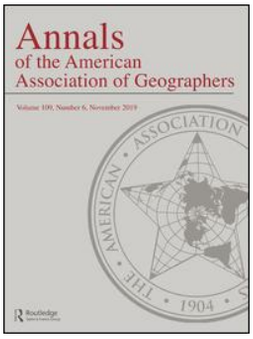

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Assessing Mobility-Based Real-Time Air Pollution Exposure in Space and Time Using Smart Sensors and GPS Trajectories in Beijing

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Using real-time data from portable air pollutant sensors and smartphone Global Positioning System trajectories collected in Beijing, China, this study demonstrates how smart technologies and individual activity-travel microenvironments affect the assessment of individual-level pollution exposure in space and time at a very fine resolution. It compares three different types of individual-level exposure estimates generated by using residence-based monitoring station assessment, mobility-based monitoring station assessment, and mobility-based real-time assessment. Further, it examines the differences in personal exposure to $PM_{2.5}$ associated with different activity places and travel modes across various environmental conditions. The results show that the exposure estimates generated by monitoring station assessment and real-time sensing assessment vary substantially across different activity locations and travel modes. Individual-level daily exposure for residents living in the same community also varies significantly, and there are substantial differences in exposure levels using different approaches. These results indicate that residence- or mobility-based monitoring station assessments, which cannot account for the differences in air pollutant exposures between outdoor and indoor environments and between different travel-related microenvironments, could generate considerably biased estimates of personal pollution exposure. *Key Words: indoor environment, real-time exposure to air pollution, smart technologies, travel modes, the uncertain geographic context problem.*

本研究运用可携式空气污染感应器与手机全球定位系统轨迹在中国北京所搜集的实时数据，在极细微的分辨路上展现智慧科技与个人的活动—旅行之微观环境，如何影响个人层级在时空中的污染暴露量。本研究比较通过运用以居住为基础的监测站评估、根据移动的监测站评估，以及根据移动的实时评估所产生的污染暴露估计。此外，本研究检视与横跨各种环境条件的不同活动场所和旅行方式有关的$PM_{2.5}$个人暴露量。研究结果显示，由监测站评估和实时感应评估所生产的暴露估计量，在不同的活动地点和旅行模式之间有着显着的差异。居住在相同社区中的个人层级每日暴露量差异显着，且运用不同的方法亦会得到显着的暴露层级差异。这些研究结果意味着，以居住或移动为基础的观测站评估，无法考量室内与室外环境、以及与旅行相关的微观环境之间的空气污染暴露的差异，因而可能产生个人污染暴露量的大幅偏误。*关键词：室内环境，实时空气污染暴露，智慧科技，旅行方式，不确定的地理脉络问题。*

Usando datos de tiempo real de sensores portátiles de contaminantes aéreos y de trayectorias de Posicionamiento Global de teléfonos inteligentes, recogidos en Beijing, China, este estudio demuestra cómo las tecnologías inteligentes y los microambientes de actividad viajera individual inciden sobre la evaluación de exposición a la contaminación a nivel de individuo en el espacio y en el tiempo, a resolución muy fina. El estudio compara tres tipos diferentes de estimativos de exposición a nivel individual, generados mediante el uso de evaluación de la residencia a partir de una estación de monitoreo, evaluación de estación de monitoreo basada en movilidad, y evaluación en tiempo real basada en movilidad. Además, se examinan las diferencias de exposición personal al $PM_{2.5}$ asociada con diferentes lugares de actividad y modos de viaje a través de varias condiciones ambientales. Los resultados muestran que los cálculos de exposición generados por evaluación con estaciones de monitoreo y la evaluación por sensación en tiempo real varían sustancialmente a través de diferentes localizaciones de actividad y modalidades de viaje. La exposición diaria a nivel de individuo para residentes que habitan en la misma comunidad también varía significativamente y

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hay diferencias sustanciales en los niveles de exposición cuando se usan diferentes enfoques. Estos resultados indican que la residencia o las evaluaciones con estaciones de monitoreo basadas en movilidad, que no puede responder por las diferencias en exposición a contaminantes aéreos entre ambientes interno y externos y entre diferentes microambientes relacionados con viajes, podrían generar cálculos considerablemente sesgados de exposición personal a la contaminación. *Palabras clave: ambiente interior, exposición a la contaminación aérea en tiempo real, modos de viaje, problema de contexto geográfico incierto, tecnologías inteligentes.*

Air pollution and its adverse health effects are a major health concern worldwide. Health geographers and public health researchers have conducted pollution exposure assessment for decades. Many epidemiological studies, for instance, have examined people's exposure to air pollution and its health effects using air quality data obtained from stationary monitoring stations and a static residence-based approach. In these studies, people who live in the same area (e.g., in the same residential neighborhood) are assigned the same value of air pollution exposure derived from stationary and sparse monitoring stations (Jerrett et al. 2005; Hoek et al. 2013; Kumar et al. 2015). Using such geographic areas as contextual units, residence-based exposure assessments are suitable for large population-based studies and long-term monitoring of outdoor air pollution (Monn 2001; Steinle, Reis, and Sabel 2013).

Studies based on this static residence-based approach have several limitations, however, that might undermine the reliability of their findings. For instance, they ignore human mobility and thus do not take into account people's exposures to environmental contexts besides their residential neighborhood and variations in personal exposure for people living in the same residential neighborhood. They use sparse stationary monitoring station data that do not accurately capture the space–time dynamics of air pollution. The uneven geographic distribution of stationary and sparse monitoring stations might introduce considerable uncertainty during the exposure modeling process (Avery et al. 2010; Gray, Edwards, and Miranda 2013). Because individuals are mobile in space and time and often undertake activities outside of their residential neighborhood, personal air pollution exposure is influenced by the complex interactions between the spatiotemporal dynamics of air pollution and human mobility. The static residence-based approach ignores individuals' space–time behaviors and, as a result, its use could lead to biases in exposure assessments and health effect estimates (Lu and Fang 2015; Chen, Song, and Jiang 2018).

As some recent studies indicate, past research that ignores human mobility and uses sparse stationary monitoring station data could face two major methodological issues that are especially relevant when assessing individual exposure to air pollution: the uncertain geographic context problem (UGCoP) and the neighborhood effect averaging problem (NEAP). The UGCoP is the problem that the use of different delineations of spatiotemporal contexts could lead to different research findings about the health effects of environmental influences on individuals (Kwan 2012; J. Wang and Kwan 2018; Zhao, Kwan, and Zhou 2018; Kwan et al. 2019), and the NEAP is the problem that ignoring people's daily mobility and exposures to nonresidential contexts could lead to biased estimations of personal exposure and the neighborhood effect (Kwan 2018a, 2018b; Kim and Kwan 2019).

