Air Quality, Atmosphere & Health (2026) 19:175
https://doi.org/10.1007/s11869-026-02063-9

$PM_{2.5}$ and PM_{10} exposure assessment: a comparative analysis between personal monitoring and environmental data

Alessio Carminati[1] · Francesca Borghi[1,2] · Eleonora Pagani[1] · Giacomo Fanti[3] · Sabrina Rovelli[1] · Carolina Zellino[1] · Andrea Cattaneo[1] · Andrea Spinazzè[1] · Domenico Maria Cavallo[1]

Received: 21 November 2025 / Accepted: 22 July 2026

Abstract

The evaluation of personal exposure to PM is a critical component of risk assessment: one of the main challenges is represented by the difficulty in simultaneously obtaining extensive and accurate personal exposure data for large populations. This study provides an empirical comparison between personal $PM_{2.5}$ and PM_{10} exposure measurements and routinely available ambient data from fixed monitoring stations and air quality models in a hybrid working scenario. Time-activity information was also explored to identify activity patterns descriptively associated with larger discrepancies between personal and ambient estimates. To achieve this goal, a complex scenario consisting of a working day from home and a working day from office was considered. Personal exposure data were compared with daily average ambient data retrieved for both the residential and workplace addresses of each subject, using three different approaches: (i) Address-Specific; (ii) Residential-Address; (iii) Workplace-Address. According to the results, ambient data may provide useful proxies for average exposures whereas their ability to represent individual exposure was limited. Exceptions were observed for $PM_{2.5}$ ambient data from monitoring for the Address-Specific and Residential-Address references. The main discrepancies were observed at high personal exposure levels, where ambient data showed a strong tendency to underestimate. Finally, larger discrepancies were descriptively associated with selected activity patterns, including indoor free time away from home, personal care, and secondhand smoke exposure.

Keywords Particulate matter · Personal exposure · Comparison · Ambient pollution · Exposure variability · Microenvironment

Abbreviations

A-E	Absolute Error
A-S	Address-Specific
CCC	Concordance Correlation Coefficient
CF	Correction Factor
FARM	Flexible Air quality Regional Model
HEPA	High Efficiency Particulate Air
HI	Harvard Impactor

✉ Alessio Carminati
acarminati@uninsubria.it

Francesca Borghi
francesca.borghi12@unibo.it

Eleonora Pagani
epagani4@uninsubria.it

Giacomo Fanti
giacomo.fanti@unimi.it

Sabrina Rovelli
sabrina.rovelli@uninsubria.it

Carolina Zellino
czellino@uninsubria.it

Andrea Cattaneo
andrea.cattaneo@uninsubria.it

Andrea Spinazzè
andrea.spinazze@uninsubria.it

Domenico Maria Cavallo
domenico.cavallo@uninsubria.it

1 Department of Science and High Technology, University of Insubria, Como, Italy

2 Department of Medical and Surgical Sciences, University of Bologna, Bologna, Italy

3 Department of Clinical Sciences and Community Health, University of Milan, Milan, Italy

Published online: 04 August 2026

PM	Particulate Matter
Q1	First quartile
Q3	Third quartile
R-A	Residential-Address
R-E	Relative Error
RH	Relative Humidity
T	Temperature
TAD	Time-Activity Diary
W-A	Workplace-Address
WFH	Working From Home
WFO	Working From Office

Introduction

Air pollution is a widely recognized issue for human health, responsible for more than eight million premature deaths worldwide annually (Health Effects Institute 2024). Among air pollutants, airborne Particulate Matter (PM) is one of the most concerning, since once inhaled, it can reach the respiratory tract and settle in the tracheobronchial tree (PM_{10} fraction), and respiratory bronchioles and alveoli ($PM_{2.5}$ fraction) (Kim et al. 2015; Landrigan 2017; Manisalidis et al. 2020). This can potentially lead to adverse health effects, mainly (but not only) on the respiratory and cardiovascular systems. The prevalence and incidence of diseases related to pollutant exposure are the focus of epidemiology. In epidemiological studies the assessment of exposure to airborne pollutants is typically based on ambient air measurements, even if they are not the best approach to evaluate the personal exposure of individuals (Morawska et al. 2013; Zaccai 2004; Zou et al. 2009). Personal sampling, performed through light and wearable devices, is considered as the reference method (i.e., the most accurate and representative) in exposure assessment (Broich et al. 2012) given that it is performed in the breathing zone, defined as the hemispherical volume within a 30 cm radius of the nose and mouth (Asbach et al. 2017; Cattaneo et al. 2010; Esmen and Hall 2010). However, it is inherently limited as a method for measuring human exposure levels for large population, due to obvious practical and resource limitations (Koehler and Peters 2015; Zou et al. 2009). To overcome this problem, ambient air concentration measures or estimates are alternatively attributed to individuals or populations. Ambient air quality is typically evaluated through static monitoring stations equipped with certified reference instruments for measuring regulatory pollutants. Monitoring stations' distribution in the territory is highly variable, leading to a potential poor spatial variability in certain areas(Castell et al. 2017) and - possibly - a loss of representativeness for the greater variable ambient pollutants, especially those affected by anthropic and natural local conditions, such as PM (Casati et al. 2007; Ebelt et al. 2023; Kim et al. 2015; Kousa et al. 2002). Moreover, although ambient concentrations are an important contribution to the personal exposure of a subject, they cannot represent the real exposure, since they are not able to capture many pollution sources, like those in indoor environments (where pollutants concentration levels can be significantly higher or lower than those outdoors) (Avery et al. 2010; Bo et al. 2017; Du et al. 2010; Kim et al. 2015). An alternative approach in exposure assessment to both environmental and personal monitoring is represented by modeling. Models are various calculation tools that allow for obtaining individual or population exposure estimates using available input data, such as concentration levels from monitoring stations, and integrating spatial interpolation methods (Koehler and Peters 2015; Manisalidis et al. 2020; Steinle et al. 2013; Wilson et al. 2002; Zou et al. 2009). However, models for estimating exposure to air pollution can require several input parameters to improve final data quality, increasing their complexity and the number of data to be collected. This leads to the need to achieve a cost-benefit trade-off which may result in data that are not always highly accurate and precise (Blanco et al. 2023; Gulliver et al. 2015; Spinazzè et al. 2017, 2019). Therefore, one of the main problems related to the exposure assessment to particulate matter (but also other air pollutants in general) for large groups of subjects is the difficulty of obtaining accurate and extensive personal exposure data at the same time, as well as developing an accurate and economical method to measure personal exposure (Brhlikova et al. 2011; Farzadfar et al. 2011). Several studies in the literature focused on the contribution of indoor sources to personal exposure, but without investigating associated errors in exposure levels estimate (Abdullahi et al. 2013; Bo et al. 2017; Morawska et al. 2013; Oliveira et al. 2019). Another problem is that in studies where population exposure data are attributed from monitoring stations or modeled data, these usually refer to the residential address of each subject. In this way, significant potential exposure variability factors, such as the spatial heterogeneity of the airborne concentrations of pollutants or the possibility that the subjects can spend a significant portion of their day elsewhere (i.e., at school or at work), are not considered (Dias and Tchepel 2018; Hoek et al. 2008; Monn 2001). Previous studies have already shown that spatial variability, temporal variability, individual mobility, and microenvironmental contributions can strongly affect the agreement between ambient concentrations and personal exposure (Dias and Tchepel 2018; Shafran-Nathan et al. 2018). Therefore, the issue is not whether such factors matter, but how routinely available ambient proxies perform when they are applied to specific and changing daily-life scenarios. These aspects, however, correspond to different exposure scenarios, each of which may lead to varying degrees of accordance between personal exposure and ambient data. One emerging scenario is represented by the remote working which has experienced a significant spread since the COVID-19 pandemic. Remote working allows individuals to carry out their office activities either at the workplace or in alternative settings, most commonly at home, for one or more days during their working week (Borghi et al. 2025), leading to complex exposure conditions to define. Building on data collected in a previous study, the authors aimed to provide a targeted empirical assessment of exposure misclassification in a specific and increasingly relevant scenario, namely remote working. In particular, personal exposure assessment error to PM (i.e., $PM_{2.5}$ and PM_{10}) was quantified by comparing personal exposure data (acquired via direct-reading instruments) to regulatory monitoring stations and modeled ambient data, considering the possibility of obtaining them both from residential and workplace addresses for a group of selected subjects. In this way the extent to which these ambient proxies could approximate personal exposure under different location-reference assumptions was explored. Moreover, an exploratory approach was adopted to identify activity patterns associated with the largest discrepancies between personal exposure and ambient estimates.

Materials and methods

Study design

Coherently with the aim of the study, $PM_{2.5}$ and PM_{10} exposure data were collected via personal monitoring for a population of selected subjects. More in detail, the study population consisted of 35 individuals living and working in the Lombardy region (Italy), recruited in a previous study conducted by Borghi e co-workers (Borghi et al. 2025). Data were collected from May 2021 to May 2022. Each subject was continuously monitored with three personal direct-reading monitors model Aerocet-831 (abbreviated "Aerocet"-Aerosol Mass Monitor, Met One Instruments, Inc., Grants Pass, OR, USA; accuracy ± 10% to calibration aerosol; time resolution: 1 min) for two consecutive days: one of Working From Home (WFH) and the other Working From Office (WFO). All manufacturer guidelines were strictly followed to ensure the collection of quality-controlled data. A zero-calibration using an appropriate HEPA (High Efficiency Particulate Air) absolute filter (99.96% removal efficiency for 0.45 µm particles) was performed before and after each monitoring session. In addition, the accuracy of the instruments used (± 5%) was verified through intercomparison tests with factory-calibrated instruments. To ensure better quality and, therefore, comparability of data, the measurements of the instruments were corrected ad-hoc (more details in the paragraph "Data treatment"). Each subject, during their monitoring period, filled in a questionnaire and a Time-Activity Diary (TAD) to allow for the collection of personal and ambient characteristics, as well as performed activities (i.e., (i) desk work, (ii) laboratory work, (iii) break, (iv) meal preparation and consumption (also abbreviated as "meal"), (v) personal care, (vi) indoor free time at home, (vii) outdoor free time at home, (viii) indoor free time away home, (ix) outdoor free time away home, (x) exposure to secondhand smoke (also abbreviated as "secondhand smoke"), (xi) use of means of transport (also abbreviated as "means of transport"). Enrolled subjects included teaching staff, Ph.D. students and trainees at the University of Insubria (Como and Varese, Italy), as well as subjects outside the university context. The participants spent their WFO day in academic, administrative, or commercial offices. During the monitoring campaign, all the subjects were working and living in a limited geographical area (provinces of Como, Milano, Monza and Brianza and Varese, in the Lombardy Region, Northern Italy). Further details are reported in (Borghi et al. 2025).

