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Air pollution exposure monitoring using portable low-cost air quality sensors

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ABSTRACT

Urban environments with a high degree of industrialization are infested with hazardous chemicals and airborne pollutants. These pollutants can have devastating effects on human health, causing both acute and chronic diseases such as respiratory infections, lung cancer, and heart disease. Air pollution monitoring is vital not only to citizens, warning them on the health risks of air pollutants, but also to policy-makers, assisting them on drafting regulations and laws that aim at minimizing those health risks. Currently, air pollution monitoring predominantly relies on expensive high-end static sensor stations. These stations produce only aggregated information about air pollutants, and are unable to capture variations in individual's air pollution exposure. As an alternative, this article develops a citizen-based air pollution monitoring system that captures individual exposure levels to air pollutants during daily indoor and outdoor activities. We present a low-cost portable sensor and carry out a measurement campaign using the sensors to demonstrate the validity and benefits of citizen-based pollution measurements. Specifically, we (i) successfully classify the data into indoor and outdoor, and (ii) validate the consistency and accuracy of our outdoor-classified data to the measurements of a high-end reference monitoring station. Our experimental results further prove the effectiveness of our campaign by (i) providing fine-grained air pollution insights over a wide geographical area, (ii) identifying probable causes of air pollution dependent on the area, and (iii) providing citizens with personalized insights about air pollutants in their daily commute.

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1. Introduction

Air pollution is one of the factors that endangers people's health at large. As our society evolves and more sources of pollution are present in the environment, the impact of air pollution becomes increasingly prominent. This is especially true in densely-populated areas that offer a wide range of infrastructure such as public transportation, factories, and other urban facilities. The World Health Organization (WHO) estimates that worldwide around 7 million people die from the effects of air pollution every year (WHO). Air pollution is indeed responsible for causing heart disease, strokes, lung cancer, and chronic respiratory diseases (Jasarevic et al., 2014; Jiang et al., 2016; Peel et al., 2007). Moreover, 9 out of 10 people breathe air that exceeds WHO's recommendations pertaining the level of pollutants in the air(WHO). As such, air pollution is a widely-spread phenomenon that affects not only individual's health, but also puts a high burden on the health care system and broader economy, with costs associated to days off work and possible job loss (Birnbaum et al., 2020).

The assessment of the air quality is predominantly carried out by high-end monitoring stations whose prohibitive cost limits their deployment to only a few stations per city. These monitoring stations incur high maintenance costs and are mostly located in dense areas or in the vicinity of city centers, leaving large geographical areas uncovered. As a result, the available air quality information is coarse-grained. Indeed, areas located far away from these monitoring stations might suffer a lower accuracy of reported values as the data is extrapolated over a wider geographical area. To the contrary, the deployment of wireless sensors into public transportation vehicles such as buses, trams, and trains to monitor the air quality results in a wider spatial coverage (Motlagh et al., 2021). However, sensory readings are still limited to the locations where such vehicles traverse (Gao et al., 2016; Saha et al., 2017). To address the limited coverage, there has been a clear shift toward leveraging the power of the crowd, and thus aim at a high-resolution air quality data reporting. Existing projects, however, have been limited to studying benefits to individual citizens and demonstrating the feasibility of collecting data from the crowd (Robinson et al., 2018; Zappi et al., 2012; Predi'c et al., 2013, pp. 303–305; Thompson, 2016; Bales et al., 2019) and further research is needed to make these solutions a viable long-term solution. In addition to obtaining air quality information through the crowd that carries portable and low-cost air quality sensors, another benefit of citizen-based monitoring is that it also supports estimating the impact of air pollution on people's health. In this context, the most crucial air pollutants are particulate matters (PMs) (Dominici et al., 2014) and gaseous pollutants such as CO_2 and NO_x. PMs are typically classified according to the size of the particles forming them into $PM_{2.5}$ and PM_{10}, with 2.5 and 10 indicating the maximum diameter of such particles in μm. Exposure to PMs has been shown to increase the risk of several syndromes, including attention deficit hyperactivity disorder, autism, loss of cognitive function, anxiety, asthma, chronic obstructive pulmonary disease, hypertension, and stroke (Thompson, 2018). Fortunately, due to the physical characteristics of the PMs, the inhaled dosage of these pollutants can be computed, and thus their health effects can be estimated. For instance, Nyhan et al. (Nyhan et al., 2014) demonstrate how heart rate variability is linked with the inhaled PM dose in people's lungs. Similarly, Yin et al. (Yin et al., 2017) highlights that the $PM_{2.5}$, which is inhaled in both outdoor and indoor environments, is associated with high blood pressure; in addition, computing inhaled PM dosage also helps assessing cardiovascular effects.

