide an extra layer of privacy protection, data sets were protected with passwords, e.g., including for end users (Rebeiro-Hargrave et al., 2020).

3.5.3. Intellectual property aspects

When citizens are involved in research based on citizen science and co-design principles, intellectual property perspectives, according to Scassa and Chung (2021), can be considered based on four broad categories, depending on the nature and level of their inclusion: (i) classification or transcription of data; (ii) data gathering; (iii) participation as a research subject; and/or (iv) the solving of problems, sharing of ideas, or manipulation of data. With the increased levels of inclusion and contribution, intellectual property questions in terms of inventorship or authorship are becoming more important.

Intellectual property was addressed in some capacity, generally considering the technology used in the research, e.g., a general declaration of the source of funding for a specific technology used (Grossberndt et al., 2020), creating a company and the transfer of technology rights (Lefevre and Issarny, 2018), or using a trademark symbol when mentioning the technology (Dalla Valle et al., 2017). Seresinhe et al. (2019) dealt with pictures collected by citizens with an app and stated that the photos taken were the intellectual property of the photographers and not of the app they submitted them to. This opens up questions on the authorship of ideas and the contributions of citizen scientists in research.

4. Discussion

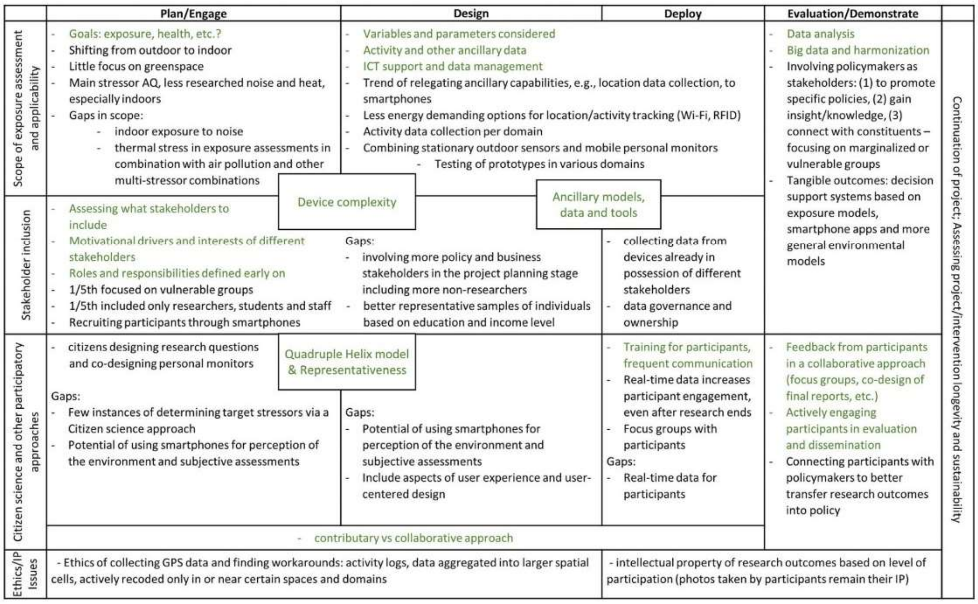
The lessons learned from the literature review are analysed through four general phases of the waterfall methodology (Ruël et al., 2010) of personal monitor applications for exposure assessments. These lessons are summarized based on the natural progression of a project in sequential form. Each phase is structured as follows: (1) definition of the stage and the inclusion of related reviews, (2) general findings and conclusions based on the literature reviewed, and (3) a short reflection and identified gaps. The following phases are elaborated (4D):

- phase 1 – DEVISE: defining the context of use and needs
- phase 2 – DESIGN: tool and protocol selection
- phase 3 – DEPLOY: engagement and data collection
- phase 4 – DEMONSTRATE: data analysis and implementation of results

The waterfall methodology (Ruël et al., 2010) used in the discussion is adapted from the field of project management, where several distinct and sequential phases exist within a project, e.g., scoping, design, development, testing, and deployment. This approach allows observation and critical evaluation of each phase (in the case of this review the 4D phases), and an opportunity to identify gaps and needs, and provide recommendations for future research.

4.1. Review matrix

Results of the review, focusing on the general outcomes, gaps, and needs, have been collected in a matrix, shown in Fig. 11. Overarching themes and characteristics have been identified and are listed in green text in each respective phase and evaluation criterion. Similarly, more specific conclusions and gaps are shown in black text. Phases and criteria often overlap and coincide, though this matrix offers a more methodological and delimitated presentation of the results.



	Plan/Engage	Design	Deploy	Evaluation/Demonstrate	

Scope of exposure assessment and applicability	- Goals: exposure, health, etc.?
	- Shifting from outdoor to indoor
	- Little focus on greenspace
	- Main stressor AQ, less researched noise and heat, especially indoors
	- Gaps in scope:
	  - indoor exposure to noise
	  - thermal stress in exposure assessments in combination with air pollution and other multi-stressor combinations
		- Variables and parameters considered
		- Activity and other ancillary data
		- ICT support and data management
		- Trend of relegating ancillary capabilities, e.g., location data collection, to smartphones
		- Less energy demanding options for location/activity tracking (Wi-Fi, RFID)
		- Activity data collection per domain
		- Combining stationary outdoor sensors and mobile personal monitors
		  - Testing of prototypes in various domains
				- Data analysis
				- Big data and harmonization
				- Involving policymakers as stakeholders: (1) to promote specific policies, (2) gain insight/knowledge, (3) connect with constituents – focusing on marginalized or vulnerable groups
				- Tangible outcomes: decision support systems based on exposure models, smartphone apps and more general environmental models
					Continuation of project; Assessing project/intervention longevity and sustainability

Stakeholder inclusion	- Assessing what stakeholders to include - Motivational drivers and interests of different stakeholders - Roles and responsibilities defined early on - 1/5th focused on vulnerable groups - 1/5th included only researchers, students and staff - Recruiting participants through smartphones	Device complexity Gaps: - involving more policy and business stakeholders in the project planning stage including more non-researchers - better representative samples of individuals based on education and income level	Ancillary models, data and tools - collecting data from devices already in possession of different stakeholders - data governance and ownership		
Citizen science and other participatory approaches	- citizens designing research questions and co-designing personal monitors Gaps: - Few instances of determining target stressors via a Citizen science approach - Potential of using smartphones for perception of the environment and subjective assessments	Quadruple Helix model & Representativeness Gaps: - Potential of using smartphones for perception of the environment and subjective assessments - Include aspects of user experience and user-centered design	- Training for participants, frequent communication - Real-time data increases participant engagement, even after research ends - Focus groups with participants Gaps: - Real-time data for participants	- Feedback from participants in a collaborative approach (focus groups, co-design of final reports, etc.) - Actively engaging participants in evaluation and dissemination - Connecting participants with policymakers to better transfer research outcomes into policy	
	- contributary vs collaborative approach				
Ethics/IP Issues	- Ethics of collecting GPS data and finding workarounds: activity logs, data aggregated into larger spatial cells, actively recoded only in or near certain spaces and domains		- intellectual property of research outcomes based on level of participation (photos taken by participants remain their IP)		

Fig. 11. Matrix with results of the review. Green-coloured text represents more general aspects and important keystones in each respective category. Other, more specific outcomes are in black text, and specific gaps are addressed separately.

4.2. Phase 1 – defining the context of use and needs: DEVISE

Devising an inclusive, multi-stakeholder plan defines Phase 1. Aspects considered in this phase include: (spatio-temporal) definition of the study domain, integration of information from various sources, assignment of roles for stakeholders involved, co-creation and participant involvement, etc.

Multi-domain assessments have become more common. Simultaneously collecting data in indoor and outdoor environments has become more pertinent, as people spend a majority of their time indoors. AQ is described as the main and important stressor (indoors and outdoors) in most papers. Noise exposure is focused more on outdoor and traffic proximity domains, and more thorough insight into noise exposure indoors is lacking. There is also a gap in studies addressing the combined effect of thermal stress and exposure to air pollution or other multi-stressor combinations. Personal monitors provide new opportunities for research to move into a direction of multi-domain and multi-stressor approaches. Moreover, these approaches can provide research results/outcomes that are more comprehensive and robust. Importantly, while almost all studies focused on urban stressors, less than half collected data on the specific activities of the participants and provided context for exposure. Several papers report on using technological advances to somewhat offset the issue of a large number of participants. Future research should lean in to these approaches, and utilize extensively the time and effort-saving technologies for collecting data on activities and microlocations, e.g., by using smartphone apps, GPS, Wi-Fi, and similar. External data sources also show promise in reducing cost while keeping the same level of complexity. These can be automatically collected and integrated into data streams, though they were not frequently used in the studies considered in this review.

Per the review outcomes, the motivations and expectations of different stakeholders have been analysed based on relevance criteria, following Robinson et al. (2021). Clarity of project/study aims, as well as managing expectations early on in the process are crucial when multiple stakeholders are participating (Robinson et al., 2021), as ill-defined aims can lead to conflicts and poor communication.

The quadruple helix model of stakeholders presents an inclusive framework. Representatives of citizens, industry, public authorities, and academia bring, and make use of, their own experiences, skills, knowledge, and networks. Results show that stakeholders from academia and research are most frequent, followed by society and NGOs, while policymakers and the business sector are rare. Though civil society and NGOs are stakeholders in several studies, they are generally a source of participants or used as recruiters. Researchers should utilize the benefits of a diverse set of stakeholders, as complex urban environments often include variables and confounding factors that can be overlooked. Involving participants in all stages of the project and its products, (depending on the aims of the project) makes research more accessible, relatable and understandable to communities that will be most impacted by the outcomes. However, papers rarely describe the involvement of participants in co-designing research questions, determining target stressors, and defining research methods. Government institutions and policy makers are primarily engaged as funders or external consultants. Private sector involvement is rare, though some cases show that this can lead to new businesses based on research outcomes. The motivations of stakeholders vary. Society and NGOs are driven by their desire to take part and contribute in knowledge generation and improvements in specific environments. Governmental institutions collaborate to obtain support for their decision-making processes or access to concrete products and solutions. Knowledge transfer to policy has become a key incentive in designing research and interventions in urban environments. By involving participants in several aspects of the research, while simultaneously collaborating with governmental stakeholders, there is an increased driver/facilitator to implement policy changes.

4.3. Phase 2 – Tools and protocols selection: DESIGN

Phase 2 – design is born out of the planning phase and considers tools, e.g., personal monitors, models, apps, and protocols, for data collection, including providing data for evaluating health outcomes. Several (low-cost) sensor systems are available on the market and are designed as either portable or static. These devices can measure multiple parameters, including geolocation, AQ, noise, and temperature. Commercially available devices usually transfer data via a smartphone/Bluetooth or directly to the cloud. In addition, it has become easier to assemble a low-cost monitor, adapted to the specific requirements of the research. Aspects commonly of interest to researchers include data reliability and control over quality analysis and quality control, access to raw data, insight into the algorithms used, and protocols for data capture and transfer. Although this “DIY” approach offers more customizability, it is necessary to consider end users and to design a non-intrusive monitor (e.g., avoiding frequent charging and dealing with connectivity and data storage and transfer issues). End users might also include researchers or field workers, and the design of the device should also include their needs in relation to handling with the device or retrieving data. A careful evaluation of the availability of personal monitors on the market should be conducted in the design stage of the project. Based on the results of the review and experience of the authors, these aspects, among others, should be considered:

- Are the devices on the market already fit-for-purpose as they are or with minor requirements of adjustments?
- Could the providers of commercial devices accommodate some of the additional requests, e.g., provide an in-app option to record a higher temporal resolution of GPS data?
- When a DIY approach is used for personal monitors, should some user-experience testing be included? It is important to acknowledge that, like with other aspects of participant-based research, that there is a limited pool of participants available, and a negative experience with a device or series of devices could discourage potential participants from collaborating in future studies.

For the purpose of exposure assessment, the collection of ancillary data such as activity and microlocation/microenvironment data in combination with modelling tools such as AQ or noise spatial maps can be employed. Several studies integrated ancillary data when employing multiparametric monitoring, where they combined data from various types of sensors, stationary/fixed, wearable/portable, intake analysis (such as monitoring breathing rate), location/activity logging, as well as qualitative measurements aiming at capturing subjective evaluations. Based on the collected data, several recommendations for future research can be made:

- By collecting ancillary data, e.g., activity and microlocation/microenvironment data, research results can provide a more comprehensive understanding of exposure and improve the accuracy of exposure assessment.
- Integrating multi-sensor data, including stationary/fixed, wearable/portable, and intake analysis, can provide a more varied look at exposure, and identify possible sources of urban stressors.
- Modelling tools, e.g., AQ or noise spatial maps, can be used to identify patterns and trends in exposure and make predictions about future exposure levels.

Qualitative measurements and subjective evaluations, can provide a more nuanced understanding of exposure, and include aspects that sensors do not capture (e.g., experiencing more stress by certain noises than others, even when the sensors show the same level of noise). This is particularly of interest when considering individual’s health and well-being.

Phase 2 can also include collecting data for evaluating health outcomes. Most studies assessed perceived health and wellbeing, as they evaluated how participants perceived their health and how this perception was related to measured urban stressors. These outcomes, among others, were generally assessed qualitatively through detailed or semi-structured questionnaires, interviews, or smart phone applications. Studies can include biometric data, such as heart rate, respiratory rate, and physical activity levels, that can provide valuable information about an individual's physiological response to exposure. Combining biometric data with perceived stress can introduce a more nuanced view of exposure-related health outcomes.

4.4. Phase 3 – engagement and data collection: DEPLOY

Aspects considered in the deployment phase are multifaceted and include discussions of challenges with non-expert stakeholders, access to monitoring technology, research representativeness, intellectual property, and privacy issues. When non-expert stakeholders are engaged, there are several challenges to be considered. Froeling et al. (2021) analysed some of these challenges, applicable to participatory environmental monitoring projects. Several conclusions can be drawn based on the reviewed literature, reflected within the challenges previously outlined by Froeling et al. (2021):

(i) Expertise required by participants: Review results show examples of providing participants with the necessary training, keeping in touch throughout the sampling period, and being open to questions and possible modifications to the study protocols. Including participants as an equal stakeholder in research design and implementation provides an opportunity to identify more issues that could be addressed and which are of interest to the local community. Focus groups also provided an opportunity to gain insight, pre, during, and post the sampling period. A structured focus group can discover flaws in research communication and dissemination by directly observing and commenting on the approaches used. Involving the non-professional public also means, among other things, the risk of biased and unreliable reporting, data collection, and analysis. With this in mind, there should be a manual or machine-driven process of checking if this input is valid and appropriate.

(ii) Issues regarding available monitoring technologies and data quality: Studies in this review used apps and other technical solutions to alleviate some of the pressure on researchers to train participants. The results indicate that involving participants with real-time data increases their engagement, even after the research ends. On the other hand, a more involved approach by participants puts additional pressure on researchers to provide some kind of feedback, as the participants see their involvement as more integral to the research project. If the research enables real-time data to be presented to participants, this could be advantageous to both groups – participants and researchers. By providing real-time data, there is less of a need to compile and deliver extensive user data reports, and at the same time participants can analyse their own raw data autonomously.

(iii) Statistical representativeness of participating citizens: A classic problem in participatory research is achieving true representativeness of the general public by the selected group of participants, which can directly affect the usefulness of the results and their generalization and upscaling. Most of the studies that provided information on target groups considered all residents in an area, while some involved exclusively participants from a vulnerable group, e.g., children, the elderly, or people with disabilities. A fifth of the studies primarily employed researchers or students. The issue of poor representation could be offset by expanding participant recruitment to a diverse group of stakeholders involved in the research. With the inclusion of a diverse set of stakeholders from all quadruple helix groups, a wider pool of participants becomes accessible. Moreover, this approach can ensure and that the interests and needs of different groups are represented, leading to more inclusive and equitable decisions throughout the study design and implementation.

(iv) Data governance and ownership: At the outset, it is necessary to clearly define the conditions of data management, data ownership, as well as the intellectual property derived from it. Four papers discuss intellectual property issues. One study considered the intellectual property of photographs taken for the purpose of the research. Photos were the intellectual property of the photographers/participants and not of the app they submitted them to. The changing role of citizens from passive data collection or being just a subject of research to active participation in research also calls for changes in ethical guidelines. To this end, Ficorilli et al. (2021) call for the inclusion of new elements in various sections of classical ethical approvals, study protocols, information sheets, as well as informed consent.

4.5. Phase 4 – data analysis and implementation of results: DEMONSTRATE

Evaluation and reflection on data gathered in collaboration with all stakeholders follows the data collection phase. This phase entails reflection on the level of citizen science actually reached and the assessment of applications, demonstrability, and tangible outcomes. Citizens and urban communities are, in most cases, targeted as the main beneficiary of the research outcomes. On the other hand, laypeople do not necessarily have the necessary skills to conduct research. This is evident in the studies, as a majority of them included citizens as data collectors – crowdsourcing. Several papers report a higher level of involvement where participants were interviewed or invited into focus groups. This, in turn, provided additional feedback to researchers on how to communicate with and prepare participants to accurately collect data. By engaging participants more, researchers can communicate more effectively. In turn, this reduces the need for additional resources and effort.

As exposure assessment research evolves, it should include applicability and demonstrations of use in urban environments. Tangible outcomes can be included as an indicator on how well the research provides wider uses in planning, policy making, exposure reduction, and other aspects. Half the included papers reported tangible outcomes, with most of these being various monitoring systems, smartphone applications, or environmental models. Models dealt with AQ, taking advantage of new sensing technologies to improve resolution. The final users of research outcomes and products are usually policymakers. Some papers implied, that certain tangible outcomes were produced, though they did not list or describe them in the paper or link to any additional sources. More demonstrations of how tangible outcomes are produced and disseminated would be a welcome addition in literature of this topic.

This review showed that exposure research often does not include the "demonstrate" step. Usually, participants and other stakeholders receive a set of data or different models or test cases, not accompanied with a demonstration. An effective way of demonstrating the applicability of results is by engaging citizens. They can interpret and communicate further on their own, which can result in behavioural changes and consequently translate into policy measures (through bottom-up approaches) and, into changes in their local community. Demonstrating the conclusions of the research to participants is not necessarily in the scope of each research. Those that do include this aspect should consider a more inclusive approach to 1) better argue the relevance of their research, 2) induce behavioural change in individuals and local communities, 3) more effectively transfer research to policy and potentially ensure funding for future public-funded research, and 4) provide future incentives to recruit participants from a diverse pool and reduce biases.

5. Conclusions

A review of 86 papers relevant to the topic of individual-level exposure to urban stressors was performed. A waterfall model was used to assess the scope of exposure assessments, inclusion of stakeholders, citizen engagement and participation, and ethical and intellectual property aspects. Multiple trends, gaps, and needs were identified. Air pollution is the primary stressor assessed, followed by noise and heat stress. Multi-stressor evaluations are rare, as are studies that include activity and movement data to contextualize exposure. Future studies should address a lack of multi-stressor and multi-domain approaches for exposure assessment, in order to provide a more comprehensive overview of exposure to urban stressors. Devices used in individual-level studies are often designed for the specific study or sourced commercially. When designing sensors within a project, a user-centred design should be employed, having in mind the participants using the device and researchers/field workers accessing the data. Providers of commercial devices can often accommodate researchers with specific requests, and this is something worthwhile enquiring about before designing work-arounds.

With regard to stakeholder involvement based on the quadruple helix model, most are engaged from the general public/NGO group, followed by government/policymakers and the business/private sector. Research based on urban stressors should strive to reach a diverse group of stakeholders, which (i) bring different perspectives and experiences to observe overlooked variables and confounding factors, (ii) provide new opportunities and connections with local communities, (iii) improve knowledge-transfer and influence policy-making, (iv) improve representation and widen the pool of possible participants, and in turn ensuring more inclusive and equitable decisions. Citizens are rarely involved in a project before or after data collection, though certain examples show that a more involved approach boosts engagement and motivation, even after the research has been concluded. Engaging citizens and policymakers also helps to improve communication effectiveness, offers more opportunities for transfer of research to policy, and can aid the identification of issues in the local community that would be of interest for future research.

Tangible outcomes and demonstrations often include improvement of existing exposure models or the development of new models, as well as advancements in smartphone application design.

From the study review conducted, it can be concluded that enhancements in sensor technology and increasing public awareness of urban stressors have led to more efficient environmental and health risk management approaches and to solutions which will inevitably present a solid basis for improved public health in the future.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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3.2 Manuscript 2: Comparing Airborne Particulate Matter Intake Dose Assessment Models Using Low-Cost Portable Sensor Data

Section 3.2 consists of a scientific article published in Sensors in 2020, authored by Rok Novak, David Kocman, Johanna A. Robinson, Tjaša Kanduč, Dimosthenis Sarigiannis, and Milena Horvat.

Assessing the validity of the personal monitors used in research is paramount. The following article addresses this issue with a described approach of collocating a specific device used in the ICARUS sampling campaigns, i.e., the PPM, with a reference research-grade monitor. While the device was extensively tested within its design phase, a simplified on-site validation, under specific local conditions, provided additional assurances for data accuracy. Results showed that the device provided reasonably accurate data, which could be used as intended in the ICARUS project. This was used as a basis for comparing different particulate matter intake dose models. Models were ranked based on complexity, defined by the number of variables in the model, and the types of data used (personal monitor-based or not). More complex models, utilizing personal monitor data and more variables, provided more information in terms of estimates during high-exposure/dose events. On the other hand, less complex models gave sufficient fit-for-purpose outcomes and did not rely on using personal monitor data.

The validation step confirmed the validity of the PPM, providing a solid basis for the data to be used in the following articles in the thesis. Moreover, a thorough assessment of different intake dose models supported the use of two of the models in the articles in Section 3.5.

I contributed to the conceptualization of the collocation and model comparison, collection, analysis, and visualization of the data, writing of the original draft, and reviewing and editing the final version. Moreover, as with the articles in Sections 3.3, 3.4, 3.5, and 3.6, I contributed to the participant recruitment, data collection, curation, harmonization, validation, and visualization, in the scope of the ICARUS project.

sensors MDPI

Article

Comparing Airborne Particulate Matter Intake Dose Assessment Models Using Low-Cost Portable Sensor Data

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Abstract: Low-cost sensors can be used to improve the temporal and spatial resolution of an individual's particulate matter (PM) intake dose assessment. In this work, personal activity monitors were used to measure heart rate (proxy for minute ventilation), and low-cost PM sensors were used to measure concentrations of PM. Intake dose was assessed as a product of PM concentration and minute ventilation, using four models with increasing complexity. The two models that use heart rate as a variable had the most consistent results and showed a good response to variations in PM concentrations and heart rate. On the other hand, the two models using generalized population data of minute ventilation expectably yielded more coarse information on the intake dose. Aggregated weekly intake doses did not vary significantly between the models (6–22%). Propagation of uncertainty was assessed for each model, however, differences in their underlying assumptions made them incomparable. The most complex minute ventilation model, with heart rate as a variable, has shown slightly lower uncertainty than the model using fewer variables. Similarly, among the non-heart rate models, the one using real-time activity data has less uncertainty. Minute ventilation models contribute the most to the overall intake dose model uncertainty, followed closely by the low-cost personal activity monitors. The lack of a common methodology to assess the intake dose and quantifying related uncertainties is evident and should be a subject of further research.

Keywords: dose assessment; particulate matter; minute ventilation; low-cost sensors; uncertainty assessment

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1. Introduction

Application of low-cost air quality (AQ) sensors is on the rise and is being used to determine air pollution in cities [1–4], monitoring of indoor AQ [5–7], and for exposure assessment [8–10]. Traditionally exposure studies use data from monitoring stations, questionnaires, or biomarkers [11], and more recently land-use regression models [12,13] and other modelling techniques [14], while the most sought-after method is measuring intake dose on a personal level [15]. To this end, low-cost sensors that have become smaller and more energy-efficient, and now enable subjects to carry these

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devices with them, can significantly improve the temporal and spatial resolution of information needed [16]. However, although continuous and rapid advances in sensing technologies are resulting in improved accuracy, these devices still need extra validation and/or calibration before being put to use [9,17,18]. They could employ a wide array of options to achieve more accurate results, such as comparing with reference analysers [8] or using sophisticated artificial intelligence approaches [19]. On the other hand, assessing intake dose is not only dependent on the concentrations of pollutants, but also other factors, mainly a person's breathing rate or ventilation [20]. Several studies throughout the past three decades have shown that minute ventilation is corelated with heart rate [21–24]. Ventilation can be estimated by various approaches and models, which differ mostly by the number and type of variables used, from more generalized approaches using sex, age, and ethnicity [25] with different kinds of activities [26], to more specific and complex models with additional variables such heart rate [27], forced vital capacity and breath frequency [28], and hip circumference [29]. All of these approaches do offer some advantages, often as trade-offs to accuracy. Less complex approaches use personal information, such as age and sex, and determine minute ventilation from generalized population data [25,30], while more complex models use continuously monitored variables, such as heart rate (HR) [27,28].

The aims of this study are as follows:

- to evaluate the applicability of different intake dose models by assessing the uncertainty associated with each input variable;
- to estimate how the uncertainty propagates forward and affects the uncertainty of the model;
- to compare the results calculated with the models on two contrasting individuals;
- to evaluate the complexity of the models, time, and resource requirements and the burdens participants have in providing the data.

In this work, four different approaches to assess the PM intake dose are compared, using data obtained by two participants included in the sampling campaign conducted within the ICARUS H2020 project [31], which was separated into winter (February) and summer (May) campaigns, and took place in the first half of 2019. The participants carried a portable PM sensor and a heart rate monitor with them at all times and measured indoor and outdoor concentrations of PM during the entire seven-day period.

The uncertainty associated with each intake dose assessment model was quantified and the hypothesis was that the less complex models would provide data with more uncertainty, as they use variables that have higher uncertainties and are based on more generalizations (e.g., average minute ventilation for a 60-year-old female in a less complex model, in contrast with minute ventilation derived directly from measured heart rate in more complex models). Propagation of uncertainty from low-cost sensors and minute ventilation models to intake dose assessments was investigated. A crucial component of the overall uncertainty assessment is to determine the validity of the PM concentration data from the low-cost sensor. To this end, the performance of the low-cost PM sensor was evaluated by collocating it with a reference instrument in an office environment. Moreover, uncertainties calculated and presented for each minute ventilation model were not consistent from paper to paper, as was the nomenclature regarding exposure science and metrology. These issues are addressed and discussed.

2. Materials and Methods

2.1. Terminology and Nomenclature

Terminology and nomenclature used in this work are based on the following sources. Terms regarding the human–pollutant interaction (e.g., "personal exposure", "intake dose", "exposure assessment") were adopted from the Official International Society for Exposure Analysis glossary by Zartarian et al. [31]. Terms related to metrology and statistics (e.g., "uncertainty", "reproducibility", "validity") were adopted from the International Vocabulary of Metrology [32].

2.2. Measuring Particulate Matter Concentrations

A portable Arduino based low-cost PM measuring unit (referred to as PPM) was developed for the ICARUS project [33] by IoTech Telecommunications, Thessaloniki, Greece [34], and used in this research. Using Plantower, Beijing, China, pms5003 sensor [35], based on the laser light scattering principle, the PPM unit provides data for concentrations of PM in one-minute resolution.

PM concentration data are provided in three size classes/channels: <1 µm (PM_1), <2.5 µm ($PM_{2.5}$), and <10 µm (PM_{10}). A detailed description of the instrument with specifications is provided in the Supplementary Materials.

Weekly and daily averages of $PM_{2.5}$ and PM_{10} measurements from the collocation and personal monitors were additionally compared with values obtained from the government run AQ station, near the centre of Ljubljana (2 km from where the collocation took place), to determine if the values were close. The averages were compared to determine if the values measured by the sensors were in the same range as those measured at the AQ station.

Collocation of the PPM Unit with a Reference Instrument

The PPM unit was collocated with a GRIMM (Durag Group, Hamburg, Germany) Model 11-A (1.109) Aerosol Spectrometer (GRIMM), which was used as a research-grade reference instrument for PM measurements. The collocation lasted one week, from 5 to 12 March 2019, and was located at an office space with open windows at Jožef Stefan Institute, Ljubljana, Slovenia (LAT: 14.4879, LON: 46.0424). The PPM unit provided data with minute resolution and GRIMM with five-minute resolution. Data recovery for the measuring period was 100% for the PPM unit and 99.8% for GRIMM. A more detailed description of the instrument is available in the Supplementary Materials.

There was a four-hour period with light precipitation during the collocation, the mean (min – max) temperature throughout the week was 12.3°C (6.3°C–16.3°C) and relative humidity was 55% (36–65%).

2.3. Measuring Heart Rate and Physical Activity

Continuous HR measurements were made by using a commercial smart activity tracker (SAT), a Vívosmart 3 from Garmin International [36]. The data were in minute temporal resolution and provided values for HR, specific physical activity, steps taken, calories "burned", distance walked, and stress.

Uncertainty of SAT was estimated based on the work of Oniani et al. [37], who compared the same device (Garmin Vivosmart 3) with an ECG (electrocardiogram). In their work, four participants were selected, and equipped with four SAT devices each. An 80-min treadmill test was performed with each participant, with four different speeds of walking, while being connected to an ECG monitor. The results were presented with MAPE (mean absolute percentage error) and ICC (intraclass correlation) for each device, in comparison to the ECG.

2.4. Calculating Personal Intake Dose of Airborne Particulate Matter

Intake dose of PM was calculated as a product of PM concentration, in this case, PM_1 concentrations for one-minute average values (as the results of the collocation showed, this proved to be the measurement with the lowest uncertainty associated with it), measured with a PPM device, and minute ventilation data, which was determined by four different models described below. The intake dose model (M1–M4) calculation is presented in Equation (1):

$$intake\ dose = \dot{V}_E * PM_1, \tag{1}$$

where $\dot{V}_E$ presents minute ventilation (L min^{-1}) and PM_1 is the particulate matter concentration measured with the PPM sensor (µg m^{-3}).

Two of the described models (M1 and M2) use HR as a variable, and two (M3 and M4) do not, and in turn use average minute ventilation data for specific population groups. Comparison between the four models was performed based on the data from two participants involved in the ICARUS personal exposure assessment campaign in Ljubljana:

- P1: 60-year-old Caucasian female participant, weighing 62 kg, height 166 cm. P1 participated in the campaign between 17 and 23 February 2019, and was located in Ljubljana the entire period. P1 was employed as an office worker.
- P2: 35-year-old Caucasian male participant, weighing 66 kg, height 178 cm. P2 participated in the campaign between 14 and 21 May 2019, and was also located in Ljubljana the entire period. P2 was employed as a bike courier.

Using only one participant could skew the results, including another participant with a contrasting profile (different personal characteristics, such as sex, height, and age) enables a more thorough comparison. Two participants are enough for the purposes of this research, as the goal is to compare models and not validate them for larger groups.

2.4.1. Model 1 (M1)

Minute ventilation model in M1 ($\dot{V}_E^1$) is based on the work of Greenwald et al. [28], who modelled minute ventilation with HR, age, sex, and forced vital capacity (FVC) as variables, with the explicit goal to use these data in pollution intake dose estimates. Data from 471 subjects from 8 different studies were compiled in their research and enabled the researchers to gather a dataset of 14,550 one-minute data points. Here, their best performing model was selected, using HR data, combined with information about the subject's sex, age, height, and weight (used in determining FVC):

$$\dot{V}_E^1 = e^{-9.59} HR^{2.39} age^{0.274} sex^{-0.204} FVC^{0.520}, \tag{2}$$

where $\dot{V}_E^1$ presents minute ventilation for M1; *age* is the age of the participant in years; *sex* is the participants sex, where value 1 is male and 2 is female; and *FVC* is forced vital capacity.

FVC factor was estimated using the Global Lung Function Initiative methodology [38]. FVC for P1 was 3.32 l (lower limit at 2.61 l, upper at 4.16 l, for a 90% confidence interval) and for P2 5.37 l (lower: 4.30 l, upper: 6.45 l, for a 90% confidence interval).

M1 is calculated based on Equation (1).

2.4.2. Model 2 (M2)

$\dot{V}_E^2$ is based on the work of Zuurbier et al. [27], who used a simplified approach with only HR and sex as variables:

$$\dot{V}_E^2 = (a * HR + b)^e, \tag{3}$$

where $\dot{V}_E^2$ presents minute ventilation for M2, HR stands for heart rate, and a and b present the slope and intersect based on sex (a is 0.023 and 0.021, b is 0.57 and 1.03, for females and males, respectively). Their model is based on a study performed with 34 participants.

M2 is calculated based on Equation (1).

2.4.3. Model 3 (M3)

$\dot{V}_E^3$ follows an approach by Sarigiannis et al. [25], modelling mercury intake by combining age and ethnicity-specific data of activity patterns, inhalation rates, and body weight, with a specific type of microenvironment. Madureira et al. [30] use a similar approach for indoor intake dose of bioaerosol particles. Each observation is multiplied with a breathing rate factor corresponding to the (hourly) activity self-reported by the participant, but the model does not use any continuous variable, such as HR.

Following the described methods [25,30], in this research, activity reported by the participant in a time activity diary (TAD) was differentiated into four groups, as listed in the U.S. Environmental Protection Agency (EPA) Exposure Factors Handbook [39]: sedentary and passive activities (includes sleep, nap, resting, working behind a desk, and watching TV), light intensity activities (cleaning, cooking), moderate intensity activities (walking, working in garden), and heavy intensity activities (sports, hard manual labour). Average minute ventilation was provided by this handbook for each type of activity, differentiated by age, sex, and body weight. $\dot{V}_E^3$ uses this information to determine minute ventilation for each hourly interval.

M3 is calculated based on Equation (1).

2.4.4. Model 4 (M4)

$\dot{V}_E^4$ uses one of the most basic approaches to determine minute ventilation using only a few general data points for the subject: age, sex, and weight. The EPA Exposure Factors Handbook, which provides estimated minute ventilation according to the mean values determined for specific groups [39], also provides generalized data for time spent in micro-locations, doing specific activities for each (age and sex) group. With this information, using Equation (4), it is possible to calculate average minute ventilation, weighted for per cent of time spent doing each activity.

$$\dot{V}_E^4 = (sP * aV_P + sLi * aV_{Li} + sMi * aV_{Mi} + sHi * aV_{Hi}) * BW, \tag{4}$$

where $\dot{V}_E^4$ is minute ventilation for M4; and *sP*, *sLi*, *sMi*, and *sHi* present daily shares of time spent doing *P*—passive, *Li*—light intensity, *Mi*—moderate intensity, and *Hi*—high-intensity activities, respectively. The *aV* factors present average ventilations for that specific activity, according to age group and sex. Factor *BW* is the subjects body weight, which must be included because the $\dot{V}_E$ data in the EPA handbook are presented in "per kg of body weight" form.

M4 is calculated based on Equation (1).

2.5. Statistical Analysis and Determining the Uncertainty

After collocating PPM with the GRIMM, to determine the validity, a Wilks–Shapiro test was conducted for each time-averaging interval to numerically determine normality and a q–q plot was made to visually determine normality. The distribution was non-normal, which prompted the use of the Spearman rank-order correlation test. For each comparison, a scatter plot was made with a linear regression line and 95% confidence interval. RMSE (root mean square error), MAPE (mean absolute percentage error), MAE (mean absolute error), R^2, slope, and intercept values were calculated.

Summary statistics were calculated for all four models, PM_1 concentrations, and HR, and for the results iterating M1 over different heights and weights, as presented in the Supplementary Data.

The uncertainty for the PPM was estimated by collocating it with the GRIMM, which has a reproducibility of 5% for the whole range [40]. This measure is carried forward to the PPM device through the collocation process, which enabled the calculation of several statistical measures of agreement (R^2, MAPE, MAE, RMSE, MAE%). According to the GRIMM manual description, the MAPE measure is the closest, and the uncertainty from the GRIMM is carried forward through the following equation:

$$u(PPM) = \sqrt{u(Grimm)^2 + u(comparison)^2}, \tag{5}$$

where u is the uncertainty.