There are growing concerns with addressing these methodological issues through reducing potential biases and increasing the accuracy of pollution exposure assessment in recent years. This has contributed to the development of mobility-based dynamic exposure assessment that simultaneously considers the spatiotemporal variability of air pollutant concentrations and human mobility (Yoo et al. 2015; Park and Kwan 2017). Increasing the accuracy of pollution exposure assessment is important because it can help improve our understanding of the impacts of exposure to air pollutants (e.g., fine particulates) on human health and well-being, especially for vulnerable or disadvantaged groups such as young children, the elderly, pregnant women, and people with respiratory or cardiovascular diseases (Yoo et al. 2015).

The rapid development and widespread use of smart technologies—such as wearable location-aware devices like Global Positioning System (GPS) devices, smartphones, and air quality sensors—in recent years have greatly facilitated the development of mobility-based dynamic assessment of personal exposures to air pollution. These technologies have considerably advanced the acquisition of accurate

data on human space–time behaviors at fine spatiotemporal resolutions (J. Wang, Kwan, and Chai 2018). They could provide detailed space–time information essential for personal exposure assessment and have been increasingly used in geographic and epidemiological research (Castell et al. 2017; Jerrett et al. 2017; Rai et al. 2017; Caryl et al. 2019; Kwan et al. 2019).

Using GPS devices or smartphones, the potential biases and inaccuracy in assessments of personal exposure to air pollution can be mitigated. First, human mobility can be taken into account in exposure assessments. For instance, individual-level information on travel modes and activity type, location, time, and duration can be spatiotemporally linked to pollution concentrations derived from stationary monitoring stations (Nazelle et al. 2013). Some research indicated that individual-level exposure estimates could differ substantially for residents living in the same neighborhood, mainly due to their different movement trajectories (Dons et al. 2011; Yoo et al. 2015; Park and Kwan 2017). Compared to the conventional static residence-based approach, such mobility-based monitoring station assessment provides improved personal exposure estimates by considering individuals' daily mobility (Kwan 2013).

This mobility-based monitoring station approach still has two limitations, however—that is, the dependence on the air quality data from a limited number of monitoring stations and inability to account for the differences in air pollutant concentrations between outdoor and indoor environments—that can also be mitigated by deploying smart technologies (Fang and Lu 2012). Because people generally spend most of their time in indoor environments, using only their outdoor exposures could lead to erroneous personal exposure assessments (Hoek et al. 2013). People's indoor pollution exposures might be independent of or quite different from the outdoor environments because it depends on specific indoor factors like ventilation, air conditioning, and the concentrations of harmful substances from sources like tobacco smoke, cooking, and heating with solid fuels or natural gas (Steinle, Reis, and Sabel 2013; Q. Wang et al. 2019). Indoor pollution exposure should thus be an important element in personal exposure assessments, and it has received increasing attention in research and policymaking in recent years (Zou et al. 2009; Steinle, Reis, and Sabel 2013). Moreover, there is great variability in air pollutant concentrations within different transportation modes or travel microenvironments (e.g., traveling in a bus, subway, or a private car), which have been found to play an important role in personal exposure assessment (e.g., Adams et al. 2001; Kaur, Nieuwenhuijsen, and Colvile 2007; Huang et al. 2012; Cepeda et al. 2017).

Thus, to also take into account individuals' exposures to air pollution in specific indoor and travel microenvironments, smart sensing technologies (e.g., air pollutant sensors) can be used to directly measure personal real-time pollution exposure (Mead et al. 2013; Piedrahita et al. 2014). Portable air pollution sensors integrated with GPS can simultaneously monitor individuals' geographic locations and measure real-time pollutant concentrations in individuals' immediate surroundings at very fine spatiotemporal resolutions (Panis 2010; Lu and Fang 2015). Compared with residence-based or mobility-based monitoring station assessments, mobility-based real-time assessments (RTAs) can take into account the differences in personal exposures between indoor and outdoor environments and between different transportation modes or travel microenvironments, as well as the differences due to the use of individual protective measures (e.g., using an air purifier at home, reducing travel, or changing travel modes; Steinle, Reis, and Sabel 2013; Jiao, Xu, and Liu 2018). Note that some studies have observed considerable differences between personal real-time exposures derived from portable sensors and modeled exposures derived from stationary monitoring station data, thus indicating the need for the use of smart sensors in personal exposure assessment (Nieuwenhuijsen et al. 2015). Moreover, because smart sensors can provide real-time information on pollutant concentrations at very high spatiotemporal resolutions (ranging from one-second intervals to several minutes), the information they provide allows people, especially those already at risk, to make informed decisions to effectively avoid high pollution exposure (Kumar et al. 2015). Possibly due to the high cost and additional efforts involved in research using wearable tracking and sensing devices (Gerharz, Antonio, and Klemm 2009), however, studies that analyzed and compared personal mobility-based real-time air pollution exposure at very fine spatiotemporal resolutions in various indoor and outdoor environments have been limited to date, particularly in developing countries like China.

In this research, we use smart technologies and advanced geospatial methods to examine how individuals' space–time behaviors and the spatiotemporal dynamics of air pollutant concentrations in different microenvironments influence individual-level real-time exposure in space and time. Using data collected with GPS devices, activity-travel diaries, and wearable air pollutant sensors in Beijing from December 2017 to February 2018, we compared three different types of exposure estimates at both the activity and travel episode level and the individual level generated by residence-based monitoring station assessment, mobility-based monitoring station assessment, and mobility-based RTA. Further, we examined the differences in personal exposure to fine particulates between different activity places (e.g., homes, workplaces, shops, and outdoor locations) and different travel modes (e.g., walking, cycling, public transport, and private car) across various environmental conditions (e.g., on lightly or heavily polluted days) in Beijing, China. The results indicate that the exposure estimates obtained by assessments based on monitoring station data and real-time data vary substantially between different activity locations and travel modes. There are also substantial differences in personal exposure levels between estimates obtained from different approaches, suggesting that the residence- or mobility-based monitoring station assessments could generate considerably biased estimates of personal pollution exposure. This study illustrates how smart technologies can help us analyze and visualize personal pollution exposure in space and time at very high resolutions, which in turn helps address both the UGCoP and the NEAP.

