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Relationships between fixed-site ambient measurements of nitrogen dioxide, ozone, and particulate matter and personal exposures in Grand Paris, France: the MobiliSense study

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Abstract

Background Past epidemiological studies, using fixed-site outdoor air pollution measurements as a proxy for participants' exposure, might have suffered from exposure misclassification.

Methods In the MobiliSense study, personal exposures to ozone (O_3), nitrogen dioxide (NO_2), and particles with aerodynamic diameters below 2.5 µm ($PM_{2.5}$) were monitored with a personal air quality monitor. All the spatial location points collected with a personal GPS receiver and mobility survey were used to retrieve background hourly concentrations of air pollutants from the nearest Airparif monitoring station. We modeled 851,343 min-level observations from 246 participants.

Results Visited places including the residence contributed the majority of the minute-level observations, 93.0%, followed by active transport (3.4%), and the rest were from on-road and rail transport, 2.4% and 1.1%, respectively. Comparison of personal exposures and station-measured concentrations for each individual indicated low Spearman correlations for NO_2 (median across participants: 0.23), O_3 (median: 0.21), and $PM_{2.5}$ (median: 0.27), with varying levels of correlation by microenvironments (ranging from 0.06 to 0.35 according to the microenvironment). Results from mixed-effect models indicated that personal exposure was very weakly explained by station-measured concentrations ($R^2 < 0.07$) for all air pollutants. The R^2 for only a few models was higher than 0.15, namely for O_3 in the active transport microenvironment (R^2: 0.25) and for $PM_{2.5}$ in active transport (R^2: 0.16) and in the separated rail transport microenvironment (R^2: 0.20). Model fit slightly increased with decreasing distance between participants' location and the nearest monitoring station.

Conclusions Our results demonstrated a relatively low correlation between personal exposure and station-measured air pollutants, confirming that station-measured concentrations as proxies of personal exposures can lead to

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exposure misclassification. However, distance and the type of microenvironment are shown to affect the extent of misclassification.

Keywords Air pollution, Personal exposure, Fixed stations, Exposure misclassification, Microenvironments

Introduction

Measurement error or exposure misclassification is a challenge in air pollution epidemiology. Accurate measurement of air pollution exposure over a continuous period is complex and error-prone. Furthermore, precise ways to measure air pollution exposure minimizing noise are unavailable or widely impractical in extensive studies. A number of epidemiological studies in the past assessed air quality levels within a specified geographical area and assigned them to subjects living in that area to estimate the air pollution-related adverse health effects [1, 14, 54]. Another commonly used method in those studies was to assign nearby fixed station-monitored air quality levels as a proxy for individual exposure [7, 13, 31]; M et al., 2019 [37]. Although these fixed measurement techniques meet regulatory requirements and provide accuracy and precision, the high cost and maintenance requirements of these stations make it difficult to install a dense network of monitors within an area. Consequently, this approach might not precisely capture the variation in air pollutants within a city or provide sufficient resolution for epidemiological studies [17].

While results remain far from conclusive [55], several studies using fixed station-monitored ambient measurements have documented positive associations of air pollution exposure with adverse health events [12]; Y.-M. Liu & Ao [35, 52, 54],. However, this technique of using fixed station-monitored air quality levels ignores the spatial and temporal variations in exposure for each person. These variations, resulting from individuals' mobility patterns, transitions between microenvironments with varying pollution sources, and other life circumstances, may often exceed those captured at fixed stations [20, 34, 40]. In addition, the impact of switching between microenvironments or between indoor sources results in variability in personal exposure over time that is not correlated with the variation in outdoor air pollution levels. Epidemiological studies using fixed station-monitored ambient concentrations as a proxy for personal exposure therefore suffer from exposure misclassification [55]. It is well-established that ignorance of exposure misclassification in epidemiological studies may lead to biased estimation or incorrect inference [5, 50]. Also, the bias can be towards the null or away from it, depending on the direction and magnitude of the exposure misclassification among diseased and non-diseased people [48, 53].