All models used in this research had some measure of agreement listed in their evaluation. Not all measures were the same, which makes some of the results incomparable between the models.

$\dot{V}_E^1$, from Greenwald et al. [28], had the uncertainty expressed as "per cent error", which is "the difference between predictions and observations from cross-validation", and in IQR (interquartile range). The median (IQR) per cent error was −0.664 (45.4)% [28]. With the Supplementary Data, provided by the authors of the paper, it was possible to calculate other statistical measures (R^2, MAPE, MAE, RMSE). This calculated uncertainty presupposes that all the variables used are categorical (in the cases of sex and weight, this is correct) and without uncertainty. This is not the case in this research, where the SAT device has some uncertainty associated with it, as does the FVC value, with both having different exponents in the model (2.39 for HR and 0.52 for FVC). To determine the overall uncertainty of the model, all the component uncertainties were combined.

$\dot{V}_E^{2}$, based on Zuurbier et al. [27], had its uncertainty presented with mean R^2 values for each sex, with SD and range [27]. In this case, the mean (SD) R^2 values were 0.89 (0.06), 0.90 (0.07), and 0.90 (0.07) for women, men, and all together, respectively. Uncertainty explained in this way is different than in $\dot{V}_E^{1}$ and cannot be compared. To obtain a better comparison of the $\dot{V}_E^{1}$ and $\dot{V}_E^{2}$ models, the supplementary data from Greenwald et al. [28] were used to calculate minute ventilation with the $\dot{V}_E^{2}$ model Equation (3) and compare it with the measured minute ventilation values in the Supplementary Data. The same statistical measures were calculated for $\dot{V}_E^{2}$, as they were for $\dot{V}_E^{1}$. The SAT uncertainty was also incorporated in the overall uncertainty of the model.

$\dot{V}_E^{3}$ uses data from tables provided by the EPA for certain age groups, which includes mean minute ventilation values and some specific percentiles, such as the 5th and 95th percentile. The difference between these two values provides a 90% confidence interval for the values used in this model. Table 1 shows the percentiles of minute ventilation for P1 and P2 participants involved in this research. The difference between the mean and the percentile is slightly larger at the 95th percentile than at the 5th percentile, with the average value being 34% for the 95th and 30% for the 5th percentile. The overall uncertainty estimate was determined as the mean of all the differences with SD.

Table 1. Mean, 5th, and 95th percentile minute ventilation values for P1 and P2 with calculated differences between the percentiles and the mean, provided in the Environmental Protection Agency (EPA) Exposure Handbook [39].

	Activity	Mean [L/min]	5th % [L/min]	95th % [L/min]	$\frac{\lvert 5^{th} - mean \rvert}{mean}$	$\frac{\lvert 95^{th} - mean \rvert}{mean}$
P1	**Sedentary and Passive**	4.1	2.9	5.6	0.30	0.36
	Light intensity	10	7.4	13	0.25	0.30
	Moderate intensity	21	14	30	0.31	0.43
	High intensity	39	24	58	0.38	0.46
P2	**Sedentary and Passive**	4.4	2.9	5.3	0.35	0.22
	Light intensity	11	11	13	0.05	0.22
	Moderate intensity	24	15	32	0.36	0.37
	High intensity	43	27	58	0.36	0.36

Although $\dot{V}_E^{4}$ uses a similar approach as $\dot{V}_E^{3}$, the uncertainty is different as the "share of the day" values also have 5th and 95th percentile values and are not definitive, as in $\dot{V}_E^{3}$. As shown in Table 2, the differences between the 5th and 95th percentiles and the mean vary quite substantially between lower and higher intensity activities, with an average of 12% (14% for P2) in the "sedentary and passive" category, and 121% (132% for P2) in the "high intensity" category. Each uncertainty interval was weighted by the percentage of the day it represents, in contrast to the percentage it "should" represent, which in this case is $\frac{1}{4}$. To assess the final uncertainty for $\dot{V}_E^{4}$, the uncertainty from minute ventilation, as shown in Table 2, must be added by the method used in Equation (5).

Table 2. Mean, 5th, and 95th percentile daily share of activity for P1 and P2, with calculated differences between the percentiles and the mean, provided in the EPA Exposure Handbook [39].

	Activity	Mean [hours]	5th % [hours]	95th % [hours]	$\frac{\lvert 5^{th} - mean \rvert}{mean}$	$\frac{\lvert 95^{th} - mean \rvert}{mean}$
P1	**Sedentary and Passive**	13	11	14	0.12	0.12
	Light intensity	6.5	4.1	9.4	0.37	0.45
	Moderate intensity	4.6	1.7	7.1	0.63	0.56
	High intensity	0.3	0.03	0.9	0.91	1.5
P2	**Sedentary and Passive**	12	11	14	0.13	0.14
	Light intensity	5.7	2.8	10	0.51	0.83
	Moderate intensity	5.7	1.3	8.9	0.78	0.56
	High intensity	0.4	0.03	1.0	0.92	1.71

As calculating the intake dose is a product of PM concentration values and calculated minute ventilation values, the uncertainty propagation is calculated by the method described in Equation (5).

All the calculations and visualizations were made in R v3.61 [41].

3. Results

3.1. Results of the Collocation

Figure 1 shows the correlation plots between GRIMM and PPM for the collocation with three different time intervals (5, 30, and 60 min) and all three particle size classes (1, 2.5, and 10 μm). Increasing the particle size reduces the linearity of the data points along the linear model regression line, which is also apparent in the R^2 values that start at ~0.97 for PM_1, drop to ~0.89 for $PM_{2.5}$, and further drop down to ~0.68 for PM_{10} particles. As presented in Table 3, R^2 values slightly increase with larger time intervals, as evident with PM_1 particles (from 0.97 to 0.98) and with PM_{10} particles (from 0.66 to 0.69). These increases are relatively minimal and counteract the increase in the confidence interval with larger time intervals. Similarly, as in the case of R^2, RMSE values increase as the size of the particles increases.

Mean (min–max) concentrations recorded for the PPM were 13.2 (0.4–47.4) μg/m^3, 18.4 (0.8–61.6) μg/m^3, and 20.6 (1.0–69.8) μg/m^3 for PM_1, $PM_{2.5}$, and PM_{10}, respectively, while the mean (min–max) GRIMM values were 11.7 (1.6–40) μg/m^3, 15.2 (2.4–44.6) μg/m^3, and 19.4 (2.7–103.4) μg/m^3 for PM_1, $PM_{2.5}$, and PM_{10}, respectively. These numbers generally coincide with measurements from the government-run AQ station in Ljubljana, which showed an average concentration of 11.4 μg/m^3 for $PM_{2.5}$ and 18.9 μg/m^3 for PM_{10} [42,43] for the same time period. For $PM_{2.5}$, the PPM device measured 7.0 μg/m^3 higher average values than the AQ station, and the GRIMM device 3.8 μg/m^3 higher values. For PM_{10}, these values were 1.7 μg/m^3 higher for the PPM, and 0.5 μg/m^3 higher for GRIMM. As the distance to the AQ station was 2 km, some deviation is expected and these numbers fall in this range of expectations.

Although the PPM unit was validated for 5-, 30-, and 60-min intervals, intraclass differences of R^2 and RMSE values varied less than interclass differences. The uncertainty associated with 1-min values for each size class should, therefore, be similar to the values calculated for 5-min averages. These results show that the PM_1 values with the highest possible temporal resolution (1-min) have the least uncertainty, and are used to calculate intake doses.

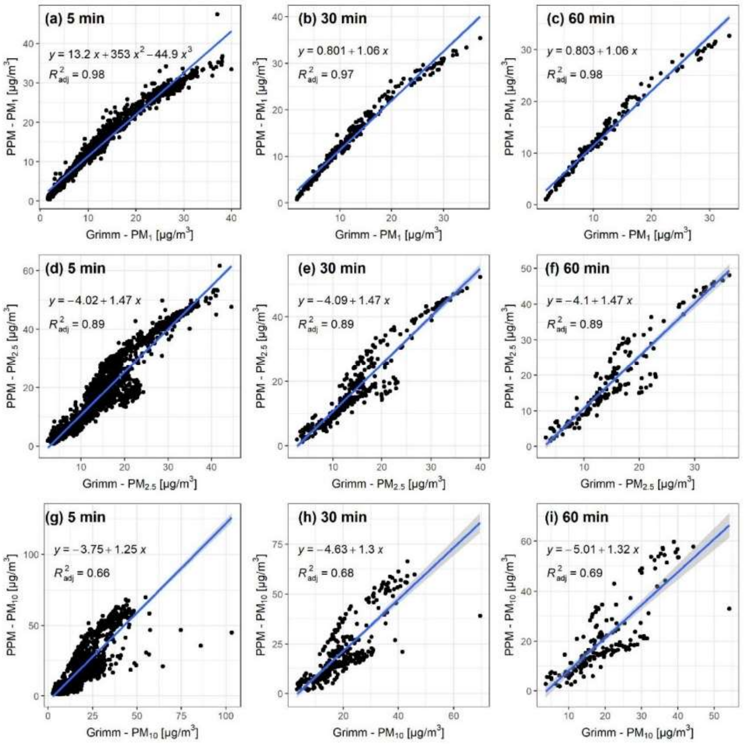

Figure 1. Correlation plots from collocating the portable Arduino based low-cost particulate matter (PM) measuring (PPM) unit with GRIMM. Rows present different sizes of particulate matter (PM_1 (**a**–**c**), $PM_{2.5}$ (**d**–**f**), PM_{10} (**g**–**i**)) and columns different time intervals (5 min (**a**,**d**,**g**), 30 min (**b**,**e**,**h**), 60 min (**c**,**f**,**i**)).

Table 3. Relationship between portable Arduino based low-cost particulate matter (PM) measuring (PPM) unit and GRIMM. RMSE, root mean square error.

PM class	Time	R^2	RMSE	Intercept	Slope
PM1	5 min	0.97	2.15	0.83	1.06
	30 min	0.97	2.01	0.80	1.06
	60 min	0.98	1.96	0.80	1.06
PM2.5	5 min	0.89	6.30	−4.02	1.47
	30 min	0.89	6.17	−4.09	1.47
	60 min	0.89	6.11	−4.10	1.47
PM10	5 min	0.66	9.07	−3.75	1.25
	30 min	0.68	8.76	−4.63	1.30
	60 min	0.69	8.58	−5.01	1.32

3.2. *Intake Dose Results*

The results of the calculations, based on all four intake dose models, are shown in Figure 2, plot (a), accompanied by plotted PM_1 values for each participant in plot (b) and HR values in plot (c).

As evident in plot (b), the PM_1 concentrations were higher for P2 than for P1. This is also evident in Table 4, where the summary statistics for PM_1 concentrations show higher numbers for P2. The mean PM_1 values for P1 and P2 were 8.1 $\mu g/m^3$ and 28.6 $\mu g/m^3$, respectively, which is more than a three-fold difference, and the maximum PM_1 values were 87.0 $\mu g/m^3$ and 338.0 $\mu g/m^3$ for P1 and P2, respectively. The measured $PM_{2.5}$ values were in the same range as values reported by the government-run AQ station in Ljubljana. Summary statistics for HR show that the maximum and standard deviation (SD) values were higher for P2, but the differences are not as pronounced as with PM concentrations.

M1 and **M2** intake dose assessments show a strong relationship. As evident in Table 4, both have similar descriptive statistics, except the maximum intake dose value, which is noticeably higher for M1 with both P1 and P2.

M3 follows a somewhat similar pattern as M1 and M2, although some deviations are evident. For P1, M3 mean value is ~15% higher than that of M1 and M2; the SD is almost double; and the maximum value is 11% and 26% higher than M1 and M2, respectively. The median and the Q1 and Q3 values are 10–30% lower. Similar ratios are found for P2, except the median value is almost half that of M1 and M2.

M4 shows noticeably different results for P1 and P2. As evident from plot (a) in Figure 2, the results of M4 for P1 mostly follow the same trend as the other models. The summary statistics for M4, shown in Table 4 (for P1), show somewhat higher values than those of M1 and M2. For P2, as shown in Figure 2, the M4 results do not follow the trend of the doses based on other models as well as for P1. Although the mean, SD, and Q3 values are lower than in the other three, the median is almost the same (262.6 ng/min for M1 and M2, and 263.3 ng/min for M4).

Table 4. Descriptive statistics for intake dose assessments based on all four models, PM_1 concentrations, and heart rate (HR) values for both participants. Recovery represents the percent of data recovered, where 100% is the entire period of observation. Sum represents the accumulated dose for the entire week of observation.

	Participant 1 (P1)					
	M1	**M2**	**M3**	**M4**	**PM1 [$\mu g/m^3$]**	**HR [bpm]**
Mean	60.2	58.8	69.6	75.9	8.1	63.8
SD	58.9	53.1	99.6	55.3	5.9	11.9
Median	43.3	44.4	29.1	65.8	7.0	62.0
Q1–Q3	25.0–73.7	26.2–74.3	16.6–63.1	37.6–104	4.0–11.0	55.0–70.0
Min–Max	0.0–729	0.0–609	0.0–820	0.0–818	0.0–87.0	38.0–148
Recovery [%]	78.2	78.2	80.7	80.7	80.7	97.2
Sum	599,520	580,128	589,983	617,486	67,352	/
	Participant 2 (P2)					
	M1	**M2**	**M3**	**M4**	**PM1 [$\mu g/m^3$]**	**HR [bpm]**
Mean	415	359	493	314	28.6	66.3
SD	476	359	698	280	25.5	18.2
Median	263	262	109	263	24.0	63.0
Q1–Q3	108–542	140–465	91.5–595	219–373	20.0–34.0	52.8–76.0
Min–Max	0.0–5110	0.0–4033	0.0–5313	0.0–3708	0.0–338	39.0–170
Recovery [%]	66.7	66.7	51.2	68.1	68.1	98.6
Sum	2,764,423	2,391,141	2,522,915	2,136,003	194,702	/

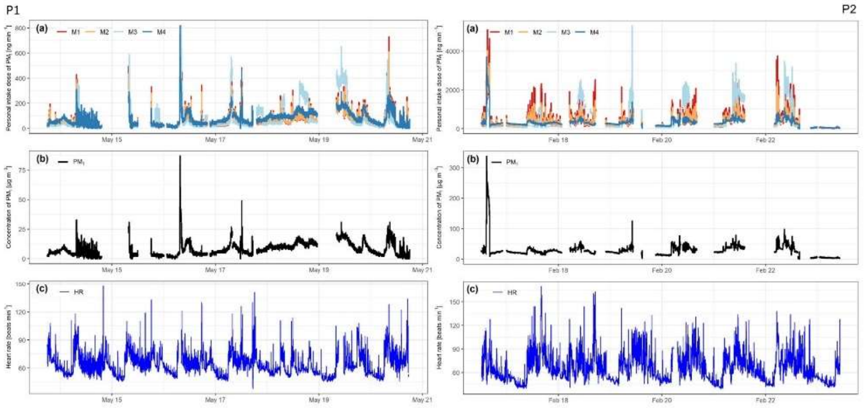

Figure 2. (**a**) Calculated intake dose of PM_1 for all four models, (**b**) measured concentrations of PM_1, and (**c**) heart rate in beats per minute. Left side for participant 1 (P1) and right side for participant 2 (P2).

3.3. Results of Quantifying Uncertainty

All the sensors used in this research have some uncertainty in their measurements, which is carried on to minute ventilation and intake dose calculations.

3.3.1. Uncertainty in PM and Heart Rate Sensors

The results for the statistical measures of agreement with the reference data calculated for the PPM were as follows: $R^2 = 0.97$, MAPE = 15.62%, MAE = 1.66, RMSE = 2.15, and MAE% = 14.17%. After including the uncertainty (listed as reproducibility) of the GRIMM, the overall uncertainty of the **PPM** is ~16%, which is estimated with the uncertainty propagation Equation (5).

The results from Oniani et al. [37] show that there is some disagreement between the **SAT** devices and the ECG. MAPE values ranged from 4.34% to 16.00% (mean: 9.82%, median: 8.85%, SD: 3.56%), and ICC from 0.91 to 0.02 (mean: 0.67, median: 0.71, SD: 0.25).

3.3.2. Uncertainties for Minute Ventilation Models

$\dot{V}_E^1$ statistical measures of agreement with the reference data were as follows: $R^2 = 0.82$, MAPE = 28%, MAE = 6.47, and RMSE = 9.41. Combining the mean value of the SAT uncertainty (9.82% ± 3.56%; weighted: $9.82\% \pm 3.56\% * 2.39 = 24\% \pm 9\%$), the mean value of the FVC 90% confidence interval (~22% ± 2%; weighted: $22\% \pm 2\% * 0.52 = 11\% \pm 1\%$) and the MAPE of the model, using the approach described in Equation (5), yields an estimate of overall uncertainty for $\dot{V}_E^1$ of ~38% ± 9%.

$\dot{V}_E^2$ calculated statistical measures were as follows: $R^2 = 0.72$, MAPE = 32%, MAE = 7.68, and RMSE = 11.68. Adding the uncertainty in the SAT (9.82% ± 3.56%, adjusted to $9.82\% \pm 3.56\% * e = 27\% \pm 10\%$) to the 32% uncertainty in the model gives an estimate of the uncertainty of ~42% ± 10% for $\dot{V}_E^2$.

$\dot{V}_E^3$ uncertainty estimate was determined to be ~35% ± 7%, which can be considered an overall uncertainty value, in this case, for a 90% confidence interval.

$\dot{V}_E^4$ uncertainty for the "share of day" variable is ~30% ± 16% for a 90% confidence interval. The final average value with SD for overall uncertainty estimate, with minute ventilation uncertainty included, is calculated to ~46% ± 17% for a 90% confidence interval.

3.3.3. Propagation of Uncertainty

By adding the uncertainty from the PPM device, the final uncertainties for the intake dose assessment are 41% ± 9% and 45% ± 10%, for intake dose assessment models **M1** and **M2**, respectively, and 38% ± 7% and 49% ± 17% for **M3** and **M4**, respectively.

4. Discussion

Collocating the PPM with the GRIMM showed that the low-cost sensor provides valid data. These results showed that the sensor is fit for purpose, especially if the results of the smallest particles measured (PM1) are considered.

Two participants were chosen to avoid skewed results. Most of their characteristics (age, height, sex, gender, nature of their work, sampling season) were different enough to enable an indication of the model's response to the variation of respective input variables.

M1 and M2 intake dose assessment models show a strong relationship (Figure 2), deviating mostly in peak concentrations, where M1 predicts a higher intake dose than M2. This is more evident with P2, where the calculated intake dose is higher and the peaks are more pronounced. Interestingly, although M1 uses more variables and was determined based on a larger number of participants in multiple research than M2, they show similar results. M1 shows a greater response to higher concentrations of PM than M2. M1 showed the highest intake dose to be 17% and 21% higher with P1 and P2, respectively, than M2. P2 was exposed to PM_1 concentrations more than three-times higher than P1, and the difference in M1 and M2 rose. This indicates that M1 is more sensitive to elevated concentrations, which could be a crucial aspect when determining the acute intake dose.

There are more peaks, which are more pronounced in the M3 intake dose assessment model, but the median values indicate that most of the calculated values are lower than in M1 and M2. Although, the weekly intake doses do not differentiate much between the first three dose assessments and are all around 0.59 mg for P1 and between 2.39 mg and 2.76 mg for P2. Calculating the intake dose on a larger time interval would be as good with M3 as with M1 or M2. The issue, in this case, would be the exaggerated response of the model to elevated concentrations. A better realignment of the calculated values in M3 to M1 and M2 could be possible with a different interpretation of the TAD and categorizing each activity more in line with the HR associated with it.

M4 intake dose assessment model results show that M1 and M2 are influenced by the HR variable and do correspond to changes, most notably in time intervals with elevated HR and concentrations of PM, while M4 does not. As it is only an "adjusted" PM value, meaning that all the PM measurements are multiplied with the same value, it is not influenced by the higher HR differences, present with the results from P2.

Uncertainty is associated with all stages of calculating intake dose of PM. There is inherent uncertainty in the GRIMM, PPM, and Garmin devices, and uncertainty that comes from calculating minute ventilation from HR, and all the generalizations associated with it. Using different models, published in individual papers, shows that presenting uncertainty is not uniform in this field. Papers describe the relationship between modelled and measured data with different statistical measures, which makes assessing uncertainty difficult and sometimes incomparable. Although uncertainties calculated for each minute ventilation model are not entirely comparable, the uncertainties for $\dot{V}_E^1$ and $\dot{V}_E^2$ can be compared separately, as can those for $\dot{V}_E^3$ and $\dot{V}_E^4$.

Calculated statistical measures for $\dot{V}_E^1$ and $\dot{V}_E^2$ show that $\dot{V}_E^2$ has poorer agreement with the reference data (lower R^2 value) and higher errors (higher MAPE, MAE, and RMSE). The model with more variables ($\dot{V}_E^1$) can calculate data that are closer to the measured data for minute ventilation. Both models have their uses, and although $\dot{V}_E^2$ has poorer results of calculated statistical measures than $\dot{V}_E^1$, it requires less information about the participant. Relatively high standard deviations in the uncertainty ($\sim\frac{1}{4}$ of the value) show that the real uncertainty of the models is even closer than the uncertainty values themselves would suggest.

Because the uncertainties for $\dot{V}_E^3$ and $\dot{V}_E^4$ were calculated in the same manner, they can be compared. The results are as expected, where $\dot{V}_E^4$ has a higher uncertainty than $\dot{V}_E^3$ because the share of daily activity has a certain level of uncertainty, which is propagated to the minute ventilation estimate, which is also presented with an uncertainty interval.

The uncertainties calculated through a series of steps do provide some measure of the validity of each minute ventilation model. Each of the models was provided with a specific measure of agreement between the modelled and measured data, but as these measures were different, they are not entirely comparable. This was somewhat compensated with further calculations for $\dot{V}_E^1$ and $\dot{V}_E^2$. Further research is needed to validate each model directly with reference data.

5. Limitations

Collocating the PPM device took place in a room with open windows, so the environment was a mixture of outdoor and indoor, which is not the case during the deployment phase. Moreover, only one PPM device was evaluated during colocation with the reference instrument. To truly determine the validity of the sensor, more devices should be subjected to collocation for longer periods and in different seasons and conditions. The device was stationary for the entire period, which is not representative as the device is designed to be mobile. Indeed, most of the time, the device is stationary in real-life circumstances, for example, in the office, at home, in the bedroom, or in a car. The collocation of the device would be needed while it is mobile. Using the GRIMM device for the collocation was the only available option at the time, but in further validation of the PPM device, it should be compared to a certified government AQ station or similar.

Data from two participants were used for the models. There were certain differences between the participants, but they were also both Caucasian and had a similar height and weight. The latter is also discussed in the Supplementary Materials. For both participants, there were some data missing, and the TADs were somewhat incomplete or inconsistent. All of the models were also validated indirectly by validating the minute ventilation and particulate matter concentrations separately. Future research should develop methods for direct validation of the models, using real-time data with a high temporal resolution for each observed variable, with research-grade instruments.

Measures of uncertainty were provided for all minute ventilation models, but were inconsistent and not entirely comparable.

6. Conclusions

A comparison of the four different approaches to assess intake dose, using data from low-cost sensors, was presented. Collocating the PPM device with a more expensive, research-grade instrument showed that the sensor provides good data, and was reliable enough to use it to determine intake dose of PM. Agreement with the reference instrument was better with smaller-sized particles, but the differences for different time averaging intervals were only marginal ($\Delta R^2 = 0.01$–0.03). Considering these results, PM_1 concentrations were used for modelling, with the highest temporal resolution possible (1 min).

Four different minute ventilation models with increasing levels of complexity were used to determine minute ventilation, which was then used to calculate the intake dose of PM. Intake dose assessment models M1 and M2, which used HR as a variable, showed good agreement with each other, although M1, which was more complex and used sex, age, height, weight, and FVC as variables, showed more pronounced peaks and a stronger response to elevated HR and PM concentrations than M2, which only used sex as a variable (apart from HR). Intake dose assessment M3 and M4 did not use HR as a variable, but relied on generalized population data for specific activities, differentiated by sex and age. M4 showed better agreement with M1 and M2 than M3, but this could be the result of inaccurate activity classification. With further optimization, M3 could be improved and better realigned with other models.

Comparing the uncertainties between all the minute ventilation models was not possible, owing to different measures of uncertainty being reported for each model. After some additional calculations, a direct comparison of $\dot{V}_E^1$ and $\dot{V}_E^2$ was possible and between $\dot{V}_E^3$ and $\dot{V}_E^4$. $\dot{V}_E^1$ had lower uncertainty than $\dot{V}_E^2$, which is mostly associated with the model itself and less with the SAT and other variables. The comparison of $\dot{V}_E^3$ and $\dot{V}_E^4$ showed that $\dot{V}_E^3$ had less uncertainty associated with it than $\dot{V}_E^4$, which was a direct consequence of $\dot{V}_E^4$ using another set of generalized population data to determine "share of the day" for each specific activity, for which $\dot{V}_E^3$ had data from TADs. The minute ventilation models contributed the largest share to the overall uncertainty of the intake dose assessment models, followed by the SAT and finally the PPM.

As evident in this work, there are several different approaches for calculating the intake dose of pollutants. This stems also from different goals that the developers of these models set out in their respective studies. While some validate existing models, others try to evaluate the models predicting ability. Future research can use these results to determine which model best suits their needs and resources. While more complex models provide dose calculations on a minute-by-minute basis and have less uncertainty, they also require more resources in terms of sensors used and invested time by the researchers and the participants. This paper can also provide several options for future research in PM intake dose assessment, from developing models with less uncertainty, using location data and different sensors, and using the described models on larger groups.

As low-cost sensor technology is rapidly developing, there is an ever-expanding field of possibilities of how to implement such technologies for sensing and intake dose assessments. To allow comparability between the results of these measurements and calculations, a more homogeneous approach to presenting these finding and the uncertainties associated with them is needed. This work is a contribution towards this goal—by using appropriate terms and methods, this paper will contribute to further developing a unified methodological and terminological approach in this type of research. Modelling the intake dose of PM, by determining certain variables with low-cost sensors, was shown to be possible. Although there are many advantages, there is uncertainty that comes with this kind of sampling, and researchers need to account for this aspect in reporting their data. As this technology and these approaches become more widespread and distributed in the general public, users must be made aware that these data can come with wide margins of uncertainty and should only be used as a general guideline and not a scientific fact.

Supplementary Materials: The following are available online at http://www.mdpi.com/1424-8220/20/5/1406/s1, Figure S1: Boxplots of intake dose calculations with different height and weight variations as 67 referenced in Table S3, Table S1 Basic specifications for GRIMM Model 11-A, Table S2: Excerpt from Plantower pms5003 datasheet with some relevant figures about the functionality of the sensor, Table S3: Matrix of all variations for four different weights and heights. The Supplementary Materials (SI) contain extended descriptions of the sensors used in this research, a more detailed overview of the data collection process, and a brief investigation of the influence of weight and height of the participant on the final results.

Author Contributions: R.N. and D.K. conceptualized the idea, collected the data with J.A.R. and T.K., analyzed, validated and visualized the data, and prepared the original draft. D.S. coordinated and led the design efforts for the ICARUS project. M.H. headed the project on a local level, ensured funding and contributed to the final review and editing. All authors approved the content of the manuscript. All authors have read and agreed to the published version of the manuscript.

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3.3 Manuscript 3: Combined Use of Wearable Biometric and Environmental Sensors for Complex Activity Recognition in Participatory Exposure Research Using Machine Learning

Section 3.3 consists of a scientific article submitted to Scientific Reports in 2023, authored by Rok Novak, Johanna A. Robinson, Tjaša Kanduč, Dimosthenis Sarigiannis, Sašo Džeroski, and David Kocman.

This article discusses the use of personal monitors, combined with machine learning methods for complex activity recognition in participatory exposure research. Two groups of individuals wore the devices while manually recording activities, with one group recording activities with one-hour resolution and the other with one-minute resolution. The collected data was used to learn models with three classification algorithms. Results showed improved accuracy when activities were recorded at a finer temporal resolution and vaguely defined activities were divided into more detailed categories. The outcomes demonstrated the utility of combining data from wearable environmental and activity sensors to improve the process of recording activities in exposure assessments.

The approach described in this article demonstrates the additional uses of personal monitors in research, apart from providing exposure data with high spatio-temporal granularity. An increasing adoption of personal monitors in exposure research presents an opportunity to leverage machine learning as a tool for exploring further potential of these technologies.

My contribution to this manuscript was in the conceptualization, specifically comparing the two different groups by using machine learning. Moreover, I proposed and executed a second round of data collection with minute resolution, and contributed to the participant recruitment phase, data collection, validation, curation, and visualization. I prepared the original draft of the article, and collaborated in reviewing and editing the final version.

An initial proof of concept for this article was published as a conference paper in the 7th International Electronic Conference on Sensors and Applications in 2020, entitled Low-Cost Environmental and Motion Sensor Data for Complex Activity Recognition: Proof of Concept, authored by Novak, Rok, Kocman, David, Robinson, Johanna A., Kanduč, Tjaša, Sarigiannis, Dimosthenis, Džeroski, Sašo, and Horvat, Milena.

Combined Use of Wearable Biometric and Environmental Sensors for Complex Activity Recognition in Participatory Exposure Research

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Abstract: Practitioners in participatory exposure research use time activity diaries to track behavior and assess exposure to stressors like air pollution. Machine learning (ML) methods can reduce manual recording by constructing models with data from low-cost wearable sensors. Complex activities, like smoking and cooking, pose challenges for recognition due to specific environmental conditions. In this work, wearable environment/ambient and wrist-worn activity/biometric sensors were combined for complex activity recognition in an urban stressor exposure study. Environmental sensors provided particulate matter concentrations, temperature, and humidity data. Two groups wore the devices while manually recording activities. Group H (88 individuals) recorded hourly, and group M (18 individuals) recorded minutely. The dataset was used to train models with three classification algorithms, selected based on their performance, computational requirements, and explainability: k-Nearest Neighbours (IBk), decision trees (J48), and random forests (RF). Accuracy improved with finer temporal resolution and detailed activity categories. Misclassifications were higher for vague activities (resting, playing), while well-defined activities (smoking, cooking, running) had few errors. Including environmental sensor data increased accuracy for all activities, especially playing, smoking, and running. Combining wearable environmental and activity sensors demonstrated the potential of ML for activity recording in exposure assessments.

Keywords: wearable sensors; particulate matter; exposure; activity recognition; machine learning

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1 Introduction

Exposure studies often rely on participants or subjects to provide information about their movement and activities, relevant to the study. Time Use Diaries or Time Activity Diaries (TADs) have been extensively used to record specific activities and their relation to economic or health factors [1]. While TADs have been mostly paper-based, in the last decade, activity tracking transitioned to smartphone apps and web-based applications, improving diary data quality [2]. On the other hand, there are indications that using smartphone apps can increase nonresponse levels due to several factors, e.g., not owning a smartphone and unfamiliarity with digital tools, though there are options available to overcome some of these issues [3].

Analysing everyday activities of individuals can present a useful way to compartmentalize human behaviour, and subsequently assess exposure to stressors, such as pollution or noise. Strong evidence exists that different activities increase exposure to stressors, e.g., elevated levels of airborne particulate matter when dusting, folding clothes, making a bed [4], smoking cigarettes [5], vaping [6], or when walking/vacuuming on carpeted flooring [7,8], and increased exposure to noise on public transport [9]. Manually recording activities by a large group of individuals can be imprecise or require more resources [10]. An important constraint is temporal resolution, which has to be suited to participants/subjects, their availability and responsiveness. When individuals self-report activities, there is little control over how precise the reports are, especially when taking into account recall bias and reliability [11–13]. Reviewing TAD data in this study showed a possible error rate of up to 5-10% for each activity. To reduce the probability of human error, different approaches are employed, e.g., user-cantered study design to construct better TADs [14] and using GPS and other variables as activity identifiers to reduce manual input [15–17].

Different classification algorithms, developed over the past decades could potentially classify different activities by using data recorded with sensors as learning data. Equipping each individual with low-cost sensors would provide data about their movement, physiology, and environment. Relying solely on movement data or environmental data does not necessarily provide enough information to predict complex activities. This study utilized machine learning methods for classification, in combination with sensor and activity data, to provide a proof of concept for an alternative to manually recording complex activities. Furthermore, the approach was centred on analysing the usefulness of these tools to non-expert users involved in participatory research. To this end, two groups of participants, equipped with biometric and environmental sensors, recorded their activities with different temporal resolutions. The collected data was used to learn three different classification algorithms and observe how accurately each of them classifies simple and complex activities, and determine the role of different temporal resolutions. Overall, the aims of this study are:

(i) With a combined dataset (from environmental and biometric sensors), assess if individual activities can be determined by using different classifiers, and compare their predictive performance.
(ii) Determine the influence of different temporal resolutions of the collected data on the predictive performance of each classifier.
(iii) Assess the added value of each respective device used.

1.1 Air quality and environmental data from personal monitors

Low-cost personal sensors and monitors that measure ambient conditions are becoming increasingly popular. Particulate matter concentrations, temperature, relative humidity, and various gasses are just a few of the parameters that can be measured with low-cost personal sensors and monitors. These devices have certain drawbacks, mainly the uncertainty of their results [18,19], although they have been improving in the past years [20] and are "cautiously encouraged" for monitoring indoor air quality [21].

Certain complex activities, e.g., cooking, cleaning, and smoking, are characterized by distinct environmental conditions (smoke, resuspension of particles, high humidity), which could potentially provide enough data for a classification algorithm to identify them. Environmental sensors for temperature, humidity, and light have been successfully used to aid in activity recognition [22], though particular matter data is not utilized frequently.

1.2 Human activity recognition

Current human activity recognition (HAR) methods allow us to distinguish certain activities by using low-cost sensors without manual input. Progress has been made in utilizing sensors and other components (accelerometer, compass, gyroscope, barometer, magnetometer, GPS, etc.) present in smartphones to achieve good prediction accuracy for some specific actions, events, or activities (such as walking, running, falling, etc. [23,24]), although dedicated activity trackers (usually worn on the wrist) are more sophisticated and provide more accurate data [25,26]. On the other hand, even as these devices are better at HAR, they still have insufficient accuracy for more complex activities (dusting, cleaning, playing cards, etc.), but provide reasonably accurate heart rate measurements (RMSE between 4 bpm and 16 bpm, depending on activity) [27,28]. In some instances, they have shown good accuracy for certain complex activities, e.g., smoking [29], by utilizing hand gestures.

Several technical challenges still facing complex HAR exist, according to Chen et al.[30]:

1. Difficult feature extraction, due to activities having similar characteristics.
2. Expensive and time-consuming collection of activity data leads to annotation scarcity.
3. Person-dependent activity patterns, temporal variability of activity concepts, and diverse layout and composition of sensors on a person lead to sensory data heterogeneity.

4. Composite or complex activities have several actions associated with them, and are more difficult to classify. Similarly, concurrent and multi-occupant activities where a person is performing multiple activities at once or with multiple people.
5. A high computational cost is associated with HAR systems that have to provide instant responses and fit into portable devices.
6. Privacy and interpretability of the collected data have to be considered.

Combining data from different environmental and biometric sensors and devices could provide enough information to distinguish different activities and somewhat resolve the listed challenges. Coming from different low-cost sensors, the data would need to be cleaned and harmonized before being put to use.