Method

Study Area and Data

Air pollution is a major environmental problem and public health concern in Beijing. With an annual average $PM_{2.5}$ concentration of above 80 $\mu g/m^3$ in 2015, the air quality in Beijing was among the worst in the world (Ma et al. 2017). Air pollutant concentrations vary spatially and temporally in Beijing, with frequent high pollution and persistent smog episodes in winter. This study focuses on the Meiheyuan community, which is located in the inner suburban area of northern Beijing, adjacent to the railway, highway, the Fifth Ring Road, and some other pollution sources (Figure 1). Housing types in this community are diverse, including price-controlled commercial housing and low-rent housing for low- or medium-income residents and *danwei* housing for employees allocated by their work units at discounted prices (Y. P. Wang and Murie 2011). Using the Meiheyuan community as a case study, we aim to highlight the differences in individual-level pollution exposure obtained from different exposure assessments for residents living in the same residential neighborhood.

The survey was conducted in Meiheyuan from December 2017 to February 2018. Using a stratified sampling approach, we recruited a total of 117 residents aged eighteen to sixty years old to participate in the survey via six waves. Smart air pollutant sensors, GPS tracking devices, and activity-travel diaries were used together to collect data on individuals' space–time behaviors and real-time exposures to fine particulates ($PM_{2.5}$). Specifically, each participant was asked to carry a GPS-equipped smartphone and a portable air pollutant sensor all the time over a continuous forty-eight-hour period that covers a workday and a weekend day (e.g., Friday and Saturday or Sunday and Monday). The GPS trajectories and real-time $PM_{2.5}$ concentrations in each participant's immediate surroundings were recorded simultaneously at one-second intervals. Moreover, each respondent was asked to complete a questionnaire and a two-day activity-travel diary that collected information about their sociodemographic attributes, health status, activities, and travels (e.g., activity types, places visited, and travel modes used). Finally, the survey obtained valid data from 112 participants. Table 1 presents the sociodemographic characteristics of the participants. In addition, hourly data on $PM_{2.5}$ concentrations from the thirty-five stationary monitoring stations in Beijing were also collected for the corresponding survey days and used in this research.

Procedure

In this study, we aim to compare three different types of exposure estimates generated by using residence-based monitoring station assessment, mobility-based monitoring station assessment, and mobility-based RTA. For the residence-based approach, we assumed that participants are nonmobile and used their residential location as their single spatial location throughout the day (Figure 2A). We first used

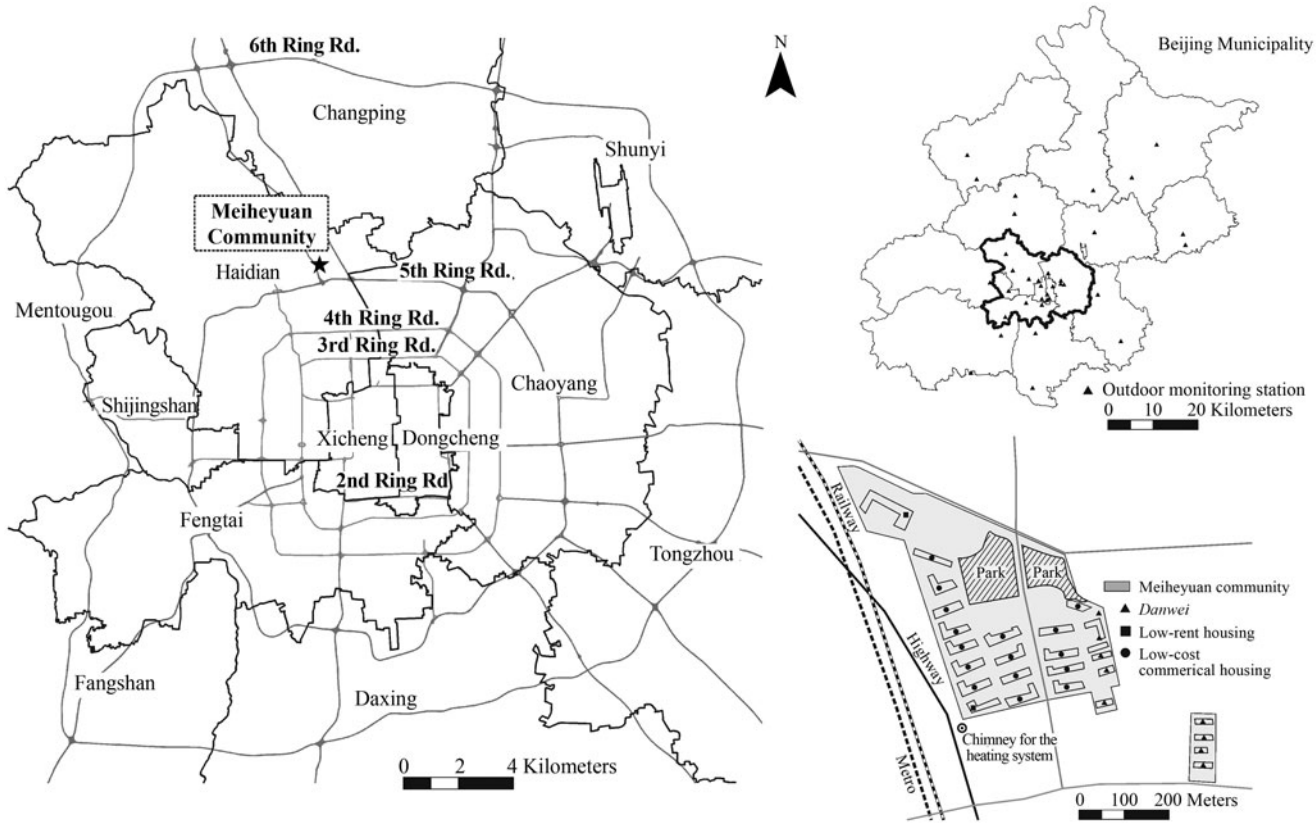

Figure 1. The study area.