Recent studies on air pollution have found that within city variations in traffic emitted pollutants, such as nitrogen dioxide (NO_2), black carbon, and particles with aerodynamic diameters below 2.5 μm ($PM_{2.5}$), are higher than variations between cities [30, 56]. For example, a study in the UK illustrated that NO_2 measured at two points that were 50 m apart differed by a two to three-fold ratio in concentration [25]. A review including 18 studies concluded that the correlation coefficient ranged between 0.09 and 0.83 (median: 0.56) between fixed station-monitored and personally measured $PM_{2.5}$ [2]. Likewise, another study conducted in 2017 (March-June) revealed that the correlation between station-monitored and personal sensor-monitored $PM_{2.5}$ was poor (R^2 of 0.18–0.32) in non-laboratory settings [45]. The low magnitude of correlation suggests that portable sensors are useful for reducing the magnitude of error in exposure classification by continuously monitoring person-level exposure [40, 46], which is critical for the estimation of unbiased associations between air pollution exposure and health outcomes [4]. In addition, using air quality sensors allows researchers to access air quality-related information in real-time [16, 38], which may be useful in specific projects.

In this study, we compare two approaches for estimating exposure to 3 air pollutants (i.e., $PM_{2.5}$, NO_2, and ozone (O_3)): (1) minute-level concentrations measured with a personal air quality monitor (PAM), and (2) hourly ambient concentrations recorded by a nearby fixed station. We hypothesize that the accuracy of background air quality levels, reported by nearby fixed stations, in representing personal exposure may depend on the type of microenvironment in which the participant is and their distance from the fixed station. Thus, we aim to compare personal exposure levels with station-monitored air pollutants across different microenvironments to provide insights into the magnitude and determinants of misclassification—a topic that has not been explored before.

Methods

Data for this study come from the MobiliSense study wave 1, conducted in the Grand Paris, France (Paris City and some surrounding municipalities) from May 2018 to October 2020. Participants were recruited through a two-stage stratified random sampling procedure. In the first stage, neighbourhoods were randomly selected from the first and last quartiles of neighbourhood road traffic density within each quartile of neighbourhood income. In the second stage, dwelling units were randomly selected within the pre-selected neighbourhoods. The sampling method and participant recruitment process are described in further detail in our previous publication

[10]. In total, 289 participants agreed to participate in the study. Out of 289 participants, 6 abandoned during the study, 2 did not participate in the mobility survey, and air pollution data could not be retrieved for 35 participants due to PAM failure, resulting in 246 actual participants.

Data collection and processing

Time-activity profiles

GPS data collected at a 5-sec resolution with BT-Q1000XT GPS receivers were processed with the TripBuilder Web mapping application [51] in order to identify places visited by individuals, their trips, and the transport modes used in each trip. The detail of the algorithms is discussed in our previous publication [3, 9]. The start and end times of trip stages and stays at visited places, obtained from the processed GPS data, were cross-verified with participants during a mobility survey conducted over the phone. This survey permitted to add and correct information related to those trips and visited places that were incorrectly assessed with the GPS receiver. Also, missing or incomplete trips were manually added during the mobility survey (see Appendix 2).

Personal exposure to gaseous pollutants and $PM_{2.5}$

PAM with electrochemical sensors was used to monitor NO_2 and O_3 at 10-sec resolution, later aggregated at the minute level. Meanwhile, $PM_{2.5}$ was measured at 1 min resolution with an optical particle counter. These air pollutants were simultaneously measured during our study on the 1st, 2nd, 5th and 6th days (over a 6-day monitoring period). The performance of the PAMs was characterized in outdoor co-locations with reference instruments, as described in Appendix 1, adopting the methodology described by Chatzidiakou and colleagues in 2019 [11]. These co-locations also permitted to derive calibration equations for air pollutant concentrations considering temperature and cross-sensitivity between gases (Appendix 1).

Fixed station-monitored concentrations of air pollutants

Station-monitored $PM_{2.5}$, NO_2, and O_3 concentrations were extracted at an hourly level for all the geographic coordinates continuously recorded with GPS receivers and mobility survey (i.e., for all individual location points, as explained above and in Appendix 2 by matching their timestamps to those reported by the nearest Airparif air quality monitoring station. We then assigned those hourly values to all the spatial location (GPS and mobility survey) points of the corresponding hours to acquire the minute-level observations. For example, the station measurement reported at 10:00 am was assigned to all location points between 10:00 and 10:59 am, if the station remained the closest one. The location of the fixed monitoring stations as well as the participants' residential locations are illustrated in Fig. 1.