1.3 Machine learning: classification

Classification is one of the major tasks in machine learning, where an algorithm learns, from examples in the training data, how to assign a specific class to the testing data. A task of this kind is to classify emails as "spam" or "not spam". In its most rudimentary form, an algorithm would check in a labelled training dataset which words or phrases are associated with a spam email and which are not. With these learned associations, the algorithm would be used on a new (testing) dataset, classifying new emails into "spam" and "not-spam". This is an illustrative task of binary classification, whereas activity classification usually requires multi-class classification, where there are several different classes, such as walking, running, cleaning, smoking, and so on. A variety of algorithms can be used for classification, including *k*-Nearest Neighbors [31], Decision Trees [32], Naïve Bayes [33], Random Forests [34], Gradient Boosting [35], Support Vector Machine [36], etc.

Classifiers have been used in various HAR applications that use smartphones and low-cost activity trackers or other mobility sensors, in some cases with accuracy >98% [37], and in most cases >80% [38,39]. Combining these data points with ambient conditions, such as temperature and relative humidity measured with a smartphone (which has certain drawbacks [40]) or with static sensors, has shown up to 99.96% of correctly classified activities, such as walking, sitting, cycling, running and other similar, less complex activities [41,42].

These approaches have utilized an array of different classifiers with varying results, where some algorithms, such as Naïve Bayes, achieve an average accuracy of 43.29%, as compared to Random Forests, with the accuracy of 99.96% [42] and 99.86% [41]. Fewer studies have attempted to identify more complex activities, such as cooking, cleaning, gardening, playing, smoking, and others, as they are more difficult to characterize or distinguish from each other. Dernbach et al. [43] report over 90% accuracy for simpler activities, for all classifiers (except Naïve Bayes with ~74%), while the accuracy for more complex activities was ~50% (only for K-star, otherwise between 35% and 50%). As complex and simple activities are broad terms, it is useful to define them. Sousa Lima et al. [44] provide a good explanation to delimit these two types of activities: *"Simple or low-level activities are those activities that can only be recognized by analysing data from one or more sensors in a short period of time (e.g., walking and running). While complex or high-level activities can be seen as a set of low-level activities that can be recognized over a long period of time (e.g., work and shopping)."* This research focuses mainly on more complex activities, while also including some simpler ones (running, sleeping).

More traditional, shallow algorithms are used in this research, in contrast to deep learning methods, as they have several advantages in light of our approach. Deep learning methods increase the computational requirements of a system, which is more difficult to achieve if the classification is performed on smaller and less powerful devices, e.g., a smartphone, wearable sensor or low-performance office laptop. This can be offset by using advanced methods of feature extraction [45], which could in turn make this approach less accessible to non-ML experts. Furthermore, research shows certain algorithms to be better explainable to lay individuals, i.e., tree-based algorithms [46]. Shallow algorithms used in this research can be more easily explained to participants involved in the research, and be more accessible to researchers analysing the data. More emphasis is put on the ability of explain artificial intelligence algorithms used, as they becomes more prevalent in research and policy decisions [47,48].

2 Methodology

2.1 Data Collection

Two sets of data were used for this research, collected from participants living in Ljubljana, Slovenia:

- The first set (group H – hourly data) was collected as part of the ICARUS H2020 project from 88 participants [49]. The participants were involved in the winter (February to March 2019) and summer (April to June 2019) season of the campaign, for approximately 7 days, and equipped with two sensor devices, a Smart Activity Tracker (SAT) and a Portable PM measuring device (PPM). Basic personal information was obtained from each participant (age, body mass, sex, etc.). All participants had to fill out a TAD, where information about their activities was provided for each hour. They could select their hourly activity from 7 indoor activities (resting, sleep, playing, sports, cooking, smoking, cleaning) and 2 outdoor activities (running, sports). The activities chosen to be included in the TAD were based on the criteria developed within the ICARUS project, based on available research and activity pattern databases [50]. Sensor data, collected with 1-minute resolution, was aggregated to 1-hour resolution by calculating the mean value. A detailed description of the sampling campaigns was published by Robinson [51].
- The second set (group M – minute data) was collected from September to November of 2020 from 18 participants. They were equipped with the same devices as the first group. An important distinction was that they a) had more activities to choose from and b) had to log activity data on the scale of minutes, not hours. The activities used for group M were modified activities from the initial ICARUS TAD. Sensor data with 1-minute resolution was used as-is.

All participants involved in the study provided their informed consent. Ethical approval for the ICARUS project in Slovenia was obtained from the National Medical Ethics Committee of the Republic of Slovenia (approval nr. 0120-388/2018/6 on 22 August 2018). The data in this paper were selected only from participants in Slovenia, and all methods were performed in accordance with the relevant guidelines and regulations.

A graphic representation of the methodology and dataflows used in this work is shown in Fig. 1.

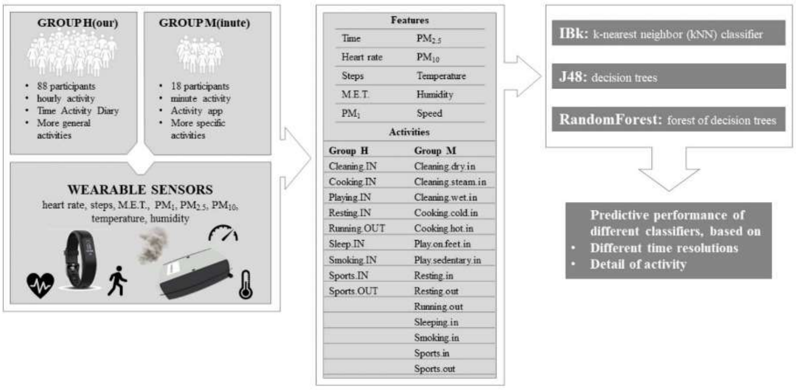

Fig. 1 Schematic representation of the overall methodology and data flows used in this work

2.1.1 Smart Activity Tracker

A Garmin (Garmin, Olathe, KS, USA) Vivosmart 3 activity tracker was strapped on each participant's wrist for the entire duration of the data collection period, except for two hours when the device had to be recharged. Information about the participant (sex, age, body mass, height, etc.) was logged into the device before deployment. The temporal resolution for the data was one minute. Data for Average minute heart rate [beats per minute], Steps [number of steps], and Metabolic Equivalent of Task (M.E.T.) [between 0.01 and 45.60] was collected from each participant. The SAT provided several other variables, though they were not relevant to the scope of this research. Raw data, e.g., accelerometer, was not accessible.

2.1.2 Portable Particulate Matter sensing device

This low-cost PPM device was developed for the ICARUS project by IoTECH (IoTECH Telecommunications, Thessaloniki, Greece), using a Plantower pms5003 sensor (Nanchang Panteng Technology Co., Ltd., Nanchang, China). This sensor uses the Optical Particle Counting principle to measure particle size and mass concentration in real time. A fan draws particles into a beam of light illuminating each particle as it passes through, with scattered light being recorded on a photodetector and converted into an electrical signal. The device provided data at a one-minute resolution. Participants carried it with them the entire period, although they were instructed to "have it in the same room", as the device needed to be recharged every six to seven hours or continuously plugged into a power source. Group M was provided with a power bank with 10.000 mAh capacity, which prolonged the use of the device to ~24 hours. The PPM provided minute-resolution data for PM_1, $PM_{2.5}$, PM_{10}, Temperature [°C], Relative Humidity [%] and Speed [km/h]. Some other variables were also provided by the PPM, though they were out of the scope of this research. The PPM was validated by co-location with reference research-grade sensors [52].

2.1.3 Activity recording

Group H was provided with 7 blank daily Time Activity Diaries (TADs), where they were able to fill in circles for each activity they did for every hour of the day. These files were collected and digitalized. Information about all indoor and outdoor activities was used. An example of a TAD can be found as supplemental information in Novak et al. [53].

Group M installed the Clockify app [54] on their smartphone which had activities already pre-set by the research team on the online portal. Several activity-tracking apps were tested and reviewed, and though the Clockify app was generally meant as a time-tracking app for work and projects, it had the functionalities that were needed for this research. Each participant selected the activity they were beginning to perform and the timer would start. After they finished the activity, they would select the next activity which would automatically finish the first one. The time stamps had date, hour, minute, and second information. While the activity data technically had a 1-second resolution, it was rounded to the nearest minute. The reasoning was fourfold: (1) few instances of activities with duration of <1 minute, (2) the compiled dataset would be unnecessarily large, (3) the changes between activities included in the analysis are not relevant on <1-minute resolution, (4) all sensor data had a 1-minute resolution.

To record more than one activity simultaneously was deemed as out of the scope of this research. The recorded data was exported from the Clockify portal in .csv format.

2.2 Dataset Overview

Sensor, TAD, and Clockify portal data were harmonized and compiled into two datasets: group H with 228,267 observations, and group M with 70,139 observations. Each observation was associated with 10 variables (time, PM_1, $PM_{2.5}$, PM_{10}, temperature, humidity, speed, heart rate, steps, M.E.T., activity):

- time – indicating a time-of-day, a specific hour when the measurement took place (from 0 to 23)
- PM_1, $PM_{2.5}$, PM_{10} – particulate matter concentrations in three size classes, recorded as non-negative integer value (PPM)
- temperature, humidity – ambient temperature and humidity, recorded as float value (PPM)
- speed – calculated based on GPS module data, recorded as float value (PPM)
- heart rate –heart rate per minute, recorded as a positive integer value (SAT)
- steps –number of steps per minute, recoded as a non-negative integer value (SAT)
- M.E.T. – a non-negative integer value (SAT)
- activity – recorded on TAD or in the Clockify app

The minimum requirement for each observation to be included in the dataset was an activity label, and at least one non-empty variable. Data preparation was done in R [55].

The number of included instances of each activity, for each dataset (group M and group H), are listed in Table 1. All activities were capped at 5000 instances for each group. When >5000 instances were available, a random selection was made from the dataset. Resting and sleeping were capped for group M. The ceiling was determined based on several iterations which showed a considerably longer time to build the models without having an impact on the overall performance.

Table 1: Activities and number of instances of each activity in each of the two datasets

Group M		Group H	
Activity/Task	Nr.	Activity/Task	Nr.
Cleaning.dry.in	438	Cleaning.in	5000
Cleaning.steam.in	416	Cooking.in	5000
Cleaning.wet.in	516	Playing.in	5000
Cooking.cold.in	387	Resting.in	5000
Cooking.hot.in	1923	Running.out	5000
Play.on.feet.in	85	Sleep.in	5000
Play.sedentary.in	469	Smoking.in	5000
Resting.in	5000	Sports.in	5000
Resting.out	225	Sports.out	5000
Running.out	80		
Sleeping.in	5000		
Smoking.in	769		
Sports.in	361		
Sports.out	774		

Basic statistics for all numeric variables in the final datasets are presented in Table 2. All values were within expected limits. All PM variables had a ceiling fixed at 180 μg/m^3 as the highest possible value, otherwise, the mean, median, and quartile values are as expected. Mean and median values for speed are low, as >20 km/h values were removed, as there are no activities included in this research, where speed could be >20 km/h. PM statistics are similar between the groups. There are some differences in max and min temperature and relative humidity, which is due to a larger and more diverse dataset for group H and data from two seasons. Speed, heart rate, steps, and M.E.T don't show wide discrepancies. These results shows that the two datasets are quite similar when observed through basic statistics, which was a key aim that was set when collecting data for group M. The two groups should have the same general characteristics and differ only in the temporal resolution of the data collected to facilitate an accurate comparison of the classification results. Mean values of all variables for each activity are available in the Supplementary Information. These show that the values are in line with expectations as there are generally higher concentrations of PM outdoors than indoors, though this is somewhat dependent on season, time of day and specific activity [56,57].

Table 2: Basic statistics for all numeric variables in the dataset.

	median		*mean*		*max*		*min*		*1stQ*		*3rdQ*	
Variable	H	M	H	M	H	M	H	M	H	M	H	M
PM_1 [μg/m^3]	9.00	8.00	15.2	12.9	180	180	0.00	0.00	5.00	4.00	17.0	17.0
$PM_{2.5}$ [μg/m^3]	12.0	12.0	21.2	19.1	180	180	0.00	0.00	7.00	6.00	24.0	25.0
PM_{10} [μg/m^3]	13.0	13.0	23.7	21.2	180	180	0.00	0.00	7.00	7.00	26.0	27.0
Temperature [°C]	24.1	23.5	24.0	23.5	35.2	34.6	5.80	8.50	22.8	21.9	25.3	24.8
Relative humidity [%]	32.7	39.8	33.0	40.3	80.7	67.2	6.70	19.7	28.0	35.8	37.9	45.3
Speed [km/h]	0.52	0.00	1.21	0.52	20.0	20.0	0.00	0.00	0.00	0.00	1.70	0.54
Avg. heart rate [bpm]	71.0	62.0	74.1	65.9	205	177	34.0	38.0	62.0	56.0	83.0	72.0
Steps [nr.]	0.00	0.00	5.40	3.23	276	157	0.00	0.00	0.00	0.00	0.00	0.00
M.E.T. [ml O2/kg/min]	0.07	0.07	0.16	0.40	25.3	6.11	0.01	0.00	0.07	0.07	0.08	1.00

2.3 Classifiers Used

As referenced in section 1.3, appropriate classifiers for the scope of this research are *k*NN, Decision Trees, and Random Forests. All analyses were performed by using the WEKA 3.8.3 [58] "Explorer" application. The specific classifiers within WEKA that were used in this research are listed in Table 3, which also contains short descriptions of each of the classifiers.

Table 3: Classifiers in WEKA used for this research, with short descriptions.

Classifier	**Description**
IBk	Instance based learner [31], otherwise known as the *k*-nearest neighbour (*k*NN) classifier; *k*NN takes the *k* closest examples (typically according to a Euclidean distance) to the given instance in the feature space and counts how many of the *k* belong to each class. The new instance object is classified by plurality vote.
J48	J48 is a Java implementation of the C4.5 decision tree algorithm developed by Ross Quinlan [32]. It can be used for classification and allows a high number of attributes. Deemed as a "machine learning workhorse", ranked no. 1 in the Top 10 Algorithms in Data Mining [59]. To classify data from a testing set, each sample from the data is propagated through the tree (according to the conditions satisfied by its attribute values). When an example reaches a leaf node, it is assigned the class value of that node.
RandomForest	Constructs a forest of decision trees in a randomized manner. Developed by Leo Breiman [34]. The Random Forest (RF) method is an ensemble learning method for classification, which constructs a forest of decision trees in a randomized fashion. Each tree is constructed from a different randomly selected subset of the dataset (bootstrap/sample), with a subset of (randomly chosen) features considered to select a split at each step of tree construction. When the forest is applied to a new instance, each tree votes for one class. The output is the class that gets the most votes from the individual trees.

2.4 Parameter settings for the classifiers

The settings for all classifiers were at their WEKA defaults. IBk used 1 nearest neighbour for classification and did not perform distance weighting. J48 trees were pruned. RF contained 100 trees.

2.5 Feature ranking using the Relief approach

Not all attributes in the dataset are necessarily useful for classification models and some can be omitted. In turn, this can reduce the time and computational cost of building the model. The features in these datasets were ranked by using the Relief approach, i.e., Relief Attribute Evaluator in WEKA, with 10-fold cross-validation. Relief "*evaluates the worth of an attribute by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different class*" [60].

2.6 Performance metrics

There are many measures of the performance of classifiers, typically defined for each class value (and then averaged across the different class values). These include true positive and false positive rates, precision, recall, and others. Classification accuracy is defined as the percentage of instances that have been classified correctly: It is the most commonly used indicator of performance. Another performance metric is Kappa (K), which allows for direct comparison between models as it shows how closely the classified instances match the labelled data, while also considering random chance (agreement with a random classifier). A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of a probabilistic binary classifier, and the area under the ROC curve is also often used as a performance metric.

Performance metrics are typically calculated based on the entries of the confusion matrix for a given classifier C and a given dataset D. The entry in row x and column y specifies the number of instances from D that actually belong to class x, but have been classified as class y by the classifier C. The diagonal entries of the matrix specify the numbers of correctly classified instances. The confusion matrices for all three classifiers and the two groups are provided in the supplementary information.

For a given class x, the diagonal entry corresponds to the number of true positives (TP) for class x. The sum of all non-diagonal entries of column x corresponds to the number of all instances incorrectly classified as x (false positives). Based on TP and FP, the precision for x is calculated as

$$Precision = \frac{TP}{TP + FP}$$

The performance of all three classifiers on unseen cases was estimated by using the 10-fold cross-validation procedure. Cross-validation reduces the variance in the performance estimates by averaging over different partitions of the dataset. The dataset is divided into 10-subsets (folds), which in turn are used as testing sets (while all remaining instances are used as training instances). This procedure ensures that every instance from the dataset appears in the test set exactly once.

3 Results and Discussion

3.1 Feature importance and ranking

Feature ranks and merit are listed in detail in the Supplemental Information. Time (hour of day) was ranked at the top for both groups, which stems from the fact that people mostly perform certain activities at specific times during the day, the most obvious being sleeping during night time. This attribute is then followed by the heart rate, humidity, and temperature in both groups, though in a different order. The largest differences between the H and M groups comes when observing ranks 5, 6, and beyond, where group H has steps, speed, and M.E.T. followed by PM variables, which all have the lowest average merit. In group M, PM_{10} and $PM_{2.5}$ have an average rank of 5 and 6, respectively, and PM_1 an average rank of 9.2. This discrepancy could stem from the different temporal resolutions used in recording sensor data (minute) and activity data (hour).

As the dataset was relatively small the decision was to not remove any of the attributes, and all were used to learn the models: PM_1, $PM_{2.5}$, PM_{10}, humidity, temperature, speed, heart rate, steps, M.E.T. and time.

3.2 Overall predictive performance of classifiers

Table 4 shows a comparison of the most relevant metrics for all the classifiers used in this research for group H and group M. Random Forest (RF) shows the highest Correctly classified (CC) values for both groups, and IBk the lowest CC values. For group H, the percent of correctly classified instances increases gradually from IBk to J48 (Δ11.3%) to RF (Δ6.4%). On the other hand, for group M the share of correctly classified instances jumps up between IBk to J48 (Δ42.6%), but then only marginally increases from J48 to RF (Δ0.3%). This difference could be a consequence of the different number of instances for each activity between the two groups. Some activities in group M have <500 instances, while all activities in group H have 5000 instances. The trend for Kappa is similar to CC, though all values for J48 and RF are ~0.06 lower than the correctly classified percent (divided by 100). Though there is some disagreement on the applicability of the Kappa statistic in the context of "The Paradox of Cohen's Kappa" [61,62] and what are the guidelines for evaluating it [63], in this context a value of >0.7 can be interpreted as moderate to strong agreement. Both J48 and RF fall in this category for group M. For group H, all Kappa values are <0.5. Importantly, the difference between J48 and RF for group M is only 0.01.

Calculated values for TP and precision again follow the CC and Kappa metrics in showing that J48 and RF provide the highest precision. The RF model for group M has the highest ROC area (0.97), indicating the lowest FP and highest TP rate.

Table 4: Summary of results for all models for both groups

Classifier/Metric	CC [%]		Kappa		TP		FP		Precision		ROC	
	H	M	H	M	H	M	H	M	H	M	H	M
IBk	35.2	34.3	0.3	0.2	0.4	0.3	0.1	0.1	0.4	NA	0.6	0.6
J48	46.5	76.9	0.4	0.7	0.5	0.8	0.1	0.1	0.5	0.8	0.8	1
RF	52.9	77.2	0.5	0.7	0.5	0.8	0.1	0.1	0.5	0.8	0.9	1

An important evaluator that is not included in the table is the time it took to construct each model. For IBk the time to build the model was <1 second for both groups. This is a positive aspect for IBk, though all the evaluation metrics show that this model is not suited for this type of data in comparison with J48 and RF. For group H, J48 took 4.67 seconds to build the model and 0.42 seconds for group M. In contrast, the RF-based model took 121.89 seconds for group H (more than 57-times as much time as J48), and 24.16 seconds for group M (26-times as much as J48). As these two models perform very similarly based on the evaluation metrics, the time it takes to build and cross-validate the model is a relevant factor when considering which one to use. In the case of the group M subset of data, it would be for efficient to use the J48 classifier as the improvement in the correctly classified percent of instances doesn't offset the time and processing power that has to be allotted. Real-world applications, based on collecting data with personal sensors, experience larger volumes of instances and would have to account for considerably longer run times. When a ML approach is applied to improve classification of activities and reduce the probability of human errors, time and processing power should be considered. In line with the 5th challenge listed in section 1.2, reducing the number of unnecessary instances, e.g., for sleeping, and selecting a more fit-for-purpose algorithm, would reduce the computational cost associated with activity recognition.

3.3 Predictive performance per group and activity

Results comparing the predictive performance of the used classifiers for group H (Table 5), show similar results as described in section 3.2. J48 and RF show overall higher TP rate, Precision and ROC area values, compared to IBk. These differences are more obvious in simpler activities, i.e., running, sleeping, sports, with a 0.3 difference in ROC area between IBk and J48/RF, and a $\leq$0.2 ROC difference for other, more complex activities. This result highlights the drawbacks of hourly recorded activity data, with less resolution on dynamic changes in more complex activities.

Table 5: Summary for group H, showing TP, FP, precision and ROC for all classifiers

	TP			FP			Precision			Recall			ROC		
Class/Classifier	IBk	J48	RF	IBk	J48	RF	IBk	J48	RF	IBk	J48	RF	IBk	J48	RF
Cleaning.in	0.3	0.4	0.5	0	0.1	0.1	0.5	0.4	0.5	0.3	0.4	0.5	0.6	0.8	0.8
Cooking.in	0.5	0.5	0.4	0.1	0.1	0.1	0.3	0.4	0.5	0.5	0.5	0.4	0.7	0.8	0.8
Playing.in	0.3	0.4	0.4	0.1	0.1	0.1	0.3	0.4	0.5	0.3	0.4	0.4	0.6	0.8	0.8
Resting.in	0.4	0.3	0.3	0.2	0.1	0.1	0.2	0.3	0.3	0.4	0.3	0.3	0.6	0.7	0.7
Running.out	0.3	0.6	0.8	0	0	0	0.6	0.7	0.7	0.3	0.6	0.8	0.7	0.9	1
Sleep.in	0.7	0.8	0.8	0	0	0	0.8	0.7	0.7	0.7	0.8	0.8	0.8	1	1
Smoking.in	0.4	0.3	0.5	0.1	0	0.1	0.3	0.5	0.5	0.4	0.3	0.5	0.6	0.8	0.9
Sports.in	0.2	0.4	0.6	0	0.1	0.1	0.5	0.5	0.6	0.2	0.4	0.6	0.6	0.8	0.9
Sports.out	0.2	0.4	0.5	0	0.1	0.1	0.4	0.4	0.5	0.2	0.4	0.5	0.6	0.8	0.9
Weighted average	0.4	0.5	0.5	0.1	0.1	0.1	0.4	0.5	0.5	0.4	0.5	0.5	0.6	0.8	0.9

The IBk results for group M showed several activities with values of 0 in all evaluation classes, having a considerably worse predictive performance result than J48 and RF classifiers, as evident in Table 6. Running stands out in the ROC area metric for IBk, with a relatively low FP rate, compared to its TP rate. Unique characteristics of running, compared to other activities, such as high values for heart rate, speed, steps, intensity, and lower temperatures and PM concentrations, could contribute to a better predictive performance. J48 and RF show a ROC and FP value of 1 and 0, respectively, for running. Results for group M show similar patters as group H with simpler activities showing better performance of all classifiers. On the other hand, group M TP and precision values are on average higher, compared to group H. Cooking has a TP rate of 0.5 in group H, and while the TP rate for cooking.cold.in shows a value of 0.4, the cooking.hot.in had a TP value of 0.8. The latter is associated with specific environmental conditions that can make it more distinguishable from other activities, e.g., higher temperatures and PM concentrations. Contrary to this assumption, the activity of playing does not show the same pattern. Playing.on.feet, associated with dust resuspension and an elevated heart rate, would be more distinctive than playing.sedentary. Although, on average, the group M playing activities have better metrics, compared to group H.

These conclusions are corroborated with the confusion matrix results, available in the SI. Activities with value definitions having more misclassified instances, in contrast to well-defined activities. For example, out of the 5000 instances of resting in group M for J48 (Table S4 in SI), 3738 are correctly classified. Out of the incorrectly classified, two thirds (818) are labelled as sleeping, and one fifth as cooking.hot.in. Moreover, activities often have a high number of their misclassified instances labelled as resting. Out of 769 instances of smoking, 102 are misclassified as resting. On the other hand, 96 instances are misclassified as cooking.hot.in, which would be expected as both activities can show high concentrations of PM.

Furthermore, sleeping and resting have well-defined time intervals, low heart rate, and no movement. They are consistently indicated by all participants and evenly distributed. Unlike other activities, sleep is uninterrupted for several consecutive hours, resulting in minimal distorted minute values within an hour. For instance, if a person runs for only 20 minutes but claims it as the main activity for that hour, only 1/3 of the data supports this claim, while the remaining 40 minutes include other activities.

Resting is also somewhat characterized by longer consecutive time intervals without interruptions. It also has a high FP rate and low precision in both groups. It is the second most frequent activity chosen by participants (behind sleeping) in the study, frequently overlapping with activities. Resting could be understood as a "default" activity, chosen when no other activity fits the description. It is a vaguely defined activity and open to interpretation. Participants tend to include various activities under this term, e.g., reading a book, playing board or computer games, watching television, chatting with friends, taking a leisurely walk, napping, having a dinner party, etc. All of these activities can differ in many aspects, such as heart rate, movement, speed, or PM concentrations, which would make accurate predictions more difficult. While more detailed activity classification would improve on this point, it would increase the burden on participants.

Table 6: Summary for group M, showing TP, FP, precision and ROC for all classifiers

	TP			FP			Precision			Recall			ROC		
Class	IBk	J48	RF	IBk	J48	RF	IBk	J48	RF	IBk	J48	RF	IBk	J48	RF
Cleaning.dry.in	0	0.5	0.4	0	0	0	0.1	0.6	0.6	0	0.5	0.4	0.5	1	1
Cleaning.steam.in	0	0.6	0.5	0	0	0	NA	0.6	0.7	0	0.6	0.5	0.5	1	1
Cleaning.wet.in	0	0.4	0.5	0	0	0	NA	0.6	0.5	0	0.4	0.5	0.5	0.9	1
Cooking.cold.in	0	0.4	0.4	0	0	0	0.6	0.5	0.4	0	0.4	0.4	0.5	0.9	1
Cooking.hot.in	0.3	0.8	0.7	0.3	0.1	0.1	0.1	0.6	0.6	0.3	0.8	0.7	0.5	0.9	1
Play.on.feet.in	0	0.6	0.4	0	0	0	NA	0.8	0.9	0	0.6	0.4	0.5	0.9	1
Play.sedentary.in	0.5	0.9	0.8	0	0	0	0.4	0.9	0.9	0.5	0.9	0.8	0.7	1	1
Resting.in	0.4	0.7	0.8	0.2	0.1	0.1	0.4	0.8	0.7	0.4	0.7	0.8	0.6	0.9	0.9
Resting.out	0.4	0.4	0.5	0	0	0	0.1	1	0.8	0.4	0.4	0.5	0.7	1	1
Running.out	0.6	0.8	0.9	0.1	0	0	0	0.9	0.9	0.6	0.8	0.9	0.8	1	1
Sleeping.in	0.4	0.9	0.9	0.1	0.1	0.1	0.6	0.8	0.9	0.4	0.9	0.9	0.7	1	1
Smoking.in	0.6	0.7	0.7	0	0	0	0.5	0.9	1	0.6	0.7	0.7	0.7	1	1
Sports.in	0	0.2	0.4	0	0	0	NA	0.8	0.6	0	0.2	0.4	0.5	0.9	1
Sports.out	0	0.8	0.9	0	0	0	1	0.9	0.9	0	0.8	0.9	0.5	1	1
Weighted Average	0.3	0.8	0.8	0.1	0.1	0.1	NA	0.8	0.8	0.3	0.8	0.8	0.6	1	1

3.4 The added value of the devices used

One aim of this research was to determine what is the respective contribution of the two devices used – the SAT and PPM, to the performance of activity classification. An assessment was conducted in WEKA, based on the data collected in Group M, as it showed the best performance between the two groups. The RF and J48 classifiers were used to classify the data from Group M (1) without the data collected with the PPM, i.e., all PM data, temperature, relative humidity and speed, (no PPM), (2) without just the particulate matter data (no PM), and (3) without the data collected with the SAT, i.e., heart rate, M.E.T. and steps (no SAT). The results showed, as evident in Table 7, that in the case of J48 the share of correctly classified instances is not reduced much if the PM or SAT data are removed (by 0.7% and 1.4%, respectively). On the other hand, if the PPM part of the dataset is removed entirely, the share of correctly classified instances falls to 60.1%. The RF models show similar values and trends.

However, the overall number to not show certain nuances, e.g., the results without the SAT data show that a lowered TP rate for sports.out from 0.8 to 0.6 (for J48). Though the difference is not as evident for running and sports.in, there is still a small decline in the classification accuracy. This result shows that for specific activities, the SAT data increases accuracy. Similarly, for the dataset without the PM data, accuracy for smoking, running outside, and playing are lower, all of which are activities with increased exposure to PM, though the difference is less pronounced than with the absence of SAT data. On the other hand, removing the entire PPM dataset (for RF) shows worse accuracy for all activities, especially for playing.on.feet (-0.4), smoking (-0.3), play.sedentary (-0.3), and cleaning.wet (-0.2). The latter could be explained by the absence of the data on relative humidity.

Collecting data on PM concentrations and other environmental variables are partial improvements on the 1st and 4th technical challenges listed in section 1.2. With more specific data on environmental conditions, the characteristics are more distinct and can improve feature extraction. Moreover, as complex activities have several actions associated with them, more data on the overall environment could offset the lack of data on these specific activities.

Table 7: Instances correctly classified instances by the J48 and RF models, based on selectively removing all PPM, only PM, and SAT data from the Group M dataset, respectively.

	Correctly classified instances [%]			
Classifier	Baseline	no PPM	no PM	no SAT
J48	76.9	60.1	76.2	75.5
RF	77.2	62.5	76.6	77.2

4 Conclusions

4.1 Summary of results

Two groups of participants were equipped with devices that measured their exposure to PM and their physical activity, while they logged their activity data with a paper TAD with hourly resolution (group H) and a smartphone app with minute resolution (group M). The aim was to determine the feasibility of complex HAR using low-cost personal environmental and biometric sensor data with three different classification models. This could in turn reduce or completely remove the necessity of participants in exposure studies to manually record their activity data.

Results showed an improved accuracy when (1) the activity time resolution was changed from 1-hour to 1-minute resolution, and (2) more vague activities, e.g., cleaning, cooking, playing, were divided into more detailed categories. Most misclassified instances belong to activities with vague definitions (resting, playing), while well-defined activities (smoking, cooking, cleaning, running) have fewer misclassified instances. Accuracy increased for all activities, especially playing, smoking, running, when the environmental sensor data was included.

All the used classifiers for group H showed accuracy above 35%, with RF being the most accurate with 52.9%. As the training data consisted of hourly labelled activities, this meant lower resolution and more errors (some activities don't last an hour, and most don't last exactly a set number of full hours). An improvement of labelling data by the minute was proposed and evaluated with group M, which showed a noticeable improvement in all measures of performance (e.g., the accuracy of ~77% for J48 and RF models). This was an expected outcome, as the sensor data was also recorded in minute intervals, and provided a good starting point to achieve activity prediction without resorting to manually recording data, which is prone to errors.

All of the models, for both groups, showed the most misclassified instances with resting. This could be the result of a vague definition of resting in comparison with sleeping, running, and most other activities. An educated guess of how the activities would be ranked from most vague definition to least vague would be: resting, playing, sports, cleaning, cooking, running, smoking, and sleeping. Resting could include naps, sitting behind a computer, reading a book, watching TV, hanging out with friends and family, or going for a short walk. All of these activities could have very different values of the observed variables. This is also true for sports, which is a wide term, and in the case of this dataset doesn't include running. What category should then jogging and speed-walking fall into?

When separated into more specific activities for group M, these activities showed moderate improvement, especially when considering more relevant activities as pertaining to exposure to particulate matter. When dividing cooking into two activities, hot and cold, the results show that cooking using a heat source can be identified more easily, and produces better results in terms of classification. A similar trend is present for cleaning, though the results are not as clear as for cooking.

On the other hand, sleeping or smoking are quite well-defined activities where there is little room for subjectivity. Even if smoking indoors includes using vaporizers, hookahs, pipes, or other gadgets, the observed variables would still presumably show similar results (elevated levels of PM, sedentary activity in enclosed space, not moving, relatively high heart rate, during the day, etc.), as would sleeping (in a chair, on a bed, on transport, taking a nap, etc.).

4.2 Limitations and future work

Shallow algorithms used in this research could be replaced by deep learning algorithms that could provide more accurate data. Additional steps could be taken to improve accuracy, e.g., noise removal, scaling, feature extraction, segmentation, hyperparameter tuning. On the other hand, these approaches would be less understandable to non-experts. It could also limit accessibility in terms of available software. In participatory-based research, frequently lead by non-experts in the field of ML, the selection of algorithms and approaches should be considered based on several factors, apart from accuracy – computation requirements, visualization options, understandable and explainable architectures/principles, etc. Similarly, more complex approaches used in participatory research could be exclusionary, as it would be more difficult to understand for lay individuals, even more pronounced for individuals with less technical skills and knowledge.

Moreover, more ambiguous or subjectively defined activities should be separated into better-defined activities, as listed above. Although this would impose greater challenges when collecting data for the participants, it could provide more detailed final results and improve the classification. A necessary focus would be to evaluate which of these activities are more relevant to the specific study or research and only use the classification models to predict those.

Overall, several additional suggestions and possible improvements are proposed for future research:

- Use of direct movement sensor (accelerometer, gyroscope, magnetometer) data from the SAT.
- Addition of possible other variables to be measured with SAT, e.g., skin temperature and conductivity.
- Utilization of the data from smartphones (light, movement, location, indoor/outdoor, crowd density, barometer, accelerometer, gyroscope, magnetometer, etc.).
- Fusion of data with government monitoring station data to improve correlations of the measured temperature and humidity.
- Use of static sensor data at home, at the workplace, or in the car to improve or correct measurements made by wearable sensors.
- improvement of an app for logging activity data by providing the participant with (a) a warning when the devices detect a possible change of activity due to changes in parameters and (b) providing suggestions for possible activities ranked from most likely to least likely based on this research.

Half of the challenges listed in section 1.2 remain unaddressed within the scope of this research, i.e., challenges 2, 3 and 6. While the demonstrated approach in this work does not require detailed personal data (as described in challenge 6), arguably the predictive performance could potentially be improved by including personal characteristics and GPS tracking. Moreover, the inclusion of ambient environmental data does not provide any tangible solutions to increase the quantity of annotated data or reduce sensory data heterogeneity. An argument could be made, to a degree, that collecting data on more variables could require fewer instances of annotated data.

An important improvement to participatory studies would be to reduce the burden of participants filling out time activity diaries, while simultaneously reducing the chance of human error. This research shows that machine learning, informed by low-cost personal environmental monitors, can improve the process of recording activity data by reducing or potentially, in the future, completely freeing study participants from recording their activities. Combining the results of this research with environmental stressors, measured with portable low-cost sensors will provide a more detailed picture of exposure and intake dose on an individual scale. Further research is needed to test, validate and improve these approaches.

As low-cost sensors become more widely used and individuals are able to gain access to more information about their living environment, researchers must provide adequate tools to assess and improve accuracy. A promising step forward would be to reduce the input of individuals and increase the role of machine learning. This research shows that a novel approach of using classification methods with data from low-cost portable environmental and activity sensors can be used to recognize specific activities without direct manual human input.

Statements and Declarations

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Data availability: The datasets generated during and/or analysed during the current study are not publicly available due to privacy issues, but are available from the corresponding author on reasonable request.