Ambient concentration levels were also collected from static reference monitoring stations and by air quality modeling. Both ambient data were obtained from the Agency for Prevention and Environment of the Lombardy Region ("ARPA Lombardia") website (ARPA Lombardia 2025c, 2025b, 2025a). ARPA monitoring station network provides daily average concentrations of different pollutants across the regional territory. Since stations are not available in every municipality, $PM_{2.5}$ and PM_{10} data were obtained from the monitoring station closest to each subject's residential and workplace addresses. For ambient modeled data, ARPA provides municipal-level air quality estimates derived from the three-dimensional Eulerian FARM (Flexible Air quality Regional Model), making modeled $PM_{2.5}$ and PM_{10} concentrations available for all municipalities. For this reason, data were obtained from the ARPA website (ARPA Lombardia 2025b) using the same approach as for the monitoring station data, selecting values corresponding to each subject's residence and workplace municipalities. A schematic representation of the study design is reported in Fig. 1. Moreover, weather parameters were considered in this study, as they can affect PM (as well as other air pollutants) concentration levels (Alameddine et al. 2016; Kaur and Nieuwenhuijsen 2009; Onat et al. 2019; Owoade et al. 2012; Tian et al. 2014). As done for air quality data, weather data were downloaded from the ARPA website (ARPA Lombardia 2025a) for both the weather monitoring station closest to the residential address and the one closest to the workplace address for each of the two monitoring days of each subject. The meteorological parameters considered are

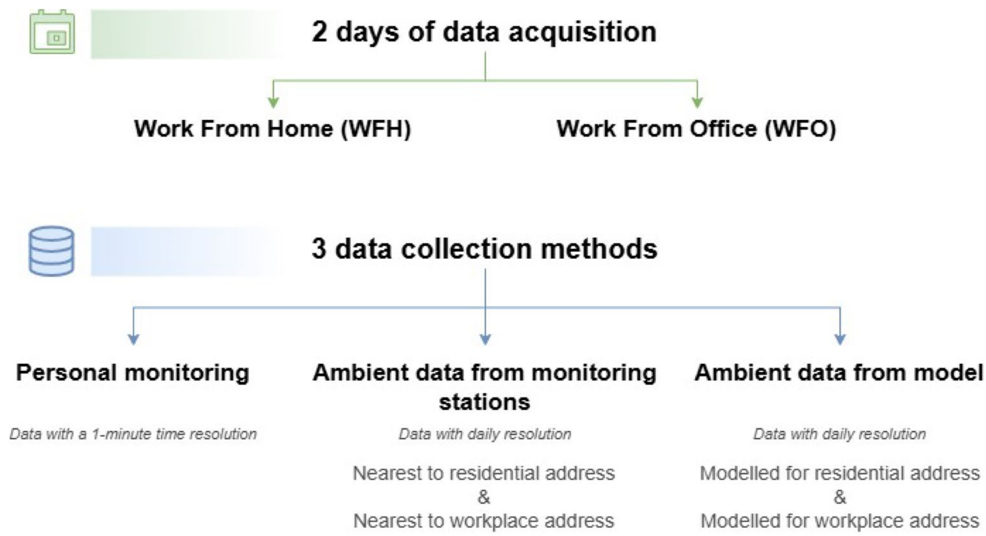

Fig. 1 Schematic representation of the study design

the following: temperature - T (°C), relative humidity - RH (%), rainfall (mm) and wind speed (m/s).

Data treatment

Data collection and initial processing were already carried out and described in Borghi et al. 2025; the main steps are briefly summarized below. Personal data collected through the personal real-time monitors used in this study are affected by an intrinsic measurement error (Borghi et al. 2025). To address this issue, data were corrected *a posteriori* with a seasonal and location correction factor (CF), obtained through a comparison between exposure concentration measured via each Aerocet and via a gravimetric reference method for $PM_{2.5}$ (a Harvard Impactor MS&T Area Sampler Diagnostic and Engineering, Inc., Harrison, ME, USA, named here as "HI" - Harvard Impactor), during a simultaneous sampling period. Details of the procedure can be found elsewhere (Babich et al. 2000; Borghi et al. 2025; Yanosky and MacIntosh 2001). Although the CF was derived from $PM_{2.5}$ comparisons, it was also applied to PM10 to harmonize the correction procedure across particle-size fractions. This assumption was retained because no parallel PM_{10} gravimetric correction factor was available and is explicitly considered as a source of residual uncertainty. The concentration distributions (for each subject/monitoring day) were truncated above the 99th percentile and below the 1st percentile to exclude unrealistic values (Hänninen et al. 2003; Robakiewicz and Ryder 2000). Additionally, each personal monitoring period was time-truncated to align the exposure profiles under the two working conditions (WFO vs. WFH), ensuring a comparable time window between the two monitored days for each subject. With "truncated" data-set, geometric mean and standard deviation were calculated for both monitoring days of each subject.

Data elaborations

All the statistical analyses and data treatment presented below were performed through the following software: Microsoft Excel for Microsoft 365 MSO (Microsoft Corporation, Redmond, WA, USA), SPSS Statistics 20.0 software package (IBM, Armonk, NY, USA) and RStudio 2024.04.1 + 748 (Posit Software, PBC, Boston, MA, USA).

Error quantification

A key concept of this study is that subjects do not always stay full-time in their municipality of residence, but that they can spend a substantial portion of their day at a workplace located elsewhere. Therefore, this study considers alternative approaches for exposure assessment, based either on monitoring stations or air quality modeling, and referring to either the residential or workplace address.

Absolute and relative measurement errors (hereafter also abbreviated as A-E and R-E, respectively) for exposure to $PM_{2.5}$ and $PM_{10,}$ for all subjects for both monitoring days were calculated. A-E (μg/m^3) were calculated as the difference between monitoring stations or modeled data and geometric mean of personal exposure, used as the operational comparator in this study because it was measured in the breathing zone and corrected using the available CF. Given the interest in referring to both residence and workplace addresses to attribute exposure data, three "location references" (hereafter also referred to as "references") to quantify the error for each subject in both working days were considered (Table 1):

1. "Address-Specific" (A-S): errors were calculated considering the specific type of working day (WFH or WFO). For WFH days, errors were quantified by comparing

Table 1 Schematic representation of the errors calculated for each subject during their two monitoring days (WFH and WFO) according to the three approaches: (i) Address-Specific; (ii) Residential-Address; (iii) Workplace-Address

Location reference		Working day (Personal data location)	Ambient data location
i.	Address-Specific	Working From Home	Residential
		Working From Office	Workplace
ii.	Residential-Address	Working From Home	Residential
		Working From Office	Residential
iii.	Workplace-Address	Working From Home	Workplace
		Working From Office	Workplace

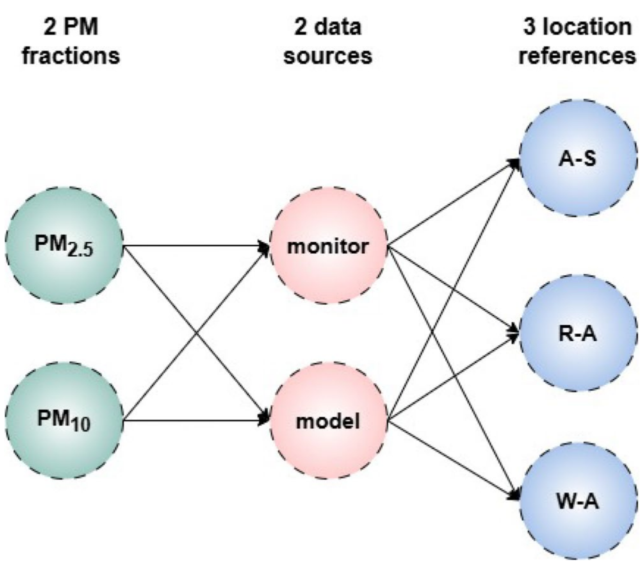

Fig. 2 The 12 "cases" given by the combination of the two PM fractions, two data sources and three location references. A-S: Address-Specific; R-A: Residential-Address; W-A: Workplace-Address

personal exposure to ambient data from monitoring stations closest to the residence address and to data modeled for residential municipalities. Instead, for WFO days, errors were quantified by comparing personal exposure with ambient data from monitoring stations closest to the workplace address and ambient data modeled for workplace municipalities.

2. "Residential-Address" (R-A): errors were calculated comparing the personal exposure to data provided from monitoring stations closest to the residential address and modeled data for residential municipalities, both for WFH and WFO days.
3. "Workplace-Address" (W-A): errors were calculated comparing the personal exposure to data provided from monitoring stations closest to the workplace address and modeled data for workplace municipalities both for WFH and WFO day.

Table 2 Explained 12 cases, meaning the 12 different (absolute/relative) errors calculated for each subject

"Case" number	Location reference	PM fraction	Ambient data source
1	Address-Specific	$PM_{2.5}$	Monitoring station
2	Address-Specific	$PM_{2.5}$	Model
3	Address-Specific	PM_{10}	Monitoring station
4	Address-Specific	PM_{10}	Model
5	Residential-Address	$PM_{2.5}$	Monitoring station
6	Residential-Address	$PM_{2.5}$	Model
7	Residential-Address	PM_{10}	Monitoring station
8	Residential-Address	PM_{10}	Model
9	Workplace-Address	$PM_{2.5}$	Monitoring station
10	Workplace-Address	$PM_{2.5}$	Model
11	Workplace-Address	PM_{10}	Monitoring station
12	Workplace-Address	PM_{10}	Model

Missing ambient values were not imputed. Missing observations were primarily due to the unavailability of monitoring-station data for the relevant location and monitoring day. The number of expected, available, and missing observations for each pollutant, data source, and location-reference approach is reported in Table SM1.

Since A-E and R-E were calculated for both $PM_{2.5}$ and PM_{10}, obtained from monitoring stations and model and considering each of the three references for the comparisons, a total of 12 different "cases" (i.e., way to calculate the error for each subject during both monitoring days) resulted from this combination. Figure 2 provides a schematic overview of these different approaches, bringing to the twelve different cases and better highlighted in Table 2.

Activity patterns associated with exposure discrepancies

Once both absolute and relative error were calculated, the distribution of time spent in each activity was explored in relation to the largest positive and negative discrepancies between ambient estimates and personal exposure. This exploratory analysis was intended to generate hypotheses on activity-related contributors to exposure misclassification, rather than to demonstrate independent causal effects of specific activities. To achieve this goal, three "cluster-subjects" were identified based on the distribution of the errors. These 3 cluster-subjects were named as (i). "Median subject"; (ii). "Outlier < 10th percentile" subject (also namely "Outlier < 10th "); iii. "Outlier > 90th percentile" subject (also namely "Outlier > 90th "). This process was followed for each of the 12 cases (Table 2). It is worth noting that these "median" and "outlier" labels are used only for descriptive purpose and do not imply the identification of statistically defined exposure phenotypes.

More in detail, these three derived subject groups were obtained through a series of intermediate steps (Fig. 3). For each case, the study population was divided into three groups based on the frequency distribution of their errors: (i) those below the 10th percentile, identifying subjects with large negative errors; (ii) those between the 10th and 90th percentiles, representing subjects with lower or moderate errors; and (iii) those above the 90th percentile, identifying subjects with high positive errors.

After dividing subjects into three groups, the second step involved analyzing the time fractions (with respect to the monitoring period) dedicated to each activity. For the two groups with subjects characterized by high errors (i.e. those below the 10th percentile, and those above the 90th percentile), the average time fractions spent on each activity were calculated across all subjects within each group, resulting in two representative profiles: the "Outlier < 10th percentile" and the "Outlier > 90th percentile" subjects. For the group of subjects with errors between the 10th and 90th percentiles, percentile values for each activity's time fraction were computed, including the minimum, first quartile (Q1), median, third quartile (Q3), and maximum. These values were used to define and characterize the "typical" subject (i.e., the so-called "Median subject").

In this way, the time fractions of each activity were compared among the three cluster-subjects, by considering where the values of the *outlier* subjects fell in relation to the percentiles of the *median* subject. This approach allowed us to observe and assess whether spending more or less time on each activity corresponded to a higher absolute error, regardless of its positive or negative sign.

Results

Descriptive analyses

Tables 3, 4 and 5 present the results of descriptive analysis about daily average time fractions spent on each activity, ambient and personal PM concentrations and meteorological data, respectively.