Table 1. Key sociodemographic attributes of the survey participants

Variable	Description	*N*	Proportion (%)
Gender	Male	54	48.2
	Female	58	51.8
Age	18–30	20	17.9
	30–49	65	58.0
	50–60	27	24.1
Monthly income (RMB)	<3,000	13	11.6
	3,000–6,000	22	19.6
	6,000–10,000	22	19.6
	10,000–15,000	21	18.8
	15,000+	34	30.4
Housing type	*Danwei* housing	32	28.6
	Low-rent housing	29	25.9
	Price-restricted commodity housing	51	45.5

Notes: $N = 112$. RMB = renminbi, official Chinese currency.

the hourly air quality data from the thirty-five stationary monitoring stations in Beijing and kriging interpolation to create twenty-four hourly $PM_{2.5}$ concentration surfaces for each survey day. We then extracted the $PM_{2.5}$ concentration values at each participant's residential location for each hour and used their standardized sum as the person's static exposure estimates. In contrast, the mobility-based monitoring station assessment simultaneously takes into account each participant's activity-travel patterns in space and time, such as activity place, duration, and sequences, as well as the spatiotemporal dynamics of air pollution (Figure 2A). Using the hourly $PM_{2.5}$ concentration surfaces derived from the monitoring station data and GPS-integrated activity diary data, we extracted each participant's exposure to $PM_{2.5}$ by identifying the intersection between his or her daily movement trajectories and the twenty-four hourly layers of $PM_{2.5}$ concentrations. Individual exposure to air pollution is again obtained as the standardized sum of these twenty-four hourly exposures, which capture the variations in a person's pollution exposure due to changes in his or her location and in pollution concentrations in the environment. For these two assessments that rely on the data collected at the thirty-five stationary monitoring stations, we have conducted cross-validation to evaluate the kriging results and find

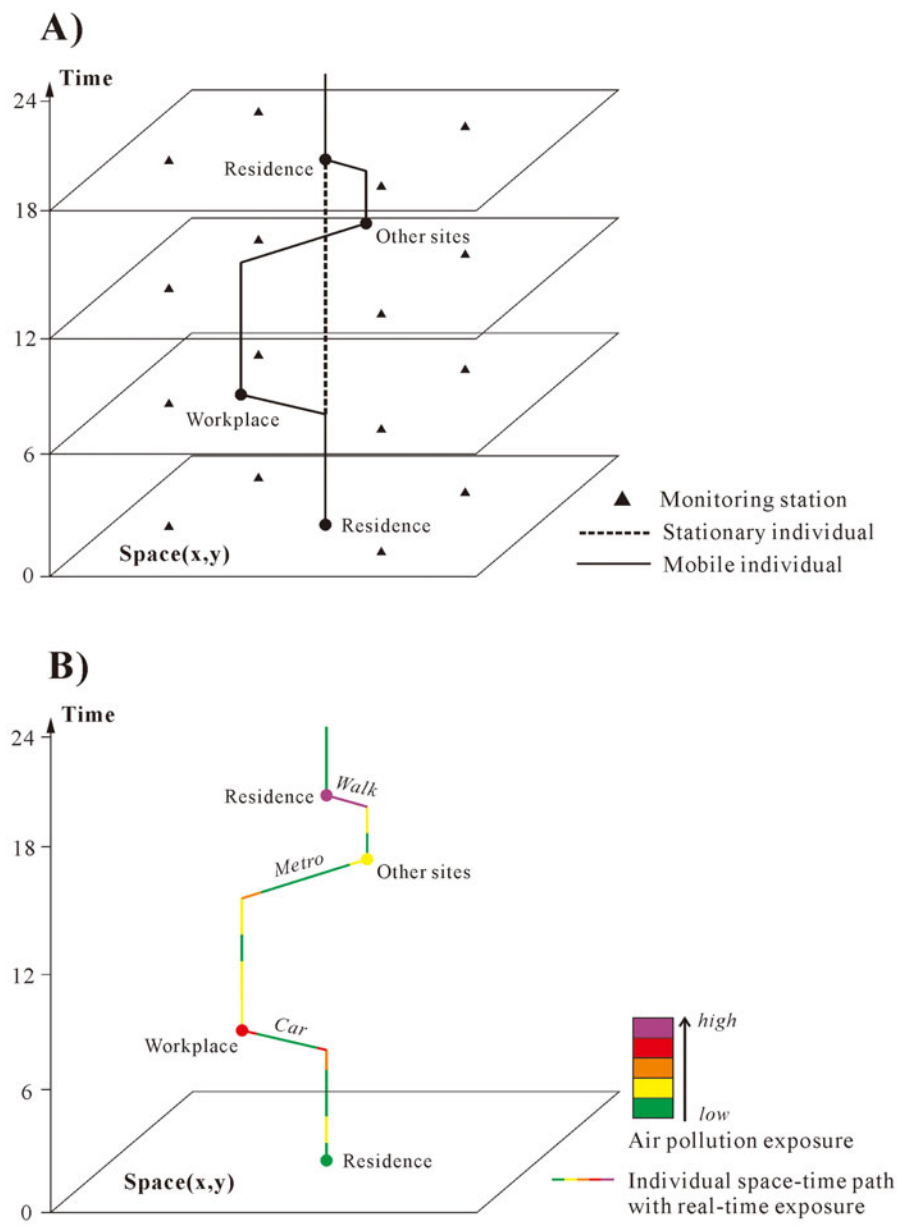

Figure 2. Personal exposure assessments: (A) residence-based or mobility-based monitoring station assessment and (B) mobility-based real-time assessment.

that this interpolation technique shows good performance ($R^2 = 0.94$).

To generate the mobility-based RTA, we extracted $PM_{2.5}$ concentrations from the air pollutant sensors (AirBeam from HabitatMap) and GPS trajectories from participants' smartphones, which were both logged at one-second intervals. This approach incorporates the real-time spatiotemporal interactions between air pollution and individual movement and the differences between indoor and outdoor exposures as well as between different travel modes or travel microenvironments (Figure 2B). Because low-cost portable sensors might have lower specificity or sensitivity when compared to expensive monitoring station sensors (De Vito et al. 2009; Lewis and Edwards 2016), we conducted field testing and calibration to evaluate the performance of the portable sensors under different urban conditions using the colocation calibration technique, which was implemented as follows. First, the AirBeam sensors were placed near a stationary monitoring station, which was used to provide the reference data. Data on $PM_{2.5}$ concentrations were then collected from both the portable sensors and the stationary monitoring station at the same time over two