Ethics Approval: Ethical approval for the ICARUS project in Slovenia was obtained from the National Medical Ethics Committee of the Republic of Slovenia (approval nr. 0120-388/2018/6 on 22 August 2018). The data in this paper were selected only from participants in Slovenia. All methods were performed in accordance with the relevant guidelines and regulations.

Informed Consent Statement: Informed consent was obtained from all individual participants involved in the study.

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Supplemental Information

Combined Use of Wearable Biometric and Environmental Sensors for Complex Activity Recognition in Participatory Exposure Research

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Overview of the dataset: all variables per activity

For a more thorough overview of the dataset, the mean values of all variables for each activity were calculated and plotted in Fig. 1 for group H and in Fig. 2 for group M.

Running stands out in both groups with the highest values of speed, heart rate, steps, and MET (though the last two are absent for group M due to technical issues with the SAT), and lowest for temperature. sports.OUT and sports.IN also stand out in all these values, while also having low mean PM concentrations. Low PM concentrations for sports are more pronounced in group H, though the values between the IN and OUT activities are reversed between the groups – higher PM for OUT in group H and higher IN for group M. Importantly, sports.IN has also a higher average temperature and relative humidity than sports.OUT.

The highest PM values, by far, are evident for smoking in both groups. This trend is more evident in group M where mean values exceed 80 μg/m^3 and are more than 50 μg/m^3 above the next highest value – cooking. In group H, the difference is between 10 and 20 μg/m^3 (50 μg/m^3 for smoking vs 35 μg/m^3 for cooking). Sports, running, and sleep show the lowest PM values, which is also in line with expectations, as there is less dust resuspension while sleeping and lower concentrations outdoors when performing sports. The slightly lower PM values of sports.IN compared to sports.OUT in group H is more difficult to explain. It could be a consequence of the TAD data logging time resolution in group H, where a person could be performing a sports activity outdoors for only 30 minutes while logging the entire hour as sports.OUT, even if half the hour was spent indoors where PM concentrations were higher. Sleep shows the lowest mean speed, heart rate, number of steps, and MET, all of which is expected. It does not stand out in terms of temperature and humidity.

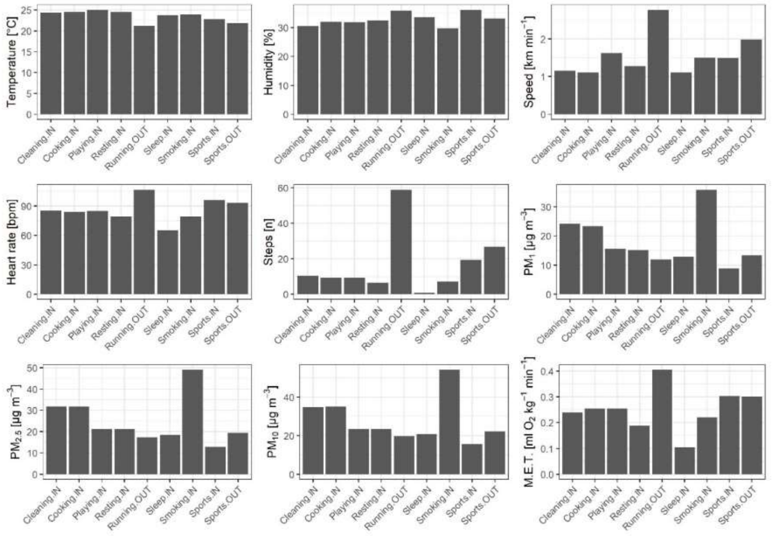

Fig. 1 Average values for all variables, per activity, for group H

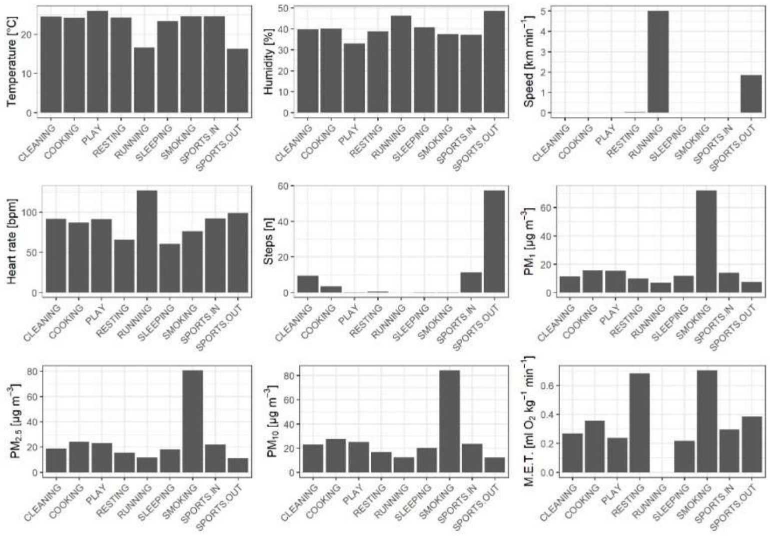

Fig. 2 Average values for all variables, per activity for group M

Results: confusion matrices

Results produced in WEKA included confusion matrices for each classifier (IBk, J48, RF) and both groups (group M and group H). Confusion matrices, as described in section 4.6, provide a summary of prediction outcomes on a classification problem and show the total number of correctly classified (diagonal entries) or incorrectly classified instances (all nondiagonal entries) for each class: Each row in the matrix covers all of the instances that belong to one class (X), and each column covers the instances that are predicted to belong to (classified as) class Y. The confusion matrices for each classifier and each group are shown in Table S1 (IBk, H), Table S2 (IBK, M), Table S3 (J48, H), Table S4 (J48, M), Table S5 (RF, H) and Table S6 (RF, M).

Table S1: IBk confusion matrix - group H

classified as ->	a	b	c	d	e	f	g	h	i
a=cleaning.in	1421	726	616	872	139	115	774	167	170
b=cooking.in	231	2286	297	1033	86	144	634	148	141
c=playing.in	209	621	1430	1353	243	76	699	165	204
d=resting.in	274	664	496	1939	139	261	687	280	260
e=running.out	228	371	545	1299	1680	51	551	99	176
f=sleep.in	100	632	164	330	22	3262	256	80	154
g=smoking.in	128	653	490	1287	122	140	1757	214	209
h=sports.in	102	791	760	1057	97	208	749	1122	114
i=sports.out	167	1226	539	1055	121	59	784	87	962

Table S2: IBk confusion matrix - group M

classified as ->	a	b	c	d	e	f	g	h	i	j	k	l	m	n
a=cleaning.dry.in	3	0	0	2	237	0	67	47	37	18	24	3	0	0
b=cleaning.steam.in	0	0	0	0	137	0	0	57	31	104	21	66	0	0
c=cleaning.wet.in	2	0	0	0	218	0	31	42	44	123	56	0	0	0
d=cooking.cold.in	0	0	0	3	217	0	6	27	18	87	29	0	0	0
e=cooking.hot.in	8	0	0	0	595	0	181	401	155	314	192	77	0	0
f=play.on.feet.in	1	0	0	0	0	0	2	42	10	4	26	0	0	0
g=play.sedentary.in	0	0	0	0	96	0	226	116	0	16	8	7	0	0
h=resting.in	4	0	0	0	1203	0	24	2103	92	608	775	191	0	0
i=resting.out	0	0	0	0	105	0	0	1	84	28	3	4	0	0
j=running.out	1	0	0	0	1	0	11	1	11	50	0	5	0	0
k=sleeping.in	1	0	0	0	883	0	4	1802	14	82	2107	107	0	0
l=smoking.in	0	0	0	0	113	0	12	132	0	68	6	438	0	0
m=sports.in	0	0	0	0	195	0	7	44	5	53	57	0	0	0
n=sports.out	6	0	0	0	251	0	8	95	307	74	1	0	0	32

Table S3: J48 confusion matrix - group H

classified as ->	a	b	c	d	e	f	g	h	i
a=cleaning.in	2166	797	317	502	159	171	210	356	322
b=cooking.in	404	2708	451	354	83	143	142	325	390
c=playing.in	570	782	1761	644	237	78	141	264	523
d=resting.in	495	645	556	1599	175	348	366	307	509
e=running.out	430	342	391	243	2921	98	124	154	297
f=sleep.in	109	60	21	321	39	4189	64	183	14
g=smoking.in	373	599	432	769	233	368	1546	227	453
h=sports.in	249	582	502	429	171	135	210	2120	602
i=sports.out	511	1146	496	191	168	107	103	373	1905

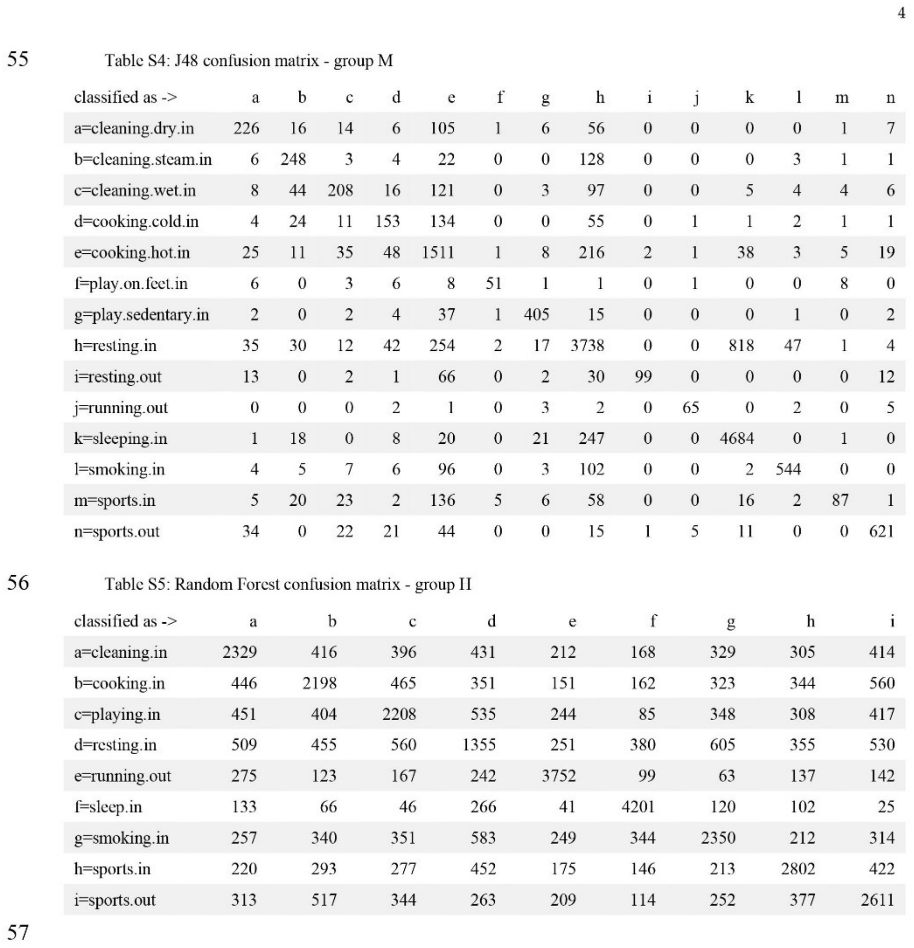

Table S4: J48 confusion matrix - group M

classified as ->	a	b	c	d	e	f	g	h	i	j	k	l	m	n
a=cleaning.dry.in	226	16	14	6	105	1	6	56	0	0	0	0	1	7
b=cleaning.steam.in	6	248	3	4	22	0	0	128	0	0	0	3	1	1
c=cleaning.wet.in	8	44	208	16	121	0	3	97	0	0	5	4	4	6
d=cooking.cold.in	4	24	11	153	134	0	0	55	0	1	1	2	1	1
e=cooking.hot.in	25	11	35	48	1511	1	8	216	2	1	38	3	5	19
f=play.on.feet.in	6	0	3	6	8	51	1	1	0	1	0	0	8	0
g=play.sedentary.in	2	0	2	4	37	1	405	15	0	0	0	1	0	2
h=resting.in	35	30	12	42	254	2	17	3738	0	0	818	47	1	4
i=resting.out	13	0	2	1	66	0	2	30	99	0	0	0	0	12
j=running.out	0	0	0	2	1	0	3	2	0	65	0	2	0	5
k=sleeping.in	1	18	0	8	20	0	21	247	0	0	4684	0	1	0
l=smoking.in	4	5	7	6	96	0	3	102	0	0	2	544	0	0
m=sports.in	5	20	23	2	136	5	6	58	0	0	16	2	87	1
n=sports.out	34	0	22	21	44	0	0	15	1	5	11	0	0	621

Table S5: Random Forest confusion matrix - group II

classified as ->	a	b	c	d	e	f	g	h	i
a=cleaning.in	2329	416	396	431	212	168	329	305	414
b=cooking.in	446	2198	465	351	151	162	323	344	560
c=playing.in	451	404	2208	535	244	85	348	308	417
d=resting.in	509	455	560	1355	251	380	605	355	530
e=running.out	275	123	167	242	3752	99	63	137	142
f=sleep.in	133	66	46	266	41	4201	120	102	25
g=smoking.in	257	340	351	583	249	344	2350	212	314
h=sports.in	220	293	277	452	175	146	213	2802	422
i=sports.out	313	517	344	263	209	114	252	377	2611

Table S6: Random Forest confusion matrix - group M

classified as ->	a	b	c	d	e	f	g	h	i	j	k	l	m	n
a=cleaning.dry.in	192	0	19	20	90	0	0	79	1	0	0	0	15	22
b=cleaning.steam.in	1	201	34	3	17	0	0	151	0	0	0	1	8	0
c=cleaning.wet.in	5	22	267	27	86	0	0	72	2	0	4	2	23	6
d=cooking.cold.in	12	2	18	166	115	0	0	53	0	0	4	2	10	5
e=cooking.hot.in	27	17	63	57	1373	0	0	287	7	0	33	4	18	37
f=play.on.feet.in	2	0	4	5	20	37	1	2	0	0	0	0	10	4
g=play.sedentary.in	1	0	5	4	44	1	361	23	0	1	16	1	4	8
h=resting.in	33	22	28	51	201	0	2	4145	1	3	494	3	9	8
i=resting.out	2	0	0	4	65	0	0	31	102	0	0	0	1	20
j=running.out	0	0	0	0	6	0	0	0	1	71	0	0	0	2
k=sleeping.in	0	10	1	6	2	0	22	484	0	0	4475	0	0	0
l=smoking.in	6	2	6	2	87	0	1	132	0	0	8	516	9	0
m=sports.in	3	0	34	4	98	1	3	64	0	1	17	0	131	5
n=sports.out	13	2	10	26	23	0	0	11	14	0	8	2	0	665

Results: Feature merits

Table 7 and Table 8 show feature merits for all attributes used to learn the models.

Table 7: Feature merits (importance scores) and ranks for group M

Group M		
average merit	average rank	attribute
0.127 ± 0.001	1 ± 0	Time
0.052 ± 0.001	2 ± 0	Heart rate
0.036 ± 0	3 ± 0	Humidity
0.03 ± 0	4 ± 0	Temperature
0.028 ± 0.001	5 ± 0	PM_{10}
0.02 ± 0	6 ± 0	$PM_{2.5}$
0.017 ± 0	7 ± 0	Speed
0.016 ± 0	8 ± 0	Steps
0.014 ± 0	9.2 ± 0.4	PM_1
0.013 ± 0.001	9.8 ± 0.4	M.E.T.

Table 8: Feature merits (importance scores) and ranks for group H

Group H		
average merit	average rank	attribute
0.193 ± 0.001	1 ± 0	Time
0.017 ± 0.001	2.5 ± 0.5	Humidity
0.017 ± 0	2.5 ± 0.5	Heart rate
0.016 ± 0	4	Temperature
0.015 ± 0	5	Steps
0.007 ± 0	6	Speed
0.001 ± 0.001	7	M.E.T.
-0.006 ± 0	8	PM_1
-0.008 ± 0.001	9	PM_{10}
-0.011 ± 0	10	$PM_{2.5}$

3.4 Manuscript 4: Assessment of Individual-Level Exposure to Airborne Particulate Matter During Periods of Atmospheric Thermal Inversion

Section 3.4 consists of a scientific article published in Sensors in 2022, authored by Rok Novak, Johanna A. Robinson, Tjaša Kanduč, Dimosthenis Sarigiannis, and David Kocman.

This article discusses the use of the PPM to assess activity-specific and general indoor and outdoor exposure to particulate matter during and after a period of high concentrations of PM, i.e., an atmospheric thermal inversion (ATI), in the Ljubljana subalpine basin. Utilizing the data collected in the ICARUS project in Ljubljana, Slovenia, showed that indoor and outdoor exposure to PM was significantly higher during the ATI period. Moreover, larger differences were observed between mean indoor and outdoor exposure to PM during the ATI period than after. This research clearly demonstrated the utility of the PPM in a specific exposure assessment scenario. While monitoring stations provide valid and referential data on the outdoor concentration of PM, personal monitors better capture exposure in indoor environments. Recorded activities provide additional context.

A concrete example of an exposure assessment using a personal monitor is demonstrated in this article. While this shows an exposure assessment for a population, it does provide some insights into exposure for specific individuals or during the activities they perform. The results of this research provide a proof of concept for using the PPM for a detailed exposure assessment, explored in Section 3.5.

I contributed to the conceptualization of comparing indoor and outdoor PM exposure during a period with ATIs, the development of the methodology, data collection, validation, curation, and visualization. I prepared the original draft and contributed to the review and editing of the final version.

sensors MDPI

Article

Assessment of Individual-Level Exposure to Airborne Particulate Matter during Periods of Atmospheric Thermal Inversion

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Abstract: Air pollution exposure is harmful to human health and reducing it at the level of an individual requires measurements and assessments that capture the spatiotemporal variability of different microenvironments and the influence of specific activities. In this paper, activity-specific and general indoor and outdoor exposure during and after a period of high concentrations of particulate matter (PM), e.g., an atmospheric thermal inversion (ATI) in the Ljubljana subalpine basin, Slovenia, was assessed. To this end, personal particulate matter monitors (PPM) were used, worn by participants of the H2020 ICARUS sampling campaigns in spring 2019 who also recorded their hourly activities. ATI period(s) were determined based on data collected from two meteorological stations managed by the Slovenian Environmental Agency (SEA). Results showed that indoor and outdoor exposure to PM was significantly higher during the ATI period, and that the difference between mean indoor and outdoor exposure to PM was much higher during the ATI period (23.0 $\mu g/m^3$) than after (6.5 $\mu g/m^3$). Indoor activities generally were associated with smaller differences, with cooking and cleaning even having higher values in the post-ATI period. On the other hand, all outdoor activities had higher PM values during the ATI than after, with larger differences, mostly >30.0 $\mu g/m^3$. Overall, this work demonstrated that an individual-level approach can provide better spatiotemporal resolution and evaluate the relative importance of specific high-exposure events, and in this way provide an ancillary tool for exposure assessments.

Keywords: personal exposure; particulate matter; atmospheric thermal inversion; personal monitoring; exposure assessment

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1. Introduction

Airborne particulate matter (PM) negatively impacts human health, reduces life expectancy, and increases mortality, and is a particularly important health risk in urban environments as traffic and other factors additionally contribute to higher concentrations of PM and other pollutants [1–5].

A common approach to assessing exposure is using monitoring stations that measure outdoor concentration levels of various pollutants and require compliance with regulatory protocols, which makes them the reference standard in an urban environment for evaluating long-term trends, outdoor concentrations, and city-wide exposure assessments [6]. On the other hand, they are expensive to operate, physically large, and consequently limited in number and coverage. While there are several options to use data from monitoring stations to estimate indoor exposure [7], static outdoor stations are not able to capture the variability of exposure based on an individual's activities and daily movement trajectory [8]. Multiple studies have shown that collecting data on air quality and exposure on an individual level, in contrast to city-wide monitoring, provides higher spatiotemporal granularity to observe individual-level exposure and daily fluctuations in diverse indoor and outdoor urban settings, including the impact of atmospheric thermal inversions (ATIs) [9–11]. Exposure assessments based on individual-level measurements usually show higher recorded values than estimates based on data from monitoring stations [12,13], and therefore assessments that use community average concentrations of PM can underestimate the health burden of air pollution [14]. Personal monitoring devices can be used to estimate negative health outcomes from exposure to higher PM concentrations [15] as well as the importance of socioeconomic variables, e.g., sociodemographic status, urban mobility, and living conditions, when assessing exposure to PM [16]. To further explore the applicability of PM monitors in individual-level exposure research, their performance should be assessed within a period that would show distinct differences in exposure during activities and in microlocations that the individual records. A period with persistent ATIs in a suitable wintertime environment (e.g., an alpine basin) could provide the necessary conditions, as it is characterized by two clearly delimited periods of high and low concentrations of PM.

ATIs that occur in urban environments, as a consequence of atypical temperature gradients, produce a "cap" which reduces the diffusion of dust, smoke, and other air pollutants [17] and can cause concentrations of air pollutants to increase, with a high level of spatiotemporal variability throughout the urban environment [18,19]. An elevated level of exposure during ATIs can lead to detrimental health effects, mostly as an increase in the incidence of acute respiratory diseases, asthma, and cardiovascular diseases [20–22]. However, increased exposure on an individual level during ATIs is still poorly understood.

A unique set of conditions present in a subalpine basin (Ljubljana, Slovenia), e.g., concave shape, extended periods of anticyclonic conditions, and drag associated with the complex topography, resulting in frequent foggy days and ATIs, which in turn cause a buildup of PM [23]. The Ljubljana basin experiences frequent short-lived inversions in all seasons, though persistent inversions occur mostly in the colder part of the year [24]. Meteorological conditions are a driving factor in determining air quality in Ljubljana, and can surpass the importance of emission ceilings [25]. Although air quality has been improving in most European cities over the past decade, Ljubljana, as of 27 July 2022, ranks 279 out of 344 cities from the European Environment Agency (EEA) member countries in terms of air quality, with an average PM concentration of 15.7 $\mu g/m^3$, measured in 2020 and 2021, labeled as "poor air quality" by the EEA [26]. ATIs, compounded by the poor air quality in Ljubljana during winter, temporarily increase exposure to PM and offer a distinctive perspective on high-exposure events in urban environments, which individual-level monitoring could help to assess in more detail.

This study used next-generation sensing and monitoring (NGSM) technology—a wearable PM monitor—to determine how these types of devices could provide fine-grained spatiotemporal resolution of personal exposure to PM_{10} in a period of persistent ATIs and immediately after, based on individual activities and microlocations. Individual-level exposure assessments were based on data obtained from personal PM monitors (PPM) used as part of the ICARUS H2020 project [27], where participants carried the devices for one week in a heating and non-heating season, and additionally provided hourly data on their activities, transport mode, and microlocations [28].

2. Materials and Methods

2.1. Collecting Particulate Matter Data

For assessing exposure on an individual level a wearable device called the PPM (shown in Figure 1) was used, which provided data on PM_1, $PM_{2.5}$, and PM_{10} concentrations, ambient temperature, relative humidity, and location/GPS data with minute resolution. The devices were designed and constructed for the ICARUS project [29] by IoTech Telecommunications, Thessaloniki, Greece [30] and are based on the Arduino platform and the Plantower, Beijing, China, pms5003 sensor [31,32]. To determine whether the device provided data that was fit for purpose and accurate, a validation was conducted by collocating the PPM with a GRIMM (Durag Group, Hamburg, Germany) model 11-A (1.109) aerosol spectrometer, which showed that the PPM had relatively high accuracy and was fit for purpose, further described in Novak et al. [33].

Figure 1. PPM device (white box attached to clothes) worn by a participant.

Participants were instructed to wear the PPM for the entire duration of the study or have it placed near them if they performed sedentary or stationary activities, e.g., office work or sleeping. The data were collected on an internal SD card and exported via a web app/portal and stored on a local drive. Each participant had to fill out a time activity diary (TAD) and indicate what the characteristic activity was that they were performing each hour of the day for seven days. Data were used from the ICARUS heating season sampling campaign, which took place from 16 February 2019 to 12 March 2019.

To observe the trend of PM_{10} concentrations in Ljubljana during and after the period with persistent ATIs, city-wide data on PM_{10} concentrations (30 min values) and meteorological conditions (temperature and wind speed) were provided by the Slovenian Environmental Agency (SEA) [34] from the urban background reference station in the Bežigrad district of Ljubljana. Preliminary observations showed that a period with persistent ATIs could have occurred in Ljubljana in the same period as the heating season sampling campaign. Data from the monitoring stations were collected for the period from 10 February 2019 to 15 March 2019 to provide additional context.

2.2. Determining ATIs

ATIs were determined by analyzing temperature gradients between stations at different elevations, per the Largeron and Staquet [35] pseudo-vertical temperature gradient method (TGM), which presupposes two assumptions: (1) horizontal homogeneity of the temperature field and (2) the quasi-linearity of the temperature profile. When these considerations are met, the ratio of the temperature and height difference between the stations ($\Delta T/\Delta z$) can be used to determine the stability of the boundary layer when the inversion occurs [35]. Kikaj et al. [23] determined that these assumptions were met for low- and medium-lying stations in and around the Ljubljana basin in the colder months of the year. High-elevation stations showed moderate correlation coefficients when calculating horizontal air temperature homogeneity and were, in the scope of this paper, only used to estimate the height of the inversion layer by determining if the inversion persisted up to the height of the station.

Measurements were collected from three automatic weather stations (AWS), one low-lying station located in the center of Ljubljana (station Bežigrad—AWS-B), one medium-lying station situated on a hill at the border of the basin (Topol—AWS-T) and one high-lying station at the northern border of the basin (Krvavec—AWS-K), shown in Table 1 with their respective elevations, coordinates, and collected parameters. The stations cover the central, western, and northwestern parts of the Ljubljana basin, as shown in Figure 2. All stations measure and report air temperature at 2 m above ground, at 7:00, 14:00, and 21:00, each day.

Table 1. Automatic weather stations (AWS) used to determine ATIs, their locations, elevations, and parameters collected.

Station	Meters above Sea Level	Coordinates	Parameters
AWS-B	299 m	46.0654 N, 14.5123 E	Temperature, PM_{10}
AWS-T	692 m	46.0940 N, 14.3713 E	Temperature
AWS-K	1742 m	46.2978 N, 14.5335 E	Temperature

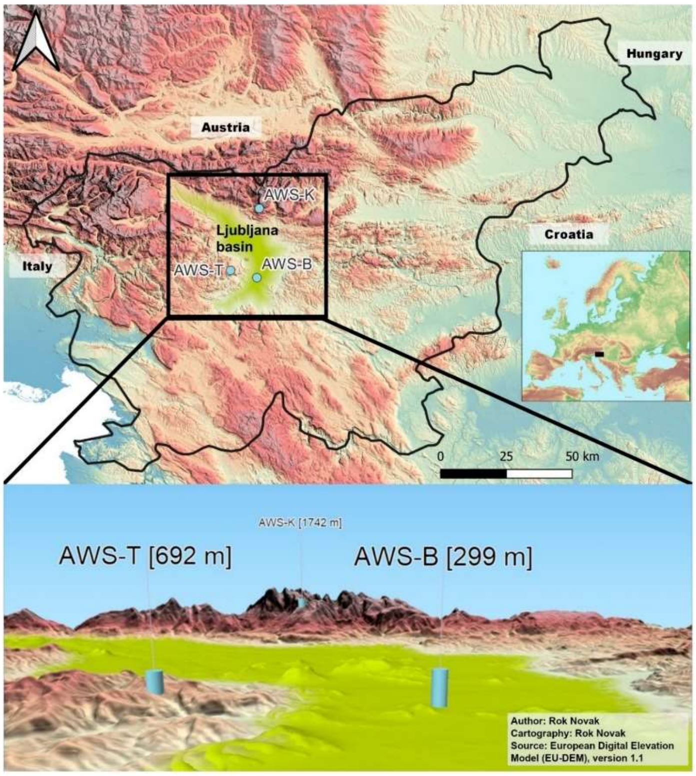

Figure 2. Geographical locations of automatic weather stations Bežigrad, Topol, and Krvavec. Top: Locations on a topographical map of Slovenia and neighboring countries with the location of the Ljubljana basin. Bottom: 3D visualization of locations and their respective elevations with vertical exaggeration (2), designed with the Qgis2threejs plugin [36] in QGIS 3.20.1-Odense [37].

As per the TGM, the ratio of the temperature difference between stations AWS-B and AWS-T to their difference in elevation ($\Delta T/\Delta z$) was used to indicate the stability of the boundary layer and consequently when an inversion occurred, as shown in Equation (1):

$$\frac{\Delta T}{\Delta z} = \frac{\Delta T_{T,B}}{\Delta z_{T,B}} \times 10^3 \tag{1}$$

where $\Delta T_{T,B}$ is the temperature difference between the AWS-T and AWS-B station and $\Delta z_{T,B}$ is the height difference between AWS-T and AWS-B station.

Positive values indicate an ATI, and periods when values consistently show $\Delta T/\Delta z > 0$ for at least 72 consecutive hours indicate persistent inversions, as shown in Equation (2):

$$\frac{\Delta T}{\Delta z} > 0 \text{ for } \geq 72 \text{ h} \tag{2}$$

The definition of 72 h for a persistent ATI is based on the criteria set by Largeron and Staquet [35].

2.3. Treatment of Data from the PPMs and TADs

After harmonizing the data sets of the PPM and TAD (described in detail in Novak et al. [38]), data were selected based on a specific set of criteria: (a) they were part of the heating period data set, (b) data were available for the period when ATIs occurred, (c) the PPM consistently provided data, and (d) the TADs were filled out.

A key procedure was to assign an indoor/outdoor label to each minute value. As the GPS data provided by the PPM did not provide accurate enough spatial resolution to determine if the person was indoors or outdoors, data on activities in the TAD and temperature measured by the PPM were used as follows:

- Outdoor activities in the TAD were: using a bicycle, walking, running outdoors, participating in outdoor sports activities, and three generic labels: “Home.OUT”, “Office.OUT”, and “Other.OUT”. For indoor activities, there were similar generic labels included, “Home.IN”, “Office.IN”, and “Other.IN”, as well as resting and sleeping indoors, playing, indoor sporting activities, cooking, cleaning, and smoking indoors. More specific activities were included in the generic labels;
- Primarily, activity and microlocation labels from the TADs were used to determine if the person was indoors or outdoors. To further refine the accuracy of the indoor/outdoor variable, ambient temperature data recorded by the PPM were used;
- During the observed period from late February to early March in 2019, the outdoor temperatures as measured by AWS-B never exceeded 19 °C in Ljubljana. Using this value as the highest base value gave an approximate highest possible temperature for outdoor activities, though it did have some drawbacks as the device could be exposed to direct sunlight and show higher values than those recorded at automatic weather stations;
- The PPM was collocated with a reference instrument (Testo SE & Co. KGaA, Lenzkirch, Germany, Testo 435-2 sensor with an external IAQ probe [39]) to assess the accuracy of the temperature measurements. Results showed that the PPM had a very high correlation (0.98) with the values recorded by the reference instrument, though the values consistently showed 4.5 °C higher values than the reference instrument. Though the PPM had precise values, they were not accurate. There are several possible causes, most probably due to the positioning of the sensor enclosed in the device close to a warm rechargeable battery. Temperature difference was even higher during the first half hour of charging the battery. This does not affect the outdoor measurements as it is reasonable to assume that the device was not charged during outdoor activities;
- Considering the above (the temperature in Ljubljana never exceeding 19 °C and the 4.5 °C (offset) higher values of the PPM), activities were removed from the outdoor

category if they had a temperature above 23.5 °C, and similarly removed from the indoor category if the temperatures were below 23.5 °C.

In some cases, certain inputs in the TADs could overlap between indoor and outdoor microlocations, where a person selected an indoor activity because it represented a majority of the hour, though they spent an amount of time in that same hour outside, e.g., preparing a meal for 40 min then going for a walk would be indicated as an indoor activity for this hour even though the person spent a third of the time outdoors. Using the temperature correction improved the accuracy of the activity dataset.

2.4. Data Selection and Evaluation

Exposure was calculated for the period between 16–22 February 2019 and 23 February to 12 March 2019, the first being the period with a persistent ATI event and two days of latency for the PM concentrations as observed at the AWS-B, and the second being the period after the inversion dispersed. Exposure in each respective domain and time period was calculated based on Equation (3):

$$E_{d,p} = \frac{\sum_{i=1}^{n} m_i}{n} \quad (3)$$

where E is the cumulative exposure, d indicates the domain (indoor, outdoor, or activity) and p the period (during ATI or post-ATI) of exposure, m_i represents each respective minute measurement in the spatiotemporal period, and n the number of measurements made in that period. A cumulative exposure approach was used to determine the baseline differences between the ATI and post-ATI periods, inter-activity differences, and how cumulative exposure assessments based on personal monitors fared in contrast to an assessment based on data collected from monitoring stations. Minute values of PM_{10} collected from the PPMs carried by the participants were aggregated and averaged based on each respective domain (temporal, spatial, activity).

The periods chosen were determined based on the results of the ATI calculations, wind speed data, and data on the height of the inversion layer. Only certain activities from the collected dataset were considered in the scope of this paper; some were removed due to the unavailability of the data in both periods, e.g., smoking and burning of incense/candles. After eliminating participants who didn't have any PM_{10} data or empty TADs, the period with persistent ATIs had fewer individuals available (3) than the post-ATI period (24). Some of the data were removed from certain participant datasets if they did not meet the required temperature criteria. Mean values with standard deviation were calculated for all indoor and outdoor activities and plotted in boxplots. A one-way ANOVA was performed on the final dataset, in combination with a Tukey's HSD (honestly significant difference) post-hoc test for pairwise comparisons.

3. Results and Discussion

3.1. ATIs

Figure 3 shows the $\Delta T/\Delta z$ values calculated for the period from 10 February to 15 March 2019 to provide some context for the observed ATIs and patterns in the fluctuations of $\Delta T/\Delta z$ [°C/km]. An ATI is defined by $\Delta T/\Delta z > 0$ °C/km, which is present several times in Figure 3, most frequently in the mornings (colored black) when the temperatures in the valley were still lower than in higher elevations. This pattern indicates diurnal inversions, formed every night due to radiative cooling of the soil, producing a very stable surface layer particularly associated with alpine valleys [35].

A persistent ATI, defined as $\Delta T/\Delta z > 0$ °C/km for at least 72 consecutive hours, as indicated in Equation (2), is present in only one period, from 16 February to 19 February, shaded gray in Figure 3, with an exception on 18 February at 14:00 with a $\Delta T/\Delta z$ of -0.25 °C/km. As this individual observation indicated only a small negative number, the decision was made to include this and the next three measurements in the period of the persistent ATI, as the daily average still showed a high $\Delta T/\Delta z$, as well as the three days following the end of this period. Importantly, the presence of the inversion is key, and the strength of the inversion does not play a vital role in the scope of this research. The days between 20 February and 22 February still experienced frequent inversions and primarily showed high levels of PM_{10} concentrations, and so were consequently included in the post-ATI period to better capture the true exposure associated with ATIs. Persistent ATIs occur in Ljubljana multiple times per year; based on Equation (2) and data collected from SEA [34] there were three periods in 2019 with persistent ATIs: 16 to 19 February, 22 to 26 October, and 23 to 27 December.

