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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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A B S T R A C T

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 μg/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)

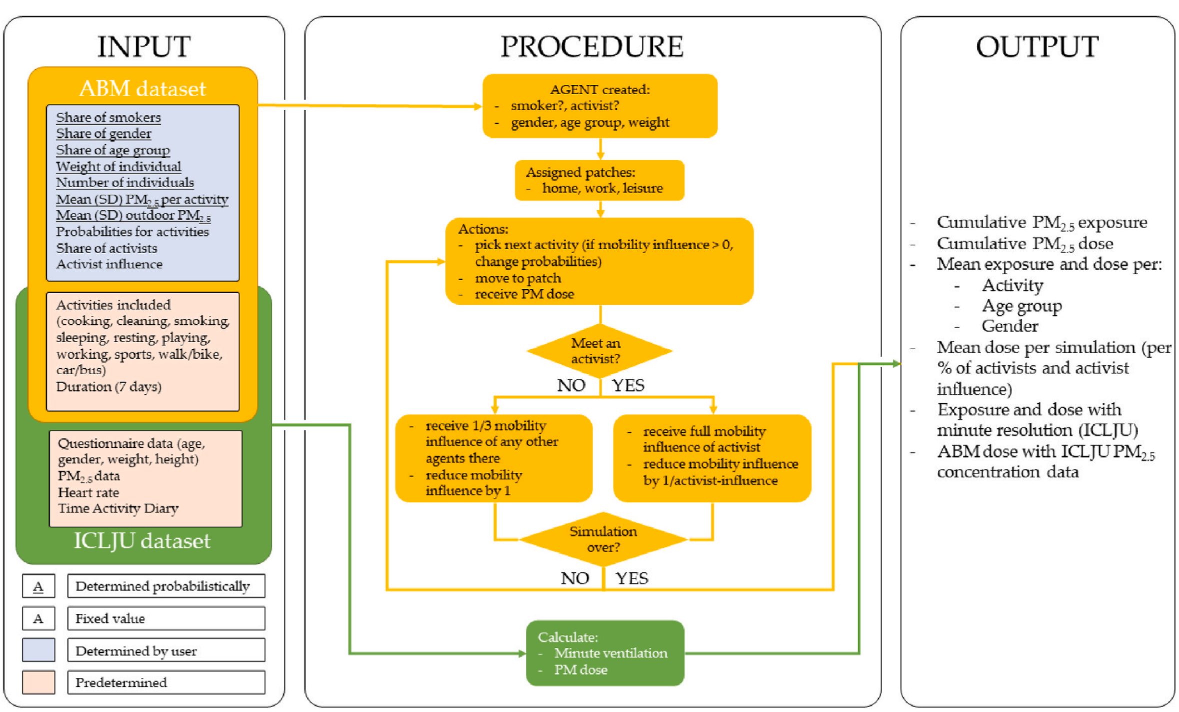

Fig. 1. Visualization of data inputs, procedures and outputs based on ABM and ICLJU datasets.

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):

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

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.