Integration of the databases

We first deleted the extreme values in sensor air pollution measurements that might have resulted from mechanical shocks, meteorological influence, or device error [NO_2 ($n=771$), O_3 ($n=807$), and $PM_{2.5}$ ($n=5219$)], resulting in 851,343 min-level observations from 246

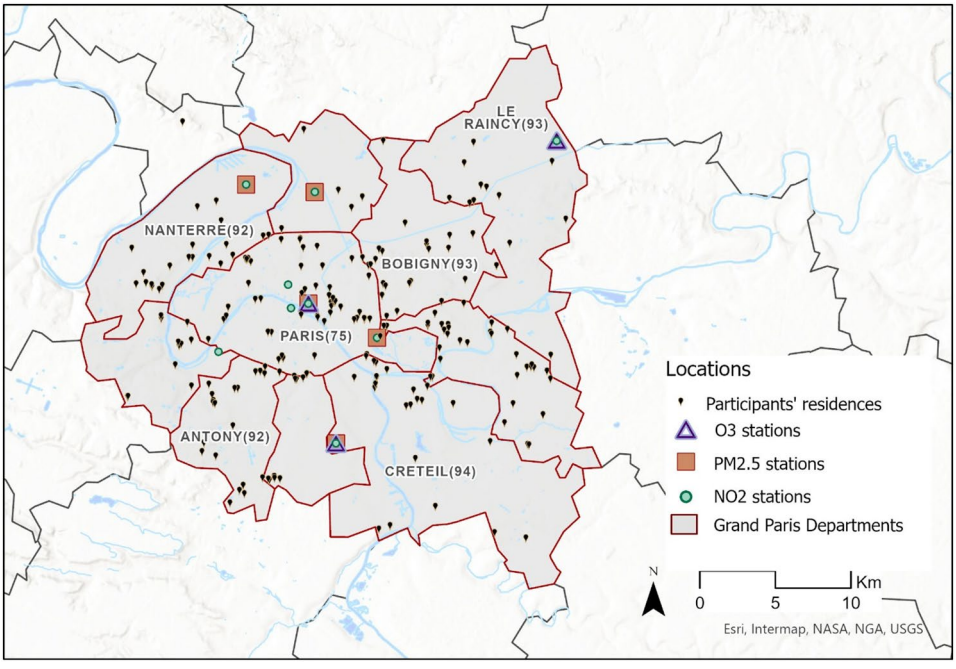

Fig. 1 Distribution of air pollution monitoring stations across our study area (Grand Paris)

participants. The sensor-measured NO_2, O_3, and $PM_{2.5}$ concentrations were aggregated at the minute level and merged with the station-measured concentrations of the corresponding pollutants using the timestamps. Observations at the minute level were classified into four different microenvironments using participants' time-activity profiles (Sect. 2.1.1). The four unique microenvironments were: visited places (home and out-of-home), active transport (walking, biking, and skating), on-road motorized vehicles (tramway, bus, taxi, and private motorized vehicles), and separated rail networks (metros and suburban trains).

Statistical analyses

Descriptive analyses

We calculated the percentage of station-monitored air pollution concentrations that were higher than personal exposure concentrations at the minute level. In order to compare the distribution and not only the absolute concentrations of air pollutants, we classified measurements from both approaches into four quartiles (according to the same cut-offs values for the two distributions) and calculated the percentage of personal exposure measurements being in the same quartile or being in a higher or lower quartile than station-monitored measurements. This analysis was performed at a global level (i.e., including data from the whole sample) and stratified by microenvironments as well.