As shown in Table 3, due to the study design, desk work has been the most performed activity, with a daily average of about 0.5 (i.e., 50% of the whole daily monitoring period), followed by free time at home indoors (mean: 0.23; median: 0.21) and meal preparation and consumption (mean: 0.10; median: 0.09). The other activities have lower averages, but it is interesting to note that some of them show a high maximum value, indicating that at least one subject has spent a lot of time on them. For example, situations related to second-hand smoke and working in a laboratory show a maximum of 0.58 and 0.50, respectively, and also, the time spent on personal care and the use of means of transport show maximum values ranging between 0.33 and 0.25, respectively, corresponding to a quarter and a third of the monitoring day. No relevant differences are notable between WFH and WFO

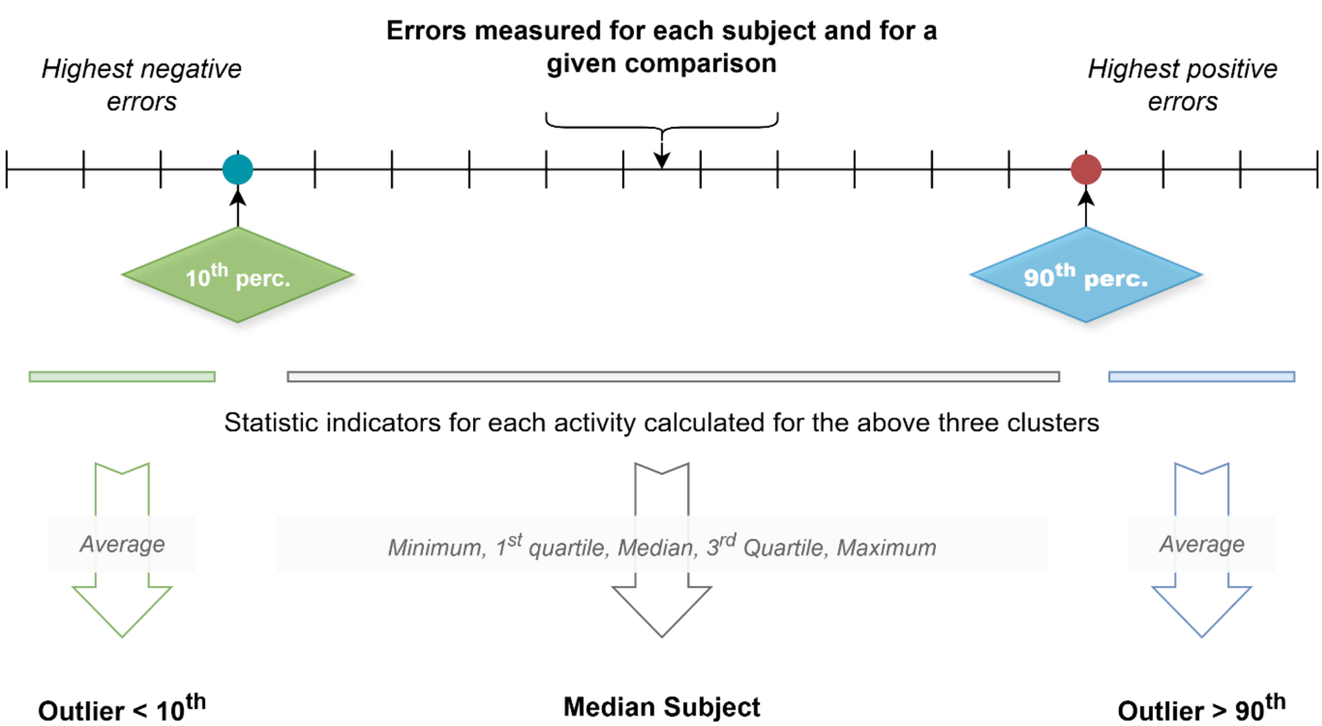

Fig. 3 Schematic representation of the approach adopted to evaluate the contribution of different activities in causing errors. 10th perc.: 10th percentile; 90th perc.: 90th percentile

Table 3 Descriptive statistics of time fractions of daily averages spent on each activity by the study population, during the monitoring days. For each activity, the first row reports the overall descriptive statistics of both monitoring days, the second row refers to WFH days, the third row refers to WFO days. N: number of monitoring days considered; Min.: minimum value; Max.: maximum value; S.D.: standard deviation

Activity	*N*	Min.	Mean	Median	Max.	S.D.
Desk work	**70**	0	**0.49**	**0.51**	0.83	0.18
WFH	*35*	*0.10*	*0.52*	*0.51*	*0.83*	*0.16*
WFO	*35*	*0*	*0.46*	*0.51*	*0.73*	*0.21*
Laboratory work	**70**	0	**0.04**	**0.00**	0.50	0.12
WFH	*35*	*0*	*0*	*0*	*0*	*0*
WFO	*35*	*0*	*0.08*	*0*	*0.50*	*0.16*
Break	**70**	0	**0.03**	**0.01**	0.14	0.04
WFH	*35*	*0*	*0.02*	*0.01*	*0.14*	*0.03*
WFO	*35*	*0*	*0.03*	*0.03*	*0.14*	*0.04*
Meal preparation and consumption	**70**	0	**0.10**	**0.09**	0.33	0.06
WFH	*35*	*0*	*0.12*	*0.12*	*0.26*	*0.07*
WFO	*35*	*0*	*0.08*	*0.07*	*0.33*	*0.06*
Personal care	**70**	0	**0.04**	**0.02**	0.33	0.06
WFH	*35*	*0*	*0.04*	*0.03*	*0.26*	*0.05*
WFO	*35*	*0*	*0.04*	*0.01*	*0.33*	*0.08*
Free time Indoor Home	**70**	0	**0.23**	**0.21**	0.59	0.15
WFH	*35*	*0.02*	*0.26*	*0.27*	*0.59*	*0.15*
WFO	*35*	*0*	*0.19*	*0.19*	*0.48*	*0.14*
Free time Outdoor Home	**70**	0	**0.01**	**0.00**	0.20	0.02
WFH	*35*	*0*	*0.01*	*0*	*0.20*	*0.03*
WFO	*35*	*0*	*0*	*0*	*0.04*	*0.01*
Free time Indoor Away Home	**70**	0	**0.01**	**0.00**	0.16	0.03
WFH	*35*	*0*	*0*	*0*	*0.13*	*0.02*
WFO	*35*	*0*	*0.01*	*0*	*0.16*	*0.03*
Free time Outdoor Away Home	**70**	0	**0.03**	**0.00**	0.17	0.05
WFH	*35*	*0*	*0.02*	*0*	*0.17*	*0.05*
WFO	*35*	*0*	*0.03*	*0.01*	*0.16*	*0.05*
Exposure to secondhand smoke	**70**	0	**0.02**	**0.00**	0.58	0.08
WFH	*35*	*0*	*0.02*	*0*	*0.58*	*0.1*
WFO	*35*	*0*	*0.01*	*0*	*0.13*	*0.04*
Use of means of transport	**70**	0	**0.05**	**0.03**	0.25	0.06
WFH	*35*	*0*	*0.1*	*0*	*0.14*	*0.03*
WFO	*35*	*0*	*0.09*	*0.11*	*0.25*	*0.06*

days, except for the work in laboratory which was obviously carried out during only the WFO day.

Descriptive analysis of particulate matter concentrations [Table 4] shows that personal monitoring campaign is characterized by the widest standard deviation, both for $PM_{2.5}$ (±25.6 μg/m^3, ±30.0 μg/m^3, ±19.8 μg/m^3 - when referring to total, WFH and WFO data, respectively) and PM_{10} (±34.6 μg/m^3, ±41.5 μg/m^3, ±24.6 μg/m^3 - when referring to total, WFH and WFO data, respectively), with minimum and 5th percentile values lower, and maximum and 95th percentile higher than those from static monitoring stations and model data. Moreover, for both PM fractions, WFH mean and median are higher than those of WFO, but these differences are not so appreciable when comparing data obtained from monitoring stations and modeling for different location references (i.e., Address-Specific, Residential-Address, Workplace-Address). Moreover, it is interesting to note that for both $PM_{2.5}$ and PM_{10}, ambient monitoring stations provided higher mean and median values than the model, suggesting that modeled estimates tended to underestimate station-based ambient concentrations in this dataset.

Finally, descriptive analysis for meteorological variables [Table 5] shows similar values for both central tendency and dispersion indicators between residential and working addresses for each meteorological parameter. This can be a predictable outcome given that all monitored subjects live and work in the same area of the Lombardy Region.

Error quantification and comparability

Error quantification

Table 6 presents the descriptive analysis of absolute and percentage relative errors, quantified for each

Table 4 Descriptive analysis for $PM_{2.5}$ (a) and PM_{10} (b) exposure and ambient levels. Data: monitoring method (*Monitoring campaign: data from personal monitoring campaign; Monitoring stations: data from ARPA static monitoring stations; Modeling: data from ARPA air quality model*). Location reference: Total: overall from WFH and WFO. WFH: Working from Home; WFO: Working from Office; N: number of data; Min.: minimum value; p_5: 5th percentile; p_{95}: 95th percentile; Max.: maximum value; S.D.: standard deviation

$PM_{2.5}$ (µg/m^3)										
(a)	**Data**	**Location reference**	**N**	**Min.**	$\boldsymbol{p_5}$	**Mean**	**Median**	$\boldsymbol{p_{95}}$	**Max.**	**S.D.**
	Monitoring campaign	Total	70	2.1	4.2	26.8	17.3	85.6	110.0	25.6
		WFH	35	2.9	3.0	31.4	18.8	103.2	110.0	30.0
		WFO	35	2.1	4.2	22.2	15.9	75.9	79.1	19.8
	Monitoring stations	Address-Specific	35	8.0	9.0	25.4	21.0	74.0	75.0	15.8
		Residential-Address	20	5.0	7.0	25.9	20.5	74.5	75.0	19.8
		Workplace-Address	49	5.0	8.0	26.1	21.0	74.0	75.0	16.9
	Modeling	Address-Specific	69	2.0	6.0	22.8	19.0	51.0	67.0	14.6
		Residential-Address	68	2.0	6.0	23.2	19.5	51.0	67.0	14.8
		Workplace-Address	70	2.0	6.0	22.7	19.0	52.0	67.0	15.0
PM_{10} (µg/m^3)										
(b)	**Data**	**Location reference**	**N**	**Min.**	$\boldsymbol{p_5}$	**Mean**	**Median**	$\boldsymbol{p_{95}}$	**Max.**	**S.D.**
	Monitoring campaign	Total	70	7.0	9.7	42.8	32.9	105.9	193.4	34.6
		WFH	35	7.4	9.5	50.2	35.5	142.7	193.4	41.5
		WFO	35	7.0	9.7	35.4	31.1	87.4	95.8	24.6
	Monitoring stations	Address-Specific	38	5.0	5.0	33.8	29.5	78.0	87.0	17.4
		Residential-Address	24	5.0	11.0	33.7	28.0	78.0	87.0	19.8
		Workplace-Address	52	5.0	9.0	34.0	30.0	78.0	93.0	19.1
	Model	Address-Specific	69	5.0	8.0	28.9	25.0	67.0	72.0	16.5
		Residential-Address	68	3.0	8.0	29.4	26.0	65.0	72.0	16.9
		Workplace-Address	70	5.0	8.0	28.6	24.5	65.0	72.0	16.1

