

Article

Real-Time Low-Cost Personal Monitoring for Exposure to PM_{2.5} among Asthmatic Children: Opportunities and Challenges

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Abstract: This study aims to evaluate the accuracy and effectiveness of real-time personal monitoring of exposure to PM concentrations using low-cost sensors, in comparison to conventional data collection method based on fixed stations. PM_{2.5} data were measured every 5 min using a low-cost sensor attached to a bag carried by 47 asthmatic children living in the Seoul Metropolitan area between November 2019 and March 2020, along with the real-time GPS location, temperature, and humidity. The mobile sensor data were then matched with station-based hourly PM_{2.5} data using the time and location. Despite some uncertainty and inaccuracy of the sensor data, similar temporal patterns were found between the two sources of PM_{2.5} data on an aggregate level. However, average PM_{2.5} concentrations via personal monitoring tended to be lower than those from the fixed stations, particularly when the subjects were indoors, during nighttime, and located farther from the fixed station. On an individual level, a substantial discrepancy is observed between the two PM_{2.5} data sources while staying indoors. This study provides guidance to policymakers and researchers on improving the feasibility of personal monitoring via low-cost mobile sensors as an alternative or supplement to the conventional station-based monitoring.

Keywords: personal monitoring; low-cost sensor; particulate matter; asthma

1. Introduction

Exposure to particulate matter (PM) has been identified as having an adverse impact on human health [1]. It is associated not only with respiratory diseases but also other

diseases such as heart disease, type 2 diabetes and dementia [2–4]. Most of these studies emphasize the cumulative effects of PM exposure over an extended period time, which emphasizes the importance of personalized continuous monitoring and the need for control of indoor and outdoor PM levels in surrounding atmosphere of individuals who experience relevant symptoms [5]. However, in many countries, air quality management and health impact evaluation are still based on ambient air monitoring using the traditional station-based system [6–8]. This monitoring system is typically equipped with high-performance and expensive sensors with strong calibration stability, producing accurate data on outdoor air quality measurements for surrounding environments [9]. The high construction and maintenance cost of station-based monitoring system has prevented the development of a sufficient number of air quality monitoring stations, which has resulted in coverage gaps and a high measurement error rate in areas far from the monitoring locations [10]. Although a variety of GIS and spatial modeling techniques have been used to create an interpolated surface of ambient PM exposure, their precision and accuracy levels are still lacking [11,12].

PM measurements from stations are often inaccurate and insufficient to be used for providing guidelines for asthmatic patients to avoid exacerbations of their symptoms since the station-based data are limited. Therefore, they are unable to indicate the true level of exposure for individuals, depending on their lifestyle, mobility and actual location. Most people nowadays tend to stay indoors for longer periods of time and the impact of indoor PM on their health is far more important than that of outdoor air pollution, especially due to its long-term exposure at low concentration levels [7]. Thus, personalized PM monitoring based on real-time locations has been proven itself to be a better alternative for exposure assessment and is being actively researched due to the advances in IoT (Internet of Things) devices and networks [13]. In particular, a growing number of researchers have attempted to explore the potential of low-cost sensors for real-time personal exposure assessment as a supplementary method tool for traditional ambient air monitoring [14–16]. However, personal PM monitoring has not been widely implemented as a guideline for clinical intervention and policy decision mainly due to various technical difficulties and financial implications [17]. The existing empirical evidences from a long-term, large-scale study are not sufficient to allow useful and general insights into the accuracy and effectiveness of real-time personal monitoring in comparison to conventional station-based monitoring.

Despite the rapid improvement of low-cost PM sensors, several limitations have been reported and attempts have been made to resolve them. First, reliability issues are still preventing a broad exploitation of low-cost portable devices. The PM measurements are heavily influenced by various factors such as aerosol size and meteorological variation [16], and each device has different ways of retrieving the PM levels [18]. A handful of recent studies have been conducted to adjust these factors [16,18,19], but there is still a long way to go. Second, limited battery performance has been reported as a critical issue for real-time monitoring since the battery for the portable IoT sensors may run out during the day causing interruption of continuous monitoring unless recharged within a reasonable time [20]. Third, most low-cost PM sensing devices require an internal calibration process or modeling which might generate arbitrary errors or systemic biases [21]. A growing number of studies have been dedicated to addressing these limitations [22,23], which would ensure the wide and effective application of real-time mobile PM monitoring using low-cost portable sensors.

In South Korea, most of the PM-related public health policies and clinical interventions remain based on outdoor environments monitored by the conventional station-based method due to the lack of efforts to promote a large-scale personalized monitoring [24,25]. Recently, a number of monitoring efforts have been undertaken including a feasibility study to assess indoor PM exposure, but most of them focused on fixed IoT devices which failed to capture the concurrent air pollution and environmental monitoring data from their real-time locations [26,27]. Despite a handful of recent studies on real-time sensing of indoor and outdoor PM exposure using a low-cost portable device in South Korea [28,29],

personally monitored PM data were not thoroughly evaluated for feasibility and accuracy in comparison to conventional data from station-based area monitoring. Therefore, this study aims to evaluate the patterns of PM_{2.5} concentrations exposed to asthmatic children in South Korea collected from their real-time locations (indoor vs. outdoor) in comparison with the corresponding air quality data from the nearest monitoring station. It demonstrated not only the potential role but also the limitations of personalized PM monitoring using a low-cost mobile sensor as an alternative or supplement to the conventional station-based ambient air monitoring. These findings would be useful for evidence-based policy intervention and patient consultation as they provide guidance to policymakers, clinicians and researchers on what efforts need to be made to improve the quality and feasibility of the personal monitoring process and how large-scale ambient air monitoring data should be used and adjusted for personalized care and intervention when personal monitoring data are not available.

2. Materials and Methods

2.1. Study Participants

Study subjects were recruited between November 2019 and March 2020 from the outpatient group visiting eight hospitals in Seoul's metropolitan area. We sampled children aged 5–15 years old who had asthma symptoms in the last 12 months and at least 12% of bronchodilator response or PC20 methacholine ≤ 16 mg/mL or PD15 mannitol ≤ 635 m. In total, 47 patients were included in the study. Their home locations, distributed around Seoul Metropolitan Area, are shown as a triangle in Figure 1.

