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When, Where, and What? Characterizing Personal $PM_{2.5}$ Exposure in Periurban India by Integrating GPS, Wearable Camera, and Ambient and Personal Monitoring Data

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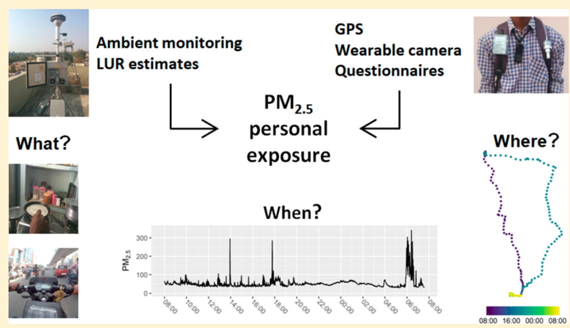
Supporting Information

ABSTRACT: Evidence identifying factors that influence personal exposure to air pollutants in low- and middle-income countries is scarce. Our objective was to identify the relative contribution of the time of the day (*when?*), location (*where?*), and individuals' activities (*what?*) to $PM_{2.5}$ personal exposure in periurban South India. We conducted a panel study in which 50 participants were monitored in up to six 24-h sessions (n = 227). We integrated data from multiple sources: continuous personal and ambient $PM_{2.5}$ concentrations; questionnaire, GPS, and wearable camera data; and modeled long-term exposure at residence. Mean 24-h personal exposure was 43.8 $\mu g/m^3$ (SD 24.6) for men and 39.7 $\mu g/m^3$ (SD 12.0) for women. Temporal patterns in exposure varied between women (peak exposure in the morning) and men (more exposed throughout the rest of the day). Most exposure occurred at home, 67% for men and 89% for women, which was proportional to the time spent in this location. Ambient daily $PM_{2.5}$ was an important predictor of 24-h personal exposure for both genders. Among men, activities predictive of higher hourly average exposure included presence near food preparation, in the kitchen, in the vicinity of smoking, or in industry. For women, predictors of exposure were largely related to cooking.



INTRODUCTION

A large burden of disease is attributable to air pollution. Long-term ambient exposure to fine particulate matter ($PM_{2.5}$) has been estimated to account for 8% of global mortality[1] and 11% of the national mortality in India.[2] Nonetheless, research on air pollution exposure in low- and middle-income countries, and especially on personal exposures, is still scarce.[3] Compared to high-income countries, ambient air pollution levels in India are generally higher and sources of exposures and time−activity patterns are potentially different.[3]

Quantifying personal exposure to air pollution is challenging because of large temporal and spatial variability in exposure.[4] Current exposure science is largely divided between two approaches: modeling exposures for large populations vs measuring exposures for small populations.[5] Most studies using the second approach have relied on self-reported time−activity data[6,7] and GPS technology[8−11] to define micro-environments as a determinant of exposure. Few of those studies also took into account other contributors to exposure, such as ambient concentrations and meteorology.[7,11]

Self-reported time−activity data mostly provide limited temporal resolution and rely on the memory and/or motivation of participants. Moreover, these data are more likely to capture activities in which the individual was actively engaged, leaving out context, setting, and other aspects of interaction with the environment that can influence exposure. These limitations make objectively measured activity and location data attractive. While GPS is now widely used as an objective alternative to self-reported location,[12] there is currently no readily available option for objective activity and contextual data. Wearable cameras, a technology that has been previously used in health studies, e.g. to assess physical activity,[13] and which we recently applied for the first time to air pollution exposure,[14] could potentially fill this gap.

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Our objective was to identify the relative contribution of time (*when?*), location (*where?*), and individuals' activities (*what?*) to personal exposure to $PM_{2.5}$ in periurban India by integrating data from multiple sources: continuous personal concentrations, continuous ambient $PM_{2.5}$ concentrations, self-reported time−activity data, GPS data, wearable camera-derived data, and modeled ambient concentrations at residence. We build on our previous work[14−17] examining those data separately by adopting a holistic approach and pooling their strengths in order to gain insights into their relative contribution to personal exposure to $PM_{2.5}$.

MATERIALS AND METHODS

Study Population. We used data from the Cardiovascular Health effects of Air pollution in Telangana, India (CHAI) project.[18] CHAI participants are a random village-stratified sample (n = 401) of the third follow-up of the Andhra Pradesh Children and Parents Study (APCAPS) intergenerational cohort[19] (n = 6225). APCAPS included residents of 28 villages from 187 to 5065 households of a periurban area in the south of Hyderabad, Telangana, India. CHAI was approved by the Ethics Committees of Parc de Salut Mar (Barcelona, Spain), the Indian Institute of Public Health-Hyderabad (Hyderabad, India), and the National Institute of Nutrition (Hyderabad, India). A subsample of 60 CHAI participants was enrolled in a panel study. Participants in the panel were selected on a random basis among those willing to participate in more extensive monitoring. Participants were monitored in up to six 24-h sessions between May 2015 and February 2016. Monitoring sessions were designed to cover all seasons. Sessions typically started at 8 a.m. to minimize disruption in the participant's daily routines. Field workers set up the devices, collected them at the end of the sessions, and answered any queries and complaints the participant had. Data gathered in the panel study and their processing are summarized in Figure 1.