In this article we present an air pollution exposure monitoring system that uses portable low-cost sensors. The system is part of the MegaSense[1] networking model that allows IoT (Internet of Things) interconnec-tion of a multitude of heterogeneous physical objects and devices. MegaSense, indeed, has attracted great attention and interest from both academia and industry in environmental sciences (Lagerspetz et al., 2019; Zaidan et al., 2020). Our monitoring approach consists of citizens that carry with them portable sensor devices while performing their daily activ-ities in indoor and outdoor environments (Motlagh et al., 2020a). The sensors report meteorological variables and particulate matter compounds. We present a campaign that lasted for two and a half month, and process and analyze the collected data.

The work in this article brings the following contributions:

(i) It presents a successful longitudinal real-world deployment of low-cost portable air quality sensors in a district of the city of Helsinki,
(ii) It demonstrates the efficacy of our campaign by showing a high-resolution and full area coverage with sensor measurements, and it validates such readings against those of expensive high-end monitoring stations,
(iii) It provides valuable findings and insights into the air pollutants in the area, as well as plausible causes and ways to mitigate it, and
(iv) Our system is capable of offering citizens personalized information on their exposure to air pollutants in their daily commute(s).

The rest of this article is organized as follows. Section 2 presents an overview of the air quality monitoring system proposed here. Section 3 evaluates the validity of our sensor data, and provides an indoor-outdoor data classification method. Section 4 discusses the experimental results of our campaign. Section 5 provides insights into personalized exposure of citizens to air pollutants. Finally, Section 6 discusses possible future work, and Section 7 concludes the article with some final remarks.

[1] https://www.megasense.org/.

2. The Experiment

This section provides a detailed description of the sensing systems and measurements used in our article. These systems perform air quality measurements in different areas and are shown in Fig. 1(b) and (c).

2.1. Pakila Campaign: Sensor Deployment and Data Collection

The Pakila district, shown in Fig. 1(a), is a good example of a detached house area where the air quality is affected mainly by the use of fireplaces and street dust. The fireplaces in these houses are often used for additional heating. As residential areas are densely populated in urban areas, the smoke nuisance to the immediate neighbor can be significant. Local air quality is also largely affected by terrain and weather conditions, which is why air quality may worsen locally, especially on cold and windy days.

The data set used in our campaign consists of sensory data collected during the time period from October 30, 2019 to January 15, 2020. A total of 40 devices were given out to citizens to carry around and measure air quality. Citizens were instructed to use the devices in Pakila, but were not necessarily limited to the area. The analysis of the measurements were considered inside an area of circa 6 km^2. The purpose of the experiment was to test the accuracy of the low-cost devices and investigate their behavior in the given area. Further tests started in winter 2020–2021 to quantify the effectiveness of using the same sensor devices to measure wood burning-specific pollutants in the area.

2.2. Reference Sensing Station in Pirkkola

In this work we use a city air quality monitoring station as our reference sensing station to validate the measurements of our low-cost sensors. This air quality station, called Pirkkola station, is located in the Pirkkola neighbourhood of the Pakila district in Helsinki, which is where our measurement campaign took place. The Pirkkola station is located in Northern Helsinki, about 9 km from Helsinki city center. The Pirkkola station is operated by the Helsinki Region Environmental Services Authority (HSY)[2] . It resides at the roadside, surrounded by wooden houses (as shown in Fig. 1(b)), and is planned to measure pollutants caused by traffic, as well as pollution sourced from the houses. Indeed, the Pakila district in Helsinki is known for its large number of private detached houses that use wood burning for heating, cooking, and heating saunas. As such, wood burning adds up to the baseline pollution profile caused by road transport. This has been the main motivation to deploy our low-cost sensors and carry out the measurement campaign in the Pakila district, whose pollution profile is strongly affected by wood burning emissions.