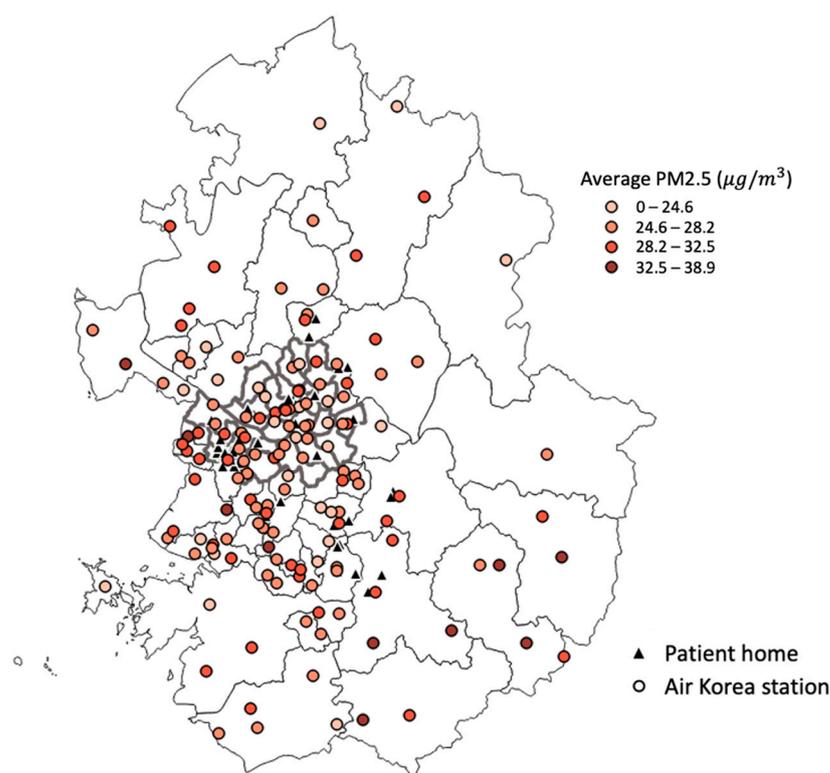


Figure 1. Distribution of 154 fixed monitoring stations and 47 patient home locations.

2.2. Station-Based PM Monitoring via Air Korea

There are 522 atmospheric air quality monitoring stations across Korea, including urban and roadside air quality stations, of which 154 are in the Seoul and Gyeonggi areas, shown as circles in Figure 1. At each station, both PM₁₀ and PM_{2.5} concentration data were measured by the β -ray measurement method every 5 min and then transmitted to the National Ambient Air Quality Monitoring Information System (NAMIS) along with

other air pollutants such as SO₂, CO, O₃ and NO₂. The data were then aggregated into hourly averages through statistical processing and stored in a database called “Air Korea” maintained by the Korea Environment Corporation [30]. The reported concentration values were provided through application to the smartphone users based on data from the station closest to their real-time location, along with user-friendly color grading on risk level (e.g., red as high risk, yellow as medium risk, and green as low risk) to help them to identify the risk at their locations and take appropriate actions [31]. Moreover, the information from the “Air Korea” data have been used as a guideline for various air quality interventions and other public health policies [32,33]. This database was used to extract the PM_{2.5} concentrations measured at the fixed monitoring station nearest to the patients’ real-time location measured via GPS during the study period, which was then integrated with the PM_{2.5} data collected for each patient via personal monitoring.

However, several concerns have been raised about the accuracy and practical applicability of the data. Most importantly, the lack of monitoring stations impedes accurate assessment of dynamic trends of particulate matters within the region even in the urban areas. For instance, on average, one station covers about 15.5 km² in Seoul, and over 108 km² in other regions in South Korea [34], which leaves wide gaps between different monitoring stations [10]. Moreover, some Air Korea stations were installed substantially higher than the recommended height, creating a gap between the measured PM values and the actual level of exposure in people living in and around the area [35]. Additionally, another valid criticism is that the Air Korea data lack the metadata that describe a measuring instrument, specifics for measurement and potential outliers [36].

2.3. Personal Real-Time Monitoring via Low-Cost Sensors

For real-time personal monitoring, we collected PM_{2.5} concentration data for the 47 study participants from December 2019 to March 2020 using a portable device with low-cost sensors. The device monitors the concentrations of PM₁₀ and PM_{2.5} measured by the light scattering method as well as temperature, humidity together using each corresponding sensor in real time (model name: PMM-130 (hereafter PICO), size: 48.0 × 48.0 × 20.6 mm, weight: 45 g, power supply: 200 mA/h). On the date of the patient’s outpatient visit, we handed out a device that was placed in a pouch and hung on a backpack, as shown in Figure 2, and advised them to always carry it when outdoors and keep it in a specific location when indoors. Patient caregivers were asked to upload the collected data to the application server every evening and the data were monitored and managed by the clinical research coordinator (CRC). The CRC kept in touch with the caregivers regularly to ensure that the data were uploaded properly and on time.

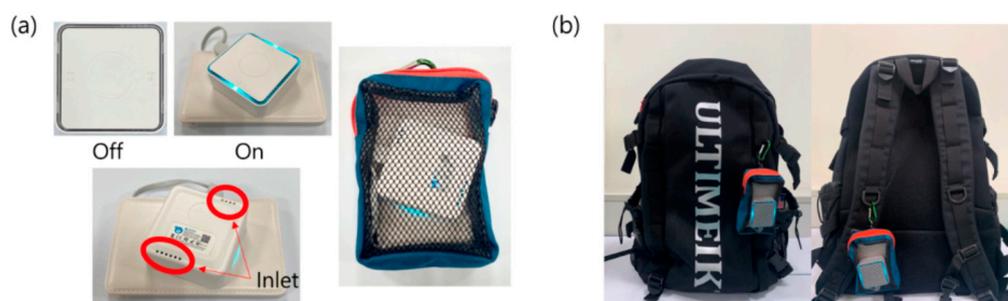


Figure 2. (a) PICO in a carrying pouch, (b) wearing appearance of PICO.