Personal $PM_{2.5}$. Participants wore a RTI MicroPEM v3.2A (MicroPEM, RTI International, Research Triangle Park, NC) $PM_{2.5}$ monitor near the breathing zone, attached to one of the straps of a secured backpack during monitoring sessions [Figure 1S, Supporting Information (SI)]. The sampling rate of the device was 10 s. Raw nephelometer measurements were relative-humidity-corrected; we processed them using the R package rtimicropem.[20,21] Data processing included a gravimetric correction with an independent collocated gravimetric monitor in two of the six sessions (pump, 111 224-PCMTX8, SKC Ltd., Dorset, UK; filter, Emfab, 113 Pallflex; Figure 1S, SI) as we detected small holes in the filters integrated in the MicroPEM devices. We applied a temperature correction for temperatures greater than 30 °C. We excluded time series with a relative difference between the post- and preflow rates greater than 20%, with a leakage or malfunction of the device (identified through the inlet and orifice pressure parameters), or with abrupt baseline shifts (32 monitoring sessions). With the resulting data, regular 1 min series were constructed by calculating the minute averages and interpolating gaps smaller than 5 min (0.13% of the total minutes). Detailed information on quality assurance of the MicroPEM data has been given elsewhere.[14]

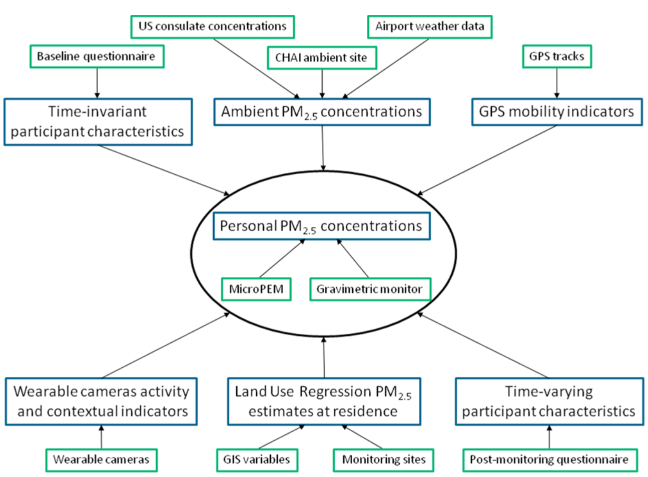

Figure 1. Data integration schema. Green boxes represent data sources. Blue boxes represent sets of variables used in the analysis. Arrows represent data management and analysis procedures.

Ambient $PM_{2.5}$ and Season. We measured hourly concentrations of ambient $PM_{2.5}$ with an eBAM device (Model 9800, 150 Met One, Grants Pass, OR) at one site in the north of the study area (Figure 2S, SI), far from traffic or other potential local sources. eBAMs are relatively mobile instruments that work by beta-attenuation methods.[22] They have been found to have good correlation with nonmobile BAM monitors.[22] The sampling frequency of the device was 15 min; we averaged the data to generate an hourly time series to attenuate measurement error. Ambient monitoring in the study area started 1 month later than personal monitoring, which resulted in 15% of sessions having missing ambient data. We backcasted the hourly ambient time series by fitting a linear model to the available data and then predicting the missing period. We used ambient hourly $PM_{2.5}$ concentrations from the US consulate in Hyderabad (a BAM monitor located 24 km from the north site, Figure 2S, SI, data publicly available), weather data from Rajiv Gandhi International Airport in South Hyderabad (16 km from the north site, Figure 2S, SI, data publicly available), and day and hour indicators as predictors of the north site ambient concentrations. The adjusted R^2 of the model was 0.49 and the 10-fold cross-validation mean absolute error was 10.3 $\mu g/m^3$ (SD of the hourly ambient time series was 21.3 $\mu g/m^3$). Furthermore, we created a categorical variable indicating the season in which the measurement took place—summer (March to May), monsoon (June to August), postmonsoon (September to November), or winter (December to February)—as well as a working day (Monday to Saturday) binary variable.

Questionnaire. All panel participants answered a baseline questionnaire before the first monitoring session, including general questions about themselves and their households. We derived data about the age, education level, occupation skill level, household income, smoking status, and primary stove type of the participants. Furthermore, a postmonitoring questionnaire was administered at the end of each monitoring session. It included questions on exposure to a range of predefined sources of air pollution in the previous 24 h (e.g., biomass stove, traffic, smoking, incense) and a self-reported retrospective diary of activities (e.g., cooking, working, sleeping, sedentary) and locations (e.g., home, workplace, outdoor in fields) with hourly slots.

GPS. Participants carried a GPS device (Etrex 20; Garmin, Inc.) in secured backpacks to measure their location every 30 s. The accuracy of the device in the study area was 4 m. GPS tracks were cleaned by detecting abrupt position changes