The air pollution sampling inlet at the Pirkkola air quality station is at about 3 m height from the ground. The Pirkkola station is an urban and distinct sensing station which covers buildings, car parking, road, and vegetation areas. The station is equipped with gas and aerosol sensors that provide data on fluxes of air pollutants. This includes measurements of temperature (T), relative humidity (RH), $PM_{2.5}$, PM_{10}, CO, and NO_2. Thus, to compare the measurements of our portable sensors, we downloaded the measurements of the Pirkkola station for the time period of our measurement campaign. Next, considering the 1-min granularity of the data collected from the Pirkkola station, we aggregated our sensor data as 1-min averages. Finally, we compared the measurement results of our sensors and Pirkkola, and validated the sensors.

2.3. Low-cost Sensors

The low-cost sensor units are based on a BMD-340 System On a Module. They connect to Android smartphones over Bluetooth LE; smartphones report their readings further to a collecting server. A Sensirion SPS30 sensor measures particulate matter (PM). The initial production cost of the low-cost sensor unit is around 250 USD (Lagerspetz et al., 2019), but expected to decrease below 100 USD in large volume production. Moreover, the sensors measure atmospheric parameters (e.g., temperature and humidity), gaseous compounds (e.g., CO_2, NO_x), and air pollutants (e.g., particulate matter), unlike cheaper sensors, such as the Wynd air quality tracker[3] and Dylos air quality monitor[4], which are limited to particulate matter only. Table 1 lists all the sensors available on the device. The sensors are enclosed in a 3D-printed case made of ESD-PETG filament.

The sensors report measurements periodically. The reported readings include temperature, humidity, pressure, carbon monoxide, nitrous dioxide, ozone, masses of detected particulate matter, amount of light, and positioning information along with a timestamp. The sensors are powered by a 3500 mAh battery. Fig. 2 shows the current draw of the sensors on the device during one measurement cycle. These cycles happen back-to-back and one cycle consists of heating up the sensing elements to the appropriate tempera-tures for measuring and gathering measurements from all the sensors. The sensors were originally designed to be carried by users for studies of outdoor air quality. To preserve battery while indoors, the units are programmed to use a long sampling interval when they are stationary, and switch to a shorter interval when they are on the move. An accelerometer sensor on-board of the unit enables to differentiate between such two states. That is, people whose velocity rate changes while moving, whether on foot or by means of a vehicle, trigger the sensors to adapt their sampling rate accordingly. While the units do not report whether they have moved or not, we deduce this from the rate at which they report readings. Based on the current draw, the calculative operation period is circa 22 h, with

[2] https://www.hsy.fi/en/air-quality-and-climate/how-is-air-quality-monitored/.
[3] https://shop.hellowynd.com/products/wynd-air-quality-tracker.
[4] http://www.dylosproducts.com/ornodcproair.html.

(a) (b) (c)

Fig. 1. (a) The districts of Pakila and Pirkkola in Helsinki are shown in the grey area. The HSY reference station in Pirkkola is shown with the green dot. (b) The HSY reference station in Pirkkola and (c) low-cost sensors used in our Pakila campaign.

Table 1
Sensors available in the sensing units.

Sensor name	Phenomena measurements
BME-280	temperature, humidity, pressure, altitude
Sensirion SPS30	PM
MiCS-4514	CO, NO_2
MQ-131	O_3

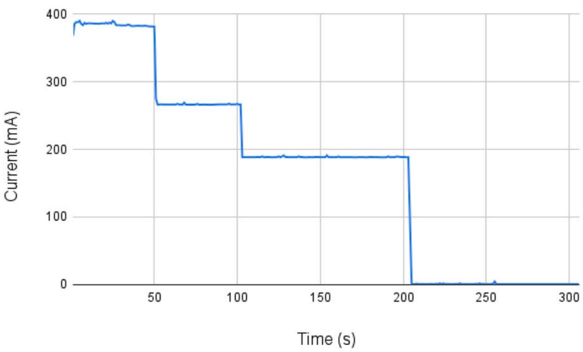

Fig. 2. Current draw of our sensor units per measurement cycle.

any inactive periods increasing the operational period.