Reliable positioning was identified through the GPS positioning system (EHS GPS Tracker, Mobile App), which allows consistent positioning during measurements. PICO measures both PM₁₀ and PM_{2.5} concentrations from 1 to 1000 µg/m³, temperature from −40°C to 125°C and humidity from 0 to 100% relative humidity (RH) and the results are stored at 5 min intervals (measured in 30 s after waiting 4 min). The device is powered by external power supply and equipped with a storage device that can record PM

measurement data in real time. The measured data were transmitted to a server through Bluetooth (BLE4.0) and Wi-Fi (2.4 GHz) while the device was being charged. The accuracy of PICO has been approved by receiving a high level of performance certification from the government-authorized agency, Korea Testing & Research Institute (KTR) and reported as 86.2% in our recent paper [26]. The calibration of PICO was performed by comparing the results from KTR with the same device used in the Air Korea monitoring stations. The accuracy was calculated as follows:

$$\text{Accuracy(\%)} = \frac{\text{The results of PMs from PICO}}{\text{The corresponding values from a reference device of KTR}} \times 100$$

We selected this PM measuring device given its measurement reliability, weight, portability, power consumption, and data transmission capabilities. In particular, the calibration of measurements based on temperature and humidity was considered in device selection since they tended to influence the measurements of portable devices with a low-cost sensor [37].

To ensure validity and consistency in measurement across the devices prior to full sampling, we collected PM data for eight days in September and November 2020 using five PICO devices and a reference device (KTR) installed at the Korea Institute of Chemical Convergence Test which has been used for official routine monitoring of outdoor air quality. Figure 3 shows statistically significant consistency across the five PICO devices (mean coefficient of variation = 0.12) throughout the testing period.

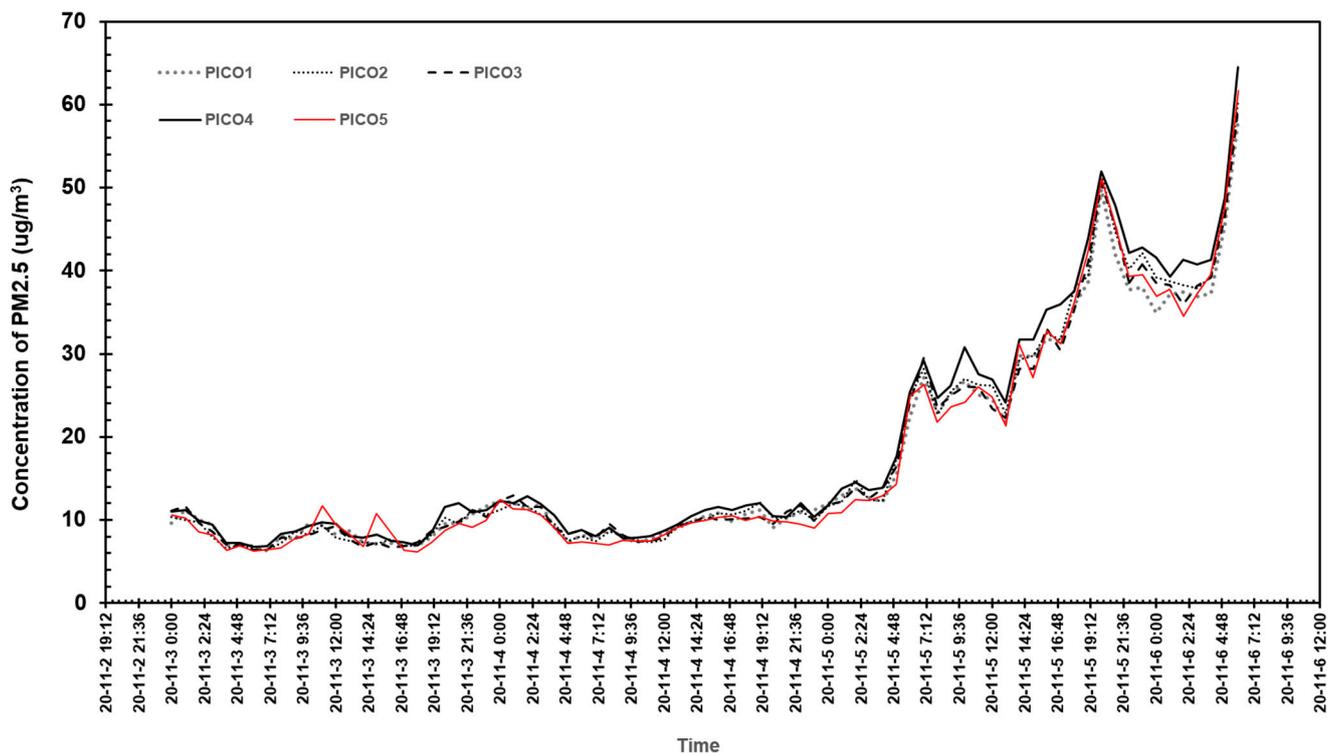


Figure 3. Comparison of PM_{2.5} measurements across the five PICO devices.

The results were used to derive a calibration formula for PM_{2.5} values from PICO based on temperature and humidity by a robust multiple regression model as follows:

$$\text{Calibrated PM}_{2.5} = 49.19 + (0.45 \times \text{measured PM}_{2.5}) - (1.44 \times \text{temperature}) - 0.006 \times \text{humidity} \quad (1)$$

Figure 4 compares the measurements of a reference device (KTR reference instruments) with an average measurement from five PICO devices: (a) before and (b) after calibration. It appears that the temporal trends of PM_{2.5} are overall similar between PICO and KTR even

before calibration (Figure 4a), but the two measurements become more nearly identical after calibration (Figure 4b).