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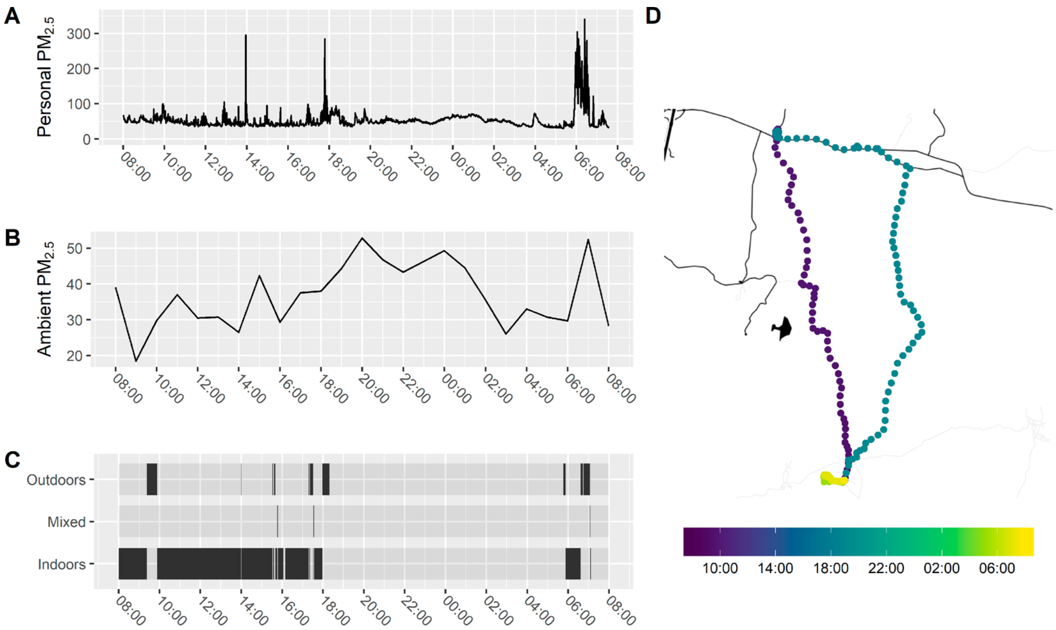

E

Variable	Value
Sex	Male
Occupation	Manual work
Education	Secondary school
LUR prediction	30.71

F

Variable	Value
Activity 8 am	Travel
Location 8 am	Outdoor village
Activity 9 am	Work
Location 9 am	Workplace

Figure 2. Example of data integration of personal (A) and ambient (B) $PM_{2.5}$ ($\mu g/m^3$) monitoring, selected wearable camera annotations (C), GPS track (D), baseline questionnaire, LUR (E), and postmonitoring questionnaire (F) for one monitoring session. GPS track map (D) created with R (version 3.4.0) using Stamen Toner (OSM) as the background map.

resulting in >1 km separation between two points and cold start position acquisition (points >50 m from the house at the beginning of the session), which were removed.[15] We computed the distance from home (previously geocoded) at each point. We applied an automated map-matching algorithm[15,23] to identify locations visited as spatiotemporal clusters of points. Clusters at a linear distance smaller than 10 m from the geocoded residence were labeled as "home"; otherwise, they were labeled as a "place other than home". Points within 30 min and 10 m of a cluster were assumed to be part of the cluster. Points between locations, i.e., not belonging to any cluster, were classified as trips.

Wearable Cameras. Participants carried a wearable camera (Autographer, OMG Life, Oxford, UK) attached to a neck-worn lanyard that took a photograph approximately every 35 s (Figure 1S, SI). Participants were asked to turn off the cameras at night to conserve battery life (approximately 10 h) or whenever they wanted privacy. These images were annotated by trained staff using a series of nonexclusive labels to identify activities (e.g., eating), objects (e.g., biomass cooking unit), and surroundings (e.g., presence in industry) present in the photographs. Furthermore, a mutually exclusive location label was assigned to each picture (indoors, outdoors, in vehicle, or mixed, e.g., standing in a doorway). The resulting annotations were further processed to obtain a regular 1 min binary time series for each label, which could be present or absent at each time point. Examples of wearable camera photographs and details about wearable camera data collection and processing have been provided elsewhere.[14]

Land Use Regression (LUR). As a part of the CHAI project, we developed a LUR model to estimate ambient annual exposure to $PM_{2.5}$ at residence.[17] Variables included in the model were tree cover, vegetation, nighttime light intensity, and longitude. The adjusted R^2 of the model was 58%.[17]

Data Integration and Compliance. We built a set of relational databases that contained the final time series and tables. Out of the 271 monitoring sessions, we included 227 (83.3%, 50 unique participants) that met our criteria for compliance during the data collection (i.e., wore the backpack according to an accelerometer and did not report disruption of the monitoring). We designed an interactive Shiny app[24] to visualize the session profiles and to quality check data processing. Figure 2 shows an example of the integrated data for one of the monitoring sessions.

Analyses. We stratified all analyses by gender based on our previous work showing marked differences in activities and mobility patterns by gender.[15] We calculated descriptive statistics of individual and household characteristics reported in the baseline questionnaire (time-invariant) and variables based on 24-h monitoring sessions (time-varying). We calculated the intraclass correlation coefficient (ICC) of log-transformed 24-h average personal exposure. We computed a Spearman correlation matrix to assess the association between continuous predictors of exposure derived from different devices.