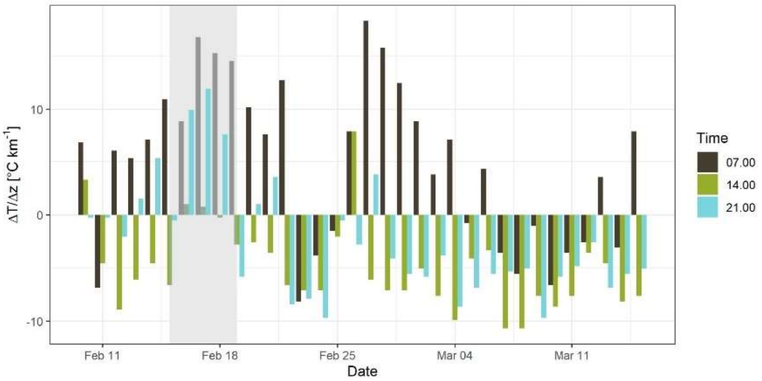

Figure 3. ΔT/Δz between Bežigrad and Topol stations from 10 February to 15 March 2019. Period with persistent ATI shaded in grey.

The period following the persistent ATI shows sporadic occurrences of inversions during morning and evening measurements, which completely stop on 22 February. After 25 February there is a period of diurnal ATIs in the morning hours with the highest ΔT/Δz value on 27 February at 18.3 °C/km. Data from AWS-B also showed that on 23 February average wind speeds increased from 0.2 to 5.0 m/s and average temperatures decreased from 9.1 °C to 1.1 °C.

Estimate of Boundary Layer Height

Data collected from the AWS-K station showed that the inversion layer did not surpass the height of the station itself (1742 m) in any of the measurements made at 12:00 in the period between 10 February and 15 March 2019. On the other hand, there were several instances in the 7:00 measuring interval, most common during the period with persistent ATIs. A case of inversion that stood out happened on 17 February 2019 at the 7:00 interval, when the AWS-B station measured a temperature of −2.1 °C, and AWS-K 6.7 °C (a difference of 8.8 °C). Moreover, observing data from the highest-lying station in Slovenia (Kredarica, at elevation 2513 m.a.s.l., some 60 km distance from AWS-B), revealed a temperature of 0.8 °C, indicating that the boundary layer was above this height on 17 February 2019 at 7:00.

3.2. PM Measurements at the Monitoring Station

As evident in Figure 4, the concentrations of PM_{10} as measured at the AWS-B started increasing as the ATIs became more frequent, peaking on 20 February, a day after the period with persistent ATIs ended. This shows a latency effect of rising PM concentrations in relation to ATIs, as the inversions continued during morning and evening measuring intervals and affected the concentrations of PM_{10}. The highest value of PM_{10} was recorded on 20 February, with 75 $\mu g/m^3$, which decreased rapidly and reached its lowest point three days later on 23 February, with 11 $\mu g/m^3$. Mean values for the high-PM period

(16–22 February, shaded green in Figure 4) and low-PM period (23 February–15 March, shaded blue in Figure 4) were 47.7 μg/m^3 and 23.2 μg/m^3, respectively, shown with dashed lines in Figure 4 for both periods.

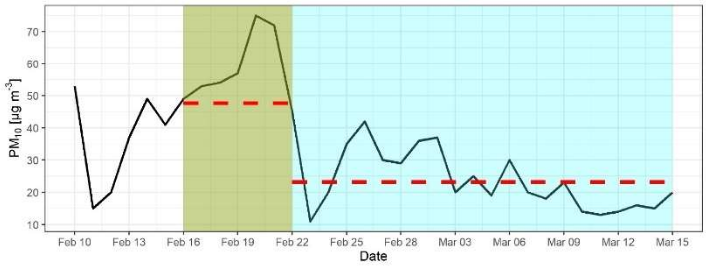

Figure 4. Measured daily PM_{10} concentrations in the observed period from 10 February to 15 March 2019, collected from AWS-B. Persistent ATI period with a latent increase of PM concentrations shaded green, the post-ATI period included in the analysis shaded blue. Dashed red lines show mean PM_{10} values for each period.

3.3. Data Collected from PPMs and TADs

The entire ICARUS dataset (in Ljubljana) consisted of 1,439,231 observations of 107 variables, which was refined to 136,115 observations of 32 variables for the purposes of this paper, including timestamps, indoor and outdoor activities, PM_{10} concentrations, and temperature. Next, the data were separated into four groups—indoor and outdoor during the ATI (with 10,622 and 1931 observations, respectively), and indoor and outdoor post-ATI period (with 59,719 and 6664 observations, respectively).

As evident in Tables 2 and 3, there are certain activities that have a large number of recorded instances, e.g., resting, sleeping, cycling, and generic "home", "office", and "other", and some activities that have few instances, e.g., sports and running. The lowest number of instances (61) are recorded for running during the period with persistent ATIs, which is due to the fact that the recorded temperatures for most of the running period were higher than the elimination criteria for outdoor activities (23.5 °C). Almost all the values for the number of instances per activity in the post-ATI period were higher, as this period was longer and included more participants. Note that the "office" activity in Table 3 shows the number of instances for outdoor activities during the individual's work hours.

Table 2. Number of instances for each indoor activity during the ATI period and in the post-ATI period.

Period	Cleaning	Cooking	Home	Office	Other	Resting	Sleeping	Sports
ATI	395	472	8535	1319	632	1414	3638	142
post-ATI	2060	3686	41,320	11,346	4921	15,525	19,287	373

Table 3. Number of instances for each outdoor activity during the ATI period and in the post-ATI period.

Period	Bicycle	Foot	Home	Office	Other	Running	Sports
ATI	1057	538	184	1170	366	61	295
post-ATI	1312	1822	1583	967	3479	294	1825

3.4. Exposure Assessment

Figure 5 shows that exposure to PM_{10} calculated based on Equation (3), as measured by the PPM, was higher indoors and outdoors during the persistent ATI event, compared to the post-ATI period. During the ATI period participants were exposed to a mean PM_{10} concentration of 43.5 $\mu g/m^3$ ($\sigma \pm 26.8$ $\mu g/m^3$) indoors, and 66.5 $\mu g/m^3$ ($\sigma \pm 23.5$ $\mu g/m^3$) outdoors, which is in stark contrast with the post-ATI period where indoor and outdoor exposures were 31.2 $\mu g/m^3$ ($\sigma \pm 56.8$ $\mu g/m^3$) and 37.7 $\mu g/m^3$ ($\sigma \pm 96.1$ $\mu g/m^3$), respectively. As determined by the ANOVA test (and subsequently the Tukey's HSD test), the differences between the means were statistically significant, and the results show that there was a real difference between all four microlocation combinations (indoors during and after ATI, and outdoors during and after ATI). This result shows that elevated levels of PM_{10} outdoors impacts the cumulative exposure to PM_{10} indoors and outdoors. Moreover, these results show that the difference in indoor and outdoor exposure was much higher during the period of ATIs (23.0 $\mu g/m^3$) than after (6.5 $\mu g/m^3$), which indicates that exposure to PM can be influenced by high-exposure events during specific activities and in specific microlocations during a period with persistent ATIs.

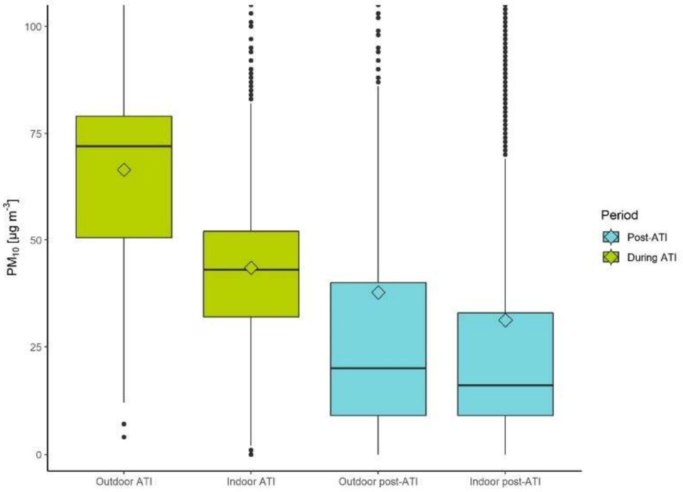

Figure 5. Calculated exposure to PM_{10} indoors and outdoors in the period with a persistent ATI event (in green) and the post-ATI period (blue), collected from the PPM devices. Values above 100 $\mu g/m^3$ were removed from the plot to better visualize the differences between mean (diamond) and median values (line).

Comparing the results obtained from the AWS-B monitoring station with the PPM data shows that the cumulative outdoor exposure assessment during the period with persistent ATIs yields a similar result regardless of which method was used (57.9 $\mu g/m^3$ for the monitoring station and 66.5 $\mu g/m^3$ for the PPM). Outdoor exposure in the post-ATI period shows a moderately different result, where the monitoring station showed a mean value of 23.2 $\mu g/m^3$ and the PPM 37.7 $\mu g/m^3$. This discrepancy could be a consequence of the PPM better capturing the actual individual exposure when the participant moved throughout the city, e.g., elevated levels of PM in some areas due to the street canyon effect [40], urban green spaces and foliage [41,42], construction sites [43], or a specific action that the person was performing. Outdoor data from the PPM showed 181 instances (3% of all recordings) of PM_{10} concentrations $\geq$200 $\mu g/m^3$ in the post-ATI period, while there were only 2 in the period with ATIs. The ability of the PPM to capture actual individual exposure is further illustrated by comparing indoor data from the PPM with monitoring stations, which showed lower concentrations for the PPM compared to AWS-B during the ATI period (43.5 µg/m^3 and 57.9 µg/m^3, respectively), and higher in the post-ATI period (31.2 µg/m^3 for the PPM data, 23.2 µg/m^3 for monitoring station).

Exposure to PM$_{10}$ (calculated using Equation (3)) while performing different indoor activities varied between 15.0 µg/m^3 for indoor sports during the post-ATI period and 69.2 µg/m^3 for non-determined other indoor activities during the ATI period, as shown in Figure 6. Indoor activities during the ATI period had mostly the highest mean values of PM$_{10}$, with the exception of cleaning and cooking, which were almost the same as in the post-ATI period. The largest difference was for indoor sporting activities, which had a difference of 32.9 µg/m^3 between the two periods. Engaging in sporting activities indoors can prompt the person in the enclosed space to open windows or doors to cool down and ventilate the room, consequently causing an influx of air with a higher concentration of PM$_{10}$ during an ATI event [44]. The next-highest difference was for other indoor activities (69.2 µg/m^3 during ATI and 38.7 µg/m^3 during post-ATI period), which often included a combination of different already-listed activities and various others. This difference is more difficult to explain due to the variability of different activities, which might include dust resuspension, use of incense, having an open window, etc.

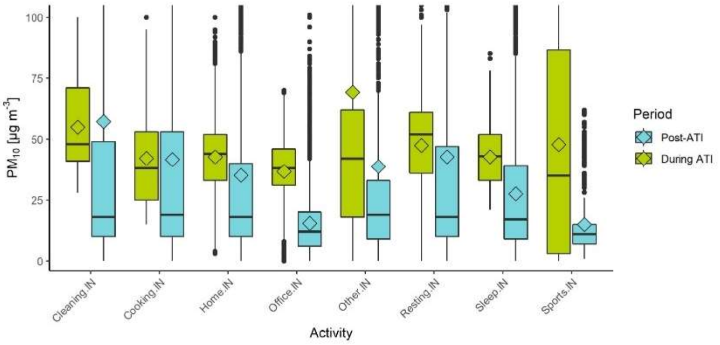

Figure 6. Exposure to PM$_{10}$ for different indoor activities, during the ATI event (green) and after (blue), collected with the PPMs. Plot limited to 100 µg/m^3 on the y axis to better illustrate the differences.

On the other hand, mean concentrations of PM$_{10}$ for the "cleaning" activity were higher in the post-ATI period by 2.3 µg/m^3, and only slightly lower for cooking (difference of 0.5 µg/m^3), though the median shows much lower values. Cooking and cleaning are important sources of indoor PM, and sporadic high emission events such as frying of food or dust resuspension during cleaning can increase exposure to a higher concentration than exposure during ATI events [45–47]. These events are not captured by monitoring stations and can even be missed by stationary indoor sensors if they are not present in all rooms. Individual-level monitoring shows data on a very granular level and includes specific high-emission events.

Figure 7 illustrates the differences between the distribution, mean, and median values of PM$_{10}$ for all outdoor activities during the ATI period and post-ATI. Almost all outdoor activities show higher recorded values during the ATI period than the post-ATI period. The differences range from 15.7 µg/m^3 for running to 45.9 µg/m^3 for outdoor sports that don't include running, with the exception of the "home" activity, which was higher during the post-ATI period by 1.7 µg/m^3. A possible explanation for a higher concentration would be that outdoor activities around the home can include gardening, burning of gardening and agricultural residues [48], and home-improvement activities that often include some kind of construction (sanding wood, mixing cement, demolishing objects, etc.) which present a source of particulate matter [49,50]. Such activities can be expected to occur more frequently during the post-ATI period with clearer weather and could elevate the concentrations of PM_{10}. Participants could also differently interpret specific outdoor "home" activities, e.g., resting on a semi-enclosed balcony. Although the mean values do not differ much for the "Home.OUT" activity, the median values show that there is still a difference between these two time periods and indicate that the higher mean value of outdoor activities in the post-ATI period could be influenced by a few high-exposure events. For illustration, if the high-exposure events (>100 μg/m^3) are removed, the mean value decreases from 61.9 μg/m^3 to 30.1 μg/m^3, while the median value drops from 33 μg/m^3 to 27 μg/m^3.

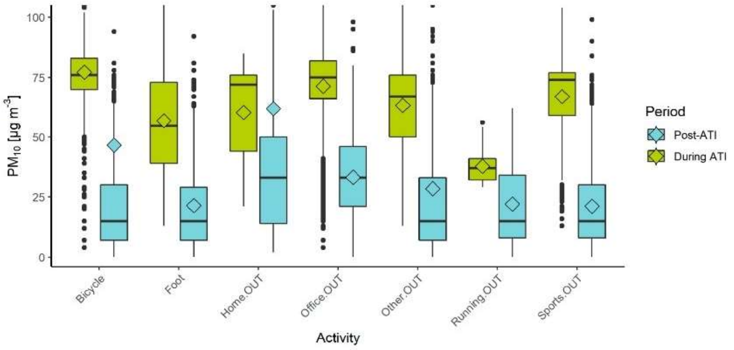

Figure 7. Exposure to PM_{10} for different outdoor activities, during (green) and after the period with persistent ATI (blue), collected with the PPMs. Plot limited to 100 μg/m^3 on the y axis to better illustrate the differences between mean and median values.

Riding a bicycle shows the highest recorded mean value of PM_{10} among all pre-classified activities, with 77.2 μg/m^3. As cyclists cover large distances and areas in an urban environment compared to pedestrians, they could potentially cross through more areas with higher concentrations of PM_{10}, e.g., construction areas, heavy traffic, and intersections [51], and increase their exposure based on extreme values, high-exposure events, and higher spatiotemporal variations [52]. Moreover, cyclists are regularly forced to share traffic lanes with motor vehicles, which increases their exposure to PM [53]. A risk-benefit balance assessment between active travel-related physical activity and exposure to air pollution shows that in areas with $PM_{2.5}$ concentrations of >100 μg/m^3, harms would exceed benefits after 90 min of bicycling per day or more than 10 h of walking per day [54]. On the other hand, our research revealed that there is a fairly large discrepancy between the mean and median value for cycling in the post-ATI period, which is a consequence of several brief high-exposure events (>100 μg/m^3) that represent 4.3% of the recorded values for the cycling activity. If these specific events are omitted, the mean value decreases from 46.5 μg/m^3 to 19.9 μg/m^3, which is close to the median value of 15 μg/m^3 (14 μg/m^3, after high-exposure values are removed).

As evident for the "foot" (walking) activities in the post-ATI period in Figure 7, pedestrians had a smaller difference between their mean and median value of exposure of 1.4 μg/m^3. Moreover, the walking activity had a smaller number of high-exposure events of >100 μg/m^3 (0.9% of all recorded values), which had a lower mean value of 181.3 μg/m^3, compared to values for cycling >100 μg/m^3 with a mean value of 633.4 μg/m^3. A similar trend is present for the period with ATIs. Pedestrians are exposed to varying concentrations of PM throughout the urban environment based on different types of road, traffic volume, time of day, and season [55], or specific high-exposure events, e.g., queuing by or walking across a crosswalk [56], which influence their cumulative exposure. As they move slower and cover less distance than cyclists, the variability can be lower, moreover, they are less frequently exposed to direct traffic exhaust than cyclists. Exposure of pedestrians is influenced by background concentrations and on smaller local roads by the pedestrians themselves who resuspend dust and might increase the concentrations of coarser fractions of PM [57].

These results illustrate how the difference in exposure between the ATI and the post-ATI period for the outdoor activities is larger than for the indoor activities, indicating that specific activities and the associated sources of PM increase exposure indoors.

4. Limitations

Certain limitations were observed in this study. Data in the ICARUS sampling campaign in Ljubljana were collected in only one non-heating season at the end of February and the beginning of March, which resulted in only a single period with persistent ATIs. This research could be further improved by analyzing multiple periods in different years and in different locations/cities, though this would present the logistical challenge of organizing yearly sampling campaigns with hundreds of participants. The sampling campaign began just as the period of persistent ATIs started, which prevented any comparisons with data prior to the ATI period.

Personal monitors based on low-cost sensors often have issues regarding their usability, data accuracy, and technical malfunctions. The PPMs used in this study frequently stopped working, did not record data, had poor accuracy of GPS data, ran out of battery, and showed data that were clearly erroneous, which resulted in data loss and also increased the workload of researchers and field workers. PM values recorded for certain activities, e.g., running, could be erroneous due to the aforementioned issues.

An additional limitation of the study was the manual logging of activity data by the participants, who frequently logged data for several days at once and sometimes mistakenly chose the wrong activity, which increased the possibility of errors. The activities did not have the same frequency in the two periods (during and post-ATI), and some were recorded only in one period and consequently eliminated from this analysis.

5. Conclusions

Within the scope of this research, an analysis of the applicability of personal PM monitor-based individual-level exposure assessments for capturing the spatiotemporal variability of individual exposure profiles was made. Two contrasting periods in terms of meteorological conditions and air quality—a period with persistent atmospheric thermal inversions (ATIs) and a post-ATI period—were used to determine how the aforementioned approach can assess exposure during specific activities and in specific microlocations. Data were collected on indoor and outdoor activities performed by participants in Ljubljana. Exposure was compared by observing the statistical values of the recorded data in the two distinct periods and comparing it with data collected from monitoring stations.

Results showed that the difference in indoor and outdoor exposure was much higher during the period of ATIs (23.0 $\mu g/m^3$) than after (6.5 $\mu g/m^3$). Indoor activities generally showed less difference in mean and median values, with cooking and cleaning having higher values in the post-ATI period than during the ATI. On the other hand, almost all outdoor activities had higher PM values during the ATI than after. Several conclusions can be drawn from these results:

1. Periods with persistent ATIs present a fitting opportunity to assess the applicability of personal monitors to capture the spatiotemporal variability of indoor and outdoor exposure. A clear distinction in terms of PM concentrations between the two periods provides an opportunity to observe how high-exposure events can influence cumulative exposure;
2. Exposure to PM_{10} is higher during periods with persistent ATIs, when ambient concentrations increase due to specific meteorological conditions. This is evident indoors and outdoors and for almost all activities, except for a few that are mainly influenced by the PM_{10} associated with the respective activity. Indoor concentrations

are lower than the outdoor concentrations during the period with ATIs, though they are still higher than indoor and outdoor concentrations in the post-ATI period;

3. Using activity data enables an individual-level scale analysis of exposure and illustrates that the influence of activities on exposure indoors should not be disregarded when assessing cumulative exposure. Activities can directly, e.g., cooking and cleaning, or indirectly reduce air quality, e.g., opening a window during a period with poor outdoor air quality;
4. Measuring exposure on an individual level is necessary to capture high-exposure events in microlocations. These results showed that several high-exposure events can greatly raise exposure levels. Additionally, personal monitors can detect trends and show how specific routines influence exposure;
5. These measurements confirm that there are high levels of exposure indoors even in high-income countries that mostly don't use solid fuels for cooking and heating. A better understanding of activity-specific exposure could provide a basis for policies that can more accurately address exposure to poor air quality.

Overall, this study demonstrated that utilizing personal monitors in exposure assessments can provide better spatiotemporal resolution and capture specific high-exposure events. These devices provide an ancillary tool that can indicate trends and guide further research.

Future work should include more detailed activities and a better spatiotemporal resolution. Personal monitors could be further improved to better record, store, harmonize and transfer data, detect outliers, have on-the-fly calibration options, and integrate multiple devices. Reducing the proportion of data that are recorded by human input via an approach with automated activity recognition could improve exposure assessments [58]. Exposure models that rely solely on outdoor measuring stations or indoor stationary devices fail to capture high-exposure events and could be improved by integrating data from personal monitors. Moreover, data from personal monitors could be integrated into agent-based models to supplement other data sources [59], e.g., monitoring stations, statistical and demographic data, etc.

This research addressed exposure to particulate matter, though there are numerous other air pollutants that could be further investigated by employing personal monitors. Moreover, current AQ guidelines often do not include indoor environments or individual-level exposure. Results obtained in the scope of this research should be further developed and transferred into policy, to include approaches that utilize data on a personal scale and the specifics related to human behavior in urban environments.

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3.5 Manuscript 5: Simulating the Impact of Particulate Matter Exposure on Health-Related Behaviour: A Comparative Study of Stochastic Modelling and Personal Monitoring Data

Section 3.5 consists of a scientific article submitted to Health and Place in 2023, authored by Rok Novak, Johanna A. Robinson, Tjaša Kanduč, Dimosthenis Sarigiannis, and David Kocman.

In this article, two approaches to assessing exposure to PM and the associated dose are compared. The first approach utilizes a stochastic model, i.e., an agent-based model (ABM), with data collected in various population level studies, and governmental monitoring stations. On the other hand, the second approach uses the environmental, biometric and activity data, collected with personal monitors in the scope of the ICARUS project (labelled as the ICLJU data set in the article). The ABM simulated 100 agents, whose actions were governed by inherent probabilities of performing an activity, based on population data. Each activity was associated with (1) an intensity level, determining how vigorous an activity is and how it affects their minute ventilation (amount of air they breathe in one minute), and (2) a pollution level of PM, based on published research. The ICLJU and ABM had comparable results, showing similar trends and a mean dose. On the other hand, the largest discrepancies were seen in the activities with the highest mean dose values. Both approaches allow to observe exposure on an individual level. They can be used in combination, with the ABM offering the option for a large population size, without data gaps, and the ICLJU validating the inputs in the ABM. Furthermore, the ABM offers numerous options to extend the model and observe more complex social interactions and how they influence the dose and exposure to PM.

An additional function was implemented in the model with agents influencing each other on their choice of transport. Specifically, all agents were capable of influencing any other agent to cycle or walk more, and in turn use the car or bus less. The influence varied based on several factors. Activists, special agents with an increased influence on other agents, were additionally implemented to explore how specific influential individuals could impact transport options, and consequently the PM dose and exposure. At low concentrations of outdoor PM this change in the model did not play an important role, and the estimated PM dose stayed almost the same. However, as concentrations rose, higher shares of activists (and their influence) caused the relative dose to increase considerably. This approach represents a foundation for further explorations of how social interactions can influence the PM dose and exposure. Potentially, the results could aid decisionmakers in designing more effective and targeted policies.

My contributions for this article include the conceptual design, methodology development, building the ABM model and collecting the input data, data analysis, curation, and visualization. I wrote the original draft of the paper and contributed to the review and editing of the final version.

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Simulating the impact of particulate matter exposure on health-related behaviour: A comparative study of stochastic modelling and personal monitoring data

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ABSTRACT

Epidemiological and exposure studies concerning particulate matter (PM) often rely on data from sparse governmental stations. While low-cost personal monitors have some drawbacks, recent developments have shown that they can provide fairly accurate and fit-for-purpose data. Comparing a stochastic, i.e., agent-based model (ABM), with environmental, biometric and activity data, collected with personal monitors, could provide insight into how the two approaches assess PM exposure and dose. An ABM was constructed, simulating a PM exposure/dose assessment of 100 agents. Their actions were governed by inherent probabilities of performing an activity, based on population data. Each activity was associated with an intensity level, and a PM pollution level. The ABM results were compared with real-world results. Both approaches had comparable results, showing similar trends and a mean dose. Discrepancies were seen in the activities with the highest mean dose values. A stochastic model, based on population data, does not capture well some specifics of a local population. Combined, personal sensors could provide input for calibration, and an ABM approach can help offset a low number of participants. Implementing a function of agents influencing others transport choice, increased the importance of cycling/walking in the overall dose estimate. Activists, agents with an increased transport influence, did not play an important role at low PM levels. As concentrations rose, higher shares of activists (and their influence) caused the dose to increase. Simulating a person's PM exposure/dose in different scenarios and activities in a virtual environment provides researchers and policymakers with a valuable tool.

1. Introduction

A 2022 report by the European Environmental Agency stated that 96% of the urban population in the European Union was exposed to levels of fine particulate matter (PM) above the latest World Health Organization guidelines (European Environment Agency, 2022). $PM_{2.5}$ are inhalable particles with a diameter <2.5 μm, which can reach the alveoli in the lungs and penetrate into the blood circulation (Jakovljević et al., 2018). Exposure to elevated concentrations of PM is associated with three of the leading causes of death in the world (stroke, ischemic heart disease, and primary cancer of the trachea, bronchus, and lung) (Juginović et al., 2021), and resulted in 238.000 premature deaths in 2021 in the EU (Health impacts of air pollution, 2022). Central-Eastern Europe reported the highest concentrations of PM, primarily due to burning of solid fuels for domestic heating and their use in industry (). Ljubljana, Slovenia, ranks 279th out of 344 cities included in the European city air quality viewer, with a mean $PM_{2.5}$ concentration of 15.7 $\mu g/m^3$ (European city air quality viewer, 2023).

Exposure is defined as "contact between an agent and a target", which in the case of inhalable PM are inhalation contact boundaries –

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conceptual surface above the nose and mouth (Zartarian et al., 2005). The exposure concentration is, for practical purposes, the average of the (well-mixed) air in the vicinity of the person (Inter-Organization Programme for the Sound, 2004). In this work PM is considered only as an inhalable substance, that does not cross an absorption barrier. The mass of PM that crosses the theoretical surface at the mouth and nose is the dose, and as it only enters through this exposure surface it is an intake dose (Inter-Organization Programme for the Sound, 2004), hereafter referred to as dose. Exposure estimates provide information on how much of a pollutant is in the vicinity of an individual. However, they do not take into account the amount of the pollutant that enters the human body through respiration. A calculated dose that includes the inhalation rate as a variable can provide more information on the effect of activities, microlocations, indoor-outdoor exposure and personal characteristics (Faria, 2020; Xie et al., 2022; Novak et al., 2020). Inhalation rate, expressed as minute ventilation (amount of air that enters the lungs per minute), can be estimated based on a person's heart rate (Greenwald et al., 2019; Zuurbier et al., 2009; Cruz et al., 2020).

A key information in determining exposure to air pollution in urban environments is the proportion of time in a day/week that a person is outdoors in the urban environment. Depending on the season and location, vigorous activities outdoors can considerably increase an individual's exposure and dose of particulate matter (Chen et al., 2020), (Novak et al., 2022). Moreover, severe activity leads to greater lung deposition of PM per minute of exercising (Cruz et al., 2021). In large part, vigorous outdoor activities in urban environments include commuting via walking or cycling, both associated with an elevated dose of particulate matter, due to high respiratory rates (Singh et al., 2021), and their proximity to motorized traffic (Adamiec et al., 2022), (Hernández et al., 2021). On average, health benefits of active commuting, due to increased physical activity, outweigh the increased exposure to air pollution and a higher dose of particulate matter (de et al., 2010; Tainio, 2016; Pasqua et al., 2018). However, exposure is highly dependent on numerous factors, e.g., length of cycling routes, time of day, physical fitness of individual, type of bicycle, proximity to motorized traffic, and can influence exposure and dose of particulate matter on an individual level. Accurately assessing an individual's dose presents a complex and difficult challenge, requiring a multi-parameter and multi-domain approach. Moreover, PM exposure studies often have to rely on data from sparse governmental stations, expensive and bulky portable research-grade sensors, or low-cost and often unreliable personal monitors (Lim et al., 2022), (Novak et al., 2023). While the latter have their drawbacks, recent developments have shown that they can provide fairly robust and accurate data (Alfano et al., 2020), (Kim et al., 2023). On the other hand, though there is a lower material costs associated with low-cost devices, additional time and effort are required for data collection, cleaning, validation and communication (Novak et al., 2021). Virtual environments and agent-based models (ABMs) offer a novel approach and provide a variety of tools to aid in exposure studies.

Agent-based modelling is a tool or approach used to simulate interactions and behaviour between agents in a virtual environment. Agents, in the case of this work human individuals, act based on a set of pre-programmed rules for their behaviour and interactions with other agents and their environment (Murphy et al., 2020). Agents can be (1) reflexive, following only if-then rules, (2) utility-based, trying different options and selecting the one that provides the best outcome, (3) goal-based, trying to achieve a specific goal, (4) adaptive agents, changing their strategies, not only decisions and learning from past experience, or a combination of two or more types (Wilensky and Rand, 2015). An ABM approach is particularly suited for urban environments as it follows a bottom-up principle, having autonomous and social features of agents that allow complex and nonlinear interactions, leading to collective behaviour and self-organization (Chen, 2012).

Multiple studies have demonstrated the use and applicability of ABMs in urban environments, for assessing exposure to particulate matter. Chapizanis et al. (2021) developed an ABM, based on the city of Thessaloniki, Greece, collecting data on the population, urban environment, movement and $PM_{2.5}$ concentrations. Additionally, personal movement, location and temperature sensors were used to inform and enhance the model. Results showed that an inhalation adjusted $PM_{2.5}$ exposure can differ considerably between housemates and neighbours due to different behaviour. ABMs allow a high level of flexibility, enabling a variety of inputs, including different environmental stressors, e.g., air pollution, or heat stress, as evident in Yang et al. (2018). A literature review of modelling approaches for assessing human exposure to environmental stressors in Yang et al. (2018) showed a shift towards using data from portable sensors. Moreover, dynamic changes in individual-level exposure require development of innovative models that can identify emerging non-linear patterns of collective exposures (Yang et al., 2018). Tools have been developed using ABMs to simulate exposure to air pollution, based on population data (Zhou et al., 2022; Shin and Bithell, 2023; Lund et al., 2020). One tool, developed for estimating exposure to non-exhaust traffic emissions showed that specific targeted policy measures could reduce exposure to PM (Shin and Bithell, 2023). A more general tool, simulates exposure to particulate matter and other environmental species for large geographical areas (Lund et al., 2020). As traffic plays an integral role in urban environments, and in PM exposure studies, research using ABMs often focuses on interactions between different entities interacting in traffic (Shin and Bithell, 2023), (Forehead and Huynh, 2018), (Wadlow et al., 2019).

Comparing a stochastic model, i.e., ABM, with individual-level environmental, biometric and activity data, could provide insight into how the two approaches assess PM exposure and dose. This comparison is facilitated by using data collected within the ICARUS H2020 (icarus2020.eu) project (ICARUS, 2020). One phase of the project included two seasonal data collection campaigns that took place in 7 European cities (Athens, Basel, Brno, Ljubljana, Madrid, Milan, Thessaloniki). Data from participants living in Ljubljana, Slovenia, was collected from February 16, 2019 to May 25, 2019. Personal environmental and biometric sensors were used, combined with time activity diaries and questionaries. As referenced in Kocman et al. (Kocman et al.), where a detailed description all protocols and devices is available, the ICARUS campaigns had three specific objectives:

i) collect data on external environmental exposure and exposure determinants by combining location, activity and air pollution data in different micro-environments,
ii) demonstrate feasibility of using new sensor and mobile technologies in collecting exposure data, and
iii) analyse and compare exposure data in several different European cities.

Published studies have utilized personal monitoring for exposure and dose assessments, and a separate smaller number of publications showed some aspects of modelling exposure by using an ABM approach. In contrast, this work provides a novel approach of comparing both a personal monitor-based, and a stochastic approach in assessing PM dose. Illustrating the shortcoming and strengths of both approaches would provide a necessary overview that can be further utilized in developing better models, designing personal monitoring-based research, and policymaking.

In this work an agent-based simulation of assessing PM exposure and dose was built to compare a stochastic model with simple rules, a simplified environment and inputs based on publicly accessible population data with data collected by using personal environmental and biometric sensors, combined with time activity diaries. Additionally, a set of rules governing the interactions between agents was added, to simulate how activists promoting cycling and walking would influence exposure and dose of non-activist agents.

2. Methodology

Two approaches were designed to assess the estimated exposure and dose of $PM_{2.5}$: a stochastic model, i.e., ABM, and a personal sensor campaign, based on a portion of the data collected within the ICARUS project and labelled as ICLJU (ICarus LJUbljana). Fig. 1 represents a simplified visualization of the input and procedures in both approaches, and the collected/calculated outputs. A legend is available in the lower left corner of the figure for type of data inputs.

2.1. Design and compilation of the agent-based model

An ABM was designed to analyse a stochastic approach to modelling exposure of individuals to $PM_{2.5}$ and assessing their dose. The influence of features and characteristics, e.g., age, gender, selecting activities, was explored. After reviewing several tools for building the ABM, NetLogo 6.3 (Wilensky, 1999), was chosen. NetLogo is a widely used agent-based modelling language and toolkit, combining a graphical user interface, model description and coding tab in one interface. As an open-source software with an easily readable language, it is accessible to a wide audience. The core design of NetLogo follows the principle “low design, no ceiling”, being accessible and having an intuitive interface, while still providing the necessary complexity to be used in cutting edge science and professional settings (Wilensky and Rand, 2015).

At its core, NetLogo consists of a virtual environment populated by agents, called “turtles”, which are programmed entities that can interact with each other and their environment. The environment is composed of a grid of cells called patches. An ABM does not necessarily have to exist in a physical space, but can describe interactions between entities such as companies or social media accounts. Patches and agents possess a variety of features and have predefined actions. An ABM allows for simple interactions performed by multiple entities at the same time, many times over, to produce emergent behaviour and properties.

The basic model in this work was designed as a grid of personal environments (homes), work spaces and leisure spaces (assigned as a space to perform sports). Each individual was randomly assigned a home patch, surrounded with 8 patches representing different activities. Individuals randomly chose one work patch and one leisure patch. All the individual’s patches represented 10 different activities, listed in Table 2, selected based on the data collected in the ICARUS project (dataset description in section 2.2). At the beginning of each hour the individual selected the activity that they will perform. Only one activity per hour was possible, analogous to the ICARUS project design. An activity was chosen based on the likelihood that it constitutes a certain portion of an average day for individuals within a specific group, e.g., young, old, male, or female. No specific limits were put on the number of times an activity could be selected consecutively or which activities could follow each other (apart from the set probabilities). A simplified example would be that sleeping represented 8 h or 1/3 of the day, which translated to approximately a 33% probability that the next chosen activity would be sleeping. The probabilities were selected based on population data collected in ExpoFacts: the European Exposure Factors Sourcebook (European Commission, 2023). The number of individuals included in the simulation was determined in the graphical user interface, using a slider. Sliders provide an option to change settings on the fly, without the need for recoding. Share of each gender, the average age of the population and the share of people that smoked was determined in the same manner. Each individual was probabilistically assigned a body weight and a baseline inhalation rate, based on their gender and age, and information obtained from the EPA Exposure Handbook, Chapter 6: Inhalation Rates (U.S. Environmental Protection Agency (EPA), 2015).

Each room was probabilistically assigned a pollution level each time that the individual performed that activity, based on data listed in

Table 1
Baseline minute ventilation for age groups (young, mid-age, old) and genders (female, male) as determined in the EPA Exposure Handbook (U.S. Environmental Protection Agency (EPA), 2015) in m^3 per minute and kg of body weight.