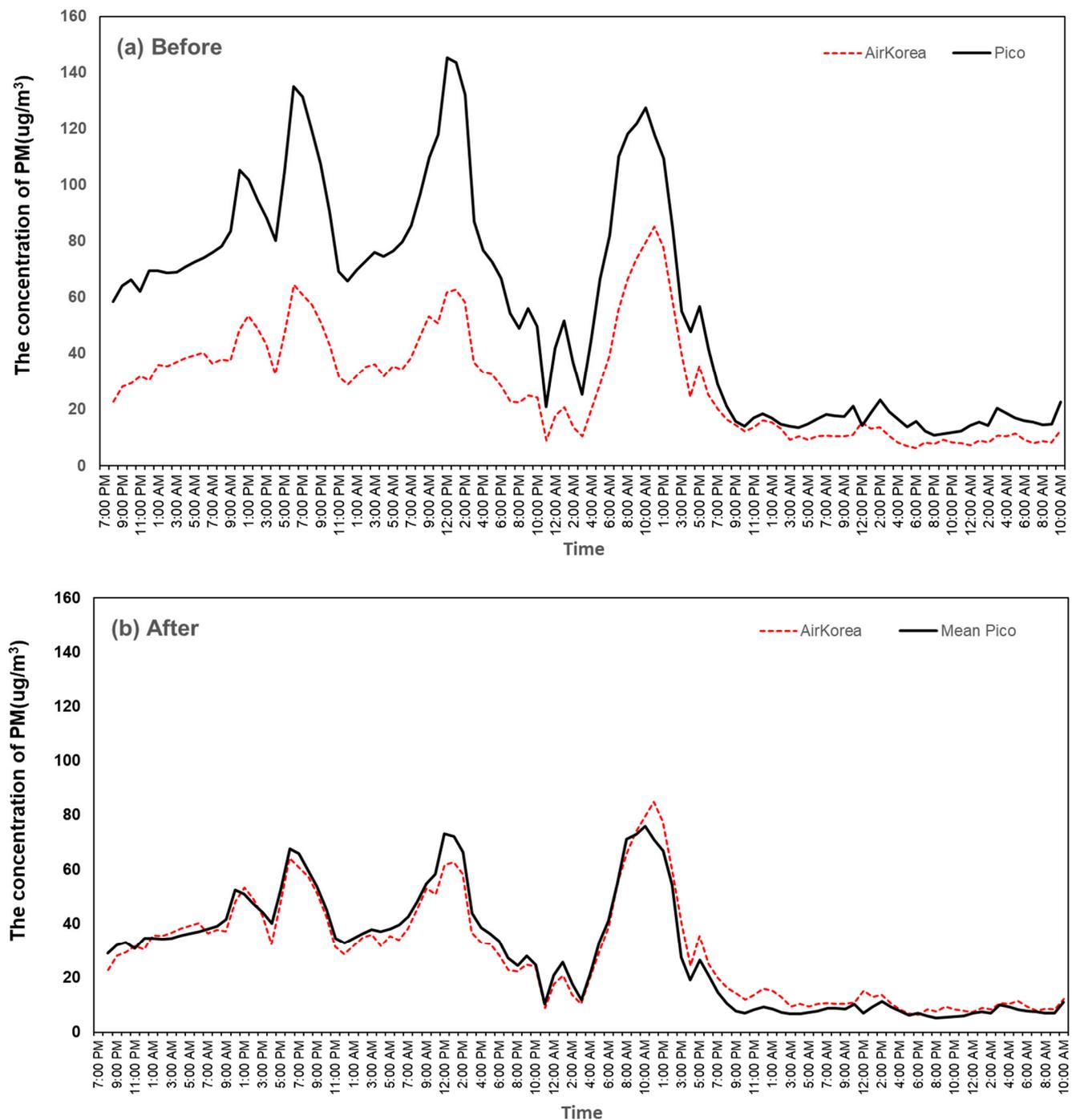


Figure 4. Temporal trends of $PM_{2.5}$: (a) before calibration; (b) after calibration.

2.4. Data Integration and Analysis

Both Air Korea data and PICO data were matched to construct the integrated database for all 47 study participants, which were used for a series of comparative data analyses on $PM_{2.5}$ measures from station-based monitoring (Air Korea) and personal monitoring (PICO). Each data point from PICO was assigned to one of three spatial categories based on each participant's daily mobility pattern: indoor (home), indoor (other than home) and outdoor, indicating where the respective $PM_{2.5}$ reading from PICO took place. Their

5-min moving distance was also calculated based on the GPS coordinates and used to identify their location as indoors/outdoors, combined with their time information (e.g., identified as outdoors if their moving speed is above a certain threshold, identified as indoors between midnight and 8am, etc.). The indoor-outdoor classification was verified by patient caregivers. In comparison analysis, not only the location but also the time of the measurements were used to evaluate the patterns of PM_{2.5} concentrations exposed to each, and all participants collected from two different air quality monitoring sources: PICO measurements at their real-time mobile locations and Air Korea measurements at the nearest fixed monitoring station.

3. Results

Figure 5 was created to compare temporal trends of the average PM_{2.5} concentration aggregated for all patients from the personal monitoring device (red lines) with that from the “Air Korea” data (black lines) throughout the study period. Overall, similar patterns were found between the two sources of PM_{2.5} data, although on average PM_{2.5} concentrations via personal monitoring tended to be lower with a larger variance across the records, compared to those from fixed monitoring stations. However, the differences between the two PM_{2.5} data vary by time and location. As shown in Table 1, the difference in hourly PM_{2.5} concentrations between Air Korea and PICO data are larger while staying indoors than outdoors, particularly in indoor environments other than home ($p < 0.01$), which indicates that the personal PM_{2.5} monitoring data correspond well with the station-based data when the individuals stayed outdoors but show a substantially smaller exposure while indoors. While they were staying outdoors, the two PM_{2.5} data sources were a lot better matched to each other during afternoon hours (noon to 8 p.m.) than morning (5 a.m. to noon) and night hours (8 p.m. to 6 a.m.). We also checked if the difference in PM_{2.5} concentrations between Air Korea and PICO were substantially larger when they were outdoor at real-time locations farther from the nearest Air Korea station. The gap was found significantly bigger when they were beyond 500 m from the closest station (1.12 vs. 0.68), indicating the role of proximity to Air Korea stations in evaluating the similarities between the personalized and station-based PM_{2.5} measures.