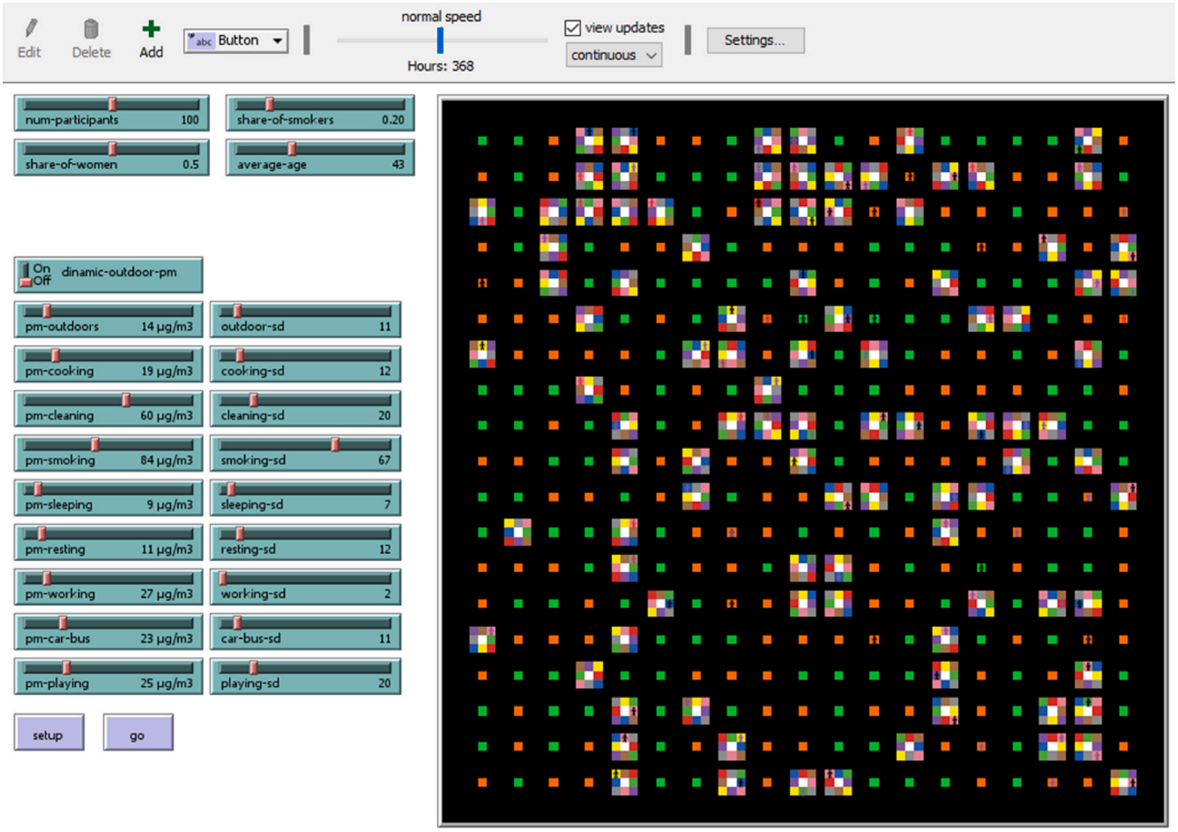

Fig. 2. Visualization of the spatial representation of the $PM_{2.5}$ exposure and dose agent-based model with the initial setting, at 368 h in the NetLogo graphical user interface.

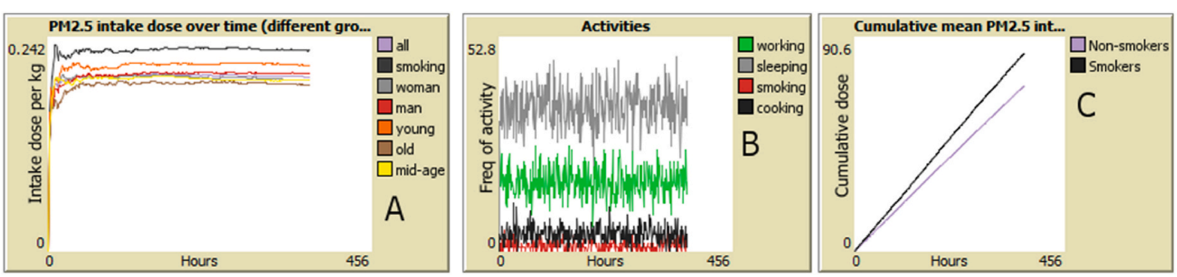

Fig. 3. Example plots of the $PM_{2.5}$ dose ABM results in Netlogo showing (A) the average dose at each hour for different groups, (B) the number of agents performing an activity (working, sleeping, smoking, cooking) at each hour, and (C) a mean cumulative dose for smokers and non-smokers.

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^{act}_{inf}), multiplied by activist-influence (act_{inf}), which is added to their prior mobility influence (mb_{inf}), as shown in Equation (2)

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

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)):

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

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.

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

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).

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

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

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, socio-economic 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)):

$$FVC = 1.1 * ((0.0576 * height) - (0.0269 * age) - 4.34) \quad (8)$$

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):