Statistical analyses

We first compared the distributions of station-monitored concentrations and personal exposures to air pollutants graphically by microenvironment using box plots, followed by paired Wilcoxon tests. In the presence of repeated measurements per participant, Spearman's correlation was estimated for each participant separately, describing the within-individual associations between personal and station-measured air pollutants. In order to accurately quantify the variability of correlations across participants, the median along with the 2.5th percentile and 97.5th percentile of these within-person correlation coefficients were calculated at the global and microenvironment level. Mixed-effect regression models were employed to associate the fixed-station ambient measurements with personal exposures as the outcome, with station-monitored concentrations modeled as a fixed effect and participants modeled as a random effect. While the slope in these models corresponds to the strength of the relationship between the station-monitored concentration and the personal exposure, the intercept is a constant referring to the gap in concentrations between the fixed-station ambient measurements and the personal measurements. Additionally, we calculated the coefficient of determination (R^2) using a method developed by Nakagawa & Schielzeth 2017 [39] for random intercept mixed models. In addition to the global analysis, we stratified our analyses by microenvironments. All the analyses were done at the minute level. R software (version 4.0.3) was used for all the statistical processing/analyses, while ArcMap 10.8.1 was used for processing geographic points and drawing maps.

Sensitivity analyses

We also estimated the mixed-effect regression models associating the fixed-station ambient measurements with personal exposures on the datasets created by retaining observation points that were at the most at 10 km and 5 km from the nearest fixed-station, as explained in Sect. 2.1.3 We calculated the R^2 from each model to determine how the variability in personal exposure was explained by fixed-station measured air pollution concentrations.

Results

Participants' characteristics and behaviours

Among the 246 participants, 57% were women. Participants were 50 years old on average (range: 33, 67 years). 22% were living in Paris, and the rest in the suburbs; 70% had a higher diploma than high school, while 5% had lower educational attainment than a high school diploma: 66% of participants had a permanent job, 3% were unemployed, and 12% were retired. Therefore, although our sample is not representative of the background population, it includes a substantial diversity of individual profiles.

Over the 57.7 h contributed on average by each participant, a participant spent 2 h in active transport, 1 h and 52 min commuting with on-road transport, 53 h and 40 min in places (indoor and fixed outdoor places, including the residence), and 1 h and 21 min commuting with rail networks. In other words, most study observations (93.0%) were from places, followed by active transport (3.4%), and the rest were from on-road and rail transport, 2.4% and 1.1%, respectively.

Descriptive statistics

Descriptive statistics [median (2.5th percentile, 97.5th percentile)] on station-monitored and personal exposure to air pollutants are reported in Table A2. Station-monitored concentration was always greater than the personal concentration measured with the sensor regardless of the microenvironment visited (Fig. 2 and Appendix Figures A1-A3), except for O_3 in active transport, where the distributions of station-monitored and personal exposure were fully overlapping (Figure A2). Although the median for station-monitored $PM_{2.5}$ concentrations were slightly greater than that for personal concentrations in separated rail transport, their distribution was largely overlapping

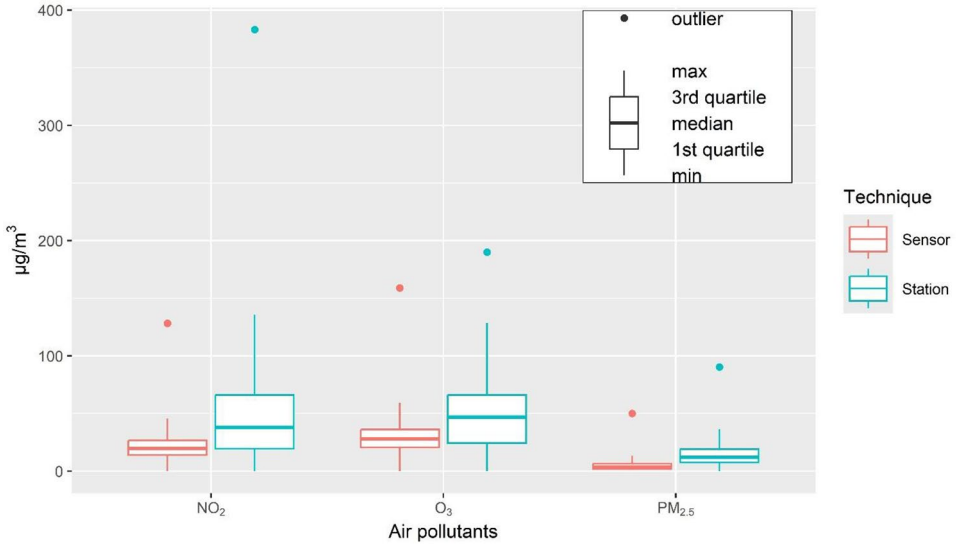

Fig. 2 Comparison of the distribution of station-monitored and personal exposure to air pollutants at the minute level