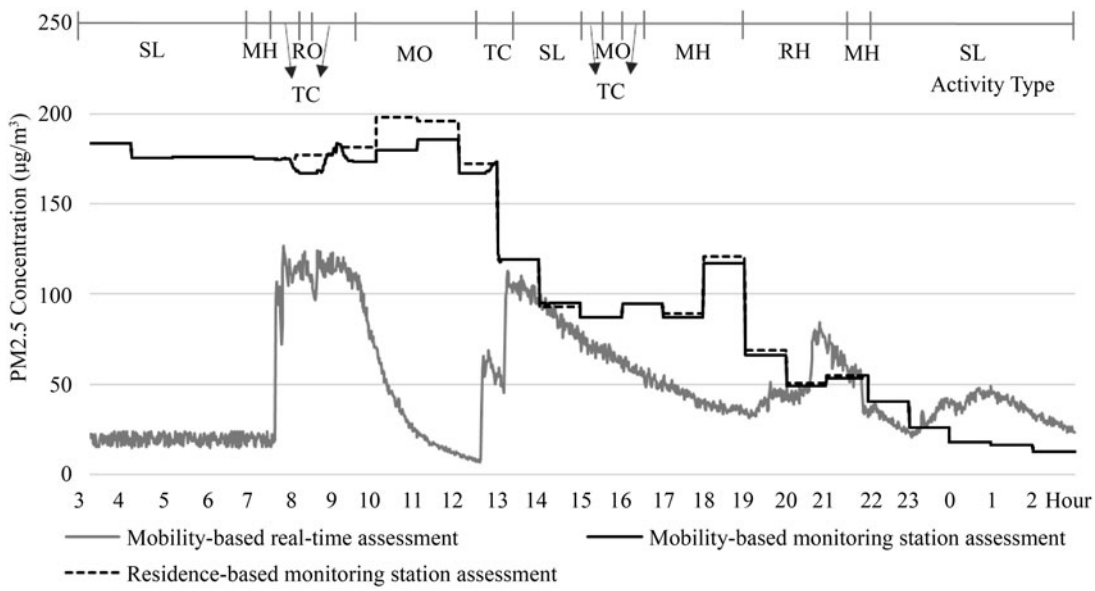

Figure 3. Temporal variations in exposure estimates at different activity locations on a weekend day, 14 January 2018. *Note:* SL = sleeping; MH = maintenance activity at home; RO = recreation activity outside home; MO = maintenance activity outside home; TC = travel by car; RH = recreational activity at home.

days with different environmental conditions. Using regression modeling, a strong correlation was found between the $PM_{2.5}$ concentrations obtained by the AirBeam sensors and monitoring station measurement ($R^2 = 0.86$). The portable sensors showed good performance during the field test, and there were no missing data during the colocation calibration period. Moreover, to compare each participant's daily average exposure to $PM_{2.5}$ between different assessments, we calculated the sum of the twenty-four hourly exposure estimates derived from the monitoring station assessments and the sum of the per second exposure estimates from the mobility-based RTAs. These different types of exposure sums were then standardized by the number of the respective measurement periods on a day.

Comparative Assessments of Personal Exposure in Space and Time

Comparing the Temporal Variations of Different Individual Exposure Assessments

Using the air pollution data and GPS trajectories, we first used one representative respondent to illustrate and compare the temporal variations in individual exposure estimates during each activity and travel generated by the three types of exposure assessments described earlier. As shown in Figure 3, there was little variation between the static residence-based and mobility-based monitoring station estimates (MSEs) throughout the day, because the respondent spent much time at home on a weekend day when ambient air pollution was relatively high. In contrast, the variation between the mobility-based RTA and MSE was substantial, because the RTA accounted for the differences in exposure between indoor and outdoor environments and individual protective measures (e.g., using an air purifier at home). For instance, when sleeping and performing maintenance activities (e.g., eating meals) at home before 8 a.m., the respondent turned on an air purifier to avoid high exposure to pollution at home and, as a result, the real-time exposure was much lower than the monitoring station estimates. When traveling and performing recreational activities outside the home between 8 a.m. and 10 a.m., however, real-time exposure to pollution increased significantly but still was less than the MSE, mainly due to the differences between indoor and outdoor environments. In contrast, due to pollution from smoking and heating at home in the evening, the respondent's real-time exposure was higher than the MSE between 9 p.m. and 10 p.m. These results indicate that widely used monitoring station assessments tend to overestimate individual exposure levels when ambient air pollution is relatively high and, more

Table 2. Exposure estimates at different activity locations using different types of assessments

			Low daily concentration		Middle daily concentration		High daily concentration	
			M	*SD*	*M*	*SD*	*M*	*SD*
Indoor locations	Home	MSE	10.58	7.12	35.98	18.02	78.02	10.50
		RTA	45.33	50.24	47.64	38.55	65.91	15.11
	Workplace	MSE	9.41	2.26	23.77	11.78	79.06	8.28
		RTA	26.78	32.48	32.23	28.19	53.40	8.33
	Shops	MSE	9.36	1.17	25.40	10.95	96.60	9.91
		RTA	17.83	14.41	23.60	12.50	72.19	10.76
	Other	MSE	9.68	4.44	27.91	14.39	104.03	8.59
		RTA	31.26	31.74	44.68	47.06	71.56	10.10
Outdoor locations		MSE	9.14	1.72	27.83	9.65	83.65	10.65
		RTA	25.45	44.31	35.47	32.66	104.87	7.87

Notes: MSE = mobility-based monitoring station estimation; RTA = real-time assessment. Low daily concentration is daily mean $PM_{2.5}$ concentration $\leq 25\,\mu g/m^3$; middle daily concentration is $25\,\mu g/m^3 <$ daily mean $PM_{2.5}$ concentration $\leq 75\,\mu g/m^3$; high daily concentration is $PM_{2.5}$ concentration $> 75\,\mu g/m^3$.

important, individual activity-travel contexts or microenvironments have a significant impact on personal exposure to air pollutants ($PM_{2.5}$) in space and time.

Comparing Different Types of Exposure Estimates across Activity Places

Because air pollution concentrations vary between indoor and outdoor environments, we then compared the exposure estimates generated by mobility-based MSEs and RTAs at different activity locations. Further, to compare the variation across various environmental conditions, we divided the survey days into three categories based on the daily average $PM_{2.5}$ concentrations released by the Chinese Ministry of Environmental Protection. As shown in Table 2, there were obvious variations in $PM_{2.5}$ concentrations among different activity places, and the exposure estimates generated by MSE and RTA varied substantially across different activity locations. When the ambient air quality was good (i.e., with daily mean concentration of $PM_{2.5}$ less than $25\,\mu g/m^3$), estimates from RTA were higher than MSE across different activity locations, particularly for residential locations, possibly due to the fact that RTA takes into account various sources of particulate matter pollution such as cooking, smoking, and traffic-related emissions in various indoor and outdoor environments. In contrast, on days with high levels of air pollution (i.e., with a daily mean $PM_{2.5}$ concentration higher than $75\,\mu g/m^3$), estimates from RTA were lower than MSE in various indoor locations but higher in outdoor environments. These results suggest that monitoring station assessments tend to underestimate personal exposure levels in indoor environments, particularly at home, when the ambient air quality is good and overestimate individual exposure in indoor environments when ambient air pollution levels are relatively high.