Table 5 Descriptive analysis for meteorological data. Location reference: monitoring station reference address; T: temperature; RH: relative humidity; N: number of data; Min.: minimum value; p_5: 5th percentile; p_{95}: 95th percentile; Max.: maximum value; S.D.: standard deviation

Meteorological Variables									
Location reference	Meteorological parameters	*N*	Min.	p_5	Mean	Median	p_{95}	Max.	S.D.
Residential address	T (°C)	60	1.1	2.8	11.6	10.1	20.7	23.4	5.7
	RH (%)	42	35.8	38.6	63.3	61.4	89.7	96.1	17.0
	Wind speed (m/s)	18	0.9	0.9	2.0	1.7	5.8	5.8	1.2
	Precipitation (mm)	67	0.0	0.0	1.2	0.0	7.2	18.0	3.8
Working address	T (°C)	68	2.3	3.2	12.1	11.3	21.2	23.2	5.7
	RH (%)	62	28.4	34.7	59.0	55.5	88.0	94.1	16.5
	Wind speed (m/s)	44	0.6	0.8	1.6	1.4	3.3	3.9	0.8
	Precipitation (mm)	70	0.0	0.0	0.8	0.0	7.2	11.6	2.5

subject by comparing personal exposure with PM concentrations collected by fixed monitoring stations and the model, according to the three location references. As can be observed, the number of comparisons varied across location references, as measured ambient data were not always available from the reference monitoring station, as also shown in Table SM1. Focusing on absolute, a comparable trend is observable among each location reference. Means and medians of $PM_{2.5}$ A-E (both for monitoring stations and model data, as well as PM_{10} A-E from monitoring stations) are characterized by quite low values (almost all lower than ± 5.0 µg/m^3, meaning closer to zero). In contrast, for PM_{10} comparisons (for which personal monitoring concentrations were corrected through the CF retrieved for the $PM_{2.5}$), A-E from modeled data show higher values (in the range − 9 and − 14 µg/m^3). These outcomes are not so appreciable when considering relative errors. More specifically, means and medians of $PM_{2.5}$ for Address-Specific and Workplace-Address approaches show the highest values, in contrast with the A-E. Moreover, $PM_{2.5}$ always shows higher mean R-E (both for monitoring and model data) than PM_{10} for the same location reference. This latter trend is almost reversed when considering median values, with the exceptions of $PM_{2.5}$ medians for the Address-Specific and Workplace-Address approaches. Also, it is worth noting that modeled data provide lower values (in absolute terms) for mean and median errors (both absolute and relative) than the respective ambient data errors (i.e., error calculated for the same PM fraction and for

Table 6 Descriptive analysis of quantified absolute and relative errors for Address-Specific (a), Residential-Address (b) and Workplace-Address (c) references. Relative errors are reported in the square brackets N: number of data; 10th perc.: 10th percentile; Min.: minimum value; 90th perc.: 90th percentile; Max.: maximum value; S.D.: standard deviation

Absolute and Relative Errors: Address-Specific - Personal										
(a)	**Pollutant**	**Ambient data comparison**	**N**	**Min.**	**10th perc.**	**Mean**	**Median**	**90th perc.**	**Max.**	**S.D.**
	$PM_{2.5}$	Monitoring	35	-39.6 [-51.0%]	-17.2 [-34.2%]	3.2 [55.4%]	5.2 [51.0%]	17.0 [162.5%]	23.1 [261.7%]	14.1 [74.9%]
		Model	69	-69.2 [-86.3%]	-37.8 [-61.8%]	-3.7 [35.9%]	0.9 [10.6%]	15.2 [149.1%]	37.4 [664.7%]	19.4 [111.6%]
	PM_{10}	Monitoring	38	-146.4 [-78.6%]	-39.4 [-58.8%]	-4.6 [22.2%]	3.9 [18.6%]	24.0 [129.6%]	30.6 [271.4%]	30.7 [78.4%]
		Model	69	-147.4 [-82.0%]	-51.3 [-67.0%]	-13.8 [-1.0%]	-8.7 [-26.1%]	16.6 [115.5%]	54.2 [424.7%]	28.9 [85.5%]
Absolute and Relative Errors: Residential-Address - Personal										
(b)	**Pollutant**	**Ambient data comparison**	**N**	**Min.**	**10th perc.**	**Mean**	**Median**	**90th perc.**	**Max.**	**S.D.**
	$PM_{2.5}$	Monitoring	20	-44.9 [-59.2%]	-39.3 [-45.0%]	-2.1 [23.9%]	1.2 [14.1%]	16.6 [102.7%]	18.1 [105.4%]	18.0 [52.5%]
		Model	68	-69.2 [-86.3%]	-37.9 [-61.8%]	-3.1 [41.1%]	1.1 [14.1%]	16.4 [180.2%]	37.4 [664.7%]	19.9 [115.7%]
	PM_{10}	Monitoring	24	-56.2 [-33.3%]	-29.8 [-27.6%]	3.7 [33.5%]	9.1 [32.6%]	25.3 [104.3%]	29.1 [119.1%]	20.2 [45.0%]
		Model	68	-147.4 [-87.2%]	-51.3 [-67.4%]	-13.1 [2.2%]	-8.2 [-28.1%]	18.7 [145.2%]	50.2 [393.4%]	29.7 [88.1%]
Absolute and Relative Errors: Workplace-Address - Personal										
(c)	**Pollutant**	**Ambient data comparison**	**N**	**Min.**	**10th perc.**	**Mean**	**Median**	**90th perc.**	**Max.**	**S.D.**
	$PM_{2.5}$	Monitoring	49	-60.2 [-59.6%]	-19.2 [-38.6%]	2.5 [62.0%]	5.4 [48.0%]	17.1 [175.5%]	27.9 [664.7%]	16.1 [115.7%]
		Model	70	-65.2 [-86.3%]	-38.9 [-62.1%]	-4.1 [30.4%]	1.0 [14.7%]	14.5 [144.2%]	37.4 [565.0%]	19.2 [101.9%]
	PM_{10}	monitoring	52	-135.4 [-78.6%]	-38.3 [-57.9%]	-5.5 [21.8%]	-2.0 [-5.4%]	22.3 [157.3%]	38.9 [271.4%]	29.5 [82.7%]
		Model	70	-144.4 [-80.1%]	-50.6 [-66.9%]	-14.2 [-3.4%]	-10.0 [-28.6%]	13.9 [119.1%]	54.2 [424.7%]	28.9 [82.2%]

the same reference/comparison). Finally, all the means of A-E for the model are negative, as are the medians of both A-E and R-E when considering PM_{10} modeled data. This trend is less pronounced when considering the median or the R-E. This outcome may suggest that, on average, modeling data could lead to an underestimated exposure if compared to measured data (for the sake of clarity, a negative error in this study indicates that the value obtained from monitoring stations or modeling is underestimated compared to the measured data).

Linear regressions and concordance correlation coefficient (CCC)

Tables 7 and 8 present the results of linear regressions and Concordance Correlation Coefficient (CCC) calculated between the geometrical means of personal exposure data (independent variable) and daily average ambient concentrations from either monitoring stations or modeled estimates (dependent variables), for each case defined in Table 2. For the linear regressions, the adjusted R^2 (Akossou and Palm 2013), p-values, and the regression coefficients are reported. While adjusted R^2 indicates the proportion of variance explained by the model, it does not account for systematic deviation from the line of perfect agreement (Sykes 1993). Therefore, the CCC was also computed to assess both the precision and accuracy between personal and ambient exposure estimates.

All the linear regression models are statistically significant ($p < 0.05$) (Yanosky and MacIntosh 2001). Adjusted R square (also named "Adj. R^2" or even merely "R^2") and CCC are generally higher for linear regressions performed for $PM_{2.5}$ (R^2 and CCC ranging between 0.40 and 0.65 and 0.54–0.75, respectively) than those performed for PM_{10} (R^2 ranging between 0.26 and 0.36 and 0.37–0.46, respectively). However, the Adj. R^2 and CCC values which show the best fitting are those referred to $PM_{2.5}$ monitoring, especially for the location references Address-Specific (Adj. R^2: 0.615; CCC: 0.731) and Residential-Address (Adj. R^2: 0.645; CCC: 0.746). These outcomes are clearly observable in the linear regression graphs (Supplementary Material, Fig. SM1-SM12).

Table 7 Descriptive statistics of linear regressions for Address-Specific (a), Residential-Address (b) and Workplace-Address (c) references. Personal exposure data: type of data source assumed as the operational comparator method for PM data against which comparisons are made; Ambient data source : type of source for ambient data compared to the personal monitoring data used as comparator CCC: Concordance and Correlation Coefficient value, with the lower and upper limits of the 95% confidence interval, reported in square brackets; Adj. R^2: adjusted R square; Sig.: level of significance (p-value), considered statistically significant when <0.05; Slope: Slope factor

CCC & Linear Regression parameters – Address-Specific								
(a)	**Pollutant**	**Personal exposure data**	**Ambient data source**	**CCC**	**Adj. R^2**	**Sig.**	**Slope**	**Intercept**
	$PM_{2.5}$	Personal monitoring campaign	monitoring	0.731[0.566; 0.840]	0.615	<0.001	0.549	13.18
		Personal monitoring campaign	model	0.558[0.417–0.673]	0.427	<0.001	0.376	12.83
	PM_{10}	Personal monitoring campaign	monitoring	0.410[0.198; 0.587]	0.263	0.001	0.257	23.93
		Personal monitoring campaign	model	0.386[0.246; 0.511]	0.31	<0.001	0.267	17.51
CCC & Linear Regression parameters – Residential-Address								
(b)	**Pollutant**	**Personal exposure data**	**Ambient data source**	**CCC**	**Adj. R^2**	**Sig.**	**Slope**	**Intercept**
	$PM_{2.5}$	Personal monitoring campaign	monitoring	0.746[0.532; 0.871]	0.645	<0.001	0.537	10.83
		Personal monitoring campaign	model	0.546[0.400; 0.667]	0.401	<0.001	0.367	13.55
	PM_{10}	Personal monitoring campaign	monitoring	0.431[0.193; 0.622]	0.361	0.001	0.282	20.29
		Personal monitoring campaign	model	0.376[0.229; 0.506]	0.277	<0.001	0.258	18.45
CCC & Linear Regression parameters – Workplace-Address								
(c)	**Pollutant**	**Reference method**	**Comparison method**	**CCC**	**Adj. R^2**	**Sig.**	**Slope**	**Intercept**
	$PM_{2.5}$	Personal monitoring campaign	monitoring	0.695[0.542; 0.803]	0.545	<0.001	0.523	13.76
		Personal monitoring campaign	model	0.572[0.433; 0.686]	0.439	<0.001	0.393	12.14
	PM_{10}	Personal monitoring campaign	monitoring	0.454[0.268; 0.607]	0.293	<0.001	0.299	22.17
		Personal monitoring campaign	model	0.375[0.237; 0.498]	0.302	<0.001	0.26	17.44

Table 8 Number of times the time fraction for the Outlier < 10th subject in each activity falls within the ranges defined by the positional indices referring to the time fraction of the Median subject. The green color scale (chosen arbitrarily) used in the table is intended to highlight and bring out the different distributions more directly. < Min: lower than minimum; Min-Q1: range between minimum and first quartile (25th percentile); Q1-Median: range between the first quartile (25th percentile) and the median (50th percentile); Median-Q3: range between the median (50th percentile) and the third quartile (75th percentile); Q3-max: range between the third quartile (75th percentile) and maximum; > Max: greater than maximum