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

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

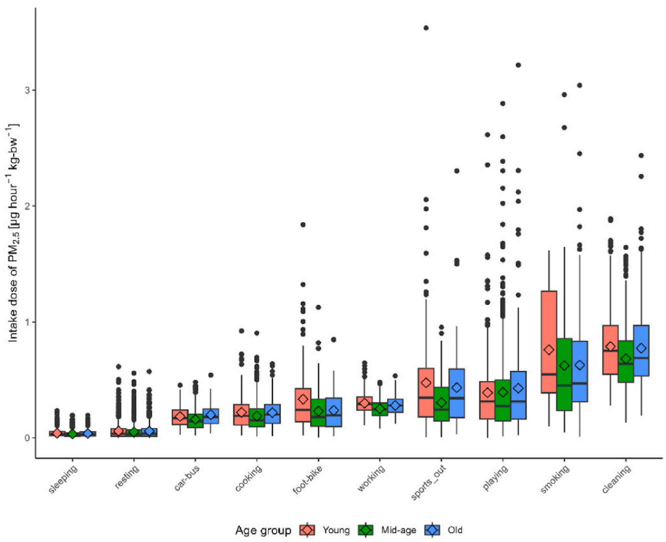

Fig. 4. Dose of $PM_{2.5}$ for all activities per age group, for the ABM dataset. Boxplots show median, 1st and 3rd quartiles, diamonds represent mean values.

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

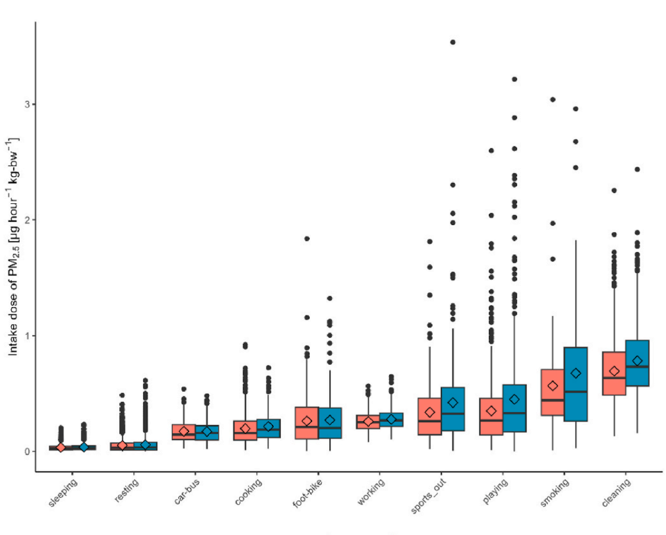

Fig. 5. Dose of $PM_{2.5}$ for all activities per gender, for the ABM dataset. Boxplots show median, 1st and 3rd quartiles, diamonds represent mean values.

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.

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 $\mu g\ h^{-1}$ kg-bw^{-1}), and the third highest in the ICLJU dataset (0.43 $\mu g\ h^{-1}$ 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 $\mu g\ h^{-1}$ kg-bw^{-1}) and SD (Δ0.57 $\mu g\ h^{-1}$ kg-bw^{-1}) values in the ICLJU dataset than the ABM, while there is little difference in the median (Δ0.02 $\mu g\ h^{-1}$ 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

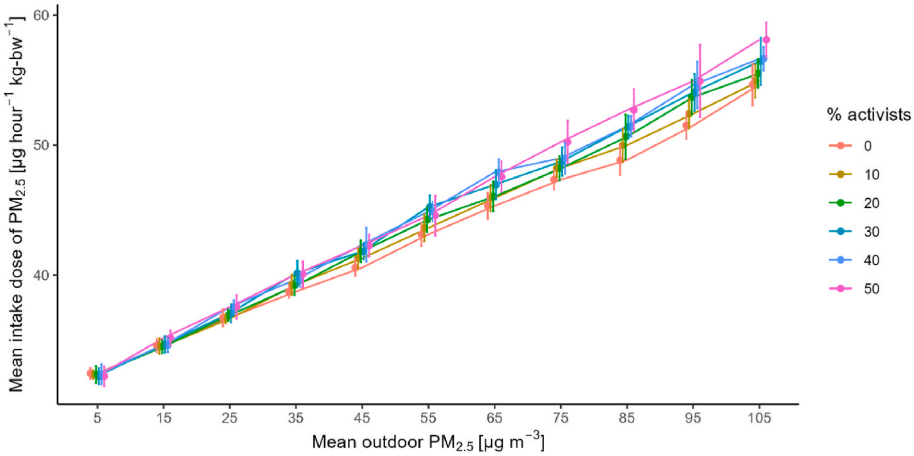

Fig. 6. Mean dose of $PM_{2.5}$ of all agents in the modified ABM at increasing levels of outdoor $PM_{2.5}$ concentrations, grouped by the percentage of population that are activists. Each point is showing a calculated standard deviation.