Table 1 Ratio [median (2.5th percentile, 97.5th percentile) across participants] of station-monitored vs. personal exposure to air pollution at the minute level by microenvironments

	NO_2	O_3	$PM_{2.5}$
Microenvironments			
Active transport (*N* = 231, *n* = 28869)	2.03 (0.34, 21.15)	0.90 (0.06, 4.51)	2.40 (0.43, 13.33)
On-road motorized transport (*N* = 183, *n* = 20623)	1.49 (0.24, 15.18)	1.55 (0.03, 8.35)	2.93 (0.43, 16.30)
Places visited (*N* = 246, *n* = 792546)	1.94 (0.33, 13.46)	1.59 (0.04, 5.37)	3.33 (0.33, 18.20)
Separated rail transport (*N* = 113, *n* = 9305)	1.61 (0.34, 14.26)	1.42 (0.04, 6.99)	1.35 (0.27, 12.30)
Pooled (*N* = 246, *n* = 851343)	1.93 (0.32, 14.19)	1.56 (0.04, 5.41)	3.26 (0.33, 17.89)

N: number of participants, n: number of minute-level observations

Table 2 Within-subject Spearman's correlation coefficient [median (2.5th percentile, 97.5th percentile) across participants] between the station-monitored and personal exposure to air pollutants at the minute level by microenvironments

	NO_2	O_3	$PM_{2.5}$
Microenvironments			
Active transport (*N* = 231, *n* = 28869)	0.25 (-0.52, 0.79)	0.33 (-0.63, 0.79)	0.35 (-0.67, 0.87)
On-road motorized transport (*N* = 183, *n* = 20623)	0.06 (-0.87, 0.77)	0.09 (-0.82, 0.79)	0.29 (-0.65, 0.86)
Places visited (*N* = 246, *n* = 792546)	0.23 (-0.30, 0.65)	0.20 (-0.38, 0.65)	0.26 (-0.32, 0.78)
Separated rail transport (*N* = 113, *n* = 9305)	0.08 (-0.64, 0.71)	0.23 (-0.49, 0.80)	0.19 (-0.70, 0.85)
Pooled (*N* = 246, *n* = 851343)	0.23 (-0.27, 0.61)	0.21 (-0.35, 0.63)	0.27 (-0.28, 0.76)

N: number of participants, n: number of minute-level observations

(Figure A3). Above 60% of the station-monitored concentrations for NO_2 and O_3 were greater than the corresponding personally measured concentrations across all microenvironments at the minute level, except for O_3 in active transport where this percentage was only 42% (Table A3). For $PM_{2.5}$, station-monitored concentrations were higher in more than 80% of the observations in every microenvironment, except in separated rail transport (65%) (Appendix Table A3).

The median of the ratio between station-monitored and personal concentrations across all observations from the participants ranges from 1.49 (on-road motorized) to 2.03 (active transport) for NO_2, from 0.90 (active transport) to 1.59 (places visited) for O_3, and from 1.35 (separated rail transport) to 3.33 (places visited) for $PM_{2.5}$ across the microenvironments (Table 1). For all the air pollutants, almost one-third of the personal exposures fell into the exact same quartile than station-monitored exposures, while another third was either higher or lower than station-monitored exposures (Appendix Figures A4-A7).