Outlier < 10^{th}						
Activity	**< Min**	**Min-Q1**	**Q1-Median**	**Median-Q3**	**Q3-Max**	**> Max**
Desk work	0	**5**	**7**	0	0	0
Lab work	**8**	0	0	0	**4**	0
Break	0	0	**3**	**6**	**3**	0
Meal	0	0	**5**	**5**	**2**	0
Personal care	0	0	0	**1**	**9**	**2**
Free time at home (indoor)	0	0	0	**6**	**6**	0
Free time at home (outdoor)	**9**	0	0	0	3	0
Free time away home (indoor)	**12**	0	0	0	0	0
Free time away home (outdoor)	0	0	0	**5**	**7**	0
Secondhand smoke	0	0	0	0	**6**	**6**
Transport	0	0	**4**	**7**	0	**1**
Total	29	5	19	30	40	9

Trend of errors

Three Bland-Altman plots (Supplementary Material, Fig. SM13-SM15), one for each location reference, were reported to evaluate possible error trends in $PM_{2.5}$ and PM_{10} (measured and modeled) ambient data (Lakota et al. 2018; Vesna 2009). All the Bland-Altman plots also report the mean differences for each pollutant and data comparison as dashed lines. For each comparison, mean bias and 95% limits of agreement were calculated. In addition, proportional bias was assessed by regressing the difference between ambient and personal exposure on the mean of the two measurements. The Bland-Altman analysis showed mean biases ranging from −14.23 to 3.17 µg/m³ across comparisons. Mean biases were predominantly negative, particularly for PM_{10} and modeled ambient data, indicating that ambient concentrations tended to underestimate personal exposure on average. The 95% limits of agreement were relatively wide, especially for PM_{10}, indicating substantial variability in the differences between ambient and personal measurements. A statistically significant negative proportional bias was identified in all comparisons, with regression slopes ranging from −0.40 to -0.90 ($p \leq 0.006$), indicating that the underestimation of personal exposure by ambient data increased as the mean concentration increased. Detailed mean biases, 95% limits of agreement, regression slopes, 95% confidence intervals, and p-values for each comparison are reported in Table SM2. Bland-Altman plots showed greater dispersion of the differences at lower average concentrations (up to approximately 30–40 µg/m^3). Overall, the differences showed a downward trend with increasing mean concentration, consistent with the negative proportional bias identified by the regression analysis. With the aim to highlight the error trends simply and clearly, in Fig. 4 are reported interpolations through a Local Polynomial Regression of data plotted in the three Bland-Altman plots.

Performed activities and quantified errors

Outcomes concerning the estimates of main activities contributing to the errors are presented in Tables 8 and 9. These tables show how the time fraction spent for each activity by subjects classified as "Outliers" (i.e. Table 8: Outlier < 10th ; Table 9: Outlier > 90th) is distributed across the range defined by the quartiles of the time fractions of the Median subject. Frequencies indicate how often the time allocated to each activity, in each comparison, fell within a specific quartile range. According to the results, three activities were most consistently associated with larger discrepancies: (i) personal care, (ii) indoor free time away from home, and (iii) secondhand smoke exposure. Concerning "personal care" activity, 11 times (out of 12) the time fraction dedicated by the Outlier < 10th is higher than the 75th percentile of the Median subject, while for the Outlier > 90th it always falls between 1st and 3rd Quartile. This pattern suggests that personal care may involve short-term sources that are captured by personal monitoring but not by daily ambient data. [Table 3]. This trend is similar to that observed for the exposure to secondhand smoke, where it emerged that the Outlier < 10th is always exposed to a time fraction greater than the 3rd Quartile of the Median subject. However, it is worth noting that this trend is just partly supported by the outcomes from Outlier > 90th, whose distribution falls 6 times lower than the minimum and 6 times between Q3 and the maximum of Median Subject. The time spent indoors away from home also looks especially important in causing errors. As observable from the tables, for the Outlier < 10th the time fractions dedicated to this activity are always lower than the minimum of the Median Subject, while for the Outlier > 90th it is always greater than the Q3 of the Median Subject. According to this outcome, spending indoor free time away from home was associated with lower personal exposure relative to ambient estimates in this dataset. Concerning other activities, the time spent by the two Outliers

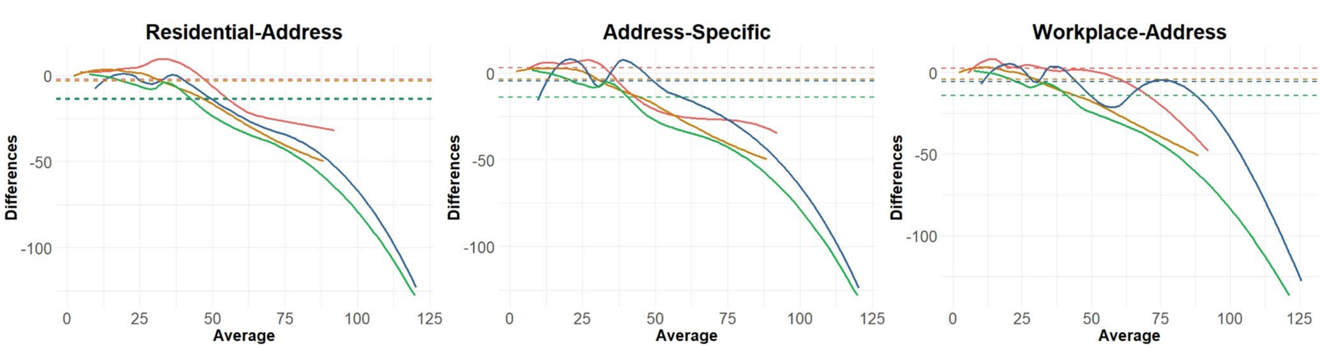

Fig. 4 Bland-Altman plots reporting Local Polynomial Regression lines, for each data comparison and reference. The x-axis reports the average between personal exposure and (measured and modeled) ambient data (µg/m^3). The y-axis reports the difference between ambient data and personal exposure (µg/m^3). Legend: – (red line) $PM_{2.5}$ Ambient monitoring vs. Personal exposure (µg/m^3); – (orange line) $PM_{2.5}$ Ambient modeled vs. Personal exposure (µg/m^3); – (blue line) PM_{10} Ambient monitoring vs. Personal exposure (µg/m^3); – (green line) PM_{10} Ambient modeled vs. Personal exposure (µg/m^3)

Table 9 Number of times the time fraction for the Outlier >90th subject in each activity falls within the ranges defined by the positional indices referring to the time fraction of the Median subject. The blue color scale (chosen arbitrarily) used in the table is intended to highlight and bring out the different distributions more directly. < Min: lower than minimum; Min-Q1: range between minimum and first quartile (25th percentile); Q1-Median: range between the first quartile (25th percentile) and the median (50th percentile); Median-Q3: range between the median (50th percentile) and the third quartile (75th percentile); Q3-max: range between the third quartile (75th percentile) and maximum; > Max: greater than maximum

Outlier > 90th						
Activity	< Min	Min-Q1	Q1-Median	Median-Q3	Q3-Max	> Max
Desk work	0	0	1	6	5	0
Lab work	5	0	0	0	7	0
Break	0	0	4	5	3	0
Meal	0	4	5	3	0	0
Personal care	0	0	3	9	0	0
Free time at home (indoor)	0	1	9	2	0	0
Free time at home (outdoor)	12	0	0	0	0	0
Free time away home (indoor)	0	0	0	0	11	1
Free time away home (outdoor)	0	0	4	8	0	0
Secondhand smoke	6	0	0	0	6	0
Transport	0	0	0	8	3	1
Total	23	5	26	41	35	2

looks similar to the Median Subject, falling more often between the Q1-Q3 range. However, among these activities, it is notable that the average time fraction for “Free time at home (outdoor)” spent by the Outliers always or almost always falls below the minimum of the Median Subject, such as this activity led both to an under and overestimation of personal exposure.

Discussion

In this study, $PM_{2.5}$ and PM_{10} exposure data obtained through different approaches were compared to evaluate the representativeness of alternative methods to personal monitoring, considering a complex scenario. Moreover, an alternative approach to evaluate the main activities which can contribute to causing differences between personal monitoring concentrations and monitored or modeled data was explored. This study should be interpreted as an applied comparison of commonly available exposure proxies, rather than as a new exposure-modeling framework. Its contribution lies in quantifying how fixed-station and modeled data perform against personal measurements when different practical location references are used in a hybrid working scenario.

Firstly, it is worth noting that each meteorological parameter shows homogeneous values between residential and working addresses, suggesting that the weather conditions are unlikely to act as a major confounding factor .

According to the results, and coherently with the literature (Brown et al. 2009; Lin et al. 2020; Mohammadyan 2012), concentration levels of particulate matter retrieved from static monitoring stations and model present a certain degree of difference compared to exposure data measured through a personal monitoring campaign. This is firstly shown by descriptive analyses of concentration levels acquired with different monitoring methods [Table 4]. In particular, average personal exposure levels to both $PM_{2.5}$ and PM_{10} exhibit higher standard deviations compared to those obtained from static monitoring stations and modeled data. This indicates that personal monitoring, which records the real exposure for a subject, has documented a larger variability among the study population than the ambient monitoring and modeling, coherently with the literature (Adgate et al. 2003; Koehler et al. 2019; Scapellato et al. 2009). This variability is even clearer when comparing the mean, median, 95th percentile and maximum values between WFH and WFO days for personal monitoring campaigns. Specifically, it is worth noting that personal exposure levels on WFH days are higher than those on WFO days. These differences are not observed in the data from monitoring stations or models, where ambient concentrations associated with the residential address and those associated with the workplace address show comparable values, likely due to the fact that the data are all referred to a quite small and homogeneous geographical area (Sarnat et al. 2010). It is reasonable to suppose that these higher values during WFH day are due to the presence of many and different sources of air pollutants and human activities. By observing the average fraction of time spent on each activity during the two working days [Table 3], notable differences were observed for meal preparation and consumption (WFH: 0.12; WFO: 0.08; ratio WFH/WFO: 1.5) and free time indoor home (WFH: 0.26; WFO: 0.19; ratio WFH/WFO: 1.37). Lower differences are observed in the WFH and WFO ratio for desk work (WFH: 0.52; WFO: 0.46; ratio WFH/WFO: 1.13), but it is the most performed activity on both days, each spent in a different environment, possibly leading to a different load in the personal exposure. Also, these three activities are those that most contributed to the total exposure of subjects during WFH, according to the previous study (Borghi et al. 2025). Therefore, spending more time inside home can lead to higher concentrations, also reported in the literature (González Serrano and Licina 2022; Morawska et al. 2017; Zhang et al. 2021), mainly due to higher background levels resulting from poorer air quality control in residential settings compared to offices. This can be due to the absence of binding guidelines for households (Ahmed Abdul–Wahab et al. 2015; Destaillats et al. 2008; Vardoulakis et al. 2020), in which the use of natural ventilation is more common than in the offices, typically equipped with HVAC (Heat, Ventilation and Air Conditioning) systems with filters (Kalmár and Kalmár 2021; Park et al. 2014). Moreover, it should be considered that some activities like meal preparation and consumption, as well as the personal care, are mainly performed at home during both days. These activities directly impact on both WFH and WFO daily exposure, respectively, but also can indirectly impact on WFH daily exposure, since they can contribute to higher background indoor home concentrations, to which subjects were exposed for much longer (as witnessed by the time fraction of "free time indoor home" activity). For completeness, also during WFO days some activities could have a relevant role, commuting above all else (Borghi et al. 2025). However, and according to the previous results, meal preparation and personal care, combined with longer time spent indoors at home during WFH, appeared to contribute more to total exposure than transport-related exposure during WFO days, supporting the aforementioned hypothesis.