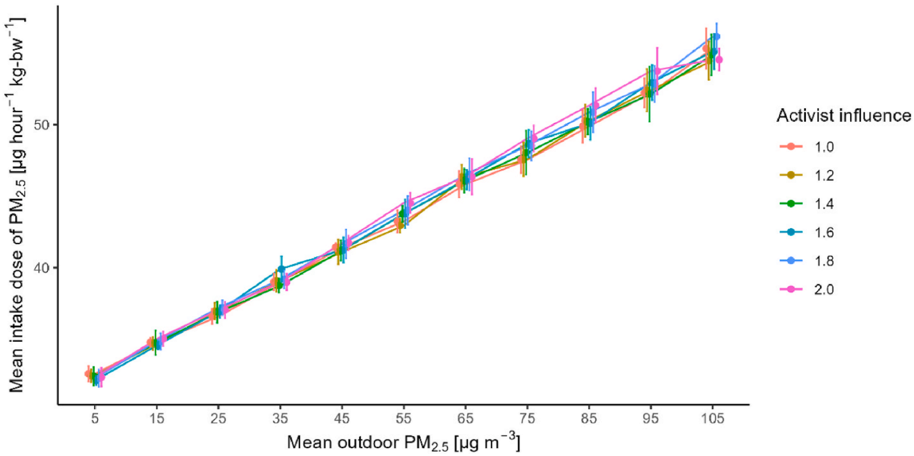

Fig. 7. Mean dose of $PM_{2.5}$ of all agents in the modified ABM at increasing levels of outdoor $PM_{2.5}$ concentrations, grouped by the percentage of population that are activists. Each point is showing a calculated standard deviation.

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

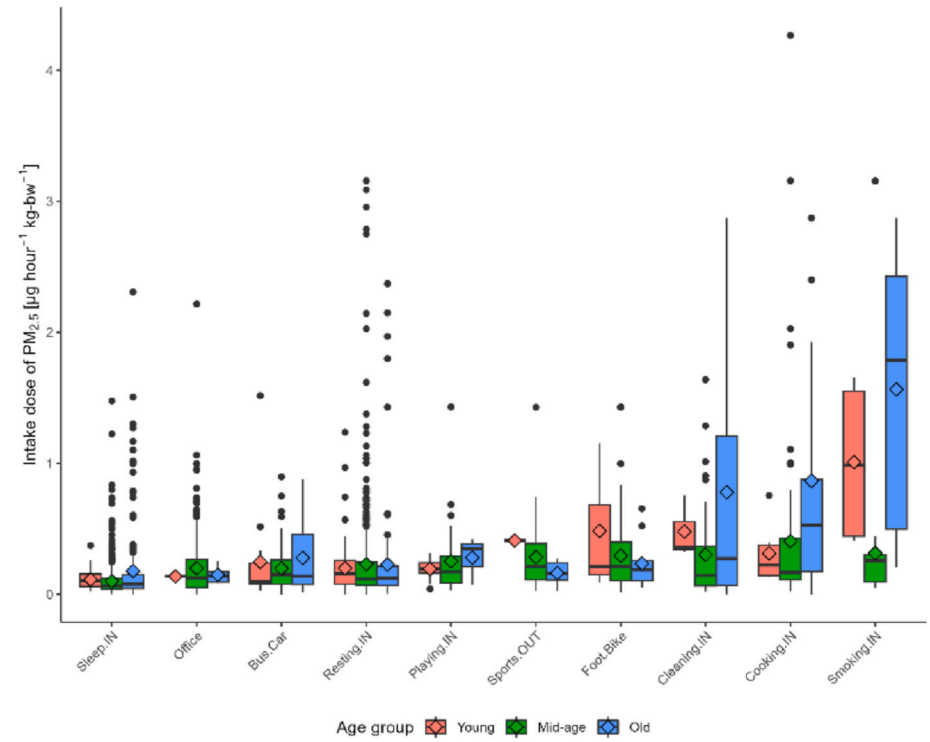

Fig. 8. Dose of $PM_{2.5}$ for all activities per age group, for the ICLJU dataset. Boxplots show median, 1st and 3rd quartiles, diamonds represent mean values.