Gender	Age group	Minute ventilation (SD) [m^3 minute-kg^{-1}]
male	young	7.57E-05 (1.10E-05)
male	mid-age	6.40E-05 (1.02E-05)
male	old	7.47E-05 (8.70E-06)
female	young	7.13E-05 (1.17E-05)
female	mid-age	5.90E-05 (1.05E-05)
female	old	6.63E-05 (8.20E-06)

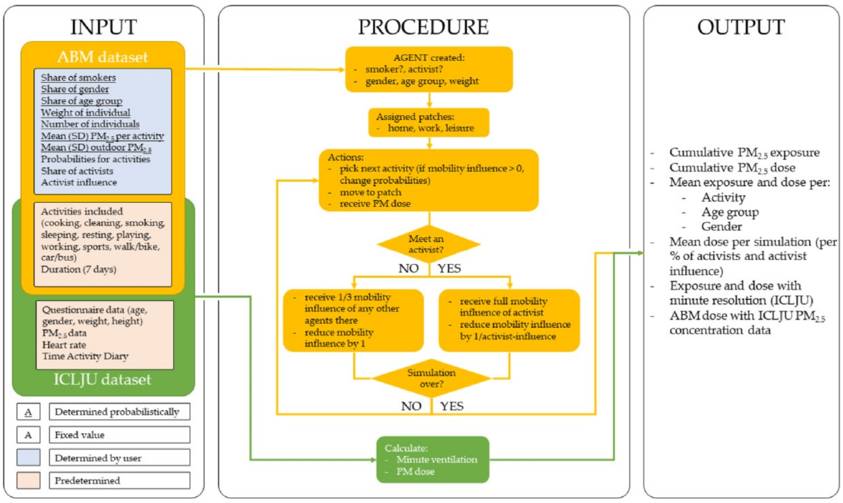


Fig. 1. Visualization of data inputs, procedures and outputs based on ABM and ICLJU datasets.

Table 2
Mean $PM_{2.5}$ (μg/m^3) concentrations, with standard deviations, during different activities.

Activity	Mean $PM_{2.5}$ (SD)	Reference for $PM_{2.5}$	M.E.T. range/ Intensity
smoking	84 (67)	Van Deusen et al. (2009)	1.5–2.0
cooking	19.2 (11.6)	Alves et al. (2020)	2.0–3.5
cleaning	60 (20)	Milner et al. (2011)	2.3–3.8
playing	25 (20)	Ferro et al. (2004)	2.2–5.8
resting	10.9 (12.0)	Canha et al. (2019)	1.1–1.5
car-bus	22.5 (10.5)	Okokon et al. (2017)	1.3–2.5
working	27.3 (2)	Saraga et al. (2014)	1.5–3.5
sleeping	8.9 (7.0)	Canha et al. (2019)	1
sports_out	14 (11)	(Slovenian Environment Agency,)	5.0–10.0
foot-bike	14 (11)	(Slovenian Environment Agency,)	3.5–6.8

Table 2. Probabilities were calculated based on a gamma distribution, due to its flexibility and ability to capture a wide range of continuous data. The mean and standard deviation values used for the alpha and lambda parameters were derived from published data, listed in Table 2. The random sampling method used with the gamma function in NetLogo, uses the default random number generator provided by NetLogo, which is based on a Mersenne Twister algorithm. This method is widely accepted and used in various computational modelling applications. Based on the activity, an intensity rate was assigned to the room, as referenced by the EPA Exposure Handbook. Intensity rates for activities in the model represent multipliers of the minute ventilation determined for sedentary and passive activities. Age and gender groups were probabilistically assigned a baseline minute ventilation as listed in Table 1 (U.S. Environmental Protection Agency (EPA), 2015).

The baseline minute ventilation represents activities with a Metabolic Equivalent of Task (M.E.T.) = 1, e.g., sleeping, napping. Minute ventilation values increase in a roughly linear manner with the Metabolic Equivalent of Task (M.E.T.) value, showing similar patterns across different age and gender groups, calculated based on data collected from the EPA Exposure Handbook (U.S. Environmental Protection Agency (EPA), 2015). Each activity has a range of M.E.T., depending on the vigour involved. The values listed in Table 2 were collected from the 2011 Compendium of physical activities (Supplemental Digital Content) (Ainsworth et al., 2011).

The $PM_{2.5}$ dose was calculated using i) the minute ventilation ($\dot{V}_E$) [m^3 $minute^{-1}$], ii) the intensity of the current activity (int_{act}) [*], iii) the $PM_{2.5}$ pollution level at that activity ($c_{PM_{2.5}}$) [μg/m^3], and the body weight of the individual ($body - weight$) [kg] shown in Equation (1):

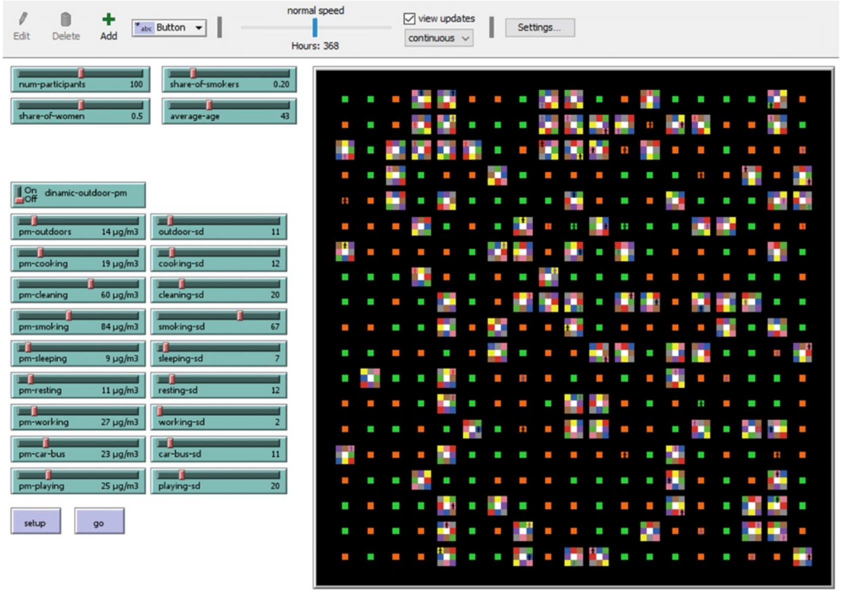
$$intake\ dose\ per\ kg\ of\ body\ weight = \frac{\dot{V}_E * int_{act} * c_{PM_{2.5}}}{body - weight} \tag{1}$$

An initial simulation, using a population of 100 agents, was conducted to compare the results with the ICLJU data, collected in Ljubljana, Slovenia (Novak et al., 2021), (Kocman et al.), (Robinson et al., 2021). $PM_{2.5}$ concentrations for each activity were acquired from published research, as shown in Table 2, using several criteria. These criteria encompassed research conducted in environments analogous to Ljubljana's cultural and daily patterns, e.g., European regions. Moreover, the data were sourced from studies that captured a designated activity akin to ICARUS. Time-specific measurements (within an hour, not daily averages) corresponding to the activity instances were included. The data ideally featured insights into data distribution, among other considerations. Data for outdoor $PM_{2.5}$ was collected from the Bežigrad governmental air quality monitoring station in Ljubljana, Slovenia, operated by the Slovenian Environmental Agency (Slovenian Environment Agency,). The outdoor value was set to the mean daily value recorded by the Bežigrad station during the same period as the ICARUS campaign took place (14 μg/m^3). Hourly values for $PM_{2.5}$ were not yet recorded at the Bežigrad station in 2019. The highest and lowest daily values recorded in the observed time period were 63 μg/m^3 and 2 μg/m^3, respectively. Although there is substantial research on the influence of outdoor air on indoor air quality (Chen and Zhao, 2011), (Tang et al., 2018), the infiltration rate highly depends on various factors, e.g., particle size, as smaller particles more easily penetrate the building envelope (Bennett and Koutrakis, 2006), outdoor $PM_{2.5}$ concentration, showing a threshold of approximately 30 μg/m^3, below which indoor sources contributed substantially to personal exposures (Bi et al., 2021), country of research (developed countries have more airtight building envelopes and rely more on mechanical ventilation), type and age of building, and other factors (Raafat et al., 2023), (Papaglastra et al., 2008). Based on these factors and the simplified nature of the model, infiltration factors of outdoor air were not included in the ABM. The share of smokers in the simulated population was determined using population data for Slovenia, published by the National Institute of Public Health (Koprivnikar et al., 2021). Similarly, the average age and share of each gender was based on population data in Slovenia, published by the Statistical Office of the Republic of Slovenia (Surs. https). In the ICARUS campaign individuals collected data for up to 7 days per season (heating/non-heating). As the ABM approach attempts to simulate aspects of the ICARUS campaign, this time limit was applied. The stochastic nature of the model requires multiple iterations to achieve some statistical robustness. As the decisions in this model were based on a predetermined set of probabilities for activities, each tick/step was considered as an iteration. The model ran for 368 h, and the first 200 h were discarded to allow ample time for the model to stabilize, and the remaining 168 h were used as the simulation result.

Fig. 2 shows a visual representation of the spatial version of the agent-based model. Sliders for different settings are placed on the left side of the interface, as it is customary in Netlogo models to have all the settings that have to be set before the model is setup and run, above and/or left of the setup/go buttons. These buttons (placed below the sliders) setup the model, e.g., create the patches, agents and their properties, and start the simulation. The hours start counting and the agents begin to move to different patches based on the activity they are performing. The visual/spatial aspect of the model in not necessary at this step. Moreover, the nature of the ABM was not fully utilized in the first iteration of the model as there were no interactions between the agents. Agents do interact with patches, when they set the pollution level in the patch, but the interaction is only one-way. On the other hand, this simplified stochastic model, designed as an ABM does provide various opportunities to design more dynamic and interactive environments where there are more two-way and multi-way interactions between agents, patches and other entities. The Behaviour Space tool in Netlogo allows for repeated simulations with a preprogramed set of rules on how some selected variables can change for each simulation, e.g., performing 6 simulations where the share of smokers increases from 0% to 100% of the population, increasing by 20 percentage points with each run.

Netlogo also offers a function to plot different variables and how they change during the simulation. This function helps in finding trends and errors while designing the model and preparing settings for the Behaviour Space tool. Examples of three plots are shown in Fig. 3, that can provide information at each hour and guide and possible improvements or changes. For example, plot A, showing the dose for different groups provides an indication that the model takes a while to stabilize, plot B provides a check that the probabilities of each activity, and the agents actually performing them line up (~1/3 agents are sleeping, ~1/4 are at work and a much smaller fraction are cooking and smoking), and plot C shows that a cumulative difference between smokers and non-smokers shows only after a few hours have passed, providing more information on how long the model needs to stabilize.

All analysis were conducted in R (R: The R Project), using packages ggplot (Wickham), tidyverse (Wickham et al., 2019), dplyr (Wickham et al., 2023), reshape2 (Wickham, 2007) and others.



Hours: 368

num-participants 100
share-of-smokers 0.20
share-of-women 0.5
average-age 43
On Off dinamic-outdoor-pm
pm-outdoors 14 μg/m3
outdoor-sd 11
pm-cooking 19 μg/m3
cooking-sd 12
pm-cleaning 60 μg/m3
cleaning-sd 20
pm-smoking 84 μg/m3
smoking-sd 67
pm-sleeping 9 μg/m3
sleeping-sd 7
pm-resting 11 μg/m3
resting-sd 12
pm-working 27 μg/m3
working-sd 2
pm-car-bus 23 μg/m3
car-bus-sd 11
pm-playing 25 μg/m3
playing-sd 20

Fig. 2. Visualization of the spatial representation of the $PM_{2.5}$ exposure and dose agent-based model with the initial setting, at 368 h in the NetLogo graphical user interface.

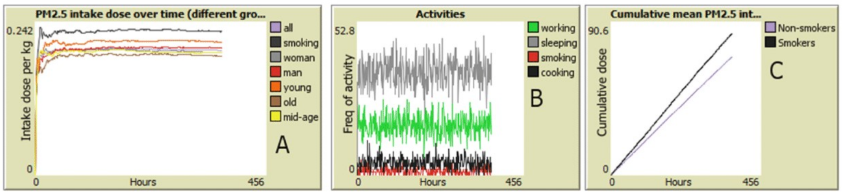


Fig. 3. Example plots of the $PM_{2.5}$ dose ABM results in Netlogo showing (A) the average dose at each hour for different groups, (B) the number of agents performing an activity (working, sleeping, smoking, cooking) at each hour, and (C) a mean cumulative dose for smokers and non-smokers.

2.1.1. *A modified ABM with a mobility influence function*

The approach described in this work does not include health impact assessments, rather it provides a comparison of tools – one based on modeling and other based on measurements - to assess exposure to $PM_{2.5}$ and the associated dose. Walking and cycling play an important role in this assessment due to the associated elevated minute ventilation, influencing the dose. Therefore, a modified ABM was built with interactions between agents that influence their decisions related to walking/cycling. This adaptation serves as a proof-of-concept or illustrative demonstration, showcasing the adaptable nature of the designed ABM to cater to specific study objectives. Furthermore, this specific modification offers the potential to further explore the connections between behavior and interpersonal dynamics that influence PM exposure and dose. While the ABM described in section 2.1 does demonstrate a stochastic approach to modeling exposure and dose, it does not include interactions between agents. Human behavior and opinions are (also) driven by interactions with other individuals, in particular by two major attractors: (1) the expert effect, with high confident individuals in the group, and (2) the majority effect, with a critical mass of people sharing similar opinions (Moussaïd et al., 2013). Enabling interactions among agents in the ABM could provide valuable insights into the dynamics of mutual influence, the significance of interaction points, and the emergence of collective behavior.

The modified ABM includes so-called "activists", individual agents that prompt other agents to reduce their probability of choosing a car/bus as their mode of transport, rather opting for walking/cycling. Two settings in the model are added: (1) share-of-activists, that determines how many agents are labelled as activists, and (2) activist-influence, providing the input on how persuasive the activists are. Share of activists can range from 0 to 50% of the population, and their influence from 1.0 to 2.0. All agents that are labelled as activists receive a random value of influence between 1 and 10, all non-activist agents begin their life with an influence level of 0.1. Whenever an agent is in a same place with another agent (on leisure/sports and work/office patches) they "are influenced", and their influence value increases. If the second agent is an activist, the first agent receives their full influence value (mb_{inf}^{act}), multiplied by activist-influence (act_{inf}), which is added to their prior mobility influence ($mb_{\inf}$), as shown in Equation (2)

$$mb_{\inf}(new) = mb_{inf}(existing) + \left(mb_{inf}^{act} * act_{inf}\right) \tag{2}$$

When the other agent is a non-activist, they receive only 1/3 of the influence ($mb_{inf}^{non-act}$), added to their existing mobility influence ($mb_{\inf}$) (Equation (3)):

$$mb_{\inf}(new) = mb_{inf}(existing) + \left(\frac{mb_{inf}^{non-act}}{3}\right) \tag{3}$$

Each hour all non-activists lose 1 influence, as their interest falls. An exception is after they randomly meet an activist at a leisure or work space. In this case, the activist influences their behavior, and they lose their influence more slowly. The rate is determined (Equation (4)) by the number of hours that have passed (h) since the last meeting, multiplied by activist-influence (act_{inf}). A baseline value of 6 h is set, which can increase to 12 h when the activist-influence is set to 2.0. If an agent comes in contact with an activist, their mobility influence will decrease by 1/6 in the first hour, 1/5 the second, 1/4 the third, and so on, until the (h) drops to 1. The agent will resume losing their mobility influence at the rate of 1 per hour.

$$mb_{\inf}(new) = mb_{inf}(existing) - \left(\frac{1}{h * act_{inf}}\right) \tag{4}$$

Activists cannot gain or lose influence, and the minimum and maximum values of influence for any non-activist agent are 0.1 and 10, respectively.

The mobility influence value effects the probability of the agent choosing a mode of transportation. A higher value increases the probability of selecting cycling/walking versus using a car/bus. Each agent is assigned a probability for both activities based on population data and their age and gender. Their baseline probability for choosing the foot/bike (p_{fb}) or car/bus (p_{cb}) activities is modified ($p_{fb(m)}$, $p_{cb(m)}$) based on the agent's mobility influence ($mb_{\inf}$) at time of choosing as evident in Equation (5) and Equation (6).

$$p_{fb(m)} = (p_{fb} + p_{cb}) * \left(\left(\frac{p_{fb}}{p_{fb} + p_{cb}}\right) + \left(1 - \left(\frac{p_{fb}}{p_{fb} + p_{cb}}\right)\right) * \left(\frac{mb_{\inf}}{10}\right)\right) \tag{5}$$

$$p_{cb(m)} = (p_{fb} + p_{cb}) - p_{fb(m)} \tag{6}$$

Agents select an activity based on the modified probabilities and end their turn for that hour. The Behavior Space tool is used to iterate the model multiple times by simultaneously varying the share-of-activists, activist-influence and pm-outdoors variables. To observe the behavior of the modified ABM, the share-of-activists was varied from 0 to 0.5 by increments of 0.1, activist-influence was varied from 1.0 to 2.0 by increments of 0.1, and pm-outdoors was varied from 5 μg/m^3 to 105 μg/m^3 (maximum hourly value of PM$_{2.5}$ recorded in Ljubljana in 2022), by increments of 10 μg/m^3. Each combination of the aforementioned variables was repeated 10 times with a time limit of 168 h. Runs were measured with several reporters, providing results of the cumulative dose of all agents, of agents by gender and age, respectively, and if the agent was an activist or not. The results were exported to a csv file and analyzed in R (R: The R Project), and plots were constructed using the ggplot package (Wickham).

2.2. The ICLJU dataset

The personal exposure ICLJU dataset was collected in the period between the February 16, 2019 and May 25, 2019 from 82 participants living in the municipality of Ljubljana. Data collected up until 12 March was labelled as "heating season", and from 27 April onward as "non-heating season". The ICLJU dataset, as a subset of the ICARUS data collected in Ljubljana and aggregated from:

- questionnaires, for each individual participant,
- Time Activity Diaries, filled out by all participants for each day they were participating, indicating their activity for each hour,
- the Personal PM monitor, providing data on PM concentrations,
- the Smart Activity Tracker, with data of their heart rate and movement.

The PM monitor was a project-built device, based on the Arduino platform, primarily used to collect geolocation and PM concentration data. The PM sensing component was a Plantower pms5003 low-cost sensing unit, produced by the Nanchang Panteng Technology Co., Beijing, China. This sensor is a nephelometer, using light scattering to estimate particle size and mass concentration in real time. The pms5003 has shown reasonably accurate and fit-for-purpose results in short-term and long-term laboratory and field evaluations (Bulot et al., 2019; Cowell et al., 2022; Masic et al., 2020). Our additional in-house evaluation of the PM monitor showed an R^2 value of 0.89 for PM$_{2.5}$ values in covered outdoor conditions (Novak et al., 2020).

The Garmin Smart Activity Tracker was utilized to gather biometric data including heart rate and movement. Heart rate measurement is achieved through photoplethysmography optical method, which employs light and a photodetector on the skin's surface to gauge blood circulation changes. Validation research has affirmed the reliability of Garmin Vivosmart series devices in recording precise and suitable data (Dorn et al., 2019), (MONTES et al., 2020), even in older adults' physical activity estimations (Briggs et al., 2021).

Data on age and gender of each participant was extracted from the questionaries. Additionally, questionnaires collected data on nationality, place of birth, occupation, education, family information, socioeconomic status, hours spent indoors/outdoors, physical activity, commuting, and some health data.

The combined ICLJU dataset consists of 1,439,231 observations across 107 variables. Some non-numeric variables in the dataset are duplicated intentionally for data validation purposes, specifically related to activity, time, and date information. This duplication aids in quickly confirming the accuracy of the cleaned data against the original dataset. Selected statistical descriptors for the numeric variables included in ICLJU are shown in Table 3.

Out of the entire dataset, specific variables were selected for the purpose of this study. These fall into three categories: (i) participant descriptors (personal ID number, age, gender, height, weight), (ii) environmental and biometric variables (PM$_{2.5}$ concentration, season, heart rate), and (iii) activities (sleeping, employment, using a car, bicycle or public transport, playing, resting, walking, performing sporting activities, cooking, cleaning, and smoking). To determine the inhaled dose of PM$_{2.5}$, heart rate was used a proxy for minute ventilation, in combination with other participant descriptors. The minute ventilation was calculated based on the Greenwald et al. (2019) model (Equation (7)):

$$\dot{V}_E^1 = e^{-9.59} HR^{2.39} age^{0.274} sex^{-0.204} FVC^{0.520} \tag{7}$$

Table 3

Selected statistical descriptors, min value, 1st quartile, median, mean, 3rd quartile, and max value, of ICLJU variables weight, height, age, PM$_{2.5}$ exposure, and mean heart rate, for all individuals in the final dataset of hourly values.

	Weight [kg]	Height [cm]	Age [years]	PM$_{2.5}$ [μg/m^3]	Mean heart rate [beats per minute]
Min.	49.0	152.0	17.0	0.0	43.0
1stQu.	63.0	169.0	38.0	6.8	62.0
Median	72.0	175.0	44.0	11.6	70.7
Mean	75.7	175.7	45.9	18.8	71.2
3rdQu.	90.0	182.0	53.0	20.9	79.6
Max.	120.0	196.0	75.0	180.0	137.9

where $\dot{V}_E^1$ [L min^{-1}] presents minute ventilation for M1; *HR* [beats per minute] is heart rate, *age* is the age of the participant in years; *sex* is the participants sex, where value 1 is male and 2 is female; and *FVC* [L] is forced vital capacity. The FVC was calculated with (Quanjer et al., 1993), (Falaschetti et al., 2004) (Equation (8)):

$$FVC = 1.1 * ((0.0576 * height) - (0.0269 * age) - 4.34) \tag{8}$$

where *FVC* presents the forced vital capacity, ***height*** and ***age*** are the measured height and age of the individual at the beginning of the research.

The dose of $PM_{2.5}$ per kg of body weight for each minute was calculated using Equation (9):

$$intake\ dose\ per\ kg\ of\ body\ weight = \frac{\dot{V}_E * c_{PM_{2.5}}}{body - weight} \tag{9}$$

where $\dot{V}_E$ presents minute ventilation [L min^{-1}], $c_{PM_{2.5}}$ is the particulate matter concentration measured with the PPM sensor [μg m^{-3}], and ***body-weight*** [kg] is the weight of the participant at the beginning of the research.

As this study assesses primarily exposure to $PM_{2.5}$ and the associated dose, some relevant statistics were calculated for each season for the data availability. There were 25 participants in the heating season who collected at least some $PM_{2.5}$ data, the lowest amount being 200 instances or 0.2% of their entire dataset, and the highest with 9949 instances or 99% of their dataset, with a mean (median) value for all 25 participants of 5445 (6116) instances or 44% (3.6%). The non-heating season had 64 participants that collected some $PM_{2.5}$ data, the lowest begin 131 instances or 0.3% of the dataset, highest with 10.392 instances and 96% of the dataset, and a mean (median) of 4969 (4839) instances and 46% (46%) of the dataset.

The dose was calculated using the $PM_{2.5}$ data and minute ventilation, calculated using average heart rate data as the main variable. Body weight, height and the persons gender are also required in the model, as referenced in equations (7)–(9). Therefore, to calculate the dose per activity, the participant had to record a minimum of three datapoints each minute or hour: the $PM_{2.5}$ concentration, the average heart rate for the time period, and the activity. In the heating season, 20 participants fulfilled all the listed criteria, with a minimum, mean, median and maximum number of instances being 200, 5071, 5788 and 9618, respectively. There were 62 participants in the non-heating season that fulfilled the same criteria and had a minimum, mean, median and maximum number of instances 128, 4267, 4092 and 9925, respectively.

A drop from the $PM_{2.5}$ number of instances in both seasons was due to some heart rate data gaps.

Some simplifications were performed for certain activities, combining them into groups of two different activities, which are, in general, described by similar characteristics:

- When a participant was at work, described as some version of a gainful employment, a uniform label "office" was assigned. Though the original Time Activity Diary offered the option to select indoor or outdoor work, these were combined, as the ABM also uses a generic "work" of "office" label in the basic version of the model. Furthermore, only a single participant in both seasons selected the option that they work only outdoors, and 12 participants said they work both outdoors and indoors, the rest (61 in the heating season and 56 in the non-heating season) selected only indoor work. Participants described a variety of different employments, e.g., cook, engineer, researcher, running coach, teacher, lawyer, economist, anthropologist, waiter, geologist, salesman, librarian, hairdresser.
- The Time Activity Diary offered separate options if the person was performing general sporting activities outdoors or specifically running. For the purpose of this research, these two categories were combined and labelled as outdoor sports.
- Walking and cycling were combined into a foot/bike label, as they are described by similar characteristics, e.g., outdoor activity, vigorous activity, elevated heart rate and minute ventilation, used for commuting. On the other hand, these two activities can differ noticeably if they are compared only to each other. Previous studies have shown that cycling and walking as means of transport, can lead to a high dose of particulate matter, and can vary significantly. In the scope of this research, these two activities were primarily determined as a contrast to driving or using a bus.
- The latter (driving and using a bus) were combined into a single activity, labelled bus/car, as they have similar characteristics, defining them as a contrast to walking and cycling, e.g., enclosed space, sedentary.
- Age groups were determined based on the data collected in the EPA Exposure Handbook (U.S. Environmental Protection Agency (EPA), 2015) for the purpose of the ABM. All the participants from in the ICLJU were also grouped in the same manner (group "young" for $<$31 years, "mid-age" for$\geq$31 and$\leq$60 years, and "old" for $>$60 years).

3. Results

3.1. Results of the ABM approach

Results from the ABM approach for assessing the $PM_{2.5}$ dose are presented in this section. The focus is on showing different dose levels associated with various activities and their correlation with age and gender of the participants. Table 4 provides a comprehensive overview of the dose and $PM_{2.5}$ values for each activity.

Fig. 4 shows the dose for all activities per age group. The ABM dataset shows the highest average dose for cleaning, for all age groups. This corresponds with the inputs in the model, where cleaning has the second highest mean $PM_{2.5}$ value and an intensity level that is almost twice as high as smoking, in turn increasing the minute ventilation. Cleaning is followed by smoking, which shows a high spread in the data, and between age groups. Agents in the young category that are smokers have a higher mean dose than the other two groups, though the differences in the means are not statistically significant. Sporting and playing activities have a statistically significant lower mean value than smoking, and less spread in the data. Though the intensity rate for sporting activities (and therefore the minute ventilation) was the highest among all the activities, the relatively low mean and SD for $PM_{2.5}$ counteracted the high intensity and produced a lower dose. The mean outdoor $PM_{2.5}$ concentrations were different between the heating and non-heating seasons, which effects the dose assessment for sporting and walking/cycling activities. Playing and sporting activities do not have a statistically significant difference in their mean dose values, though the differences in mean $PM_{2.5}$ are significant, as determined using a *t*-test.

There is less difference in the dose between genders in the ABM dataset, compared to the ICLJU dataset, when comparing results

Table 4
Selected statistical descriptors, mean, standard deviation and median, of the $PM_{2.5}$ values (μg/m^3) and $PM_{2.5}$ dose (μg/hour kg-bw) for each activity, for the ABM dataset.

	$PM_{2.5}$ values		$PM_{2.5}$ dose	
Activity	Mean (SD)	Median	Mean (SD)	Median
cleaning	60.3 (20.1)	58.0	0.73 (0.30)	0.68
smoking	89.3 (73.4)	65.4	0.64 (0.53)	0.47
playing	24.5 (20.3)	19.4	0.40 (0.38)	0.29
sports_out	12.8 (10.1)	10.3	0.39 (0.35)	0.31
working	26.9 (2.0)	26.9	0.27 (0.08)	0.26
foot-bike	12.7 (9.7)	10.2	0.27 (0.23)	0.21
cooking	18.8 (11.8)	16.6	0.20 (0.14)	0.16
car-bus	22.7 (10.9)	20.8	0.17 (0.09)	0.16
resting	10.7 (12.0)	6.7	0.06 (0.06)	0.03
sleeping	9.0 (6.9)	7.4	0.04 (0.03)	0.03

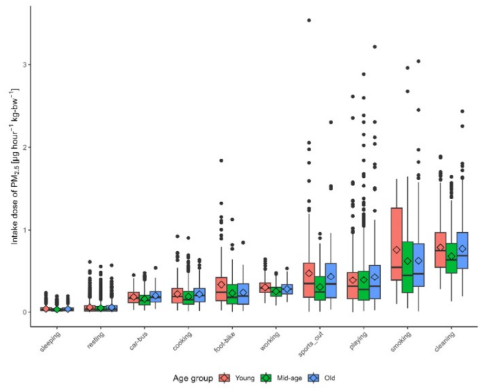


Fig. 4. Dose of $PM_{2.5}$ for all activities per age group, for the ABM dataset. Boxplots show median, 1st and 3rd quartiles, diamonds represent mean values.

between Figs. 5 and 9. As evident in Fig. 5 the differences are small, and follow a trend of men having a higher dose than women, due to their minute ventilation being higher, on average. The differences in mean values between men and women are not statistically significant, except for cleaning.

3.2. Results of the mobility influence adapted model

After running the modified ABM, with an additional mobility influence variable, for 660 runs, the results were aggregated for different populations based on the share of activists, shown in Fig. 6. The mean cumulative dose of all non-activist agents increases linearly with an increased concentration of $PM_{2.5}$ outdoors, which is an expected outcome. However, the lines connecting the increasing doses of agents based on the percentage of activists begin to diverge as $PM_{2.5}$ concentrations increase.

The trends observed in Fig. 6 are less prominent in Fig. 7, which illustrates how an increased activist influence affects non-activist agents in the modified ABM. The variable "share of activists" remains constant at 10% in this figure. Analyzing the outcomes from the analysis of varying percentages of activists, it becomes evident that the initial increase from 0 to 10% has the most significant impact on the model.

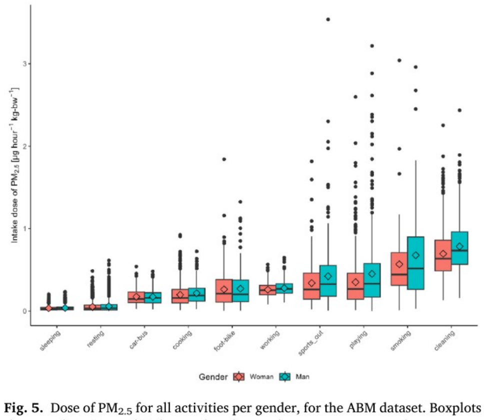


Fig. 5. Dose of $PM_{2.5}$ for all activities per gender, for the ABM dataset. Boxplots show median, 1st and 3rd quartiles, diamonds represent mean values.

3.3. Results from the ICLJU dataset

The ICLJU dataset was analyzed to show $PM_{2.5}$ exposure and dose differences between activities, different age groups and between men and women.

Table 5 shows mean and median values of recorded $PM_{2.5}$ concentrations and calculated dose for each activity included in this research. Smoking has the highest mean and median values of dose and $PM_{2.5}$. Cooking and cleaning are second and third on the list, in terms of their mean values, although the difference is not statistically significant. Despite playing having the fourth highest mean $PM_{2.5}$ concentrations, it is surpassed by foot/bike and sports in the mean dose column, as walking, cycling and sporting are associated with higher minute ventilation. The median dose values of these activities also surpass cooking and cleaning, showing that there is a propensity for these activities to have a higher dose than cooking and cleaning for most instances.

Fig. 8 shows boxplots for $PM_{2.5}$ dose per age group and activity. Smoking has an overall highest mean value, followed by cooking and cleaning. Walking or cycling come in fourth place, having a slightly higher mean dose than sports. Less physically intense activities, i.e., resting, taking a bus or car, office work, and sleeping, show the lowest doses.

Fig. 9 shows the difference in dose during different activities for the two genders considered in the scope of this work. Women show a higher dose for cleaning, cooking and smoking activities, and men show a higher dose during sports and walking/cycling. The same is true for the measured $PM_{2.5}$ concentrations, though the dose differences are more pronounced.

3.4. A comparison of results from the ABM and ICLJU datasets

Comparing the ABM dataset with the ICLJU dataset, it shows that some activities show similar mean and median dose values, while others differ, as evident in Fig. 10. Both datasets show high mean and SD values for smoking, while the median in ICLJU is lower.A wide discrepancy is evident in the cleaning activity, which has the highest mean dose in the ABM dataset (0.73 µg h^{-1} kg-bw^{-1}), and the third highest in the ICLJU dataset (0.43 µg h^{-1} kg-bw^{-1}).

Transportation/commuting activities (driving, public transport, walking, cycling) have the highest agreement between the two datasets with similar mean, SD and median dose values. Cooking has higher mean (Δ0.26 µg h^{-1} kg-bw^{-1}) and SD (Δ0.57 µg h^{-1} kg-bw^{-1}) values in the ICLJU dataset than the ABM, while there is little difference in the median (Δ0.02 µg h^{-1} kg-bw^{-1}).

While the $PM_{2.5}$ exposure data collected from different sources of literature is valid, it doesn't necessarily reflect the same conditions and exact same activities that were included in the ICLJU dataset. Although smoking, cooking, commuting and sleeping are fairly narrowly defined activities, resting, working and playing can include a wide variety of activities with very different exposure and dose profiles. These may not overlap with activities in the ICLJU (or therefore also in the ABM) dataset. To observe how a $PM_{2.5}$ personal monitor-based dataset could influence an ABM, the ICLJU $PM_{2.5}$ data mean and SD values were input in the ABM and run under the same conditions as in the initial simulation. The mean and SD values for outdoor activities (sports, foot/bike) were set as a mean value of the ICLJU results for sporting and walking/cycling activities. Results of this experiment are shown in Fig. 11, with brown boxplots showing the ABM results based on the ICLJU data, and the blue boxplots with the actual ICLJU dose data.

These outcomes show marginally less difference between the ABM simulation results and the ICLJU dataset, and less spread in the data. The mean absolute difference between the mean (SD) dose of activities went

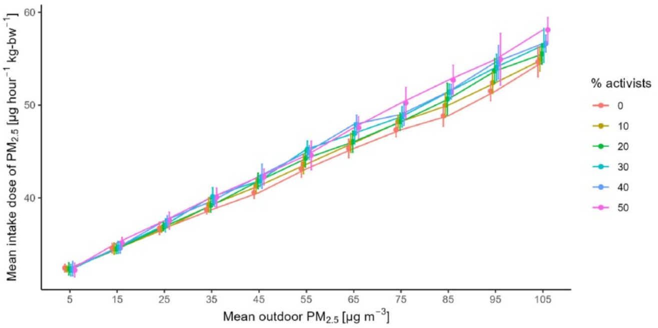


Fig. 6. Mean dose of $PM_{2.5}$ of all agents in the modified ABM at increasing levels of outdoor $PM_{2.5}$ concentrations, grouped by the percentage of population that are activists. Each point is showing a calculated standard deviation.

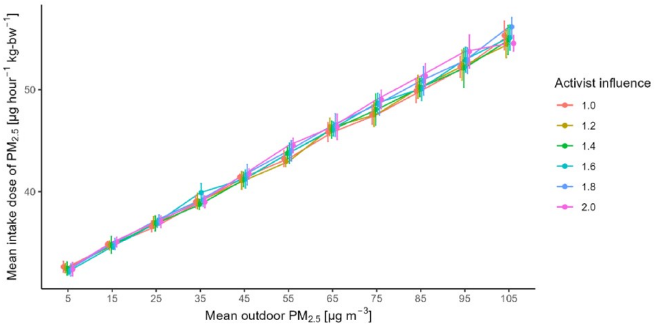


Fig. 7. Mean dose of $PM_{2.5}$ of all agents in the modified ABM at increasing levels of outdoor $PM_{2.5}$ concentrations, grouped by the percentage of population that are activists. Each point is showing a calculated standard deviation.