Further insights into the impact of this variability in concentration levels were explored by calculating the errors with three different location references. As shown in Table 6, the absolute errors for $PM_{2.5}$ data (both from monitoring stations and modeled estimates) as well as for PM_{10} data from monitoring stations, appear to be representative of average personal exposure levels, as indicated by their low mean and median values. On the other hand, when considering the relative errors, these results partly change, with $PM_{2.5}$ mean and median errors generally higher than those for PM_{10} when considering the Address-Specific and Workplace-Address references. This latter could be expected, since the smaller the concentration values considered, the greater the impact of the absolute variation on the relative error, and *viceversa*.

Overall, it is worth noting that the comparisons showing the lowest errors (both relative and absolute) are the median errors for ambient $PM_{2.5}$ modeled data for all location references, as well as median values for ambient $PM_{2.5}$ measured data for the Residential-Address and PM_{10} modeled data for Address-Specific and Workplace-Address references. Moreover, concerning these lowest errors, and except for the PM_{10} modeled data for the Workplace-Address, all of them also have a positive value, meaning that the single approach led to a slight overestimation, typically preferable to the underestimation when dealing with risk assessment (Bolte 2016). In such a case, it is difficult to evaluate the representativeness of data, since both types of errors provide important and complementary information. However, despite the complex results obtained with A-E and R-E, it seems that ambient data from monitoring stations and models may approximate average personal exposure at the study-population level, but with substantial uncertainty for some individuals and comparisons. Instead, focusing on the minimum and maximum values, and on 10th and 90th percentiles, strong differences occurred. This indicates that for some subjects, high differences between personal exposure and ambient data occurred, leading to uncertainty in personal exposure assessment.

These results are supported and better explained by linear regression analyses and CCC calculations (Table 7, Fig. SM1-SM12). Through this combined information it has been possible to investigate the level of accuracy and precision of the data from the monitoring station and model for the average daily exposures of each subject, unlike the descriptive errors which provided a more general exposure picture, attributable to the overall study population. More in detail, the highest adjusted R^2 values were observed for $PM_{2.5}$ data from monitoring stations for the Residential-Address (Adj. R^2: 0.645) and Address-Specific references (Adj. R^2: 0.615). These values indicate a moderate association between personal exposure and ambient $PM_{2.5}$ concentrations under the investigated scenario. Especially, previous reviews have reported a wide range of correlation coefficients (r) between ambient $PM_{2.5}$ concentration and personal exposure, r values ranging from 0.09 to 0.83 to 0.06–0.97, respectively (Avery et al. 2010; Chen et al.

2022). Focusing on the articles (included in the reviews) which considered a period of ~ 1 year (the same of the present study), it emerged that *r* coefficient varied between 0.4 and 0.69 and 0.39–0.72. Although the associations observed in the present study fall within the broad range reported in previous literature, direct quantitative comparisons should be interpreted cautiously because different statistical metrics, averaging periods, study populations, and exposure-assignment approaches were used across studies. However, by observing the charts for these two comparisons (Fig. SM5 and SM1, respectively), it is notable the presence of apparent high-leverage points for high personal exposure level which may contribute to underestimation and, therefore, worse correlations (Fitrianto and Xin 2022). CCCs are coherent with linear regressions, reporting the highest values for these two comparisons, ambient $PM_{2.5}$ from monitoring stations for Residential-Address and Address-Specific (CCCs: 0.746 and 0.731, respectively), even if large 95% confidence intervals are observable.

Generally, considering descriptive analysis of errors, linear regression and CCC calculations, within this study population and under the investigated WFH/WFO scenario, fixed monitoring-station $PM_{2.5}$ and PM_{10} data and $PM_{2.5}$ modeled estimates appeared able to approximate average personal exposure at the population level, although substantial uncertainty remained at the individual level. However, considering the observed errors, data from static monitoring stations and models cannot be considered reliable in the single subject personal exposure, providing data affected by a degree of inaccuracy. Exceptions are ambient $PM_{2.5}$ data when considering Residential-Address and Address-Specific references, for which greater correlation and concordance respect to personal exposure were observed.

It is notable that both the best correlations were observed with data from monitoring stations, and also that correlations with modeled data were always lower than the respective correlations performed with ambient data from monitoring stations (e.g., for "Address-Specific" $PM_{2.5}$ correlations, R^2 resulting were 0.615 for station ambient data, and 0.558 for modeled data). These evidence suggest that modeled data are even less representative of real personal exposure than ambient data measured in a fixed position. Therefore, although data from regulatory monitoring stations represent standardized ambient measurements since they are derived from sampling, the modeled data aim to reproduce those values but are necessarily affected by a higher degree of uncertainty. This uncertainty partly arises from the fact that some of the input data themselves are the result of estimates or secondary models. As described in Materials and Methods section, ARPA Lombardia employs a three-dimensional Eulerian FARM Model, which integrates emission inventories, land-use information, meteorological simulations, and outputs from global models (also including satellite observations). Although this approach is sophisticated and designed to provide the most realistic reconstruction possible of pollutant dispersion and transformation processes, it inevitably inherits uncertainties from its input data. This may explain why correlations with modeled data are consistently lower, and why model estimates tend to underestimate observed concentrations - as also evident from Table 4, where modeled concentrations are systematically lower than those measured at monitoring stations. More generally, the use of model-based estimates in air pollution studies provides valuable information on spatial and temporal scales that conventional monitoring cannot capture. For their proper integration into risk assessment, however, it is crucial to account for the uncertainty associated with both input data and model outputs, ensuring that their accuracy, precision, and representativeness are adequately characterized. In light of these considerations, it is reasonable to suppose that modeled data tend to exhibit a greater level of uncertainty compared to environmental data from monitoring stations, potentially leading to an underestimation when used to assess personal exposure.

Finally, it can be noted that observed significant correlations and CCCs for $PM_{2.5}$ between personal exposure data and data from monitoring stations are referred to the location references "Residential-Address" and "Address-Specific", but not to "Workplace-Address". This can be explained by the fact that, even during WFO day, a significant portion of time is still spent at home (e.g., in the morning and evening). The weaker correlations observed for the "Workplace-Address" scenario likely result from the fact that, during the entire WFH day and part of the WFO day, the monitoring stations used were not the ones closest to the subjects' actual locations. Also, it is notable that linear regression for "Residential-Address" presents a better correlation coefficient than linear regression for "Address-Specific". This could be due to the fact that, as mentioned, a significant part of WFO day is still spent at home and, for this day, the static monitoring station closest to home represents the personal exposure better than the static monitoring station closest to the office. Reasonably, to get greater correlation results from linear regressions and CCCs for "Address-Specific", data should be retrieved from monitoring stations and models for both home and work addresses and weighted in relation to time spent at the two locations during the day. Anyway, monitoring stations and models provide daily averages of air pollutant concentrations, hence integrating the average daily data for a fraction of time that is not representative of the real exposure could introduce further uncertainty into the data. This temporal mismatch is a likely source of exposure misclassification, because short-term peaks related to activities such as cooking, commuting, personal care, or secondhand smoke can be captured by 1-minute personal monitoring but are smoothed out in daily ambient averages.

Through Bland-Altman plots (Fig. SM13-SM15), peculiar and comparable error trends emerged. Particularly, for low exposure levels errors are quite low, with an apparent tendency to overestimate by monitoring stations and models. Then, an increase in error with a negative trend can be observed with the increase in the exposure level (in particular, above about 40–50 μg/m^3). According to descriptive analyses for quantified errors, this means that monitoring stations and models are not able to capture high exposure levels, likely reflecting short-term or microenvironmental exposure peaks that are captured by personal monitoring but not by daily fixed-station or modeled ambient data. For example, cooking, moving with means of transport and smoking are common activities that could lead to high exposure levels to PM (Boniardi et al. 2021; Dons et al. 2019; Reisen et al. 2019; Sun and Wallace 2021).

To explore activity patterns potentially associated with these discrepancies, time-activity information was compared across subjects with the largest positive and negative errors. As presented before in the results, the descriptive comparison highlighted differences in three activities: (i) personal care, (ii) free time away home (indoor), and (iii) secondhand smoke. Among these, the time spent indoors away from home provided coherent results for both the Outliers, despite the low average time spent there by the study population. In detail, the < 10th percentile Outlier (average subject with a large negative error) spent less indoor time than the minimum of the Median subject, while the > 90th percentile Outlier (average subject with a large positive error) spent more indoor time than the third quartile of the Median subject. This outcome suggests that these indoor environments, where people involved in this study spent their time, were characterized by lower PM concentrations than those inside their homes and offices, which may be characterized by a good ventilation/filtration system and/or absence of relevant PM sources. The role of time spent on personal care and those affected by the exposure to secondhand smoke emerged in the comparison table of the Outlier < 10th. As observable, for both activities the Outlier subject spent more time than the 3rd Quartile of the median subject, and this means that people characterized by a higher personal exposure than the corresponding ambient concentration were more involved in these two activities. Although personal care and secondhand smoke are recognized potential sources of PM exposure, the present descriptive analysis cannot establish whether these activities independently contributed to the observed discrepancies. Among all the activities, it is also interesting to analyses the free time spent inside home. As previously discussed, when comparing personal exposure concentration between WFH and WFO, this activity pattern could lead to higher personal exposure. However, in the present descriptive comparison, no clear pattern emerged for this activity, as the time fraction observed for the Outlier < 10th percentile fell within the distribution observed for the Median subject. Finally, a quite peculiar pattern is notable for the free time spent outdoors at home. Since during this time, personal monitoring captures outdoor concentration (i.e., the same as ambient monitoring) it is reasonable to suppose that spending more time outdoors led to a lower error and *viceversa*. Tables 8 and 9 show that both Outliers spent less time outdoors at home than the Median subject. This apparent inconsistency is likely due to the very limited time devoted to this activity by the study population, making the estimates unreliable. No relevant differences emerged for the other activities, with comparable time fractions between Outliers and Median subjects.

Strengths and limitations of the study

Some limitations and assumptions should be acknowledged. First, the study involved a relatively small sample ($n = 35$), all living and working within a restricted geographical area. In addition, personal monitoring was performed over only two working days (one WFH and one WFO), which may not fully capture the variability of each individual's exposure, also due to the truncated dataset. For this reason, the findings should be interpreted as exploratory and context-specific, and should not be generalized to other populations, seasons, geographic areas, or working patterns without further validation. Nonetheless, focusing on a specific population group offered the advantage of exploring an innovative occupational scenario while reducing potential confounding factors in the interpretation of results. Another limitation concerns the assessment of personal exposure with photometric sensors, which are intrinsically affected by measurement errors, particularly in terms of concentration magnitude. In addition, the activity-pattern analysis was descriptive and hypothesis-generating. It did not test independent associations between activities and exposure errors, and the results may be affected by co-occurring activities, WFH/WFO condition, individual behaviour, and the compositional nature of time-use data. To mitigate this issue, a correction factor specifically derived for $PM_{2.5}$ was applied, improving the alignment between monitored data and "true exposure." The same CF was applied to PM_{10}, likely providing more realistic values, though with residual uncertainty. The application of a $PM_{2.5}$-derived CF to PM_{10} remains an assumption and may have introduced additional uncertainty in PM_{10} estimates. Another limitation is the use of daily ambient data, which cannot reproduce the high temporal resolution of personal monitoring and may attenuate short-term exposure peaks.