Table 1. Spatiotemporal comparison of PM_{2.5} statistics between station monitoring (Air Korea) and personal monitoring PICO).

		N	Air Korea Mean ± SD	PICO Mean ± SD	Absolute Difference	T (p)
Locations of measurements	Indoor (home)	265,457	31.08 ± 18.50	27.31 ± 19.30	3.77	
	Indoor (other than home)	64,533	30.71 ± 17.93	25.60 ± 19.33	5.11	<0.01
	Outdoor	33,880	31.34 ± 18.49	30.33 ± 20.87	1.00	
Time slots for measurements (outdoors only)	Morning (6 a.m.–noon)	7695	32.27 ± 17.81	29.69 ± 16.70	2.58	
	Afternoon (noon–8 p.m.)	20,044	31.21 ± 19.04	31.51 ± 22.27	0.29	<0.01
	Night/overnight (8 p.m.–6 a.m.)	6141	30.58 ± 17.45	27.32 ± 20.53	3.26	
Distance from Air Korea station (outdoors only)	Within 500 m	2220	30.52 ± 18.50	31.20 ± 22.41	0.68	
	Beyond 500 m	31,660	31.39 ± 18.49	30.27 ± 20.76	1.12	<0.01

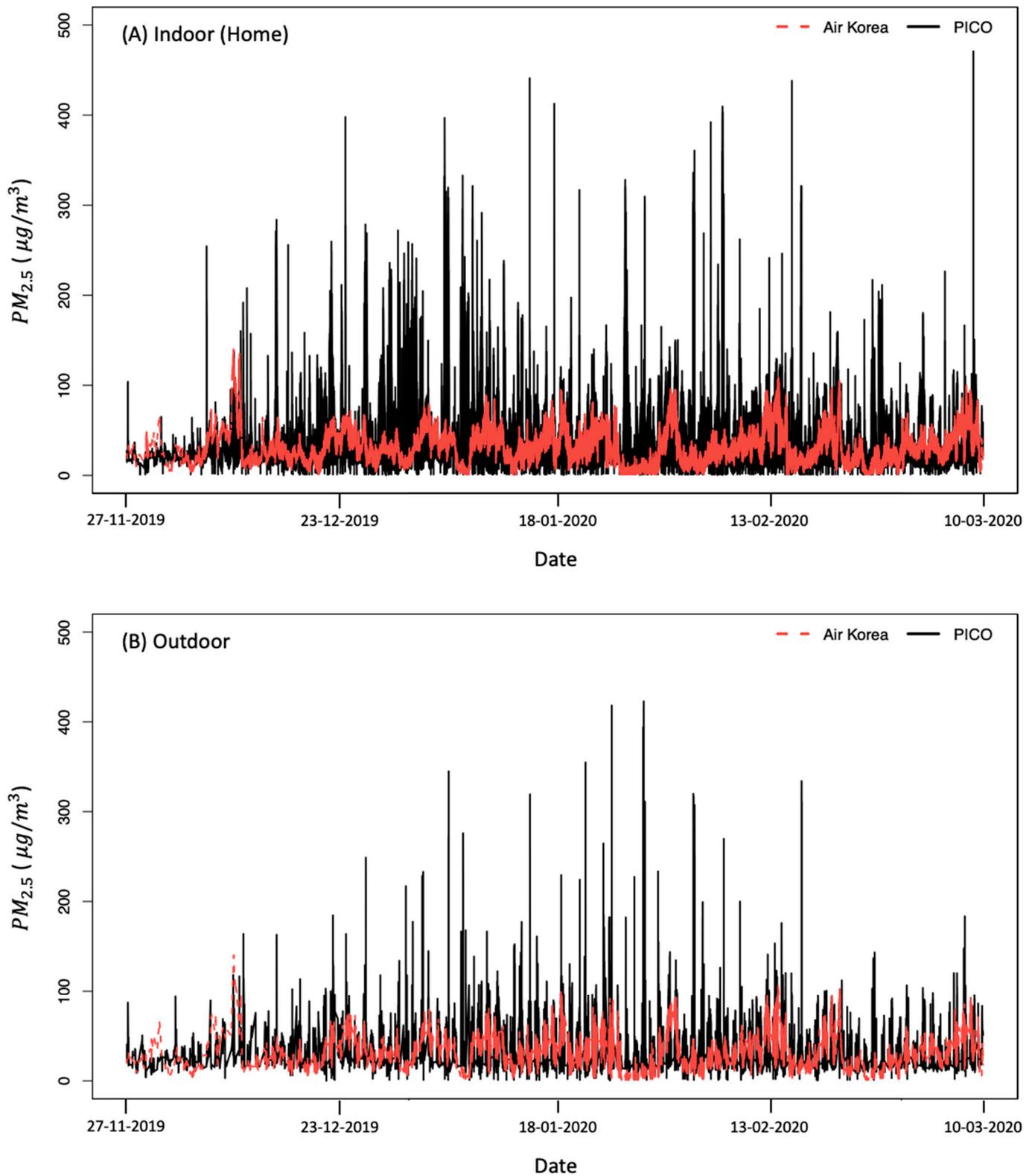


Figure 5. Cont.