Table 5
Selected statistical descriptors, mean, standard deviation and median, of the $PM_{2.5}$ values (μg/m^3) and dose of $PM_{2.5}$ (μg/hour kg-bw) for each activity, for the ICLJU dataset.

	$PM_{2.5}$ values		$PM_{2.5}$ dose	
Activity	Mean (SD)	Median	Mean (SD)	Median
Smoking.IN	47.4 (53.2)	26.5	0.63 (0.85)	0.29
Cooking.IN	34.4 (42.0)	16.2	0.46 (0.71)	0.18
Cleaning.IN	31.9 (45.9)	14.5	0.43 (0.61)	0.18
Foot.Bike	22.7 (21.8)	15.0	0.29 (0.28)	0.21
Sports.OUT	18.0 (11.1)	15.5	0.27 (0.25)	0.21
Playing.IN	24.5 (28.8)	15.0	0.24 (0.23)	0.19
Resting.IN	20.6 (27.6)	12.6	0.23 (0.36)	0.12
Bus.Car	18.9 (19.5)	12.6	0.21 (0.22)	0.15
Office	16.4 (18.2)	10.6	0.2 (0.23)	0.13
Sleep.IN	16.6 (20.0)	10.6	0.12 (0.17)	0.07

from 0.13 (0.22) μg hour^{-1} kg-bw^{-1} when comparing the ICLJU and initial ABM datasets, to 0.12 (0.18) μg hour^{-1} kg-bw^{-1} with the ABM with modified PM inputs. On the other hand, the ABM now shows the highest mean dose values for sporting activities, 2.1-times higher than in the ICLJU. The mean dose for smoking decreased by half and fell from having the highest mean dose to the sixth highest, behind foot/bike, cleaning, cooking and playing. These 4 activities all had a similar mean dose value ranging from 0.37 to 0.40 μg h^{-1} kg-bw^{-1}. Cleaning and cooking mean dose decreased slightly, while values for walking/cycling and playing increased. Sleeping, resting and car/bus mean dose decreased by up to half, compared to the initial ABM.

4. Discussion

The results presented in the previous section provide valuable insights into $PM_{2.5}$ exposure and dose during different activities, across age and gender groups.

4.1. *Interpreation of ABM results*

Although smoking was shown to have a higher mean $PM_{2.5}$ concentration, the dose is higher for cleaning, which is a more vigorous activity, with a higher minute ventilation. This is also the reason why sports and walking/cycling have the fourth and fifth highest dose, respectively, even though their mean $PM_{2.5}$ concentration values are among the lowest. Playing shows a similar mean dose as sports, due to playing being a fairly vigorous activity, combined with a high $PM_{2.5}$ value. On the other hand, driving a car or riding a bus, mostly a sedentary activity, has the fifth highest mean $PM_{2.5}$ concentration, while the dose is the third lowest.

Variations in smoking's impact on different age groups indicate the need for tailored interventions. Moreover, difference between sports and playing activities shows how intensity, ventilation, and PM2.5 levels are

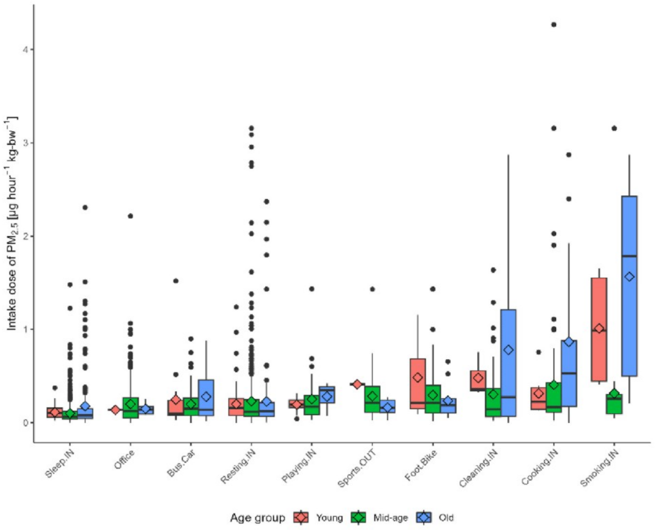


Fig. 8. Dose of $PM_{2.5}$ for all activities per age group, for the ICLJU dataset. Boxplots show median, 1^{st} and 3^{rd} quartiles, diamonds represent mean values.

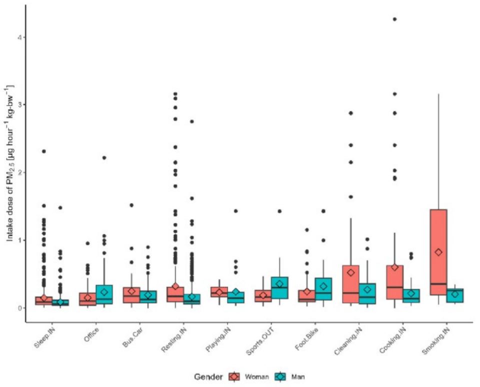


Fig. 9. Dose of $PM_{2.5}$ for all activities per gender, for the ICLJU dataset. Boxplots show median, 1^{st} and 3^{rd} quartiles, diamonds represent mean values.

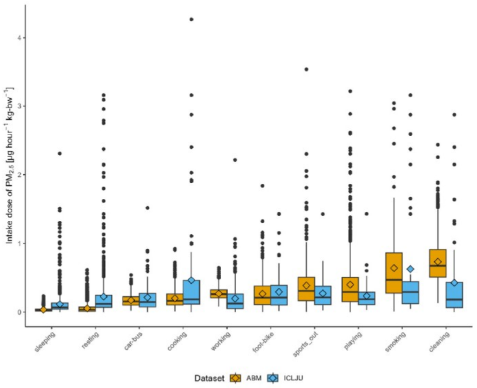


Fig. 10. Dose of $PM_{2.5}$ for all activities, comparing results of the ABM and ICLJU datasets. Boxplots show median, 1st and 3rd quartiles, diamonds represent mean values.

connected. This underscores the need for comprehensive exposure assessments on an individual level. Additionally, despite minor statistical differences, playing and sporting activities exhibit significant mean PM2.5 variations, emphasizing the importance exposure dynamics.

4.2. Activist's impact on exposure

With an increasing share of activists, and as concentrations of PM2.5 rise, the populations begin to have a different mean dose. Activists influence agents to reduce their time in the car/bus and opt for cycling or walking, which increases their time outdoors, increasing their exposure. The latter activities are also more vigorous and thus increase minute ventilation, in turn increasing the dose. As the outdoor pollution increases, the mobility influence becomes a more important factor, and as the share of activists increases, the higher the mean mobility influence in the non-activist population.

When the share of activists is kept constant at 10%, as demonstrated in Fig. 7, the mean dose remains relatively consistent among populations until outdoor $PM_{2.5}$ concentrations exceed 45 µg/m3. Beyond this point, a gradual divergence becomes apparent, with populations influenced by more influential activists experiencing a greater increase in their mean dose compared to those with less influential activists. The distinction is most notable when $PM_{2.5}$ levels surpass 95 µg/m3. It's worth noting that during the period of the highest outdoor $PM_{2.5}$ concentration, the population with a 2.0 activist influence demonstrates the lowest mean dose.

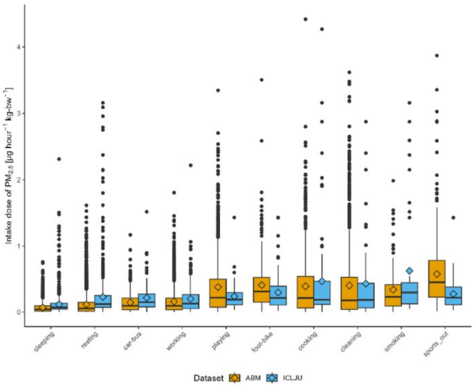


Fig. 11. Dose of $PM_{2.5}$ for all activities, comparing results of the ABM and ICLJU datasets, with the ABM simulation using $PM_{2.5}$ data from the ICLJU dataset. Boxplots show median, 1st and 3rd quartiles, diamonds represent mean values.

This discrepancy might be attributed to the inherent stochastic nature of the ABM. While running the model with 10 iterations provides more robust outcomes, outliers can still emerge and impact the final results.

In this case the share of activists was constant at 10%, although in a real population this number can vary based on location, time, observed population, definition of "activists" and other factors. Data shows that approximately 16% of modality in Ljubljana is via cycling (How the bicycle transformed Ljubljana, 2022), and that, in general, approximately 1/3 of cyclists consider themselves "Diehards" and 1/3 as "Happy Cyclists", as defined by the Cycling motivation and the impact of ITS survey (Vanwynsberghe and Vermeersch). Extrapolating from these approximations, a conclusion could be made that around 5–10% of the population in Ljubljana could be labelled as "cycling activists" within the ABM model. On the other hand, promotion of cycling as an alternative to motorized transport can be connected to climate action. Data shows that 24% of surveyed people have "donated money", "contacted policymakers", "volunteered" or "attended a protest", related to climate action (Nadeem, 2021). Broadly, this group could be considered as activists, individuals who are more engaged with this topic and prepared to actively work to move policy and convince others of the importance of acting on climate change. While these numbers are speculative and rely on several assumptions, they provide some context on a real-world number of "modality activists" as simulated in the modified ABM.

Implementing a function of mobility influence shows that when agents influence each other's decisions, it can have an effect on their cumulative dose. This model provides an example of how interactions between individuals can influence an individual's dose of $PM_{2.5}$. While it represents only one simplified interaction, influencing one specific activity, it does show the power of agent-based models and their ability to gain insight into otherwise difficult to assess phenomena.

4.3. ICLJU results insights

When separated into age groups, shown in Fig. 8, some differences emerge in the dose for the included activities. On average, smoking shows the highest values, especially for groups young and old. On the other hand, the mid age group shows a mean value that is lower than cooking, even though the median value is higher. If only hourly averages are considered, the mean values of the mid age group are not statistically different between any of the activities, except sleeping and smoking. However, the trend of sports and foot/bike having a higher median dose holds in this case. This is even more pronounced in the younger group, which shows a higher (or as high) mean dose as cleaning and cooking. The reverse is true for the older group, which shows a high dose for cooking and cleaning, and a lower dose for sports and foot/bike. The latter are even lower than the dose for playing. When minute values are considered all or most of the differences between activities and age groups are statistically significant.

The reverse trend is seen in dose differences when gender is considered, in contrast to the ABM results. Women seem to have a higher mean dose in the three activities with the highest overall dose (smoking, cleaning, and cooking). On the other hand, men have a higher dose during walking and cycling, and sporting activities. This could be attributed to more intense movements by each respective group in the listed activities. As women, on average, have a lower ventilation rate than men the higher dose could be attributed to an overall higher exposure to $PM_{2.5}$ during smoking, cleaning, and cooking.

4.4. Comparing exposure patterns between ABM and ICLJU datasets

While both datasets show comparable results, there are notable differences for certain activities. When comparing data on smoking, the results indicate that the ABM has a more homogeneous and larger population of smokers that have similar pre-programed habits. On the other hand, the ICLJU is comprised of fewer individuals with different habits, e.g., smoking with closed or open windows, smoking one cigarette or multiple in one sitting, ventilating the room after smoking. A similar trend is evident for cooking, with outliers in a small sample skewing the mean value. On the other hand, 33 individuals recorded a cooking activity, while only 10 were smoking in the ICLJU dataset. A closer inspection of the ICLJU data shows that only 3 participants (in a total of 7 h) contributed all the datapoints that show a $PM_{2.5} > 100$ µg/m3 for cooking. If these 7 instances are removed, the mean value shows a 1/3 lower dose and 2/3 lower SD. This result, similar to smoking, highlights the importance of recording individual level exposure and high exposure events to allow better targeting of exposure and harm reduction.

A probable explanation for the wide discrepancy in the dose of the activities with the highest values, e.g., cleaning, is that the mean $PM_{2.5}$ in the ABM are higher than in the ABM. The dose during cleaning in the ABM (60.3 µg/m3) is almost double that of the ICLJU dataset (31.8 µg/m3). Furthermore, the sensors provided data with a minute resolution, capturing specific high exposure events, while mean values obtained from published research did not have this information. An ABM with a higher temporal resolution and more detailed data inputs could provide better insights during high PM dose periods. Playing and sports also show lower values in ICLJU than ABM, which, in this case, could be explained by a lower intensity level in the ICLJU sample.

Resting and sleeping have low values in both datasets, though the ICLJU data shows more spread. Recording activities on an hourly basis can lead to distorted values. Activities are often not performed for exactly 1 h and do not begin or end at full hours. Resting and sleeping, two activities that tend to have more full hours (an 8-h sleeping time will probably have at least 6 full hours), are prone to having distinct outliers and thus a higher spread of data, seen in the ICLJU dataset.

Some discrepancies in the two datasets could be attributed to a different distribution of the socio-economic, educational, or occupational status of the populations. The ICARUS study (and consequently the ICLJU dataset) only included subjective socio-economic status self-assessments, and did not include indicators that would be comparable with any publicly available information on the specific population. The socio-economic status information available in the ICARUS study showed that approximately ¼ of the participants self-assessed their status as "lower income", ½ as "middle income", and ¼ as "high income". This could lead to the assumption that the populations in the ICLJU dataset and ABM dataset (Slovenian population) had a similar distribution or, at the least, not markedly different.

Experimenting by holding the PM2.5 variable constant showed changes in the difference between the ABM and ICLJU dose could be attributed to (1) the stochastic nature of the ABM and (2) different intensities and minute ventilation values associated with activities. If the assumption is that the second argument prevailed, it follows that sports and smoking had considerably higher and lower intensity rates in the ABM, respectively, compared to the ICLJU dataset. This would again call to the arguments of the ICLJU dataset having a smaller sample of individuals when observing differences in specific activities, and activities that are labelled with an hourly resolution not actually lasting a full hour.

5. Conclusions

Two approaches to estimating $PM_{2.5}$ dose were compared: a stochastic, i.e., agent-based, model, based on aggregated population and environmental data, and an individual-level dataset collected using personal environmental and biometric sensors, combined with time activity data.

Results showed that the ICLJU and ABM had comparable results, showing similar trends and a mean $PM_{2.5}$ dose. On the other hand, the largest discrepancies were seen in the activities with the highest mean dose values. Cleaning and smoking show the highest dose in both datasets, followed by sports, playing, cooking, working and walking/cycling. Using a car/bus, resting and sleeping are associated with the lowest dose. Transportation activities have the highest agreement between the two datasets. Few differences are evident between age and gender groups in the ABM results, with younger individuals and men having (on average) a somewhat higher dose. In contrast, the ICLJU data shows women having a higher dose, as well as being exposed to higher $PM_{2.5}$ concentrations. Importantly, the goal of this comparison was not to determine which approach is more accurate, rather to emphasize the strengths and flaws of each approach though a PM dose and exposure assessment.

An ABM with a mobility influence variable, increased the importance that cycling/walking plays in the overall dose estimate. At lower $PM_{2.5}$ levels, the share of activists did not play an important role. On the other hand, as $PM_{2.5}$ concentrations rose, higher shares of activists (and their influence) caused the dose to increase.

The two approaches (ABM, ICLJU) can be considered to mutually validate each other to some extent. A stochastic model, based on population data, does not capture well some specifics of a local urban population. Activities with a vague definition, e.g., cleaning, cooking, resting, can have a different meaning in different cultures and population groups. Moreover, a stochastic model does not capture well specific high exposure events of individuals. A personal sensor campaign, integrating the specifics of the local environment and population groups, could provide input for calibration of the ABM, including better capturing high dose activities. Employing the ABM approach can offer a relatively accurate insight into PM exposure/dose, providing a more viable option compared to collecting sensor and activity data from a large number of participants for an extended period of time.

Limitations of the ICLJU approach, e.g., frequent data gaps, lower numbers of participants, small number of recorded instances for certain activities, and an associated high cost, can be somewhat offset using an ABM approach. Simulating different scenarios, populations sizes and compositions, and a variety of inputs, can provide additional context to a real-world dataset and allow researchers to further explore the dataset. Additionally, a preliminary virtual assessment of a planned campaign can provide valuable input to exploring different behaviours and variables.

In future research, this ABM can be upgraded with agents that are able to adapt and learn based on their prior results with a “memory-length” variable. Such a feature would allow the user to control how many prior activities influence the agent’s probabilities for their next action. Human individual’s (in general, with few exceptions) do not have access to real-time PM personal exposure data. As the current version of the model explores PM exposure and dose, the agents are programmed to be blind to the past and choose their activities based on the probabilities of each respective activity. An updated model would implement an option to have a share of agents that are willing to change their behaviour if they see that another strategy would reduce their dose. This approach would simulate a group of individuals having access to real-time PM dose data and reacting to it.

Furthermore, the ABM is designed as modular and adaptable, allowing the inclusion of variables like socio-economic status, occupation, education, marital status, and other factors impacting PM exposure and dose. Future adaptations can accommodate this model’s flexible structure to integrate these variables, enhancing its representation of specific real-world scenarios. Moreover, exploring different record lengths in real datasets could contribute to robustness testing in the model and future research directions, including targeted validation of specific facets of the model’s performance.

Interactions between agents can be more complex, with multi-agent households, agents influencing each other for their next activity, with family and friends having a higher impact, as demonstrated in Chapizanis et al. (2021). Urban environments show high spatio-temporal fluctuations of PM concentrations based on numerous variables, e.g., proximity to PM sources, weather patterns, architecture, green and blue spaces. High resolution maps of PM, traffic, use of urban spaces, and others would further increase the detail of the model.

Combining the capabilities of the ABM with data on individual spatio-temporal trajectories, activity patterns, personal PM cloud data, and biometric data, provides researchers and policymakers with a powerful tool. Testing different variables prior to use in research or policy could increase speed and efficiency, and lead to better outcomes.

Author contributions

Conceptualization, R.N., and D.K.; methodology, R.N.; software, R.N.; validation, R.N.; formal analysis, R.N.; investigation, R.N., D.K., J.A.R. and T.K.; resources, R.N., D.K., J.A.R. and T.K.; data curation, R.N.; writing—original draft preparation, R.N.; writing—review and editing, R.N., D.K., J.A.R. and T.K.; visualization, R.N.; supervision, D.K.; project administration, D.K. and D.S.; funding acquisition, D.S. All authors approved the content of the manuscript. All authors have read and agreed to the published version of the manuscript.

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Institutional review board statement

Ethical approval for the ICARUS project in Slovenia was obtained from the National Medical Ethics Committee of the Republic of Slovenia (approval nr. 0120–388/2018/6 on August 22, 2018). The data in this paper were selected only from participants in Slovenia.

Informed consent statement

Informed consent was obtained from all subjects involved in the study.

Conflicts of interest

The authors declare no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Chat GPT v3 in order to provide some minor language editing. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Data availability

Data will be made available on request.

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3.6 Manuscript 6: Harmonization and Visualization of Data from a Transnational Multi-Sensor Personal Exposure Campaign

Section 3.6 consists of a scientific article published in the International Journal of Environmental Research and Public Health in 2021, authored by Rok Novak, Ioannis Petridis, David Kocman, Johanna Amalia Robinson, Tjaša Kanduč, Dimitris Chapizanis, Spyros Karakitsios, Benjamin Flückiger, Danielle Vienneau, Ondřej Mikeš, Céline Degrendele, Ondřej Sáňka, Saul García Dos Santos-Alves, Thomas Maggos, Demetra Pardali, Asimina Stamatelopoulou, Dikaia Saraga, Marco Giovanni Persico, Jaideep Visave, Alberto Gotti, and Dimosthenis Sarigiannis.

Data in all ICARUS sampling campaigns was collected from more than 600 participants living in seven European cities. Each participant was entitled to a final report, based on their collected data. Harmonizing the large amount of data collected in the sampling campaigns presented several challenges. With the harmonized dataset, it was possible to automate the production of the reports to a degree. On the other hand, our results showed that a thorough manual check of all the reports was needed. The reports had to be designed and structured to not confuse the participant, while also providing enough data to gain meaningful insights. Visualizations were selected based on best practices and our communication efforts with the participants, e.g., a focus group of participants (see Robinson et al. (2021)). Relative values for NO_2, CO_2, and TVOCs and absolute values for PM concentrations and meteorological parameters were visualized. Our analysis of the data showed that the absolute values for NO_2, CO_2, and TVOCs were not accurate, while the trends and relative changes provided some information. The participants were made aware of the accuracy and limitations of the device they were using in the report, and in the visualizations. Overall, a properly structured report guided participants through the data and helped them extract useful information.

I contributed to the conceptualization and design of the final report, co-wrote the code for building the report and automating the production, prepared the visualization, wrote the original draft of the manuscript, and contributed to the editing and review of the final version.

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Article

Harmonization and Visualization of Data from a Transnational Multi-Sensor Personal Exposure Campaign

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Abstract: Use of a multi-sensor approach can provide citizens with holistic insights into the air quality of their immediate surroundings and their personal exposure to urban stressors. Our work, as part of the ICARUS H2020 project, which included over 600 participants from seven European cities, discusses the data fusion and harmonization of a diverse set of multi-sensor data streams to provide a comprehensive and understandable report for participants. Harmonizing the data streams identified issues with the sensor devices and protocols, such as non-uniform timestamps, data gaps, difficult data retrieval from commercial devices, and coarse activity data logging. Our process of data fusion and harmonization allowed us to automate visualizations and reports, and consequently provide each participant with a detailed individualized report. Results showed that a key solution was to streamline the code and speed up the process, which necessitated certain compromises in visualizing the data. A thought-out process of data fusion and harmonization of a diverse set of multi-sensor data streams considerably improved the quality and quantity of distilled data that a research participant received. Though automation considerably accelerated the production of the reports, manual and structured double checks are strongly recommended.

Keywords: data fusion; multi-sensor; data visualization; data treatment; participant reports; air quality; exposure assessment

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1. Introduction

The health impacts of poor air quality have become a central point of discussion in policy development and in personal exposure studies [1–3]. A growing selection of low-cost sensors (LCSs) that measure environmental conditions allow individuals to collect data about their own living environment and estimate their exposure to different stressors [4–6]. Several issues remain regarding bulkiness, design, power consumption, data loss [7], unreliable and (unintentionally) misleading data, lack of quality control, validation and calibration [8], and user experience [9]. Providing meaningful information to individuals about their environment and related stressors is in line with the United Nations Sustainable Development Goals (SDGs) calling for participatory, integrated, and sustainable human settlement planning (Target 11.3 [10]), which can only be achieved if the public is well-informed. Several goals and targets in the SDGs are assessed based on the "Mean urban air pollution of particulate matter (PM) of different sizes" indicator [11]. Considering the often-low spatial resolution of PM measurements (i.e., at a city level), typically only sampling outdoor air pollution, the use of individual low-cost PM sensors could be useful in estimating human exposure to PM.

Airborne particulate matter concentration is only one facet of air quality, and when assessing the impact of air quality on human health, pollutants such as nitrogen dioxide (NO_2) [12], ozone (O_3) [13], and volatile organic compounds (VOCs) [14,15] should be considered. Elevated levels of indoor carbon dioxide (CO_2) concentrations can also pose health risks [16].

Data fusion techniques combine data from multiple source (i.e., sensors) and related information from databases to obtain more consistent, accurate, and useful information than can be obtained by the use of a single sensor alone, including fusing features and data to support decisions [17]. Fusing data from different low-cost sensors has previously been employed to supplement existing datasets from environmental monitoring networks with high-resolution spatiotemporal measurements from LCSs [18,19], by using mobile LCSs for air quality mapping in combination with dispersion model calculations [20] or by using stationary data with transport model results [21]. This enables the efficient integration of data derived from multiple sources at different stages of analysis and visualization.

An increase in the availability of devices with very diverse input parameters and data collection protocols poses some unique data fusion and visualization challenges, including non-standard timestamps, data gaps, different classifications, a multitude of data logging processes, etc. While LCSs generally provide a larger quantity of data, there is a lack of data on comparability from one device to another. Good metadata and documentation on how data are recorded and presented can help researchers make informed decisions and better comprehend potential issues prior to using the sensor [22]. The reliability and accuracy of LCSs may necessitate validation/calibration prior to use. Such processes are not standardized and can vary from device to device. The results are usually presented using the correlation coefficient, root mean square error, and mean absolute error, which, while useful, must be accompanied with information regarding the conditions under which the validation/calibration was performed [23]. In turn, this makes the process of data fusion and visualization more straightforward.

To facilitate data fusion and visualization, where one of the goals is to provide meaningful information to participants, there should be a greater focus on assessing the characteristics of the sensor itself, providing more context and associated uncertainties (where available) [22]. A benefit of participatory approaches, where citizens use LCSs, is the ability to gain additional (qualitative) information from the user through interviews or smartphone surveys [24] about specific environmental conditions to inform data fusion. Another benefit is the ability to obtain information about how well the sensors function.

Preparing visualizations of data for lay end users requires a balance in providing the most relevant data in an understandable way. Selecting the proper type of visualization can have a meaningful impact on the perception of the end user and the information that they are able to extract [25,26], and promote better risk assessment and reduction in exposure due to personal decision making [27]. An improvement, which is already being employed in some visualization efforts, is the ability of users to interact with the final dataset and make their own adjustments [28].

Collecting data from multi-sensor and multi-parameter data flows from hundreds of individuals involved in an exposure campaign produced unique issues and challenges which this paper specifically addresses. A key objective was to produce an aggregated and harmonized dataset that allowed for an efficient way of visualizing data via data fusion. Additionally, it provides a starting point for numerous individual-level and community-level exposure assessments and further data analysis, which will be explored in future research. An algorithm was developed that would clean, fuse, and visualize the collected data and present them to the participants in a straightforward and understandable report. This "final report" for the participants was generated in their respective local language, and included as much data as possible without making the report too long and complicated. The report aimed to provide enough details for participants to discern relevant information related to their local air quality, living environment, and behavior, with a view to eventually promote more environmental conscious lifestyles.

Specifically, the objectives of this study were to provide insights and specifics on:

- Outputs resulting from multi-sensor and multi-parameter data flows;
- Aggregation and harmonization of data collected;
- Production of tailored visualizations by fusing data from multiple sources, and automated compilation of individualized final reports.

2. Materials and Methods

Input data for data fusion and visualization were obtained from three sensor devices, data collected through questionnaires for households and individuals, and time activity diaries (TADs). They were part of the Integrated Climate forcing and Air pollution Reduction in Urban Systems (ICARUS) H2020 project, which applied integrated tools and strategies for urban impact assessment in support of air quality and climate change governance [29,30].For this purpose, about 100 participants were recruited in each of the seven selected European cities—Athens, Basel, Brno, Ljubljana, Madrid, Milano, and Thessaloniki—and were provided with all the tools required to collect the necessary data. The data were collected in two seasons in 2019—heating (winter) and non-heating (summer)—to observe any differences between the seasons, as the use of heating devices might influence air quality [31,32]. Two of the sensor devices were commercial: a smart activity tracker (SAT) and an indoor air quality (IAQ) sensing station. The third, called a personal particulate matter (PPM) sensing device, was specifically constructed for the purposes of the research project using the Arduino platform. A schematic representation of the devices and protocols used is shown in Figure 1. A detailed description of the campaign and its goals can be found in Robinson et al. [33]. All data cleaning, harmonization, fusion, visualization, and report compilation and output were done in R [34] with support from different R packages, e.g., ggplot2 [35], dplyr [36], knitr [37], and rmarkdown [38].

2.1. PPM Data

The PPM sensing device(IoTech Telecommunications, Thessaloniki, Greece) was designed for the purposes of the sampling campaign of the ICARUS project [39]. It collected PM concentration data in three class sizes (<1 µm (PM_1), <2.5 µm ($PM_{2.5}$), and <10 µm (PM_{10})) and ambient temperature as well as relative humidity data, in addition to GPS/location coordinates (including speed and altitude). As the device did not have a real-time clock (RTC) module (e.g., [40]), the timestamp was obtained by connecting it to an online server via a SIM card. Without this connection, the device did not provide data with accurate timestamps, which in turn produced several data gaps. Timestamp logging was irregular and inconsistent, as evident in an example of the dataset in section A of the Supplementary Data (SD-A).

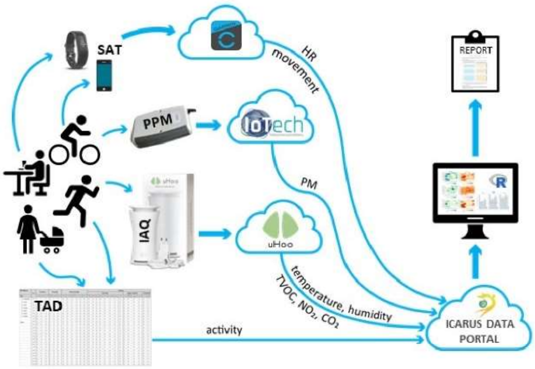

Figure 1. Schematic representation of data collection devices and protocols, transfer paths, aggregation, visualization, and delivery protocols.

2.2. SAT Data

A commercial SAT was used (Vivosmart 3, manufactured by Garmin, Olathe, Kansas, U.S. [41]) to collect heart rate and movement data with a minute resolution (e.g., average heart rate, stress level, sleep status, calories burned, etc.) As the export of data is not freely available through the Garmin interface, an additional connection between a dedicated ICARUS data portal and the Garmin Connect portal was established to transfer the data. The SAT data had very few gaps (excluding the time while the device was charging). Issues with data capture of heart rate occurred when the user did not fasten the wrist strap tight enough.

A brief overview of the SAT data was included in the final report as a summary table.

2.3. IAQ Data

A "uHoo Smart Indoor Air Quality (IAQ) sensor" (uHoo Limited, Singapore) [42], a stationary device with multiple sensors, was used in every household. At every full minute, the IAQ provided data on temperature, relative humidity, CO_2, total VOCs (TVOCs), $PM_{2.5}$, NO_2, carbon monoxide (CO), ozone (O_3), and air pressure.

Visualization of AQ parameters measured by the IAQ was limited to three parameters (CO_2, NO_2, and TVOCs) that showed the best performance during the collocation experiments with validated devices, as well as other tests. As offsets were observed for some sensors during these experiments, this specific dataset was visualized using a heatmap, focusing on relative changes in each variable over time. A heatmap, in this case, consists of tiles which are colored relative to all other tiles (lower values are lighter, higher values are darker), as implemented in Mahajan et al. [43]. Using minute values would create a heat map with small tiles, which would obscure the relative differences within a day. To counteract this, hourly values were calculated and used in the heat map, reducing the number of tiles from approximately 10,000 to 170.

2.4. ICARUS Data Portal

A dedicated data portal was constructed for the purposes of the ICARUS2020 project, and a decision support system (DSS) with it, which collected, compiled, and stored the data. The DSS additionally had a presentation tier with a user interface and a logic tier that stored the computational models and handled their execution [44]. In this study, the data portal was mainly utilized to store and obtain the PPM and SAT data in a uniform format, which allowed further manipulation and fusion of data.

2.5. TAD Data

A key data input was the TADs, which allowed the participant to record their activity, location, means of transport, and other variables for each hour of the day. These data were collected from each participant, for seven days in two seasons, for all cities, accumulating up to approximately 10,000 TADs.

There were two methods of filling in the TADs: one was to select only one option for each hour (i.e., majority activity) and the other was to allow participants to select multiple options within an hour. This posed a unique challenge in selecting which data point to use, which activity was more relevant or more characteristic for each hour.

Some manual corrections of the data were necessary in the final stages after observing some obvious mistakes in the recording of activity. As these corrections were not double-checked with the participants, only the most obvious mistakes were corrected, e.g., if a non-smoking person truly smoked in just one instance the entire period.

Because the data for activities were for hourly values and the sensor data had a minute resolution, the former was repeated 60 times per hour, which proved to be a major issue when calculating averages and trying to discern if there were meaningful differences between activities [45].

The TAD dataset was used in three visualizations, in combination with PPM and SAT data:

(a) A scatter plot was made for every PM size class and heart rate for both seasons. Additionally, the points were colored based on the activity at that minute, which allowed the reader to observe what activities took place at, for example, elevated levels of PM or elevated heart rate. Only the activities which the participant filled in were shown in the legend.

(b) A similar scatter plot as in (a) was constructed, with an additional layer which showed vertical bands or ribbons of different colors corresponding with the participant's location and mode of transport. As this added another layer of complexity to the visualization, the decision was made to provide these plots only to specific individuals who expressed interest. Though activity information was missing in several TADs, the location and transport data were logged for almost the entire period of observation (for most participants). Consequently, participants could associate specific means of transport with elevated levels of PM, and corresponding activities with a higher heart rate.

(c) The third plot showed the average weekly PM values for each activity. Six plots were constructed, three per season, one for each PM size class.

TAD data were not used in combination with IAQ data due to the higher uncertainty associated with absolute values of CO_2, NO_2, and TVOCs.

2.6. Final Report Compilation and Production

The generation of final reports for participants was performed in three phases:

(a) Generation of plots as described in points 2.1.–2.4., which was followed for all of the participants. These plots were saved locally in a jpeg format and labeled according to each participant ID.

(b) Plots were integrated in a rmarkdown script, with the customization of each report designated in an Excel file. Each participant had a custom greeting with their name and gender-appropriate pronoun. All plots and other graphics were inserted using the include_graphics function in the knitr package.

(c) Finally, the script was iterated over all participants in a separate script to allow some further customizations. Some participants had additional visualizations (see 2.5 point b), while others had some omitted due to missing data. After all the reports were generated in the participants' local language, they were manually checked for errors by local organizers in each participating city and distributed to all the participants.

In addition to the technical construction and production of the final report, the participant feedback and wishes for visualization were considered, where appropriate, by employing a user-centered approach and a structured focus group of participants [46].

2.7. Temporal Resolution and Data Treatment

A minute resolution of data was deemed as sufficient to provide enough detail of PM concentrations and exposure. The SAT and IAQ also logged data with a minute resolution, though these logs were at every full minute while the PPM sensing device logged the measurements at different fractions of the minute. These were later rounded to the nearest minute.

To compare the PM data with WHO guideline limits the minute resolution data were aggregated into daily means. More uncertainty was associated with PM daily means from the first and last day the participant was involved in the campaign, as the participants did not collect data for the entire 24 h period.

An outlier correction was performed for the PM data, where all values above 180 $\mu g/m^3$ were set to 180 $\mu g/m^3$, based on the maximum values provided by “Air quality in Europe” as part of the CITEAIR and CITEAIR II projects [47]. This approach was used only for visualizing the data and providing the final reports to participants for clearer data representation.

The PPM data showed good agreement with absolute values measured from a reference research-grade device, a GRIMM Model 11-A, and increasingly did so with larger time-averaging intervals [39].

3. Results and Discussion

3.1. A Merged Dataset

The final merged dataset had 93 columns. Due to sensor failures, data gaps, incorrect TAD filling, etc., there were several instances of empty columns or, in some cases, completely empty datasets per participant. This was appropriately labeled in the final reports.

Section B of the Supplementary Data (SD-B) presents an example of a completed dataset, with all the data harmonized to a 1 min resolution. Each dataset includes:

- Specific characteristics for each participant (age and gender);
- PPM data (PM values, temperature, humidity, battery charge level, location coordinates, speed, and altitude);
- SAT data (where several columns proved to be somewhat redundant and were therefore removed);
- IAQ data (which proved to be easiest to handle as they had a correct timestamp for each recorded value, almost no missing values, and a simple interface to download the data);
- TAD data, presented the same way as they were recorded on the physical paper sheets: location of the participant (home, office, indoor, outdoor), transport data (bus, car, foot, etc.), indoor and outdoor activities (cooking, smoking, sports, etc.), and some specific conditions for the indoor space the participant was in (burning candle or fireplace, open windows, and/or AC turned on).

3.2. Visualizing the Data

All the visualizations are presented and described here as they were shown in the final report to participants, and are collected as examples from different participants.