Despite these drawbacks, the use of direct-reading instruments compensated for some limitations of gravimetric methods: while gravimetric techniques provide more accurate absolute concentrations, they sacrifice temporal resolution and thus the ability to capture variability and the influence of specific determinants of exposure. Among the main strengths, this study investigated a specific and increasingly relevant occupational scenario, namely remote working, which is increasingly widespread yet still scarcely addressed in exposure science. The comparative design, including both WFH and WFO days for the same individuals, allowed to control for inter-individual variability and to directly assess the influence of different microenvironments on exposure. Another strength lies in the integration of multiple data sources: both fixed monitoring stations and modeled estimates were used, enabling a more comprehensive evaluation of their representativeness compared to personal measurements. In addition, the inclusion of time–activity diaries provided valuable insights into behavioral and microenvironmental correlates of exposure misclassification, bridging quantitative data with real-world activities. The application of a correction factor derived from comparison with gravimetric $PM_{2.5}$ measurements improved the comparability of the personal $PM_{2.5}$ monitoring data. Finally, conducting the study in a geographically and meteorologically homogeneous area minimized potential confounding effects, allowing a clearer interpretation of the role of personal activities and indoor environments.

Conclusions

This study suggests that ambient data from monitoring stations and models can approximate average population exposure in this specific WFH/WFO scenario, but their reliability decreases when individual exposure is considered. The most pronounced discrepancies emerge at higher concentrations, where ambient data tend to underestimate actual levels, thus compromising risk assessment accuracy. In the remote working exposure scenario, daily activities such as personal care, time spent in indoor environments away from home, and exposure to secondhand smoke were descriptively associated with larger exposure discrepancies, highlighting how indoor sources remain largely invisible to traditional monitoring systems.

From an operational perspective, while ambient data remain useful and often indispensable in large-scale epidemiological studies and exposure assessments, their exclusive use may overlook critical exposure scenarios. Exposure science should therefore move toward integrated approaches: combining ambient and modeled data with targeted personal monitoring, time-activity diaries, and microenvironmental information can improve representativeness and reduce uncertainty. In emerging contexts such as remote working, characterized by significant variability in indoor conditions, this integration is particularly crucial. Such integrated approaches may help improve exposure classification and support more robust prevention and risk-management strategies.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11869-026-02063-9.

Author contributions Conceptualization, execution, data analysis, writing-original draft preparation: Carminati A., Borghi F., Spinazzè A.; writing—review and editing: Pagani E., Fanti G., Rovelli S., Zellino C., Cattaneo A., Cavallo D.M.; supervision: Cavallo D.M., Cattaneo A., Spinazzè A., Borghi F. All authors have read and agreed to the published version of the manuscript.

Funding Open access funding provided by Università degli Studi dell'Insubria within the CRUI-CARE Agreement. No funding was received for conducting this study.

Data availability The main data supporting the findings of this study are available within the paper, its references, and Supplementary Material. Other data will be made available on request.

Declarations

Ethics approval and consent to participate This study is a secondary analysis of data collected within the study by Borghi et al. (2025), in which participants wore personal monitors and completed questionnaires and time-activity diaries. The present analysis used anonymized/de-identified data and did not involve any additional data collection. This study is observational and relies exclusively on environmental monitoring data. It does not involve identifiable personal data, or experiments on humans or animals. According to the applicable institutional/national regulations, no ethics committee approval was required. Informed consent was therefore not required.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

Abdullahi KL, Delgado-Saborit JM, Harrison RM (2013) Emissions and Indoor Concentrations of Particulate Matter and Its Specific Chemical Components from Cooking: A Review'. Atmos Environ 71:260–294

Adgate JL, Ramachandran G, Pratt GC, Waller LA, Sexton K (2003) Longitudinal Variability in Outdoor, Indoor, and Personal PM2.5 Exposure in Healthy Non-Smoking Adults'. Atmos Environ 37(7):993–1002. https://doi.org/10.1016/S1352-2310(02)00978-0

Ahmed Abdul-Wahab SA, Fah En SC, Elkamel A, Ahmadi L, Yetilmezsoy K (2015) A Review of Standards and Guidelines Set by International Bodies for the Parameters of Indoor Air Quality. Atmospheric Pollution Res 6(5):751–767. https://doi.org/10.5094/APR.2015.084

Akossou AYJ, Palm R (2013) Impact of data structure on the estimators R-Square and adjusted R-Square in linear regression. Int J Math Comput 20(3):84–93. https://www.researchgate.net/publication/289526309

Alameddine IL, Esber A, Bou Zeid E, Hatzopoulou M, El-Fadel M (2016) Operational and Environmental Determinants of In-Vehicle CO and PM 2.5 Exposure. Sci Total Environ 551–552:42–50. https://doi.org/10.1016/j.scitotenv.2016.01.030

ARPA Lombardia (2025a) ARPA Lombardia | Meteo e Clima | Form Richiesta Dati Automatici - ARPA Lombardia. https://www.arpalombardia.it/temi-ambientali/meteo-e-clima/form-richiesta-dati/. Accessed 5 April 2023

ARPA Lombardia (2025b) ARPA Lombardia | Qualità Dell'aria | Form Richiesta Dati STIME COMUNALI - ARPA Lombardia. https://www.arpalombardia.it/temi-ambientali/aria/form-richiesta-dati-stime-comunali/. Accessed 5 April 2023

ARPA Lombardia (2025c) Qualità Dell'aria | Form Richiesta Dati STAZIONI FISSE - ARPA Lombardia. https://www.arpalombardia.it/temi-ambientali/aria/form-richiesta-dati-stazioni-fisse/. Accessed 5 April 2023

Asbach C, Alexander C, Clavaguera S, Dahmann D, Dozol H, Faure B, Fierz M, Fontana L, Iavicoli I, Kaminski H, MacCalman L, Meyer-Plath M, Simonow B, van Tongeren M, Todea AM (2017) Review of Measurement Techniques and Methods for Assessing Personal Exposure to Airborne Nanomaterials in Workplaces'. Sci Total Environ 603–604:793–806. https://doi.org/10.1016/j.scitotenv.2017.03.049

Avery CL, Mills KT, Williams R, McGraw KA, Poole C, Smith RL, Whitsel EA (2010) Estimating Error in Using Ambient PM2.5 Concentrations as Proxies for Personal Exposures: A Review. Epidemiology 21(2):215–223

Babich P, Davey M, Allen G, Koutrakis P (2000) Method Comparisons for Particulate Nitrate, Elemental Carbon, and PM2.5 Mass in Seven U.S. Cities'. J Air Waste Manag Assoc 50(7):1095–1105. https://doi.org/10.1080/10473289.2000.10464152

Blanco MN, Bi J, Austin E, Larson TV, Marshall JD, Sheppard L (2023) Impact of Mobile Monitoring Network Design on Air Pollution Exposure Assessment Models. Environ Sci Technol 57(1):440–450. https://doi.org/10.1021/acs.est.2c05338

Bo M, Salizzoni P, Clerico M, Buccolieri R (2017) Assessment of indoor-outdoor particulate matter air pollution: A review. Atmosphere 8(8):136. https://doi.org/10.3390/atmos8080136

Bolte JFB (2016) Lessons Learnt on Biases and Uncertainties in Personal Exposure Measurement Surveys of Radiofrequency Electromagnetic Fields with Exposimeters. Environ Int 94:724–735

Boniardi L, Borghi F, Straccini S, Fanti G, Campagnolo D, Campo L, Olgiati L, Lioi S, Cattaneo A, Spinazzè A, Cavallo DM, Fustinoni S (2021) Commuting by car, public transport, and bike: Exposure assessment and estimation of the inhaled dose of multiple airborne pollutants. Atmos Environ 262. https://doi.org/10.1016/j.atmosenv.2021.118613

Borghi F, Spinazzè A, Fanti G, Albareda A, Ghiraldini J, Campagnolo D, Carminati A, Keller M, Rovelli S, Zellino S, De Vito G, Cattaneo A, Cavallo DM (2025) Exposure to airborne particulate matter in working from office and working from home employees. Int J Environ Health Res 35(2):319–329. https://doi.org/10.1080/09603123.2024.2352608

Brhlikova P, Pollock AM, and Rachel Manners (2011) Global Burden of Disease Estimates of Depression - How Reliable Is the Epidemiological Evidence? J R Soc Med 104(1):25–34. https://doi.org/10.1258/jrsm.2010.100080

Broich AV, Lydia E, Gerharz, and Otto Klemm (2012) Personal Monitoring of Exposure to Particulate Matter with a High Temporal Resolution. Environ Sci Pollut Res 19(7):2959–2972. https://doi.org/10.1007/s11356-012-0806-3

Brown K, Ward JA, Sarnat HH, Suh BA, Coull, and Petros Koutrakis (2009) Factors Influencing Relationships between Personal and Ambient Concentrations of Gaseous and Particulate Pollutants. Sci Total Environ 407(12):3754–3765. https://doi.org/10.1016/j.scitotenv.2009.02.016

Casati R, Scheer V, Vogt R, and Thorsten Benter (2007) Measurement of Nucleation and Soot Mode Particle Emission from a Diesel Passenger Car in Real World and Laboratory in Situ Dilution. Atmos Environ 41(10):2125–2135. https://doi.org/10.1016/j.atmosenv.2006.10.078

Castell N, Dauge FR, Schneider P, Vogt M, Lerner U, Fishbain B, Broday D, Alena Bartonova (2017) Can Commercial Low-Cost Sensor Platforms Contribute to Air Quality Monitoring and Exposure Estimates? Environ Int 99:293–302. https://doi.org/10.1016/j.envint.2016.12.007

Cattaneo A, Taronna M, Garramone G, Peruzzo C, Schlitt C, Consonni D, Cavallo DM (2010) Comparison between Personal and Individual Exposure to Urban Air Pollutants. Aerosol Sci Technol 44(5):370–379. https://doi.org/10.1080/02786821003662934

Chen J, Jahn HJ, Sun HZ, Ning Z, Lu W, Ho KF, Tony J, Ward (2022) Validity of using ambient concentrations as surrogate exposures at the individual level for fine particle and black carbon: A systematic review and meta-analysis. Environ Pollut 312

Destaillats H, Maddalena RL, Singer BC, Alfred T, Hodgson, McKone TE (2008) Indoor pollutants emitted by office equipment: A review of reported data and information needs. Atmos Environ 42(7):1371–88. https://doi.org/10.1016/j.atmosenv.2007.10.080

Dias D, Tchepel O (2018) Spatial and temporal dynamics in air pollution exposure assessment. Int J Environ Res Public Health 15(3)

Dons E, Laeremans M, Orjuela JP, Avila-Palencia I, de Nazelle A, Nieuwenhuijsen M, Van Poppel M, Carrasco-Turigas G, Standaert A, De Boever P, Nawrot T, Luc Int Panis (2019) Transport most likely to cause air pollution peak exposures in everyday life: Evidence from over 2000 days of personal monitoring. Atmos Environ 213(May):424–432. https://doi.org/10.1016/j.atmosenv.2019.06.035

Du X, Kong Q, Ge W, Zhang S, Fu L (2010) Characterization of Personal Exposure Concentration of Fine Particles for Adults and Children Exposed to High Ambient Concentrations in Beijing, China. J Environ Sci 22(11):1757–1764. https://doi.org/10.1016/S1001-0742(09)60316-8

Ebelt ST, Rohan R, D'Souza H, Yu N, Scovronick S, Moss, Chang HH (2023) Monitoring vs. Modeled Exposure Data in Time-Series Studies of Ambient Air Pollution and Acute Health Outcomes. J Exposure Sci Environ Epidemiol 33(3):377–385. https://doi.org/10.1038/s41370-022-00446-5