Main findings

Correlation between sensor and station-measured air pollutants

There was a great deal of inter-subject variability in the participant-specific air pollutant correlations between station-measured and personal concentrations, with most participants having weak and even negative correlations. For the global and stratified correlation analyses, the 2.5th and 97.5th percentiles of the correlation coefficient ranged from negative to positive for all air pollutants. In the global analysis, the median of the subject-specific correlation coefficients (between station-measured and personal concentrations) were comparable across air pollutants (Table 2). In the stratified analyses, a relatively strong within-person correlation coefficient

Table 3 Associations of station-measured air pollutants (95% CI) with personally measured air pollutant concentrations at the microenvironment level[a]

	NO_2			O_3			$PM_{2.5}$		
	Slope	**Intercept**	R^2	**Slope**	**Intercept**	R^2	**Slope**	**Intercept**	R^2
Microenvironments									
Active transport (*N* = 231, *n* = 28869)	0.18 (0.18, 0.19)	15.32 (14.04, 16.60)	0.08	0.48 (0.47, 0.49)	25.56 (23.49, 27.64)	0.25	0.35 (0.35, 0.36)	2.56 (1.84, 3.28)	0.16
On-road motorized transport (*N* = 183, *n* = 20623)	0.05 (0.04, 0.06)	30.01 (27.85, 32.17)	0.00	0.12 (0.11, 0.13)	24.49 (22.67, 26.32)	0.04	0.19 (0.19, 0.20)	3.83 (2.92, 4.75)	0.06
Places visited (*N* = 246, *n* = 792546)	0.08 (0.08, 0.08)	17.72 (17.00, 18.43)	0.05	0.11 (0.11, 0.12)	23.17 (21.99, 24.34)	0.06	0.15 (0.15, 0.16)	3.95 (3.18, 4.72)	0.04
Separated rail transport (*N* = 113, *n* = 9305)	0.07 (0.06, 0.08)	31.94 (29.63, 34.25)	0.01	0.18 (0.17, 0.20)	22.29 (20.30, 24.28)	0.11	0.50 (0.48, 0.52)	4.51 (3.20, 5.83)	0.20
Pooled (*N* = 246, *n* = 851343)	0.09 (0.09, 0.09)	17.89 (17.16, 18.61)	0.05	0.13 (0.13, 0.14)	23.06 (21.89, 24.22)	0.07	0.17 (0.16, 0.17)	3.93 (3.17, 4.70)	0.04

CI: confidence interval

[a]The multilevel linear models included a random effect at the individual level

R^2: Coefficient of determination

N: number of participants, n: number of minute-level observations

was documented for NO_2 in active transport (median: 0.25) followed by places visited (median: 0.23), whereas the coefficients were comparatively weak for separated rail transport (median: 0.08) and on-road motorized transport (median: 0.06) microenvironments. For O_3, the median of station-personal correlation coefficients across participants ranged between 0.20 (for places visited) and 0.33 (for active transport) across the microenvironments, except for on-road motorized transport, for which it was 0.09. For $PM_{2.5}$, the microenvironment-specific median correlation coefficients varied from 0.19 to 0.35, with separated rail transport having the lowest and active transport having the highest median correlation coefficients.

Associations of station-measured with sensor-measured air pollutants

The slopes of the station-personal NO_2 associations were less than 0.20 across all the microenvironments, with R^2 less than 0.10 (Table 3). Similar estimates were documented for O_3, except for the active transport microenvironment, where the slope was 0.48 and R^2 was 0.25. For $PM_{2.5}$, a relatively higher slope between the station and personal exposure was observed for separated rail transport, 0.50, with a R^2 of 0.20, followed by active transport (slope: 0.35 and R^2: 0.16).

Sensitivity analyses

Even though the R^2 for all the pollutants in the global analyses remained comparable to the main analyses (global analysis in the whole sample) when choosing 10 km as a cutoff for the distance between the station and the participants' location points (Appendix Table A4), there was a slight increment in the R^2 with 5 km as a cutoff (Table A5). Regarding the microenvironment level analyses, when using 10 km cutoff, the R^2 for all the air pollutants improved slightly in active transport and on-road motorized transport compared to the main analyses, while it did not change much in other microenvironments (Table A4). In the analyses with a 5 km cutoff, the R^2 for all air pollutants increased in the active transport, places visited, and rail transport microenvironments compared to the main analyses and to the analysis done with a 10 km cutoff, except for $PM_{2.5}$ for which the R^2 decreased slightly in active transport and rail transport (Appendix Table A5).