Comparing Different Types of Exposure Estimates by Travel Modes

Because travel modes might have a significant effect on personal exposure to fine particulates in different traffic microenvironments (Huang et al. 2012; Cepeda et al. 2017), we also compared different types of exposure estimates with respect to different travel modes across various environmental conditions. As shown in Table 3, variations in average $PM_{2.5}$ concentrations experienced from different travel modes were evident, and there were substantial differences in exposure estimates obtained from mobility-based MSEs and RTAs. Specifically, when ambient air quality was good, real-time exposures were higher than the estimates from MSE for various travel modes, such as walking, cycling, and public transport, whereas on days with serious air pollution, real-time exposures to $PM_{2.5}$ were much lower than those estimated by MSE. This suggests that pollution concentrations estimated with data from stationary monitoring stations, which fail to account for the differences in personal exposure in different travel microenvironments, are not appropriate surrogates for individual real-time $PM_{2.5}$ exposures on days

Table 3. Exposure estimates by different travel modes using different types of assessments

		Low daily concentration		Middle daily concentration		High daily concentration	
		M	*SD*	*M*	*SD*	*M*	*SD*
Car	MSE	9.05	2.28	30.04	14.45	114.34	44.88
	RTA	13.88	17.88	26.86	33.82	63.78	35.37
	Daily frequency	0.80	1.53	0.67	1.25	0.69	1.20
Bicycle/motorcycle	MSE	9.35	2.35	31.66	12.03	96.36	28.62
	RTA	16.85	14.01	36.19	29.63	63.94	37.72
	Daily frequency	1.15	1.97	0.76	1.87	0.59	1.05
Bus/subway	MSE	9.32	1.97	30.93	16.99	104.21	32.82
	RTA	28.05	42.87	30.04	19.52	64.04	28.06
	Daily frequency	0.24	0.79	0.65	1.04	0.52	1.00
Walk	MSE	8.88	1.33	29.50	15.47	101.33	35.40
	RTA	20.17	29.23	36.22	28.48	74.84	33.73
	Daily frequency	1.87	2.40	1.46	1.90	1.37	1.88
All	Daily frequency	4.05	2.59	3.55	2.22	3.17	2.18

Notes: MSE = mobility-based monitoring station estimation; RTA = real-time assessment. Low daily concentration is daily mean $PM_{2.5}$ concentration $\leq 25\,\mu g/m^3$; middle daily concentration is $25\,\mu g/m^3 <$ daily mean $PM_{2.5}$ concentration $\leq 75\,\mu g/m^3$; high daily concentration is $PM_{2.5}$ concentration $> 75\,\mu g/m^3$. Daily frequency refers to the average number of trips per day made by various transportation modes for the survey respondents.

with low or high air pollution. When ambient air pollution was moderate (i.e., with a daily mean concentration of $PM_{2.5}$ ranging from $25\,\mu g/m^3$ to $75\,\mu g/m^3$), however, there was little variation between exposure estimates obtained from RTA and MSE. Moreover, as shown in Table 3, with increasing air pollution, participants tend to decrease their daily trip frequencies significantly, especially for walking and cycling trips, and change their travel modes to motorized vehicles to avoid high exposure to air pollutants in heavily polluted environments.

Comparing Different Assessments of Individual-Level Exposure

Given the variations in activity and travel episode-level $PM_{2.5}$ concentrations in space and time, we further compared the differences in individual-level daily exposure estimates obtained from the three approaches: static residence-based assessment, mobility-based MSEs, and mobility-based RTAs. Figure 4 shows the three exposure estimates for each survey respondent on a workday and a weekend day based on the survey days. It indicates that the individual daily average exposure estimates obtained by assessments based on monitoring station data and real-time data vary substantially. By taking into account the interaction of air pollution and human mobility, the mobility-based MSE (white bars) showed some variations in individual daily exposure levels for residents living in the same residential neighborhood. Because ambient air quality was relatively good with little spatiotemporal variation on some survey days or the respondents spent much time at home when ambient air pollution was relatively high, however, there were small differences between the residence-based assessment (dark lines) and mobility-based MSE (white bars). These results tend to support the argument that mobility-based stationary monitoring assessment might be similar to static residence-based estimates if air pollution concentrations have little spatiotemporal variation or when individuals have a low level of mobility (e.g., Yoo et al. 2015).

In contrast, when taking into account the differences in air pollutant concentrations between indoor and outdoor environments or in various microenvironments, there were substantial differences in individual daily exposure to $PM_{2.5}$ between MSE (white bars) and RTA (gray bars). For instance, on a workday (e.g., 25 December 2017) when ambient air quality was relatively good, the real-time $PM_{2.5}$ exposures for some respondents were much higher than the exposure levels obtained from MSE (Figure 4A). There were greater variations between individual-level real-time exposure estimates on the surveyed workdays from 15 December 2017 to 26 January 2018, ranging from $3.12\,\mu g/m^3$ to $144.04\,\mu g/m^3$, whereas mobility-based MSEs ranged from $7.64\,\mu g/m^3$ to $59.61\,\mu g/m^3$. In contrast, on a weekend day (e.g., 14 January 2018)