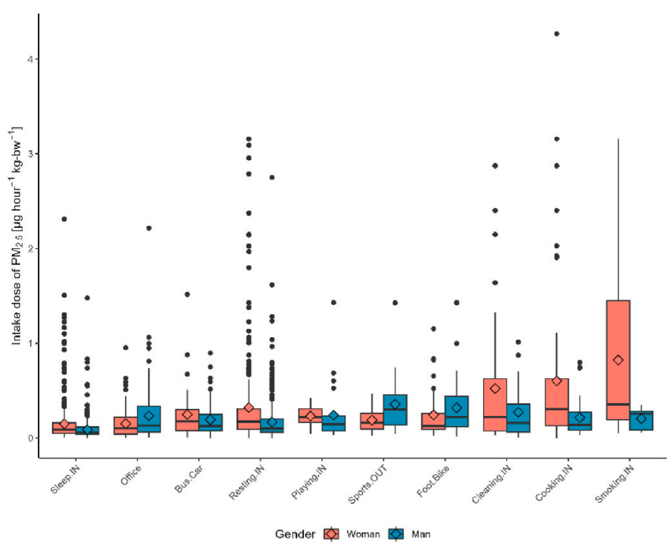

Fig. 9. Dose of $PM_{2.5}$ for all activities per gender, for the ICLJU dataset. Boxplots show median, 1st and 3rd quartiles, diamonds represent mean values.

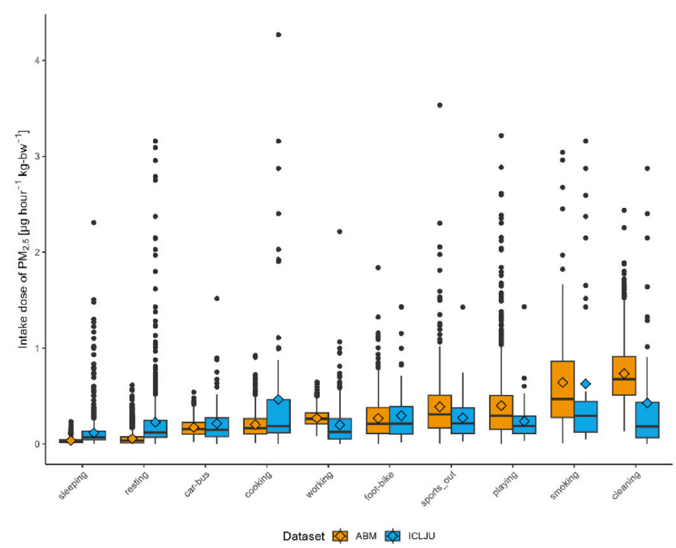

Fig. 10. Dose of $PM_{2.5}$ for all activities, comparing results of the ABM and ICLJU datasets. Boxplots show median, 1st and 3rd quartiles, diamonds represent mean values.

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.

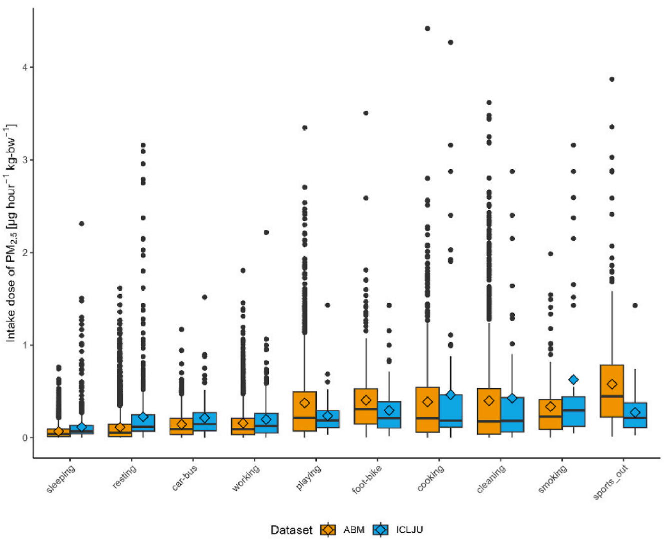

Fig. 11. Dose of $PM_{2.5}$ for all activities, comparing results of the ABM and ICLJU datasets, with the ABM simulation using $PM_{2.5}$ data from the ICLJU dataset. Boxplots show median, 1st and 3rd quartiles, diamonds represent mean values.

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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