Discussion

We found that the air pollution concentrations recorded at the nearby fixed stations were consistently higher than those captured with a personal air quality sensor. These findings agreed with the findings from Sarnat et al. and other studies [19, 32, 43, 44]. In contrast, these results conflicted with other studies reporting that the personal exposures to $PM_{2.5}$ [27, 28, 41, 45] and NO_2 [8, 27] were higher than those measured by nearby fixed stations. However, these studies did not stratify their analyses by microenvironments. Consistent with previous findings [8, 32, 43–45], correlations between personal exposures and station-monitored concentrations for NO_2, O_3, and $PM_{2.5}$ were weak with low coefficient values (< 0.35), suggesting that fixed-station ambient measurements may not be usable as accurate surrogates of personal exposure while estimating their health impact. It is to be noted that the magnitude of correlation varied considerably between participants, even for the same microenvironment, ranging from large negative to large positive coefficients, indicating that the characteristics of exposure to air pollutants were not constant across study participants. In addition, it indicates that personal exposures

may be predicted for a specific individual but not across the group of participants.

Similar to the findings from a previous study [21], the use of ambient station-measured concentrations in a regression model did not explain much of the variability in personal exposure in the global analysis ($R^2 < 0.05$). However, there was a slight improvement in the model fitness, i.e., R^2, when modeling the associations at the microenvironment level, especially for O_3 and $PM_{2.5}$ in active transport microenvironment and $PM_{2.5}$ in separated rail transport. While most epidemiological studies directly use nearby fixed-station ambient measurements to surrogate personal exposure, this study focused on determining the total variability in this exposure explained by station-measured concentrations alone. Nevertheless, some studies suggest that adding information on exposure to cooking and environmental tobacco smoke [15, 21, 47], dwelling characteristics (volume of the house [21], nature/use of ventilation [26, 44], time spent in open spaces/indoors [21, 36], and meteorological variables [41, 49] along with station-measured concentrations may improve the fitness of the model predicting personal exposure. However, we had a distinct goal in the present study, i.e., comparing the concentrations rather than improving the prediction.

We found relatively strong correlations between station and personal air pollution measurements in the active transport and visited places microenvironments. This association might be explained by the fact that walking and biking are performed in open spaces, while visited places in our study were primarily open spaces or well-ventilated shopping centers or apartments. Therefore, nearby air quality stations might be able, to some extent, to capture the exposure variability happening at the personal level in these microenvironments. Usually, on-road transport, especially private cars and taxis, is operated in short windows of time, preventing the outdoor air from entering. Also, they imply fast movement over a certain distance, which may decrease the correlation. In addition, air filters in these vehicles reduce the volume of air pollutants entering from the outer environment, decreasing the air quality station's ability to predict personal exposure within this microenvironment, as in our study [22]. Out of 246 participants included in this specific study, 141 had a registered car. The oldest vehicle was registered in 1972 and the most recent one in 2020. The median registration year was 2012, and the 10th and 90th percentiles of registration year were 2003 and 2018. Although some of the participants' vehicles were old, air filters in the more recent vehicles likely decreased the correlation between station-measured and personal air pollution.

Even if the combustion of fossil fuels does not power rails in our study area, $PM_{2.5}$ from the outer environment may enter the underground space via the ventilation system, which is often located on the ground of roads, in addition to the particles emitted by the contact between the wheels and the rail and the brakes. Some $PM_{2.5}$ components, such as black carbon, have small diameters (less than 1 μm), making them hard to be efficiently blocked by the filters installed in metro and sub-urban trains [22]. It could contribute to explaining the comparatively stronger correlation coefficients for $PM_{2.5}$ in separated rail transport. The same explanation of filter capacity could hold for O_3 in separated rail transport, even though it is secondary pollution. However, NO_2 is not produced by rail transport and is negatively correlated with O_3 [23]. This may explain the lower correlation coefficient for NO_2 in the rail-transport microenvironment.