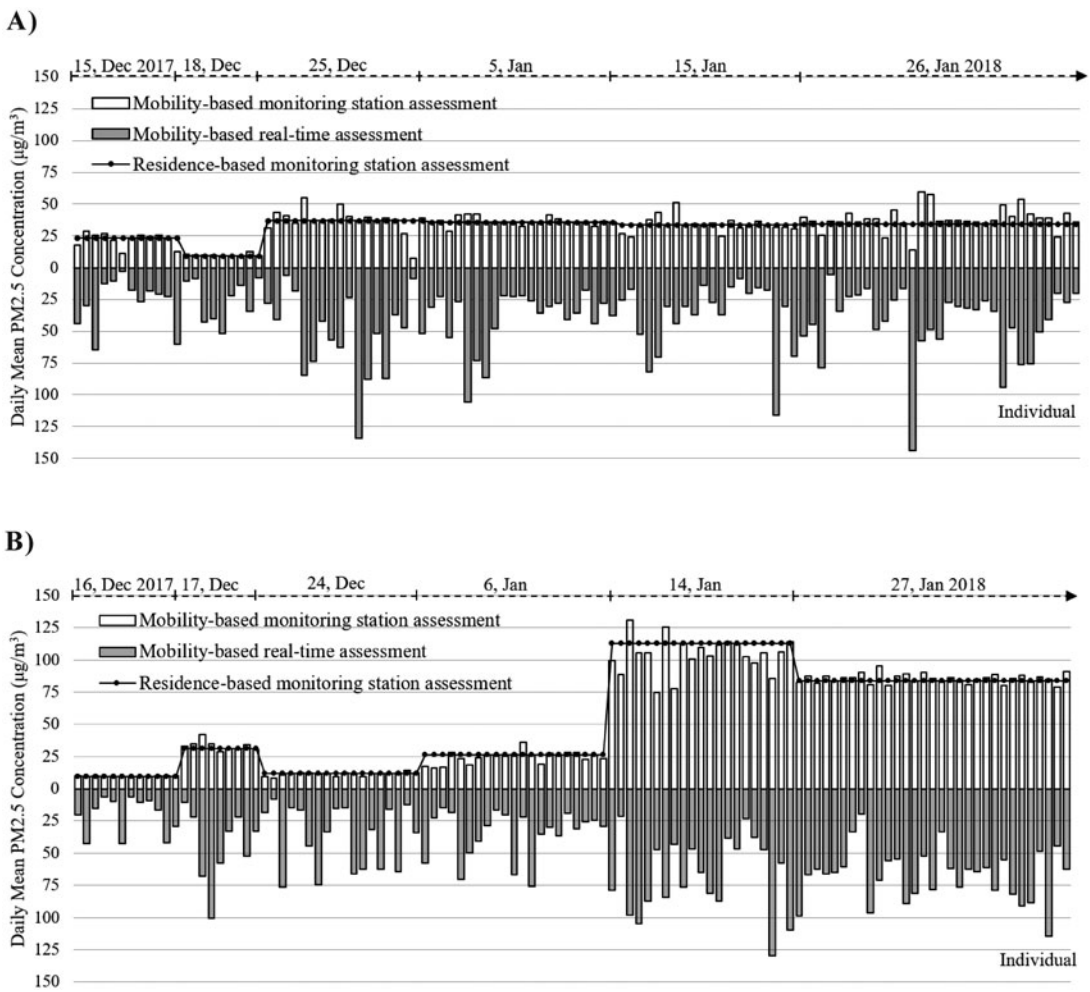

Figure 4. Comparing different assessments of individual-level exposure estimates on (A) workdays and (B) weekend days.

when ambient air pollution was relatively high, individual daily exposures to $PM_{2.5}$ obtained from RTA were much lower than those obtained from MSE, but there were greater variations between individual real-time exposure estimates (Figure 4B). This is mainly because the RTAs take into account the differences in exposure levels between indoor and outdoor environments, the various sources of particulate matter pollution like smoking, cooking, and traffic-related emissions in individual-specific spatiotemporal microenvironments, as well as individual protective measures in a heavily polluted environment such as using an air purifier at home, reducing travel, or changing travel modes from nonmotorized modes to motorized vehicles to avoid high exposure to air pollution.

To better illustrate the spatiotemporal dynamics of air pollution and human mobility, the respondents' space–time trajectories were geovisualized in 3D and color-coded based on the real-time $PM_{2.5}$ exposures obtained from the air pollutant sensors. Further, we incorporated the interpolated hourly air pollution layers derived from data provided by the limited number of monitoring stations in the 3D geovisualizations for a typical workday and a weekend day. As shown in Figure 5, participants living in the same neighborhood but with different activity-travel patterns experienced different levels of $PM_{2.5}$ concentrations, and the interpolated hourly air pollution surfaces cannot accurately represent individual-level real-time exposures in space and time at a fine resolution. For instance, on the workday (15 January 2018) between 9 a.m. and 12 p.m., some respondents were exposed to high levels of pollution when traveling on the main roads, possibly due to traffic congestion and traffic-related emissions (Figure 5A). In the evening after 9 p.m. when ambient air quality deteriorated, the real-time $PM_{2.5}$