When? To compare the daily patterns in ambient and personal exposure to $PM_{2.5}$, we smoothed both time series using generalized additive models with a smooth term for the time of day, thereby obtaining the smooth means conditional

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Table 1. Characteristics of the Study Population and Measured Personal and Ambient $PM_{2.5}$

variable	men (n^a = 25, N^b = 110)	women (n^a = 25, N^b = 117)
age (years), mean (SD)	39.2 (16.4)	47.2 (9.1)
married, *n* (%)	16 (64)	19 (76)
education, *n* (%)		
illiterate	9 (36)	20 (80)
primary education	5 (20)	3 (12)
secondary education	8 (32)	2 (8)
superior education	3 (12)	0 (0)
occupation, *n* (%)		
housework, students, retired, and disabled	3 (12)	3 (12)
manual work	21 (84)	21 (84)
nonmanual work	1 (4)	1 (4)
active smokers, *n* (%)	6 (24)	0 (0)
primary stove used for cooking[c], *n* (%)		
biomass	14 (56)	4 (16)
LPG	19 (76)	24 (96)
other	4 (16)	5 (20)
modeled residential ambient $PM_{2.5}$ ($\mu g/m^3$), mean (SD)	32.9 (2.8)	33.1 (2.6)
number of monitoring sessions, mean (SD)	4.4 (2.1)	4.7 (1.9)
personal $PM_{2.5}$ (24-h session average, $\mu g/m^3$)		
mean (SD)	43.8 (24.6)	39.7 (12.0)
geometric mean (GSD)	40.1 (1.5)	38.2 (1.3)
ambient $PM_{2.5}$ (24-h session average, $\mu g/m^3$)		
mean (SD)	29.8 (13.9)	32.2 (16.9)
geometric mean (GSD)	27.3 (1.5)	29 (1.6)

[a]*n*: Number of participants. [b]*N*: Number of monitoring sessions. [c]More than one primary stove type could be reported.

on time. We used penalized cyclic cubic regression splines, which have the property of matching the first two derivatives at the upper and lower boundaries and thus are suitable for cyclic processes such as time within a day.[25] In order to evaluate differences in concentrations according to the time of the day without smoothing, we also produced boxplots by hour. We applied this analysis to the subset of valid sessions with at least 90% of 24-h coverage of $PM_{2.5}$ monitoring (192 sessions).

Where? To quantify the contribution of locations to personal exposure, we computed daily integrated exposures to $PM_{2.5}$ (in $\mu g/m^3$ h/d) according to three self-reported (hourly diary of locations) and GPS-derived locations: "home", "places other than home" and "trips". The "home" self-reported location was defined by "indoors home" and "compound" in the diary (compounds generally referred to the area in the near vicinity of the residences[15]), "trip" was defined as "travel" in the diary, and the rest of locations were considered "places other than home". To calculate daily integrated exposures, we first integrated concentrations measured in each location over the time spent there ($\mu g/m^3$ h). We then divided the integrated exposures by the total monitoring time to obtain the integrated daily exposures (units $\mu g/m^3$ h/day).[26] We also computed the average concentration in each location derived from both data sources. We applied this analysis to the subset of 161 valid sessions with at least 90% of 24-h coverage for collocated $PM_{2.5}$, GPS (both 1 min time series), and self-reported location (hourly diary of locations).

What? To identify the contribution of specific activities to daily average and hourly personal $PM_{2.5}$ exposure, we developed two data sets corresponding to the different $PM_{2.5}$ averaging times: 24-h average (one observation per session) and hourly average (one observation per hour per session). The hourly average data set was restricted to daytime hours (8 a.m.−8 p.m.) because of the lack of wearable camera data at night. In the 24-h analysis, daytime was only considered for wearable-camera-derived indicators, thereby reflecting the daytime contribution to the 24-h exposure. The amount of missing data in both data sets is included in Table 1S (SI). We multiply imputed missing data in both data sets using the method of chained equations.[27] More details about data availability, representation thresholds, and imputation methods are given in Methods 1S (SI). In order to identify sources of personal exposure to log-transformed $PM_{2.5}$, we used linear mixed model forward stepwise model selection on the full set of predictors coming from the different devices. This analysis was done at both time resolutions, taking into account the presence of multiply imputed data, the repeated measures design, and temporal autocorrelation. Details about the model selection methods are given in Methods 2S (SI). We computed the marginal R^2[28] of the models fitted in each of the imputed data sets. All 227 compliant sessions were included in the analysis.

Data cleaning and integration, analyses, and most figures were done in R 3.4.0[29] using several packages.[30−37] GPS data were processed using ArcGIS (v10.2.1), Spatialite (v4.1.1), and QGIS (v2.12.3 Lyon) software.

RESULTS

There were equal number of male and female participants; the number of monitoring sessions was also similar for men and women (Table 1). A total of 84% of the participants lived in a stand-alone house. Dwellings were made of *kutcha* (mud brick, 6%), *pucca* (solid materials, e.g., concrete, brick, 36%), or *semipucca* (a combination of the two, 58%) and were generally well ventilated. Women were older and had lower levels of literacy than men. The majority of participants had a manual occupation (84%); the most frequent sectors were agriculture (38%), construction and industry (14%), and unskilled jobs

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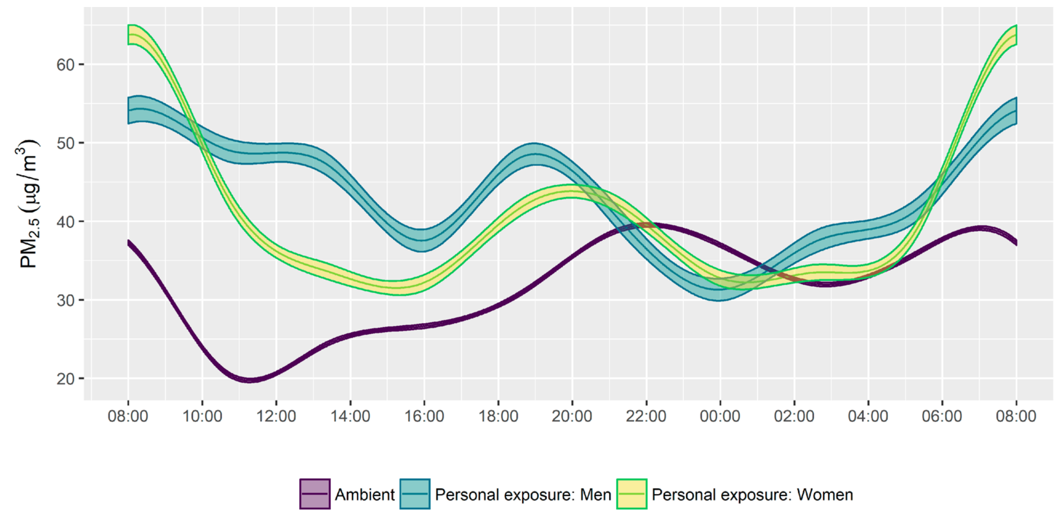