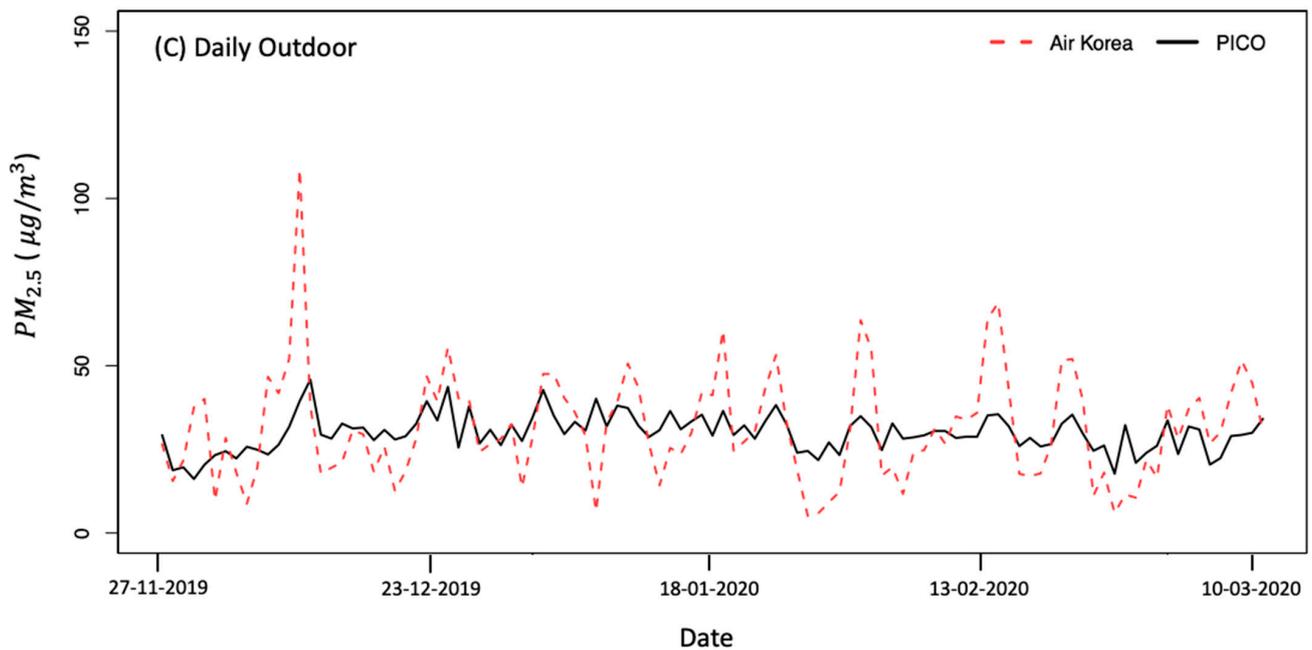


Figure 5. Comparison in temporal variations of PM 2.5 values for all patients between station monitoring (Air Korea) and personal monitoring (PICO): (A) indoor (home)—hourly, (B) outdoor—hourly, (C) outdoor—daily.

We then examined individual variation of PM_{2.5} concentrations for each of 47 patients. The boxplot in Figure 6 shows a good amount of variation on the gap of PM_{2.5} measures between station-based (Air Korea) and personal monitoring (PICO) among the patients. It appears that the Air Korea measurements were generally bigger than personalized PICO measurements for most of them, PICO measurements were found relatively higher for some patients (1-003, 5-003, 6-002), indicating heterogeneity in their life and the role of mobility patterns interacting with their neighboring environments.

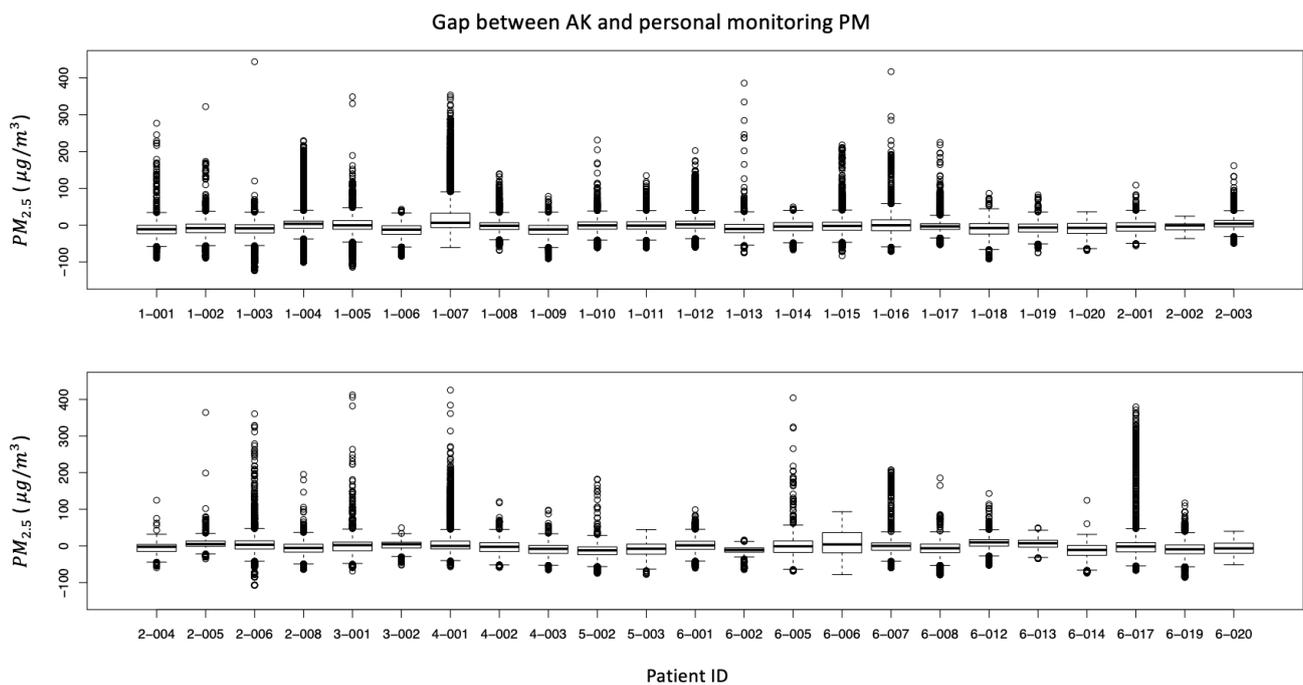


Figure 6. Box plot for the gap between station-based (Air Korea) and personal monitoring (PICO) PM_{2.5} measures for each patient.