3. Data Classification and Validation

3.1. Indoor-outdoor Data Classification

The low-cost sensors deployed in our air quality monitoring system are carried by volunteer citizens. The sensors are small in dimension, as shown in Fig. 1(c), and can be easily attached to a backpack, purse, or jacket. The volunteers carry such sensors while performing their daily tasks and going on with their routine, and thus the sensors move between indoor and outdoor environments continuously. As such, it is important to classify the sensor measurements into indoors and outdoors prior to any other data analysis. In fact, such a differentiation is crucial to successfully and effectively identify indoor (household) and outdoor (environmental) causes of air pollution (Motlagh et al., 2020b). That is, the sources of air pollution vary considerably, and so does the concentration of the different pollutants. For such a reason, findings based on both indoor and outdoor data, indistinguishably, would provide a simplistic and somewhat wrong picture of the air pollution conditions in the different environments.

Our campaign took place in winter, when the air temperature changes drastically between outdoor and indoor environments such as house, work office, shops, and gyms. That is, there is a clear and unmistakable separation between indoor and outdoor temperatures. We compare the temporal sensor data, and specifi-cally the temperature of our low-cost sensors, to the 20 °C temperature threshold (Karjalainen, 2009) and *classify* the sensor readings (of all the parameters) as *indoors* if the temperature is above such a value; and *outdoors*, other-wise. For the purposes of our experiments, this simple heuristic is sufficient as indoor air temperature in Finland is typically between +20 and + 24 °C, whereas winter temperatures are substantially different with the mean temperature being 4 °C. When such simple distinction cannot be made, more elaborate data − classification mechanisms based on machine learning are needed for separating the measurements regardless of the environmental conditions (Saffar et al., 2019, pp. 1–8; Zhu et al., 2019).

Table 2 presents the mean, median, and the standard deviation of the temperature and relative humidity readings of eight different portable sensors used in our campaign upon the indoor-outdoor data classification. We notice that the indoor temperature values vary between 25 °C and 30 °C, which is caused by effective thermal insulation and heating, other heat sources such as ovens, and additional heaters used at homes. Additionally, other indoor places such as shops or gyms have a higher density of people, which causes the room temperature to rise. Moreover, the users might sometimes place their sensors inside their pockets or backpacks, leading to a higher sensed temperature. The relative humidity, instead, is higher outdoors due to the lack of heat sources, as well as atmospheric phenomena such as rain or snow.

3.2. Data Validation

Different measurement variables can be separated between indoor and outdoor through our indoor-outdoor data classification method. In this section we compare the performance of our low-cost sensors to that of the high-end HSY monitoring station located in Pirkkola. Upon classifying the data, we compare the values of the outdoor-classified temperature and relative humidity of the low-cost sensors (see Table 2) to the data from the HSY station.

Table 3 shows the mean, median, and the standard deviation of temperature and relative humidity variables reported by the HSY Pirkkola station (Fig. 1(b)). The low-cost sensors understandably report slightly higher outdoor temperatures due to the fact that they might be partially covered during a citizen's commute, or because the sensor senses intermediate temperatures when transitioning between outdoors and indoors. Relative humidity is affected by the same factors, leading to low-cost sensors reporting lower values. Fig. 3 shows the $PM_{2.5}$ (left) and PM_{10} (right) as boxplots using the outdoor measurements of the portable low-cost sensors (LCS) deployed in Pakila, and the HSY mobile measurement station in Pirkkola. The figure shows that the $PM_{2.5}$ and PM_{10} concentrations are similar. Specifically, the median values of $PM_{2.5}$ are at 3 and 4.5 $\mu g/m^3$ for the portable sensors and the HSY station, respectively; whereas the median values for PM_{10} are at 4 and 7.5 $\mu g/m^3$ for the portable sensors and the HSY station, respectively. Likewise, the edges of the boxplot (first and third quartiles) of the $PM_{2.5}$ measurements for the low-cost sensors and the HSY mobile station are 1.5 and 8 $\mu g/m^3$, and 2 and 7 $\mu g/m^3$, respectively. Similarly, these values correspond to 2 and 9 $\mu g/m^3$, and 4 and 11 $\mu g/m^3$ for the PM_{10} measurements.

The similarity in the measurements is related to the fact that both Pakila and Pirkkola districts are only 2 km distant. This indicates that, accounting for the geographical factor, the particulate matter measurements via our low-cost portable sensors are reliable.