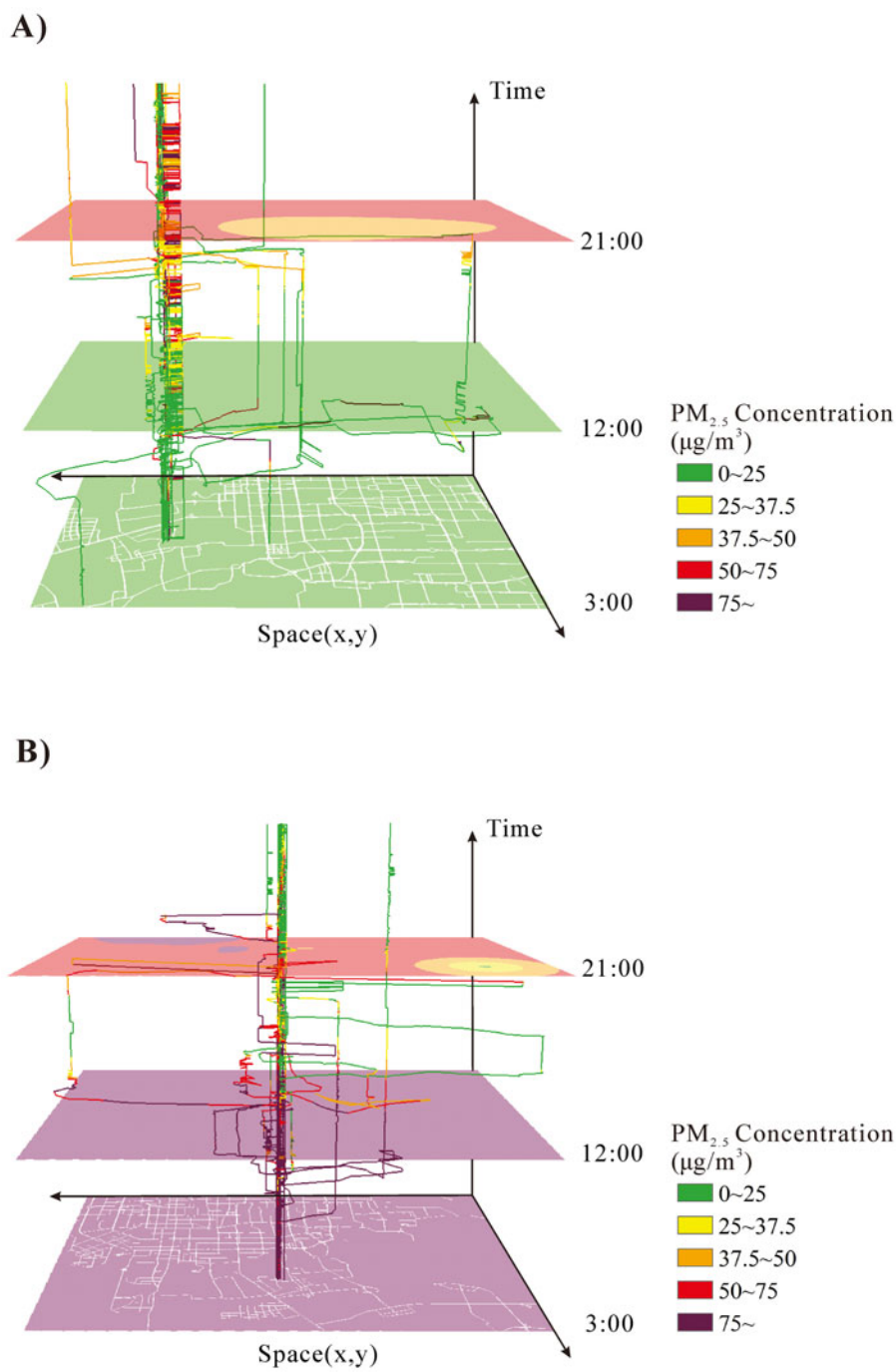

Figure 5. 3D geovisualization of respondents' space–time trajectories with real-time $PM_{2.5}$ concentrations from portable air pollutant sensors on (A) a workday (15 January 2018) and (B) a weekend day (14 January 2018). The interpolated hourly air pollution layers were derived from the static and sparse monitoring station data using the kriging interpolation method.

exposures of some respondents were very low (below 25 $\mu g/m^3$), possibly because they used an air purifier at home, whereas the real-time exposure estimates of some other participants were relatively high. The great variations in individual-level real-time exposures in space and time as well as the differences between real-time estimates and hourly monitoring station prediction surfaces were also evident on a typical weekend day (Figure 5B). Such differences should be taken into account in personal exposure

assessments, particularly when estimating short-term exposure, which can directly cause acute symptoms (e.g., acute asthma), in epidemiological research.

Conclusion

Smart technologies such as smartphones and portable sensors could collect high-resolution geospatial data on individual space–time behaviors and real-time air pollution exposures. They offer great potential for reducing the errors in exposure measurement and increasing the accuracy of personal exposure estimates that are essential for epidemiological and geographic studies (Han and Naeher 2006; Jerrett et al. 2017). These smart technologies can play an important role in real-world environmental monitoring and facilitating intelligent individual decision making. They can help residents obtain valuable information and increase their real-time awareness of the surrounding environments, as well as make more "informed, responsible choices" to optimize their daily behavior, avoid exposure to high levels of pollution, and improve their quality of life (Gabrys 2014). Smart technologies facilitate and enable the development of smart cities, in which digital technologies are used to enhance people's life quality and well-being, reduce the cost of data collection and resource consumption, and engage more actively and effectively with urban residents (Hashem et al. 2016; Nieuwenhuijsen 2016).

With recent advancements in smart sensing technologies, our focus on exposure assessment has turned from people's residential locations to their daily movements, from space to space–time, and from static monitoring to real-time sensing (Kwan 2012, 2013). Using real-time data from smartphones and air pollutant sensors collected in Beijing, this study contributes to the environmental health and geographic literature by demonstrating how smart technologies and attention to individual activity-travel microenvironments enable us to analyze individual-level exposure in space and time at a very fine resolution. We compared three different types of exposure estimates generated by residence-based monitoring station assessment, mobility-based monitoring station assessment, and mobility-based real-time sensing assessment. Further, we examined the differences in personal exposures to fine particulates associated with different activity places (e.g., homes, workplaces, shops, and outdoor locations) and different travel modes (e.g., walking, cycling, public transport, and private cars) across various environmental conditions in a realistic setting. The results showed that there were considerable variations in individual exposure to $PM_{2.5}$ in different activity places, and the exposure estimates generated by monitoring station assessment and real-time sensing assessment varied substantially between different activity locations. Because the monitoring station assessment is unable to take into account some important indoor and outdoor pollution sources, it could generate substantially biased estimates by under- or overestimating individual exposure at indoor locations, particularly at home and especially when ambient air quality is very good or very poor. Moreover, people's travel modes had a significant effect on individual exposure to air pollution, and the averaged $PM_{2.5}$ concentrations experienced when using different travel modes generated by different approaches varied substantially across various environmental conditions.

This study also found that individual-level daily average $PM_{2.5}$ exposures for residents living in the same community varied significantly, and there were substantial differences in exposure estimates obtained from different assessment methods. Real-time sensing technologies could greatly improve accuracy in the estimation of individual exposure to air pollution at very fine spatiotemporal resolutions, and they are superior to the static residence-based or mobility-based monitoring station assessments. This is mainly because smart sensing technologies take into account the differences in individual exposure between indoor and outdoor environments, various pollution sources (e.g., smoking, cooking, and traffic-related emissions) in person-specific spatiotemporal microenvironments, as well as the protective measures that people adopted in heavily polluted environments (e.g., using an air purifier at home, reducing travel, or changing travel modes). Using smart technologies, this study helps to improve our understanding of individual exposure to air pollution in space and time at very fine resolutions. It also shows how the UGCoP and the NEAP could be mitigated through deploying smart technologies to obtain more accurate estimates of individual exposures to environmental influences. Despite encouraging improvements in low-cost sensor technologies, however, more efforts are needed to conduct testing and calibration to evaluate sensor performance, improve

the consistency and durability of sensing elements, and develop better devices to improve data accuracy and sensitivity (Kumar et al. 2015). As suggested by Lewis and Edwards (2016, 31), "Well-designed sensor experiments, that acknowledge the limitations of the technologies as well as the strengths, have the potential to simultaneously advance basic science, monitor air pollution—and bring the public along."

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