Figure 3. Temporal patterns of ambient and personal $PM_{2.5}$ stratified by gender. Analysis for the 192 valid sessions with at least 90% of 24-h coverage for $PM_{2.5}$ monitoring. Smoothed means and 95% CI estimated using a generalized additive model with a smooth term for the time of day.

Table 2. Average Concentration, Daily Integrated $PM_{2.5}$ Exposures, and Time Spent According to Self-Reported (A) and GPS (B) Locations[a]

location	average concn (μg/m^3) mean (SD)	average concn (μg/m^3) GM (GSD)	time (h/d)	% time	% daily integrated exposure
A. Self-Reported[b] Locations					
Men					
home	41.8 (28.1)	37.5 (1.5)	16.4 (4.4)	68.3 (18.4)	66.1 (21.4)
places other than home	47.0 (30.2)	42.4 (1.5)	6.4 (4.1)	26.6 (17.1)	28.7 (20.5)
trip	42.5 (19.8)	39.3 (1.5)	1.2 (1.7)	5.0 (7.1)	5.2 (7.3)
Women					
home	40.2 (12.3)	38.6 (1.3)	20.8 (3.6)	86.8 (15.2)	87.7 (14.4)
places other than home	34.6 (8.1)	33.8 (1.2)	3.1 (3.6)	13.0 (14.8)	12.0 (14.1)
trip	33.1 (2.9)	33.0 (1.1)	0.1 (0.3)	0.3 (1.3)	0.3 (1.3)
B. GPS[c] Locations					
Men					
home	41 (27.7)	37.1 (1.5)	16.5 (4.6)	68.8 (19.2)	66.5 (22.7)
places other than home	50.1 (38.5)	42.3 (1.7)	4.7 (4.3)	19.4 (18.1)	22.2 (22)
trip	38.4 (12.8)	36.7 (1.3)	2.8 (2.2)	11.8 (9.4)	11.3 (9.5)
Women					
home	40.7 (13.6)	38.9 (1.3)	21.0 (4.0)	87.4 (16.5)	88.6 (14.8)
places other than home	31.8 (4.8)	31.4 (1.2)	2.4 (3.4)	9.9 (14)	8.8 (12.4)
trip	35.4 (8.2)	34.6 (1.2)	0.6 (0.9)	2.7 (3.8)	2.6 (3.6)

[a]Analysis for the 161 valid sessions with at least 90% of 24-h coverage for collocated personal $PM_{2.5}$, GPS, and self-reported locations. Data reflect the mean (SD) unless otherwise stated. [b]Self-reported locations derived from participant's diary. [c]GPS locations derived with an automated map-matching algorithm applied to the GPS tracks.

involving tasks such as loading and unloading weights, sweeping, or ground leveling and digging (26%). Most participants reported a liquefied petroleum gas (LPG) stove (86%) as their primary stove. Regular outdoor cooking was reported by 56% of the participants and 60% reported occasional nonvented indoor cooking. Session-averaged 24-h $PM_{2.5}$ personal exposures (mean 41.7 μg/m^3) were generally higher than session-averaged 24-h (mean 31.1 μg/m^3) and modeled long-term residential (mean 33 μg/m^3) ambient $PM_{2.5}$. Personal exposures were more variable for men than for women. The ICCs of the log-transformed 24-h average personal exposures were 0.3% for men and 2.4% for women, reflecting high day-to-day variability within participants.

Summary statistics of time-varying exposure predictors are included in Table 2S (SI). Most of the monitoring sessions occurred during working days (84.6%) and the monsoon season (42%). Men worked more hours than women [self-reported mean (SD): 5.2 (4.6) and 2.1 (3.0), respectively]. Women self-reported cooking for 1.9 (1.2) h/d [compared to 0.1 (0.3) in men]. Only men were found in occupational industrial settings [wearable camera, mean hours (SD): 1.7 (3.3)], but they were less often engaged in agricultural activities than women [wearable cameras: 0.6 (1.9) and 1.5 (2.8), respectively]. Moderate to high correlations were found between similar indicators coming from different data sources (Figure 3S, SI). For example, time spent cooking in the postmonitoring questionnaire and in the wearable cameras correlated moderately (0.56).