For an illustration purpose, Figure 7 show a scatterplot comparing hourly average of $PM_{2.5}$ measures between station monitoring (AK) and personal monitoring (PICO) for two selected patients. For a majority of patients including these two, the two kinds of $PM_{2.5}$ measures are relatively well correlated with each other while staying outdoors with a correlation coefficient ranging between 0.3 and 0.6, compared to 0.1–0.3 while indoors at home. These results make sense when considering substantial variation in indoor environments and activities across different individuals.

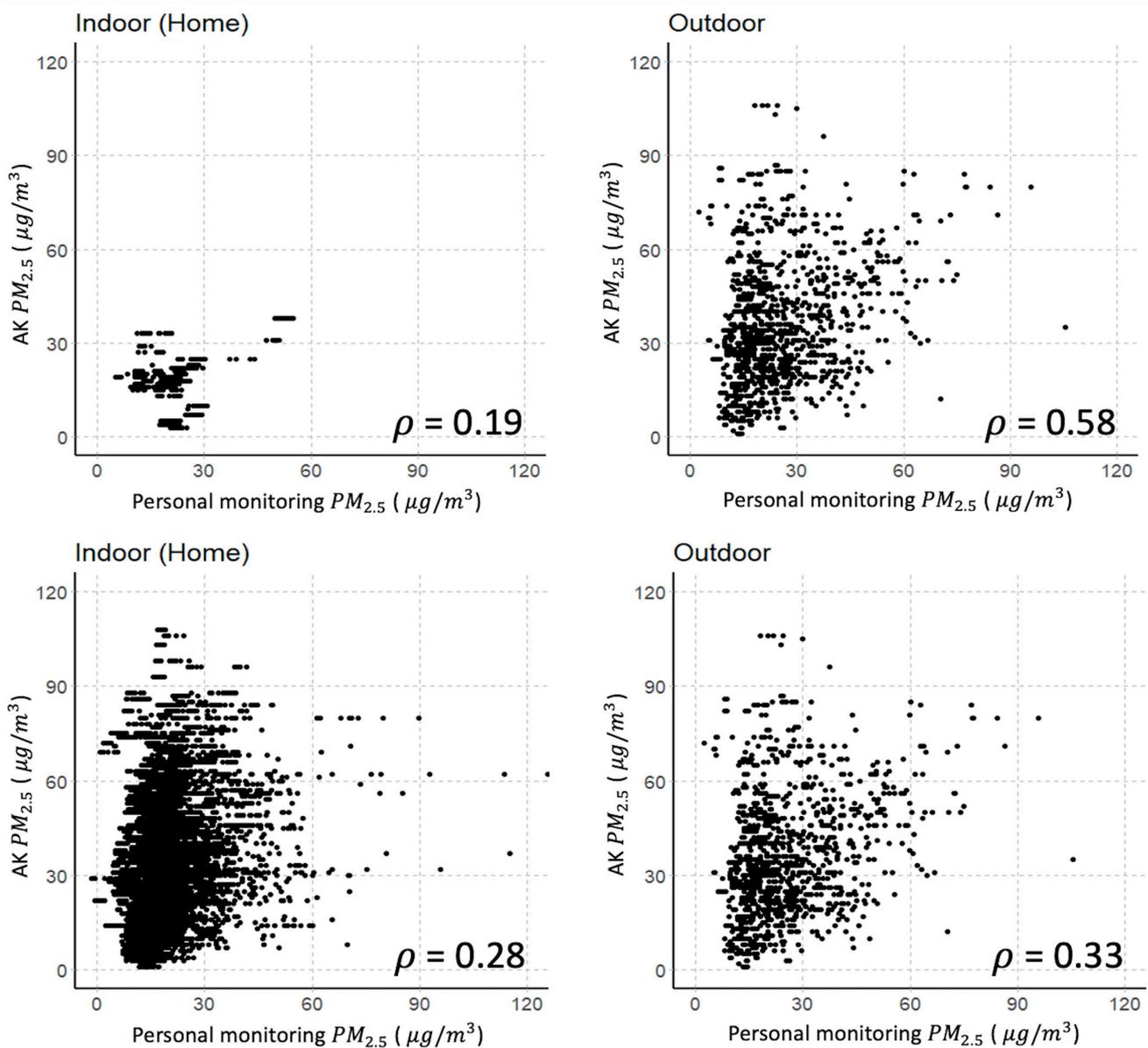


Figure 7. Scatterplot comparing hourly average of $PM_{2.5}$ between station monitoring (AK) and per Scheme 2. Bottom: 1-009).

Figure 8 also illustrates how the two $PM_{2.5}$ measures correspond to each other over time while indoors or outdoors, by comparing the data from the two monitoring sources (Air Korea and PICO) collected for two selected patients throughout the course of a 24 h time period, with the time of staying outdoors shaded in gray. Despite some fluctuations and noise, it looks evident that PICO measures are quite similar to those from Air Korea particularly when they stayed outdoors. However, a substantial discrepancy is observed between the two $PM_{2.5}$ data sources during indoors, implying that Air Korea measures may not be used as a proxy for indoor $PM_{2.5}$ exposure. Even if the indoor PM levels

were reported to be generally lower from fixed sources than from personal monitoring while the subjects were indoors (shown in Table 1), these two examples illustrate the exact opposite, indicating some level of deviation from the overall trends depending on their indoor environments and activities.