Figure 2 shows the temperature, relative humidity, and air pressure during both seasons (IAQ data). Non-heating and heating seasons are indicated as “Winter” and “Summer”, respectively, as the sampling campaign for all the cities extended from January to March 2019 for the heating season and from April to July 2019 for the non-heating season. The example visualizations are only from reports to participants from the city of Ljubljana, where the non-heating sampling campaign took place earlier than that in other cities and was therefore defined as summer. Meteorological data showed the highest accuracy when compared to reference instruments, and were in turn presented with absolute values. Although the ribbons show "optimal conditions" as per the general health and comfort guidelines (modified for the appropriate climate) [36], this information is somewhat subjective and can differ from person to person. As shown in the example in Figure 2, this person had very similar indoor temperatures in both seasons, and even though the summer values are mostly outside the "optimal zone", one could argue that a constant temperature throughout the year provides more comfort to certain individuals.

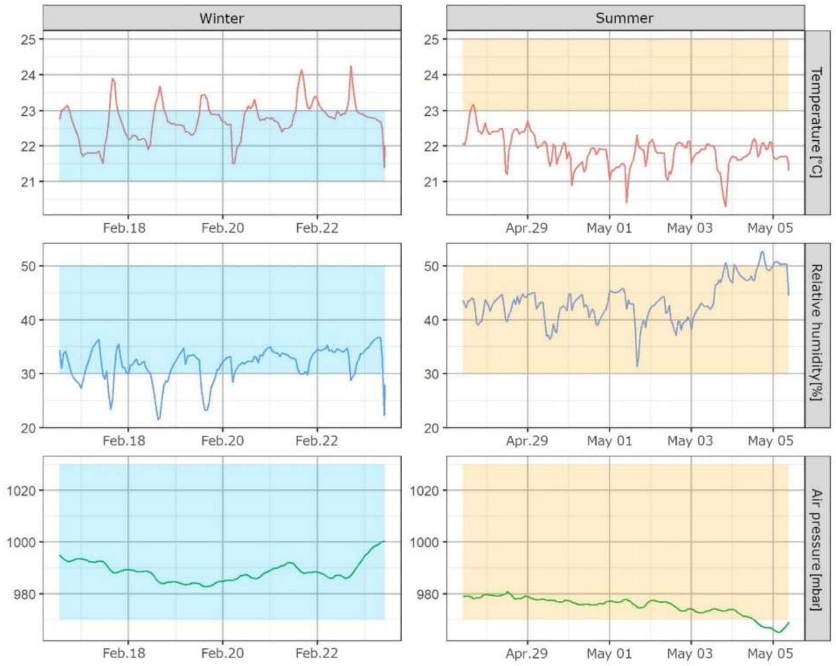

Figure 2. Faceted plots with meteorological variables—temperature, relative humidity, and air pressure; data from IAQ. Colored horizontal ribbons represent "optimal" values for each variable.

Arranging the individual plots into columns according to season makes comparisons between the seasons easier.

Figure 3 shows an example of the compiled visualizations of CO_2, NO_2, and TVOCs for this particular household. We found that these parameters typically followed expected trends, e.g., decreased values of CO_2 when opening a window and in turn increasing the NO_2 values if it was in a high-traffic area [48], as seen in Figure 3 on Tuesday the 19th of February 2019 at around 13:00, when CO_2 concentrations quickly fell and NO_2 increased rapidly at the same time. The plots allow for an intuitive way of observing relative changes in these parameters by household. We used relative values in our reports, as collocation with a reference device has previously shown that the absolute values were not accurate enough to present to participants at that time [49], though newer research shows moderate to high correlation with reference instruments in laboratory conditions [50]. These relative values still give participants an insight into their indoor air quality and possible correlations with external factors such as traffic.

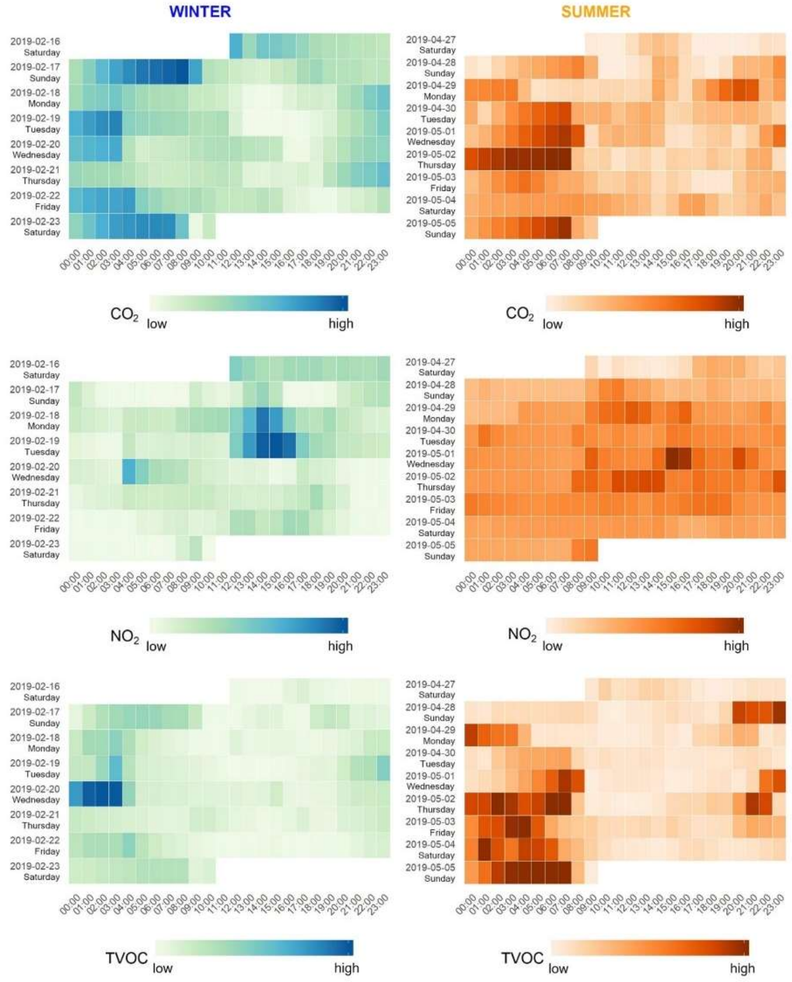

Figure 3. Faceted heatmaps of three pollutants (CO_2, NO_2, and TVOCs); data from IAQ.

The layout of the visualization allows the reader to compare trends between seasons and between pollutants. For example, higher TVOC values during the evening and night could indicate poor ventilation in combination with a specific activity that raises the concentrations, such as cooking or smoking [51]. By putting these plots in the same figure, they can immediately observe the trends in the other two parameters and come to some conclusions.

Each date is also labeled with the written day of the week (language-specific) to facilitate better observation of specific trends.

Figure 4 presents the concentrations of PM in three class sizes, heart rate, and designated activities for each minute during which the participant was involved in the data collection. Only the specific activities are shown; there is no additional information about the location of the participant, their mode of transport, or specific conditions in the household. Not including this information makes the visualizations less crowded and easier to read and understand, as determined by exchanges provided in a structured focus group [46]. All the values are also plotted with exact concentrations, given that the PPM device showed fairly accurate results compared to reference devices.

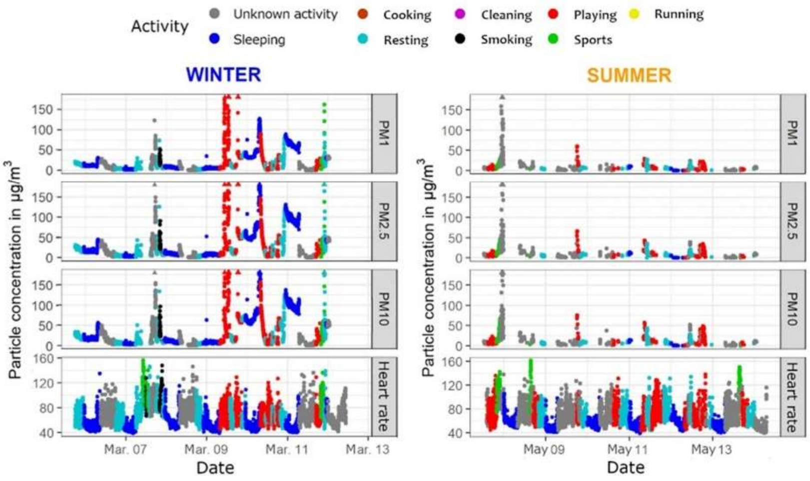

Figure 4. Three size classes of PM (PM_1, $PM_{2.5}$, and PM_{10}) and heart rate values for both seasons with each point colored according to the associated activity; data from PPM, SAT, and TAD.

The participants could deduce by themselves some interpretations and extra information from the plots, e.g., a higher heart rate when running, dips during the night, a specific time of day when the PM concentrations were elevated and if they were perhaps related to a specific activity such as smoking or cooking, etc. This level of interpretation is only feasibly possible by the participants, because they would have a more complete overview of their surrounding and activities. To avoid the issue of recall, participants could be provided with their respective TADs.

No particular difficulties were encountered with constructing this visualization, with the possible exception of some alterations to the color scale and legend to also include the activities that the participant did not perform.

An additional figure was created to include the location and transport of the participants, in addition to PM and activity values (Figure 5).

Several difficulties were encountered while constructing these plots, as the ribbons that show each activity needed a start and an end time for each location/transport at every interval. We considered only including a vertical line at each minute in the color of the location/transport, but this considerably increased the run-time per plot and was not efficient given the large number of plots to produce. An additional section of code was implemented to construct a separate data frame which had a start and an end time with a label for each location/transport. This was used in the ggplot2 geom_rect function while compiling the plot and noticeably reduced the time it took to compile each plot.

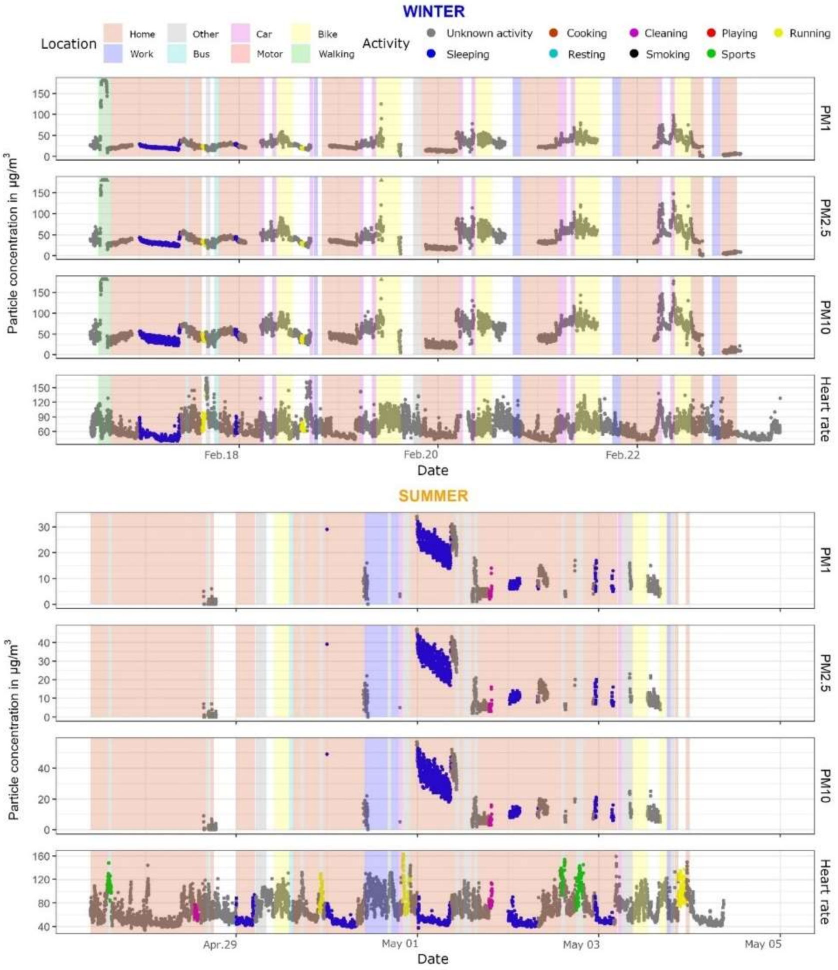

Figure 5. Three size classes of PM and heart rate values for both seasons with each point colored according to the associated activity and each ribbon representing a location or means of transport for that time period; data from PPM, SAT, and TAD.

Figure 6 shows the daily average PM concentrations for both seasons, and is the only set of plots where guidelines or recommended values could be inserted. The WHO and the EU do not have minute or hourly guidelines for concentrations of PM, though studies show that short-term exposure to elevated levels can have adverse effects on health [52,53]. The WHO does provide daily guidelines for $PM_{2.5}$ and PM_{10}, which are 25 µg/m^3 and 50 µg/m^3, respectively [54], revised in 2021 to 15 µg/m^3 and 45 µg/m^3, respectively [55].

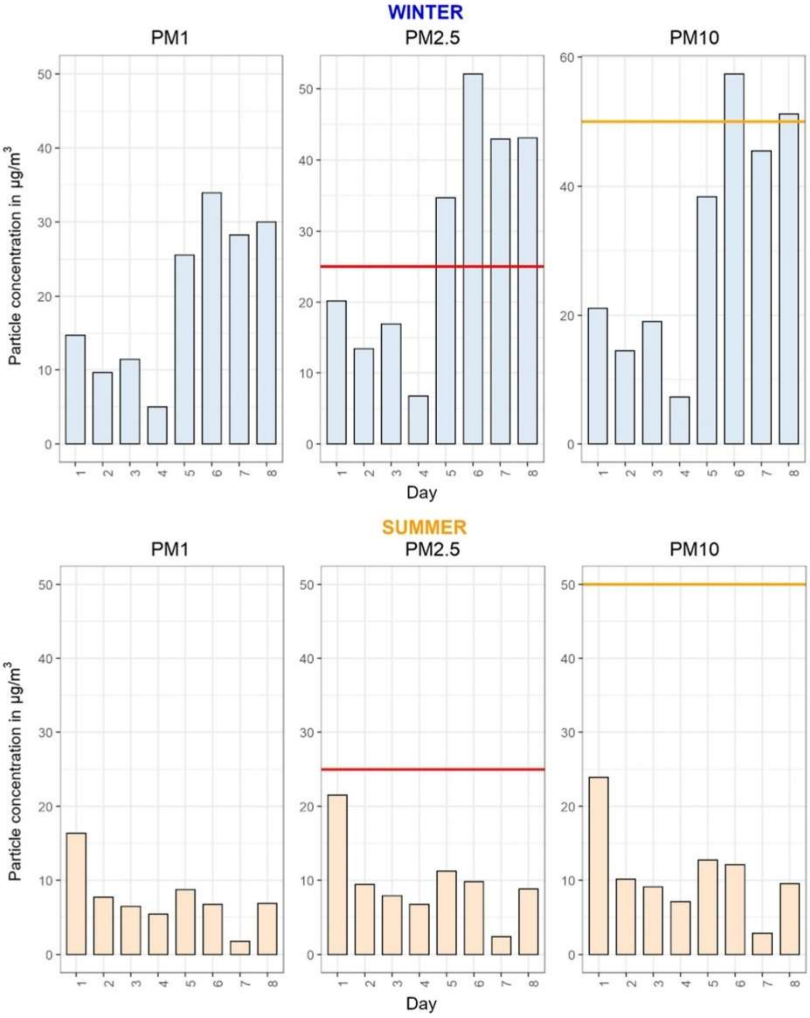

Figure 6. Faceted plots of average daily concentrations of three size classes of PM for each season, with WHO guidelines; data from PPM.

There are two important pieces of information in these plots, allowing the participant to observe (1) inter-seasonal differences and (2) day-to-day differences, while also having information about a specific size class of PM. This specific plot shows that the concentrations are generally higher in wintertime (more indoor activities, weather patterns that trap pollution in low-lying areas, combustion of solid fuels, more use of car/buses in contrast with cycling/walking, etc.), and when there are elevated levels of PM during the summer they are still much lower than in wintertime. The participant can also observe that some particular days have elevated levels of PM, which could be associated with specific activities performed that day (or weather patterns).

Figure 7 presents two tables showing the average values for each SAT variable for each day. No additional visualizations were made for the SAT data (apart from the heart rate plots in Figures 4 and 5). There were several visualizations already available on the Garmin Connect portal for each variable.

Day	Steps	Stress level	Average heart rate	Max heart rate	Sleep[h]	Kcal
1	4,922	NaN	65	128	0	120
2	11,702	25	66	170	9	389
3	17,683	43	69	163	5	346
4	10,504	26	69	142	7	194
5	8,481	22	67	131	7	158
6	10,871	17	67	134	6	189
7	10,589	22	67	138	5	185
8	1,244	8	52	128	8	7

Day	Steps	Stress level	Average heart rate	Max heart rate	Sleep[h]	Kcal
1	6,240	7	63	148	0	186
2	8,000	20	60	144	8	172
3	19,377	16	70	132	4	312
4	16,041	28	73	163	7	488
5	17,717	14	63	118	8	407
6	19,561	25	69	154	7	592
7	30,675	26	74	159	4	443
8	520	12	52	102	7	9

Figure 7. Aggregated data from SAT.

Figure 8 shows the average PM values for each activity as indicated by the participant in the TADs. There are certain shortcomings to this visualization as it does not provide any data about the number of instances for each activity, e.g., in this example there is only one hour of smoking indoors in the entire week during the summer season, but over 50 h of sleeping. Although the caption under the plots clearly states that the empty columns mean that there were no recorded instances of that specific activity, there can still be some confusion where the reader might assume that the average concentration is 0 $\mu g/m^3$.

Primarily this plot should communicate differences between the activities in each respective reason. In the example provided in Figure 8, the PM values for smoking are higher than all other activities during the summer season, but not that different from all other activities during winter. A possible explanation would be that there is less natural air circulation during the winter (opening windows or doors), though there could be other explanations. This is another prime example where detailed information about their surroundings would give the individual the most accurate assessment of what the source of the elevated concentrations of PM could be.

3.3. *The Final Report*

An example of the final report provided to all participants is shown in section C of the Supplementary Data (SD-C). The report began with a personalized greeting, a general description of the project, and the contents of the report. There were also disclaimers about the nature of the low-cost sensors and the uncertainty associated with them. The next page ("Part A") had a more detailed description of the study, the devices and approaches that were used, and what the reader should specifically focus on. "Part B" described the household conditions, focusing mainly on the data from the IAQ with Figures 2 and 3, accompanied with appropriate captions.

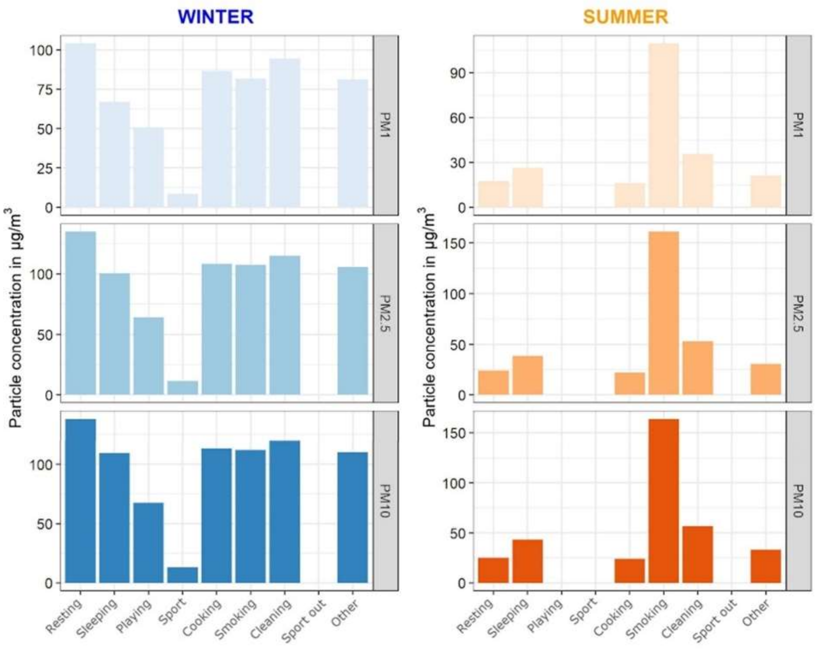

Figure 8. Faceted plots of average values of three size classes of PM (PM_1, $PM_{2.5}$, and PM_{10}) for each specific activity and each season; data from PPM and TAD.

"Part C" contained the plots concerning personal exposure to air pollutants, beginning with PM data, shown in Figures 4–6. Figure 5 was provided only to a handful of participants who had more recorded data and requested a more thorough overview for the entire duration of their involvement. The physical activity information, shown in Figure 7, was presented next and accompanied with a more detailed description of each variable, including some measures for low, average, and elevated heart rate to aid the reader in their interpretation of the data. Figure 8, showing the average PM values for each activity, was included last, with a specific disclaimer that the scales on the *y*-axis are free.

Some general recommendations on "How to improve indoor air quality" were provided at the end of each report together with two tables extracted from the uHoo sensor device recommendations and descriptions [42].

3.4. Issues Faced and Recommendations for Future Studies

Several issues were encountered while compiling, cleaning, and visualizing the data collected from LCSs. While the PPM device proved to be the most accurate when compared with a reference instrument, it also had the most issues regarding data gaps and inconsistent timestamps. Two relatively small improvements to the device would have helped, as they would make the device independent of the GPRS signal: (a) installing a real-time clock (RTC) module which would provide consistent timestamps, and (b) increasing the internal storage and buffer to record PM values without a connection to the server. Several optimizations to reduce energy usage would be possible, e.g., less frequent GPS recordings while stationary, option to only upload the data when the device is charging, etc.

On the other hand, the IAQ had very consistent data streams, accurate timestamps, and a very intuitive interface. Two improvements would make the device function more independently: (a) a small internal storage for times when there was no wi-fi signal, which would allow the device to store the data in an internal buffer and upload it when the connection was re-established, and (b) a small battery to allow the device to function during power outages.

The SAT was very reliable, had an internal storage capacity for 14 days of data, and had a battery that lasted between 5 and 7 days. An improvement would be to provide a way to verify if the data is being logged correctly. At times, the device was not placed properly on the wrist or had some other error with data logging, and this was only observable at the end of the sampling campaign. Though the SAT did provide a uniform dataset it had to be extracted by a separate process in collaboration with the company that produced the device. Accessing data from commercial devices proved complicated and preconditioned on setting up exclusive deals with companies. Even when the deal is set, the entire data retrieval process is reliant on the cooperation of the company. It would be better if the raw data streams were open access.

A key improvement for the TADs would be to allow more granular activity logging during the day, e.g., every 15 min. TADs could also be somewhat customized to different participants or days of the week, e.g., participants who perform only one activity, such as work, during morning hours could have a different TAD during workdays than during weekends. The hourly resolution of TADs caused some issues when presenting and visualizing data for the participants as the average values were skewed, due to the fact that most activities do not have a duration of one hour nor do they start and end at full hours. This meant, for example, that someone who went for a 40 min run followed by smoking a cigarette might only have recorded "running" for that hour. Even though the person could have checked both activities, there would still be no information as to which part of that full hour the "smoking" vs. "running" occurred. Recording activities minute by minute would be a heavy burden for participants, so future research should focus on other solutions, such as complex activity recognition using machine learning, smartphones, or other tools [45,56].

Visualizing the data proved challenging at times and required unique solutions. The main challenge in producing the plots in Figure 2 proved to be the horizontal ribbon with "optimal values", which had to be referenced in a way that would allow this value to be presented for each individual hour, while also enabling faceting of the plots. Additional variables with minimum and maximum data for each season were introduced, which shortened the script for the final construction of the plots.

A rather easy, though important, improvement for the plots in Figure 6 would be to show specific dates and days of the week instead of the number of days since the participant joined the sampling campaign. Participants do not always remember which day they started the campaign and would have to go back to the IAQ figure to find out. As a significant amount of time can elapse between the campaign and the distribution of reports to participants, it could be good for future studies to always indicate in the figures the date and day of the week.

Figure 8 could be improved by indicating the number of instances for each activity by coloring the bars according to a color scale reflecting the frequency of activities or by changing the width of each bar accordingly. The activities without data should be clearly marked with a symbol or a text. A requirement for a minimal amount of data should be considered to remove activities with only a few instances. The color schemes should also be intuitive, such as coloring winter blue (cold color), summer orange (warm color), or smoking black, which instinctively guides the reader.

Manually collected data from TADs were double-checked by the researchers as there were some non-obvious errors, e.g., smoking selected for a person who designated that they do not smoke, which sometimes indicated a user error and other times that the person was in fact an infrequent smoker. As with any dataset, these inconsistencies and all permutations can be very time-consuming to implement into the report-generating code. A large number of reports (and the associated data) also necessitates that there is a careful process when deciding what functions to use, and how much time and processing power they will need.

4. Conclusions

Data fusion and visualization of data obtained in personal exposure campaigns performed in seven European cities within the ICARUS project were conducted. By using a diverse set of devices (wearable and static, commercially available, and custom-made) with different temporal and spatial resolutions, a significant amount of data was obtained for each participant. Data fusion was performed in order to integrate the multi-sensor and multi-parameter datasets collected from the > 600 participants. Individualized reports were compiled for each participant with an automated process. Following these large-scale campaigns, several lessons were drawn and recommendations for future studies were provided.

Using low-cost sensors to assess air quality on an individual level presented some unique challenges, e.g., fusing data by rounding, duplicating, and removing certain parts of the timestamps, which allowed a uniform presentation on several plots. Mostly simple modifications were enough to provide some clarity and make data fusion more straightforward. Appropriate guidelines have to be considered carefully to avoid confusing the participant or giving false impressions on otherwise non-harmful concentrations of pollutants.

Participants should not be overwhelmed with the report, rather it should provide sufficient data for them to obtain as much meaningful information as possible. While the SAT provided a large amount of data, a decision was taken to only include the visualizations that were the most effective at communication. Apart from the number of visualizations, the appropriate type must also be carefully selected and curated. Our approach with relative values for NO_2, CO_2, and TVOCs provided enough data to clearly see some trends, without providing unreliable absolute data values. On the other hand, the higher reliability and accuracy of PM concentrations and meteorological parameters enabled us to provide absolute values. A clear option should be included to observe trends between days, seasons, and activities. These visualizations must also reflect the results of collocations and validations made prior to deploying these devices. Citizens must be made aware of the accuracy (and shortcomings) of the device they are using and to what extent can they rely on the results. A properly structured report will guide them through the report itself and give them enough support to extract the most useful interpretation of the data that they can.

A well-informed public can collaborate with and react to changes in their environment, be it by influencing policy decisions or making changes to their individual lifestyles and behaviors. Using LCS provides a conduit for citizens to be empowered by data that they can collect, observe, and interpret. We, as researchers, must provide the necessary tools and options for them and guide them through the process. Changes in policy can come from the top-down or from the ground-up. In both cases, the citizens that are affected by these policy changes must be active participants in designing and implementing these solutions.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/ijerph182111614/s1 (SD-A: Example of timestamp gaps in PPM dataset; SD-B: Example of dataset used for visualizations and reports; and SD-C: Example of entire report for participants).

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Chapter 4

Conclusions

This dissertation aimed to develop an integrated approach for evaluating the applicability of personal monitors in urban stressor exposure and airborne particulate matter (PM) intake dose assessments. The first step involved selecting, testing, collocating, and validating the appropriate personal monitors for the task. Once selected, the devices were deployed in a proof-of-concept exposure assessment campaign within the ICARUS H2020 project. Data from multiple streams in the project were collected and harmonized. In addition to collecting data, in this work, the feasibility of using machine-learning-supported data analysis in exposure assessments was determined. This helped to identify patterns and relationships in the exposure and dose data that may not have been immediately apparent using traditional analysis methods. Finally, a method was developed using a stochastic, i.e., agent-based model, for an integrated personal monitor-based multi-sensor airborne particulate matter exposure and intake dose assessment. This provided a comprehensive understanding of the relationship between exposure to air pollutants and PM dose that could inform policies and interventions aimed at reducing the associated negative health impacts.

Considering the first hypothesis, the validation efforts described in Section 3.2 and the results of the review in Section 3.1 confirm that personal monitors provide fit-for-purpose and accurate enough data for estimating exposure (or dose) to different air pollutants on an individual level, compared to reference research-grade instruments. Although the PPM was validated on-site using a collocation method, prior data demonstrated the reliability of the sensor. Additionally, personal monitors have a lower cost compared to research-grade sensors. However, accuracy may be reduced in specific scenarios such as high levels of humidity, extremely high concentrations of PM, or during specific activities and movements. Further research is needed to validate the accuracy of personal monitor data in different scenarios and environments. Results in Section 3.2 have shown that the PPM devices did show a high correlation with the reference research-grade instrument. This was more evident for the smaller sized particles, PM_1, while the correlation was lower for larger particles. These results correspond with the literature regarding the accuracy of the PM sensor. Moreover, the accuracy is on par with other personal or stationary PM monitors reported in the literature. Use cases for the PPM in Sections 3.4 and 3.5 have shown that the device is fit for these types of applications, i.e., individual level exposure and dose assessments.

Section 3.3 addresses the second hypothesis and presents the use of wearable environment/ambient and wrist-worn activity/biometric sensors for complex activity recognition. The results showed a moderate to high accuracy of up to 77% for correctly classified instances of simple and complex activities. However, the accuracy was considerably lower when activities were recorded per hour, compared to per minute. Additionally, the accuracy improved when vague and general activities were divided into more detailed activities. For improving the accuracy of some complex activities such as cooking and smoking, the data from the environmental personal monitor, i.e., PPM, was crucial. While movement sensors can recognize several activities, it is challenging for them to distinguish between complex activities, especially if the person is not wearing the sensor on the hand, they are using to perform an activity. Accurately predicting these types of activities is a necessity in personal exposure studies, and personal monitors can significantly contribute to this field. Therefore, the second hypothesis is confirmed with some caveats, as outlined above.

The third hypothesis, stating that in real-world conditions, increased exposure to air pollutants is dominated by relative contributions resulting from a few specific activities and microlocations only, can be discussed through the results published in Sections 3.2, 3.4, 3.5, and 3.6. Section 3.2 compares the intake dose models for PM_1 exposure of two individuals in the ICARUS campaign. Although the sample size is small, the data suggests that exposure levels are relatively low and consistent throughout the entire period, with occasional spikes during high exposure events. However, when considering movement and PM dose, additional peaks are observed that are specific to certain activities, as shown in Section 3.4. On the other hand, the same results revealed that exposure is heavily influenced by outdoor concentrations of PM, even when indoors, and solely dependent on specific activities. Results in Section 3.5 showed that the activity that a person is performing has a higher influence on the PM dose than age or gender. While there are differences in PM dose among individuals of different ages and genders performing the same activity (e.g., middle-aged individuals having a lower dose when cleaning or smoking), these differences are smaller than the differences observed between activities. Furthermore, the results based on the ICARUS dataset do not fully align with the ABM results. Overall, these findings suggest that exposure to air pollutants is generally dominated by a few specific activities when viewed on an individual level over a period of days or weeks.

Section 3.4 provides evidence to support the fourth hypothesis, which suggests that higher-resolution temporal and spatial data can lead to a more detailed and accurate assessment of an individual's exposure to air pollutants. Specifically, the analysis in this section demonstrates that indoor activities should not be overlooked in the evaluation of overall exposure. Certain activities, such as cooking and cleaning, can have a direct impact on air quality, while others, such as opening a window during a period of low outdoor air quality, can have an indirect impact. By capturing specific indoor activities, a higher resolution approach provides more context and a more robust assessment of exposure. In contrast, measuring exposure with a weekly or daily resolution cannot capture specific high-exposure events in microlocations. The results presented in Section 3.4 demonstrate that several high-exposure events can significantly raise exposure levels. Furthermore, a higher spatial and temporal resolution enables a more accurate assessment of how specific routines contribute to individual exposure.

Sections 3.4 and 3.5 provide support for the fifth hypothesis, which asserts that PM dose is dependent on physical activity and the environment of the individual. While PM concentrations affect exposure, the dose is highly dependent on the specific activity a person is performing and their environment. For example, even at moderate levels of outdoor PM, cycling vigorously can lead to a considerably higher PM dose than a leisurely walk in the same space. Results also show that the PM dose differs based on the environment, mainly due to different levels of PM. The ABM simulation demonstrates that an increase in outdoor PM concentration (without increasing indoor levels) considerably raises the PM dose for the entire population. Moreover, frequent cycling and walking, as opposed to using a bus or car, lead to an even greater increase in PM dose, as a higher minute ventilation rate associated with more vigorous activities increases the dose. This effect is further compounded during high-exposure events. It is important to note that these outcomes apply only when considering the dose of PM passing the theoretical space above the nose and mouth. Assessing the deposited dose of PM in the trachea or lungs, or the uptake of PM in the bloodstream, requires different considerations, such as particulate size, composition, and shape. It is worth noting that while PM dose and exposure during vigorous activities should be taken into account in health evaluations, in most cases, they should not discourage individuals from exercising or choosing active commuting, such as cycling or walking. As discussed in Section 3.5, a physically active lifestyle offsets any negative health effects associated with an increased PM dose in almost all cases. Furthermore, Section 3.6 emphasizes appropriate communication, which should be easy to understand, informative, and not unnecessarily alarming.

Building on the outcomes presented in this thesis, future work should focus on further developing and validating modelling approaches, exploring additional uses of personal monitors, and incorporating participatory approaches. In the existing ABM, the agents do not have a “memory” and select the next activity based on predetermined probabilities for daily activities. A further development of this model would allow agents to adapt and learn based on their prior results with a “memory length” variable. Such a feature would allow the user to control how many prior activities influence the agent’s probabilities for their next action. Individuals generally do not have real-time data about their personal exposure to PM. An updated model would implement an option to have a share of agents that are willing to change their behaviour if they see that another strategy would reduce their dose. The latter approach could be further validated within a real-world assessment.

Personal monitors provide a novel set of tools in assessing exposure to air pollution and other urban stressors. While there is a consensus that they are not on par with research-grade monitors, their accuracy and reliability have improved in recent years. This thesis presents a thorough overview of their use, inception, and outcome analysis, in a specific context. Undoubtedly, this rapidly growing and developing field of research will provide numerous opportunities in the future.

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Biography

Author of this thesis Rok Novak received a Bachelor's degree in Environmental Protection and Ecotechnologies from the Environmental Protection College in Velenje, Slovenia, where he also participated in two research projects, including a placement at the Faculty of Forestry and Wilderness Management at Hedmark University College in Norway. In 2019, he received his Master's degree in Environmental Engineering from the Faculty of Mechanical Engineering in Maribor on the topic of "Validation of low-cost sensor systems for estimating an individual's exposure to airborne pollutants", under the mentorship of Prof. Dr. Milena Horvat, and co-mentorship of Dr. David Kocman. This work was based on a collaboration with the Jožef Stefan Institute and the Horizon 2020 project ICARUS2020. In the same year, he enrolled in the "Ecotechnologies" PhD programme at the Jožef Stefan International Postgraduate School with the mentorship of Dr. David Kocman.

While collaborating in international Horizon 2020 projects ICARUS [1], SMURBS [2], Cities-Health [3] and URBANOME [4], he gained extensive knowledge on personal monitoring technologies, and exposure assessment. His work includes evaluation of novel airborne particulate matter sensors for exposure and intake dose assessment, developing systems for data aggregation, fusion and visualization, experimenting with artificial intelligence approaches for improving exposure studies, exploring the use of personal monitoring technologies for assessing individual-level exposure to urban stressors, and developing agent-based models for exposure assessment. He presented his work at numerous international conferences and workshops, and is a member of the International Society of Indoor Air Quality and Climate and the International Society for Urban Health.