When? Results in Figure 3 indicate that personal exposure to $PM_{2.5}$ was generally higher than ambient exposure except at

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Table 3. Percent Change in Personal $PM_{2.5}$ According to Predictors of 24 h (A) and 1 h (B) Average Exposure[a]

predictor	data source	% change (95% CI)[b]
	A. 24-h Average	
	Men (N = 110)	
log-transformed ambient $PM_{2.5}$ [log(μg/m^3)]	ambient	40.1 (9.4, 79.4)
season: postmonsoon (ref.: monsoon)	ambient	−7.4 (−24.2, 13.1)
season: summer (ref.: monsoon)	ambient	20.9 (−12.7, 67.5)
season: winter (ref.: monsoon)	ambient	25.2 (2.2, 53.5)
working in a mill or kiln (h)	postmonitoring[c]	17.2 (8.9, 26.1)
smoking (h)	camera	38.4 (9.1, 75.6)
presence on road (h)	camera	−3.7 (−7.7, 0.6)
	Women (N = 117)	
log-transformed ambient $PM_{2.5}$ [log(μg/m^3)]	ambient	32.9 (17.5, 50.2)
season: postmonsoon (ref.: monsoon)	ambient	4.6 (−6.5, 16.9)
season: summer (ref.: monsoon)	ambient	1.9 (−13, 19.4)
season: winter (ref.: monsoon)	ambient	18.2 (4.9, 33.3)
biomass stove at home (h)	postmonitoring	19.2 (3.1, 37.9)
mixed location (h)	camera	17 (2.4, 33.6)
presence in the kitchen (h)	camera	2.8 (0.5, 5.1)
	B. Hourly average (daytime hours)	
	Men (N = 1184)	
log-transformed ambient $PM_{2.5}$ [log(μg/m^3)]	ambient	8.7 (2.8, 14.9)
season: postmonsoon (ref.: monsoon)	ambient	7 (−7.2, 23.3)
season: summer (ref.: monsoon)	ambient	9.9 (−8.6, 32.1)
season: winter (ref.: monsoon)	ambient	37.6 (22.3, 54.7)
education: primary school (ref.: illiterate)	baseline[d]	−17.8 (−32.2, −0.3)
education: secondary school (ref.: illiterate)	baseline	−9.5 (−21.8, 4.7)
education: superior studies (ref.: illiterate)	baseline	−20 (−34.1, −2.9)
presence in the kitchen (h)	camera	66.9 (27.5, 118.6)
food preparation (h)	camera	184.4 (80.6, 347.9)
smoking (h)	camera	90.7 (12.8, 222.6)
presence in industry (h)	camera	20.4 (7, 35.4)
presence at work field (h)	camera	−14.3 (−26.1, −0.6)
presence at an office or shop (h)	camera	19.5 (0.3, 42.4)
	Women (N = 1228)	
log-transformed ambient $PM_{2.5}$ [log(μg/m^3)]	ambient	5.3 (0.5, 10.3)
season: postmonsoon (ref.: monsoon)	ambient	9.9 (0.6, 20)
season: summer (ref.: monsoon)	ambient	2.4 (−8.3, 14.3)
season: winter (ref.: monsoon)	ambient	25.3 (15.9, 35.5)
median distance from home (km)	GPS	−4.5 (−8, −0.9)
food preparation (h)	camera	51 (31.7, 73.2)
visible flame or smoke (h)	camera	689.9 (50.3, 4052.1)
biomass cooking unit (h)	camera	60.6 (4.7, 146.2)
presence in the kitchen (h)	camera	11.5 (1.9, 21.9)

[a]Models fit to multiply imputed data sets. [b]Percent change in exposure associated with a given predictor is $[\exp(\beta) - 1] \times 100$ per 1 μg/m^3 log-transformed ambient $PM_{2.5}$, 1 h of activity (continuous wearable camera and postmonitoring predictors), 1 km distance from home (continuous GPS predictor), or with respect to reference category (categorical variables). [c]Postmonitoring refers to questionnaire administered following each monitoring session (time-varying). [d]Baseline refers to questionnaire administered prior to monitoring (time-invariant).

nighttime. While women had a peak in the exposures in the morning (7−9 a.m.), men tended to have higher personal exposure during the rest of the day compared to women. Personal exposures for both genders were higher between 6 and 9 p.m. During the night, personal exposures remained mostly stable. Daily patterns of self-reported activities included in Figure 4S (SI) show that peak exposures in the morning and evening coincided with cooking times and that men were more engaged in formal work during the day. The personal $PM_{2.5}$ distribution (Figure 5S, SI) was highly skewed and reflected the presence of exposure peaks in $PM_{2.5}$ time-resolved data.

Where? The contributions of locations to daily integrated personal exposure are shown in Table 2 (detail at the monitoring session level included in Figure 6S, SI). According to self-reported locations, 66% of men's exposure occurred at home, 29% occurred in places other than home, and 5% during trips. For women, 88% of exposure occurred at home. The contribution of trips was higher when based on GPS data, reaching 11% for men. The relative proportions of exposure occurring in different locations according to both self-reported diary and GPS were proportional to the time spent in each of the locations. As defined by GPS, while average concentrations at home and during trips were similar for both genders, men experienced substantially higher and more variable $PM_{2.5}$ levels in places other than home: mean 50.1 (SD 38.5) μg/m^3 for men and 31.8 (4.8) μg/m^3 for women.