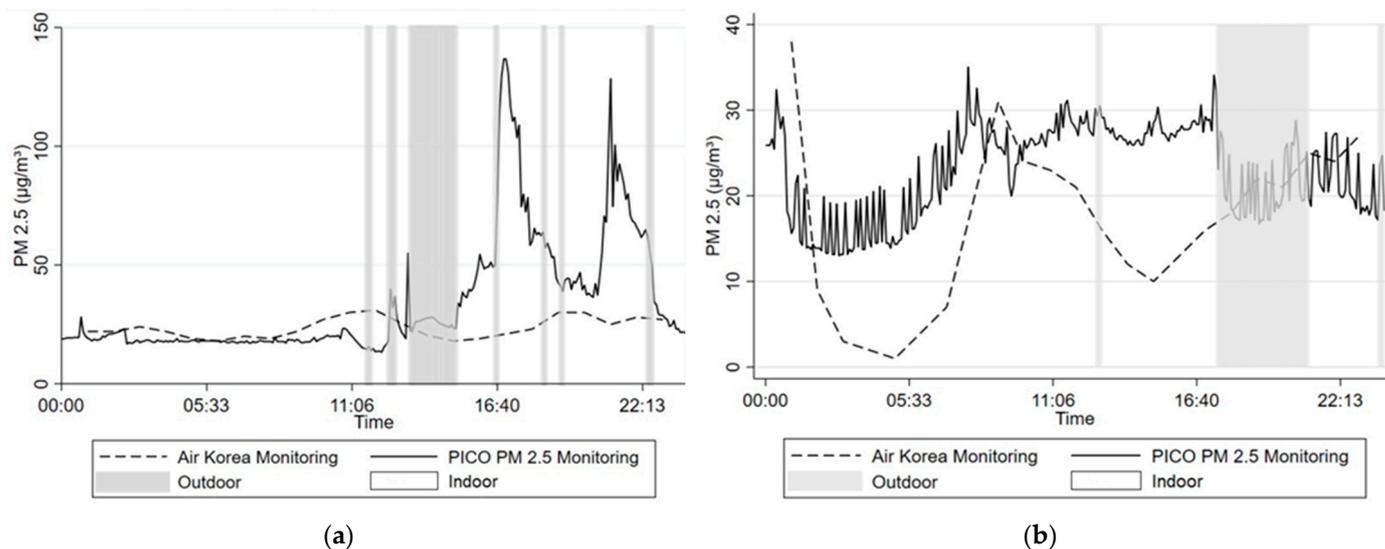


Figure 8. Temporal trend of $PM_{2.5}$ from station and personal monitoring for two selected patients (a: 1-005, b: 1-010).

4. Discussion

In this study, $PM_{2.5}$ concentrations were measured from the portable device with a low-cost sensor (“PICO”) for 47 asthmatic children living in Seoul’s metropolitan area and compared with the station-based hourly ambient $PM_{2.5}$ data (“Air Korea”) by the time and location. On an aggregate level, relatively similar temporal patterns were found between the two sources of $PM_{2.5}$ data, but average $PM_{2.5}$ concentrations via personal monitoring tended to be lower than those from fixed monitoring stations, particularly when the subjects were located indoors, during the evening or nighttime, and farther from the fixed monitoring station. However, on an individual patient level, the two $PM_{2.5}$ measures did not correspond well to each other while staying indoors due to significant variations in lifestyle, moving patterns and indoor environments across the subjects. These results not only underline the potential limitations of station-based data to assess a person’s true $PM_{2.5}$ exposure, but also highlight the role of personal monitoring via low-cost mobile sensors as an important supplement or even alternative to the conventional station-based monitoring. This is even more true since the COVID-19 pandemic began because people were forced or willing to spend more time indoors and reduce outdoor activities to avoid the risk of virus exposure [38]. It is beyond the scope of our study to identify the sources of elevated $PM_{2.5}$ measures, both indoor and outdoor, but is worth exploring in the future study.

It is known that both genetic and environmental factors have a role in the incidence or intensity of the symptoms of allergic diseases such as asthma [39]. However, primary prevention of allergic diseases by controlling a single environmental risk factor such as $PM_{2.5}$ is far from being achieved mostly because of the complex dynamics of various individual and ecological factors contributing to allergic diseases and other environmentally related diseases. Instead, a personalized prevention and proactive intervention to mitigate symptoms via exposure assessment and control could become more accurate and effective if an evidence-based analytical tool is developed to predict patient-specific risks for allergic diseases based on a close monitoring of a patient’s real-time exposure to indoor and outdoor $PM_{2.5}$. This approach has been widely recommended as part of a secondary and tertiary prevention strategy for allergic disease [40].

Accurate large-scale monitoring of air pollutants often requires costly and high-precision measurement equipment, which serve as barriers for personalized intervention

tailored to individual characteristics and exposure pathway. Despite the outstanding challenges revealed in this study, there is a great potential for low-cost, real-time sensors to be broadly implemented as a complementary PM monitoring platform to provide timely, personalized alerts and advice for vulnerable populations. Aside from the efforts to fine-tune the existing mobile sensors and devices, dedicated efforts should be made to develop GPS-enabled wearable and patchable devices as a next-generation environmental and health monitoring tool that assesses the true level of environmental exposure to the human body at every second or minute interval [41,42]. The recent development of IoT technology and deep learning algorithm could serve as promising tool for processing and analyzing the real-time air pollution data [43,44] that underpins the backbone of evidence-based personalized medicine and environmental exposure management.

Author Contributions: Conceptualization, D.J.S. and S.-C.S.; methodology, D.K.; software, Y.Y. (Yunjin Yum) and K.G.; formal analysis, Y.Y. (Yunjin Yum), K.G. and S.-C.S.; investigation, D.K., Y.Y. (Yunjin Yum), J.-W.K., W.K.K., H.-S.B., D.I.S., H.-J.Y., Y.Y. (Young Yoo), J.Y., D.H.L., S.-C.S. and D.J.S.; resources, D.J.S. and S.-C.S.; data curation, Y.Y. (Yunjin Yum); writing—original draft preparation, D.K. and Y.Y. (Yunjin Yum); writing—review and editing, S.-C.S. and D.J.S.; visualization, Y.Y. (Yunjin Yum) and K.G.; supervision, D.J.S.; project administration, D.J.S. and S.-C.S.; funding acquisition, D.J.S. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data available on request due to restrictions eg privacy or ethical The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the consent provided by participants on the use of confidential data.

Conflicts of Interest: The authors declare no conflict of interest.

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