Esmen NA, Hall TA (2010) Theoretical Investigation of the Interrelationship between Stationary and Personal Sampling in Exposure Estimation. Appl Occup Environ Hyg 15(1):114–119. https://doi.org/10.1080/104732200301935

FARM | Flexible Air quality Regional Model (n.d.) Retrieved 28 August 2025. http://www.farm-model.org/

Farzadfar F, Finucane MM, Danaei G, Pelizzari PM, Cowan MJ, Paciorek CJ, Singh GM, Lin JK, Stevens GA, Riley LM, and Majid Ezzati (2011) National, Regional, and Global Trends in Serum Total Cholesterol since 1980: Systematic Analysis of Health Examination Surveys and Epidemiological Studies with 321 Country-Years and 3·0 Million Participants. Lancet 377(9765):578–586. https://doi.org/10.1016/S0140-6736(10)62038-7

Fitrianto A, Xin SH (2022) Comparisons between Robust Regression Approaches in the Presence of Outliersand High Leverage Points. J Il Mat Ter 16(1):243–252. https://doi.org/10.30598/barekengvol16iss1pp243-252

González Serrano V, Licina D (2022) Longitudinal assessment of personal air pollution clouds in ten home and office environments. Indoor Air 32(2). https://doi.org/10.1111/ina.12993

Gulliver J, Morley D, Vienneau D, Fabbri F, Bell M, Goodman P, Beevers S, Dajnak D, Frank J, Kelly, Daniela Fecht (2015) Development of an Open-Source Road Traffic Noise Model for Exposure Assessment. Environ Model Softw 74:183–193. https://doi.org/10.1016/j.envsoft.2014.12.022

Hänninen O, Kruize H, Lebret E, Jantunen M (2003) EXPOLIS Simulation Model: PM2.5 Application and Comparison with Measurements in Helsinki. J Expo Sci Environ Epidemiol 13(1):74–85. https://doi.org/10.1038/sj.jea.7500260

Health Effects Institute (2024) *State of Global Air 2024. Special Report*. Boston, MA

Hoek G, Beelen R, de Hoogh K, Vienneau D, Gulliver J, Fischer P, Briggs D (2008) A Review of Land-Use Regression Models to Assess Spatial Variation of Outdoor Air Pollution. Atmos Environ 42(33):7561–7578

Kalmár T, Kalmár F (2021) Investigation of natural aeration in home offices during the heating season – case study. J Building Eng 35. https://doi.org/10.1016/j.jobe.2020.102052

Kaur S, Nieuwenhuijsen MJ (2009) Determinants of Personal Exposure to PM 2.5, Ultrafine Particle Counts, and CO in a Transport Microenvironment. Environ Sci Technol 43(13):4737–4743. https://doi.org/10.1021/es803199z

Kim K, Hyun E, Kabir, Kabir S (2015) A Review on the Human Health Impact of Airborne Particulate Matter. Environ Int 74:136–143

Koehler KA, Peters TM (2015) New Methods for Personal Exposure Monitoring for Airborne Particles. Curr Environ Health Rep 2(4):399–411

Koehler K, Good N, Wilson A, Mölter A, Brianna F, Moore T, Carpenter JL, Peel, and John Volckens (2019) The Fort Collins Commuter Study: Variability in Personal Exposure to Air Pollutants by Microenvironment. Indoor Air 29(2):231–241. https://doi.org/10.1111/ina.12533

Kousa A, Oglesby L, Koistinen K, Unzli NK, Jantunen M (2002) Exposure chain of urban air PM 2.5-associations between ambient fixed site, residential outdoor, indoor, workplace and personal exposures in four European Cities in the EXPOLIS-Study 36(18):3031–3039. https://doi.org/10.1016/S1352-2310(02)00232-7

Lakota EA, Cornelia B, Landersdorfer RL, Nation J, Li KS, Kaye GG, Rao, and Alan Forrest (2018) Personalizing Polymyxin B Dosing Using an Adaptive Feedback Control Algorithm. Antimicrob Agents Chemother 62(7):307–310. https://doi.org/10.1128/AAC.00483-18

Landrigan PJ (2017) Air Pollution and Health. Lancet Public Health 2(1):e4–5

Lin C, Jia DHX, Chen J, Deng F, Guo X, Heal MR, Cowie H, Wilkinson P, Miller MR, Loh M (2020) The relationship between personal exposure and ambient PM2.5 and black carbon in Beijing. Sci Total Environ 737. https://doi.org/10.1016/j.scitotenv.2020.139801

Manisalidis I, Stavropoulou E, Stavropoulos A, Bezirtzoglou E (2020) Environmental and health impacts of air pollution: A review. Front Public Health 8:14. https://doi.org/10.3389/fpubh.2020.00014

Mohammadyan M (2012) Personal Exposure and Indoor Home Particulate Matter: A Review. Iranica J Energy Environ. https://doi.org/10.5829/idosi.ijee.2012.03.03.3001

Monn C (2001) Exposure assessment of air pollutants: A review on spatial heterogeneity and indoor/outdoor/personal exposure to suspended particulate matter, nitrogen dioxide and ozone 35

Morawska L, Afshari A, Bae GN, Buonanno G, Chao CYH, Hänninen O, Hofmann W, Isaxon C, Jayaratne ER, Pasanen P, Salthammer T, Waring M, Wierzbicka A (2013) Indoor Aerosols: From Personal Exposure to Risk Assessment. Indoor Air 23(6):462–487

Morawska L, Ayoko GA, Bae GN, Buonanno G, Chao CYH, Clifford S, Fu SC, Hänninen O, He C, Isaxon C, Mazaheri M, Salthammer T, Waring MS, Wierzbicka A (2017) Airborne Particles in Indoor Environment of Homes, Schools, Offices and Aged Care Facilities: The Main Routes of Exposure. Environ Int 108:75–83

Oliveira M, Slezakova K, Pereira CD-MMC, Simone Morais (2019) Children Environmental Exposure to Particulate Matter and Polycyclic Aromatic Hydrocarbons and Biomonitoring in School Environments: A Review on Indoor and Outdoor Exposure Levels, Major Sources and Health Impacts. Environ Int 124:180–204

Onat B, Şahin ÜlküA, Uzun B, Akın Özcan, Özkaya F, Coşkun A (2019) Determinants of Exposure to Ultrafine Particulate Matter, Black Carbon, and PM2.5 in Common Travel Modes in Istanbul. Atmos Environ 206:258–270. https://doi.org/10.1016/j.atmosenv.2019.02.015

Owoade OK, Olise FS, Ogundele LT, Fawole OG, Olaniyi HB (2012) Correlation between particulate matter concentrations and meteorological parameters at a site in Ile-Ife, Nigeria

Park JS, Jee NY, Jeong JW (2014) Effects of Types of Ventilation System on Indoor Particle Concentrations in Residential Buildings. Indoor Air 24(6):629–638. https://doi.org/10.1111/ina.12117

Reisen F, Powell JC, Dennekamp M, Johnston FH, and Amanda J. Wheeler (2019) Is Remaining Indoors an Effective Way of Reducing Exposure to Fine Particulate Matter during Biomass Burning Events? J Air Waste Manag Assoc 69(5):611–622. https://doi.org/10.1080/10962247.2019.1567623

Robakiewicz P, Ryder EF (2000) Statistics: Detecting Differences Among Groups. Curr Protocols Protein Sci 21(1):A.3G.1-A.3G.22 https://doi.org/10.1002/0471140864.psa03gs21

Sarnat SE, Klein M, Sarnat JA, Dana Flanders W, Waller LA, Mulholland JA, Russell AG, Tolbert PE (2010) An Examination of Exposure Measurement Error from Air Pollutant Spatial Variability in Time-Series Studies. J Exposure Sci Environ Epidemiol 20(2):135–146. https://doi.org/10.1038/jes.2009.10

Scapellato M, Luisa C, Canova A, de Simone M, Carrieri P, Maestrelli L, Simonato, Giovanni Battista B (2009) Personal PM10 Exposure in Asthmatic Adults in Padova, Italy: Seasonal Variability and Factors Affecting Individual Concentrations of Particulate Matter. Int J Hyg Environ Health 212(6):626–636. https://doi.org/10.1016/j.ijheh.2009.06.001

Shafran-Nathan Rakefet, Yuval, Broday DM (2018) Impacts of personal mobility and diurnal concentration variability on exposure misclassification to ambient pollutants. Environ Sci Technol 52(6): 3520–3526

Spinazzè A, Lunghini F, Campagnolo D, Rovelli S, Locatelli M, Cattaneo A, Cavallo DM (2017) Accuracy Evaluation of Three Modelling Tools for Occupational Exposure Assessment. Annals Work Exposures Health 61(3):284–298. https://doi.org/10.1093/annweh/wxx004

Spinazzè A, Borghi F, Campagnolo D, Rovelli S, Keller M, Fanti G, Cattaneo A, Cavallo DM (2019) How to obtain a reliable estimate of occupational exposure? Review discussion of models reliability. Int J Environ Res Public Health 16(15)

Steinle S, Reis S, Clive Eric Sabel (2013) Quantifying Human Exposure to Air Pollution-Moving from Static Monitoring to Spatio-Temporally Resolved Personal Exposure Assessment. Sci Total Environ 443:184–193

Sun L, Wallace LA (2021) Residential Cooking and Use of Kitchen Ventilation: The Impact on Exposure. J Air Waste Manag Assoc 71(7):830–843. https://doi.org/10.1080/10962247.2020.1823525

Sykes AO (1993) *An Introduction to Regression Analysis*. 20. Working Paper. https://chicagounbound.uchicago.edu/law_and_economics

Tian G, Qiao Z, Xu X (2014) Characteristics of Particulate Matter (PM10) and Its Relationship with Meteorological Factors during 2001–2012 in Beijing. Environ Pollut 192:266–274. https://doi.org/10.1016/j.envpol.2014.04.036

Vardoulakis S, Giagloglou E, Steinle S, Davis A, Sleeuwenhoek A, Galea KS, Dixon K, Crawford JO (2020) Indoor Exposure to Selected Air Pollutants in the Home Environment: A Systematic Review. Int J Environ Res Public Health 17(23):1–24. https://doi.org/10.3390/ijerph17238972

Vesna I (2009) Understanding Bland Altman Analysis. Biochemia Med 19(1):10–16

Wilson WE, Judith C, Chow C, Claiborn W, Fusheng J, Engelbrecht, Watson JG (2002) Monitoring of Particulate Matter Outdoors. https://www.elsevier.com/locate/chemosphere

Yanosky JD, MacIntosh DL (2001) A Comparison of Four Gravimetric Fine Particle Sampling Methods. J Air Waste Manag Assoc 51(6):878–884. https://doi.org/10.1080/10473289.2001.10464320

Zaccai JH (2004) How to Assess Epidemiological Studies. Postgrad Med J 80(941):140–147

Zhang A, Liu Y, Zhao B, Zhang Y, Kan H, Zhao Z, Deng F, Huang C, Zeng X, Sun Y, Qian H, Liu W, Mo J, Sun C, Zheng X (2021) Indoor PM2.5 concentrations in China: A concise review of the literature Published in the Past 40 Years'. Build Environ 198

Zou, Bin J, Gaines Wilson F, Benjamin Zhan, and Yongnian Zeng (2009) Air Pollution Exposure Assessment Methods Utilized in Epidemiological Studies. J Environ Monit 11(3):475–490