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What? Ambient concentration and season of monitoring were important predictors of 24-h average exposure for both men and women (Table 3). Exposures were the highest in winter. Other factors for men were the number of hours reported working in a rice mill or a brick kiln [17.2% (95% CI 8.9, 26.1) increase in 24-h average exposure per additional hour spent working] and time in the vicinity of smoking according to the wearable camera annotations [38.4% (95% CI 9.1, 75.6) increase per hour in which smoking is observed in the photo]. For women, 24-h average exposure was influenced by self-reported time using a biomass stove [19.2% (95% CI 3.1, 37.9) increase per hour cooking] and time spent in the kitchen [2.8% (95% CI 0.5, 5.1) increase]. Time spent in a mixed location was associated with a 17% increase (95% CI 2.4, 33.6) in 24-h exposure per hour in a mixed location. Mean marginal R^2 for men's models was 0.48 (SD 0.07) and women's was 0.51 (SD 0.04).

A broader range of predictors were identified for hourly average $PM_{2.5}$ (Table 3). Most variables were derived from the wearable camera annotations. For men, predictors with the largest effect estimates related to time spent near cooking-related activities (food preparation, presence in the kitchen) and time in the vicinity of smoking. Time spent in occupational settings was also influential (presence in industry, presence in office or shop, working in the field). For women, the strongest predictors were related to cooking (visible flame or smoke, biomass cooking unit, food preparation). The effect of time spent in the kitchen for women was more modest compared to men. Increasing the distance from home was associated with lower hourly $PM_{2.5}$ exposure [4.5% decrease (95% CI −8.0, −0.9) per km]. Even though some of these effects were very large (e.g., visible flame or smoke), the activity would rarely occur for an entire hour (Table 2S, SI). While ambient concentrations were also predictive of hourly personal exposure, the size of the coefficient was considerably smaller than for 24-h average exposure for both genders. For most predictors, complete case estimates were similar to the multiply imputed ones, which generally had slightly greater standard errors (Table 3S, SI). Mean marginal R^2 for daytime hourly models were smaller than for 24-h models: 0.22 (SD 0.01) for men and 0.24 (SD 0.02) for women.

■ DISCUSSION

Our results identify multiple factors influencing personal $PM_{2.5}$ exposure in a sample of the general population in periurban India. Our analysis resulted in three main findings. First, personal exposures to $PM_{2.5}$ were greater than ambient concentrations during daytime and temporal patterns in exposure varied between women (peak exposure in the morning) and men (more exposed during the rest of the day). Second, the percentage of the daily integrated exposure measured at home was 67% for men and 89% for women, which was proportional to the time spent in this location. Third, ambient $PM_{2.5}$ was an important predictor of 24-h average personal exposure for both genders but was less relevant as a predictor of hourly average exposure, which was more influenced by specific activities. Among men, a range of activities was predictive of higher hourly average exposure, including presence near food preparation, in the kitchen, in the vicinity of smoking, or in industry. For women, activities predictive of exposure were largely related to cooking.

Analysis of temporal patterns of personal exposure revealed that $PM_{2.5}$ personal exposures were above ambient levels during daytime, but not nighttime, when the two converged. This difference was explained by participants' activities during the day, which resulted in higher levels of exposure compared to background $PM_{2.5}$. Similar results have been found in low-middle income countries comparing personal and ambient $PM_{2.5}$.[11,38] Comparable levels of personal and ambient $PM_{2.5}$ at night were likely due to well-ventilated buildings and the lack of indoor sources at night. Furthermore, differences in temporal patterns of personal exposure between genders reflected different daily routines: women were engaged in cooking activities while men worked more outside the home during the day, a pattern observed broadly across India.[39]

Self-reported and GPS locations were not associated with large differences in exposure within genders, resulting in location contributions to the daily integrated exposure proportional to the time spent in each of them. This agrees with some studies in high-income countries[26] but contrasts with others[8] in which transport microenvironments accounted for a large fraction of the total exposure. This could be explained by the periurban nature of the study area, in which traffic is modest and was not identified as a predictor of local spatial variation in ambient $PM_{2.5}$.[17] Between genders, we detected differences both in magnitude and variability of the average concentration in places other than home. Greater concentration mean and variability for men could be explained by the broader range of locations visited (e.g., outdoor, office, and workplace), including those more prone to high exposures (e.g., industry). In contrast, women's exposure in locations other than home occurred mostly in outdoors settings. Indeed, subsequent results identified distance from home as being associated with a lower hourly exposure in women.

A number of factors were predictive of personal exposure to $PM_{2.5}$. Time-varying ambient $PM_{2.5}$ was strongly predictive of 24-h average personal exposure. This agrees with a recent study in New Delhi, India[40] (n = 18), in which 48-h personal exposure to $PM_{2.5}$ correlated strongly with ambient $PM_{2.5}$ (R^2 = 0.51 in winter season and 0.21 in summer). Ambient $PM_{2.5}$ was less predictive of hourly personal exposure, likely due to the greater variability in exposure at this time scale. Winter season was associated with the highest personal exposures, independent of ambient concentrations, similar to results reported for a small cohort of healthy adults with no occupational exposure in New Delhi.[40] In spite of the repeated-measures study design, long-term $PM_{2.5}$ concentrations at residence estimated with a LUR model were not predictive of personal exposure. This lack of association between LUR estimates of exposure and personal $PM_{2.5}$ has been reported in other studies[41,42] and likely reflects the large day-to-day variability in personal exposure in our study population. Most predictors of personal exposure for women related to cooking activities, which is consistent with a previous study in rural India[43] that reported differences in women's exposure depending on the fuel and stove type, cooking duration, and time near stove. Male participant exposures to fine particles were also influenced by cooking, although they did not report being actively involved in it,[14] consistent with previous research in a similar population.[44] Indeed, the effect of the time spent in the kitchen was greater for men than women, possibly reflecting their presence in the environment during or shortly before meals while women also spent time there when cooking was not taking place. In addition to smoking, working in a mill or brick kiln was predictive of higher 24-h $PM_{2.5}$ among male participants in our study,

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highlighting the important contribution of occupational exposures in a sample of the general population.