Overall, our findings are concordant with previous studies; however, several reasons can explain the discrepancies between our findings and results from some other studies. One among them would be the study population; previous studies recruited patients with pulmonary disease [21, 42] or elderly subjects [44], children [33, 41], and patients with cardiovascular disease [24]. In contrast, we randomly recruited adults from the general population. Exposure metrics of diseased people and children are incomparable with those of the general population due to differences in their activity patterns (mobility), such as where they go and what activity they perform at the visited place. Besides, several studies did not recruit human subjects, but rather placed the personal monitor close to a reference instrument or in a stationary place throughout the study period and checked the correlation between the two approaches [16, 18, 29, 45]. Since this experimental design completely ignores the mobility part, i.e., transitions between different microenvironments with varying pollution sources, a well-calibrated personal monitor can be expected to mirror the measurements reported by the reference device, with a high correlation. Another reason for potential discrepancy with previous literature is the technique of assessing exposure; most studies used daily averaged levels or sampled a measurement once in 24 h [6, 18, 27, 41, 44, 45], or used hourly averaged concentrations [8, 34] without considering the share of the time spent in different microenvironments with different sources and their impact on the overall exposure. On the opposite, we considered measurement at a very high temporal resolution (at the minute level), considering participants' mobility and minute-level presence in different microenvironments.

Strengths

While most studies confined their recruitment to older people, diseased populations, or children, our study randomly selected participants from the healthy general public, making the findings more generalizable. Another strength of our study was that it included a relatively

large number of participants ($n = 246$), and a sufficient number of repeated measurements among them in different microenvironments, providing enough statistical power. To the best of our knowledge, our study is the first to report the associations between station and personal air pollution measurements at the minute level and stratify the analyses by microenvironments visited.

Limitations

The first limitation of our work is that we chose 15 km as a maximum distance between the air pollution station and participants' location points, which is wide enough to introduce exposure misclassification bias while using station-monitored ambient concentrations to estimate the personal exposure. Furthermore, about 97% and 22% of our observations were 5 km away or more and 10 km away or more from the nearby stations, respectively. Our findings may also be relevant to studies using measurements from a single station to represent the air pollution exposure of a large geographical area, a common method in previous epidemiological studies. Quantifying the level of exposure misclassification depending on the distance between a person's current position and the nearby air quality station was out of the scope of this study. Nevertheless, we performed sensitivity analyses keeping only those observations within 10 km and 5 km from the nearest fixed station. Although there was a slight improvement in the R^2 for all the pollutants while moving from a 15 to a 5 km threshold, our findings should be used cautiously, as we reduced our sample to almost 3% of its initial size while shifting from 15 to 5 km. However, future studies of this nature could fill in the gaps by assessing the degree of exposure misclassification at the personal level as a function of distance from the nearby fixed monitoring station, e.g., at 2 km, 3 km, and so on, with a larger sample than ours. Although our study included a large number of subjects and a long period of dense monitoring, there is still a need for improving the automation of the data collection process. The main bottleneck in our data collection process was the assessment of time-activity profiles. While the phone mobility survey provides a high-quality assignment of contexts to the measurements, it is lengthy and costly. To overcome this problem, one can use a sample of such annotated data as a gold standard for training a machine learning model along with expert rules to propagate the microenvironment assignment, or novel smartphone technologies for the automatic collection of microenvironment data.

Conclusion

Personal monitoring allowed us to show that personal air pollutant exposure differs from exposure information inferred from fixed-site ambient measurements. Our findings demonstrate that using fixed-station monitoring as a surrogate for personal exposure results in exposure misclassification. Our results suggest that epidemiological studies based on short-term (minutes to an hour) station-measured ambient concentrations may have reported biased effect estimates for health, and that better exposure surrogates are needed.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12942-025-00393-y.

Supplementary Material 1

Author contributions

SB: Data processing, conception of analytical methodology, statistical analysis, interpreted the results and wrote original draft. GF: Conception of analytical methodology, data processing, Review & editing. KZ: Review & editing, IA-M: Review & editing. BC: Project conception, conception of data collection and analytical methodology, development of overall research plan, study oversight, funding acquisition, writing– review & editing and supervision.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Human ethics and consent to participate declarations

Written conset form was signed by each participant before they were enrolled in the study.

Competing interests

The authors declare no competing interests.

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