We used a range of data sources with varying time resolution and included both objective and self-reported data. With the exception of time-resolved ambient concentrations, most predictors of 24-h and daytime hourly $PM_{2.5}$ exposure were derived from wearable camera data. One-minute time-resolved wearable camera data allowed detecting activities and sources of exposure that occurred for short durations. For example, the indicator "visible flame or smoke" was able to pinpoint peak exposures related to cooking for hourly $PM_{2.5}$ exposure in women. These data also captured contextual information important to understand personal exposure, such as presence in the vicinity of cooking for men. Almost all of the personal exposure variability was within participant, possibly because most participants in our study population cooked with multiple stove types and had several occupations throughout the year. Nevertheless, time-resolved ambient $PM_{2.5}$ and wearable camera data allowed us to explain approximately 50% of the variation in 24-h average exposure. As a comparison, a study that measured 62 nonsmoking pregnant women in Canada in one to three 48-h monitoring sessions[42] developed a prediction model for personal exposure to fine particulate matter with a self-reported diary of activities and locations and ambient monitoring that explained 29% of the exposure variability. In another study measuring 56 students from eight schools in Ghana, models predicting 24-h personal exposure to $PM_{2.5}$ using fixed household indicators as well as ambient concentrations, meteorology, and GPS-derived distance from several sources during the day, achieved a conditional R^2 of 0.62.[11] Finally, a study on 200 women cooking with biomass fuels in Sichuan, China, explained 52% of the variability of 48-h $PM_{2.5}$ exposure in winter and 43% in summer using household indicators, meteorology, and ambient concentrations.[38] However, none of these studies focused on a general population, in which variability in exposure is likely greater than more homogeneous subgroups.

The main strength of this study is the combination of time-resolved objective data from four different sources: personal $PM_{2.5}$, ambient $PM_{2.5}$, GPS, and wearable cameras. Another strength is the repeated measures design, which is useful to describe time-varying patterns with large day-to-day variability. We have taken a data-driven approach when analyzing the data: rather than focusing on a particular setting, gender, or exposure source, we have included multiple potential drivers of exposure in a sample of the general population and allowed the data to identify relevant factors. All data were extensively processed to ensure quality, and when possible, we made public repositories of the code used to process the data and created vignettes to orient future researchers,[20,37,45] thus contributing to open science.

A limitation of integrating multiple types of data is the relatively high percentage of sessions with missing data. However, we used multiple imputation methods to minimize the impact of missing data, and our results were similar when using multiply imputed and complete case data sets. The limited battery life of the wearable cameras (around 10 h) and uncodable images due to poor lighting conditions limited the use of those data to daytime hours. Nonetheless, temporal patterns in exposure suggest no major sources of exposure at night, and activities were mostly sedentary and could be tracked using self-reported data. The wearable cameras collected information restricted to the camera's field of view (180°); however, the sampling rate of the camera was high and was able to capture contextual information relevant to exposure. Another potential concern is selection bias in the panel sample or Hawthorne effect[46] due to the wearable cameras. We examined those issues in a previous study[14] and found that the panel population was similar to the APCAPS cohort and that participants with wearable cameras had similar activity patterns than nonmonitored participants.

Our results highlight the potential for a range of measures operating at different scales to reduce exposure to particulate air pollution in this population. Regional-scale measures are likely required to substantially reduce ambient $PM_{2.5}$ concentrations.[16] Interventions to improve access to clean cooking can be expected to reduce exposures in women and also reduce high peak exposure for men when in the presence of, but not actively engaged in, cooking. Our results also highlight the importance of occupational exposures in men in this population, which could be reduced through improved occupational hygiene. Finally, individual-level behavior change to promote smoking cessation could be expected to reduce air pollution exposure for men, among other obvious health benefits.

Our analysis demonstrates the potential of integrating multiple sources of objective data to gain insights into drivers of personal exposure. These insights may inform prioritization of air pollution control measures, as well as identify potential exposure misclassification in epidemiological studies based on ambient concentrations at residence or modeled household concentrations. The three main analyses presented (when, where, what) show an increasing degree of detail and a greater understanding of the personal exposure in this population. However, they also require an increasing amount of field work and data processing. Currently, this data-intensive approach is only feasible on relatively small numbers of people, but studies with a larger number of participants are to be expected in the future with increasing automation of data processing.[47] In that context, this work serves as an early example of what exposure assessment may look like in the future years of environmental epidemiology research.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.8b03075.

Photo of a participant of the study carrying the different monitoring devices, study area and ambient monitoring map; proportion of missing data for each of the data sources, methods used in data imputation and model selection, distribution of time-varying exposure predictors, pairwise Spearman correlation between continuous predictors, temporal patterns of hourly self-reported activities, hourly boxplots of $PM_{2.5}$ ambient and personal concentrations, contributions to daily integrated personal $PM_{2.5}$ exposure at a monitoring session level, percent change in personal $PM_{2.5}$ according to predictors of 24 h and 1 h $PM_{2.5}$ average exposure in models (complete cases) (PDF)

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Notes

The authors declare no competing financial interest.

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