Table 2
Temperature (°C) and relative humidity (%) measurements for eight portable sensors used in our campaign between October 30, 2019–January 15, 2020. The data is classified into indoors (in) and outdoors (out) by using a 20 °C as threshold (Karjalainen, 2009).

		Temperature			Relative Humidity		(RH)
		Mean(μ)	Median($\tilde{x}$)	STDV(σ)	Mean(μ)	Median($\tilde{x}$)	STDV(σ)
S1	In	28.490256	28.015	2.793984	24.413262	26.490	3.655967
	Out	8.0	8.080	3.339545	56.668278	56.530	7.950110
S2	In	28.783082	28.460	1.724610	24.298525	24.700	4.255433
	Out	4.119692	4.710	2.711688	63.716094	65.060	7.660896
S3	In	28.763541	28.065	3.553812	23.773474	21.955	5.061140
	Out	16.673704	17.845	3.015234	34.481667	33.240	9.536762
S4	In	29.155935	28.920	3.075662	20.651203	20.620	5.873494
	Out	10.041401	9.240	4.142719	51.416369	54.455	9.054895
S5	In	27.889253	27.520	2.712592	25.115952	25.470	4.327678
	Out	16.207329	17.480	3.566683	37.684232	36.930	8.618369
S6	In	28.014639	28.000	4.118464	22.355464	22.750	5.445169
	Out	7.271954	2.930	6.873828	43.768276	46.390	10.049835
S7	In	27.110353	25.900	5.186556	28.000	25.740	7.479326
	Out	7.696985	7.930	2.629968	56.962946	55.590	8.475298
S8	In	37.052778	38.480	3.553599	15.141667	14.010	3.333056
	Out	7.763833	8.230	2.907542	61.286806	60.640	6.677388

Table 3
Mean, median, and standard deviation of temperature (°C) and relative humidity (%) reported by the HSY monitoring station located in Pirkkola.

	Temperature	Relative Humidity
Mean (μ)	2.046377	89.989670
Median ($\tilde{x}$)	2.5	92.3
STDV (σ)	3.424982	8.410411

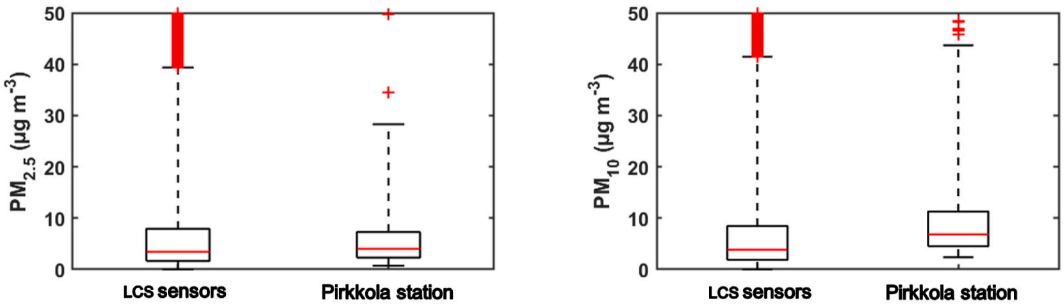

Fig. 3. Outdoor $PM_{2.5}$ (left) and PM_{10} (right) shown as boxplots with corresponding median for both low-cost (LCS) sensors and the HSY monitoring station.

4. Data Integration and Visualization

One key contribution of our work consists of providing a daily air pollution profile of the district of Pakila by means of the portable low-cost sensors. Similarly, air pollution hotspot profiles are of uttermost importance toward designing intervention mechanisms in the area (Rebeiro-Hargrave et al., 2020). In fact, such findings could facilitate decisions regarding modifications to road traffic or building of new green areas.

Particulate matter. The most common variables of interest in detecting air pollution are $PM_{2.5}$, PM_{10}, CO, and O_3 (Cogliani, 2001). Fig. 4(a) and (b) show the diurnal cycle in the form of boxplots of (a) $PM_{2.5}$ and (b) PM_{10} concentrations in indoor (grey) and outdoor (white) environments. We notice that the outdoor measurements patterns for $PM_{2.5}$ and PM_{10} are similar. That is, the emission of both

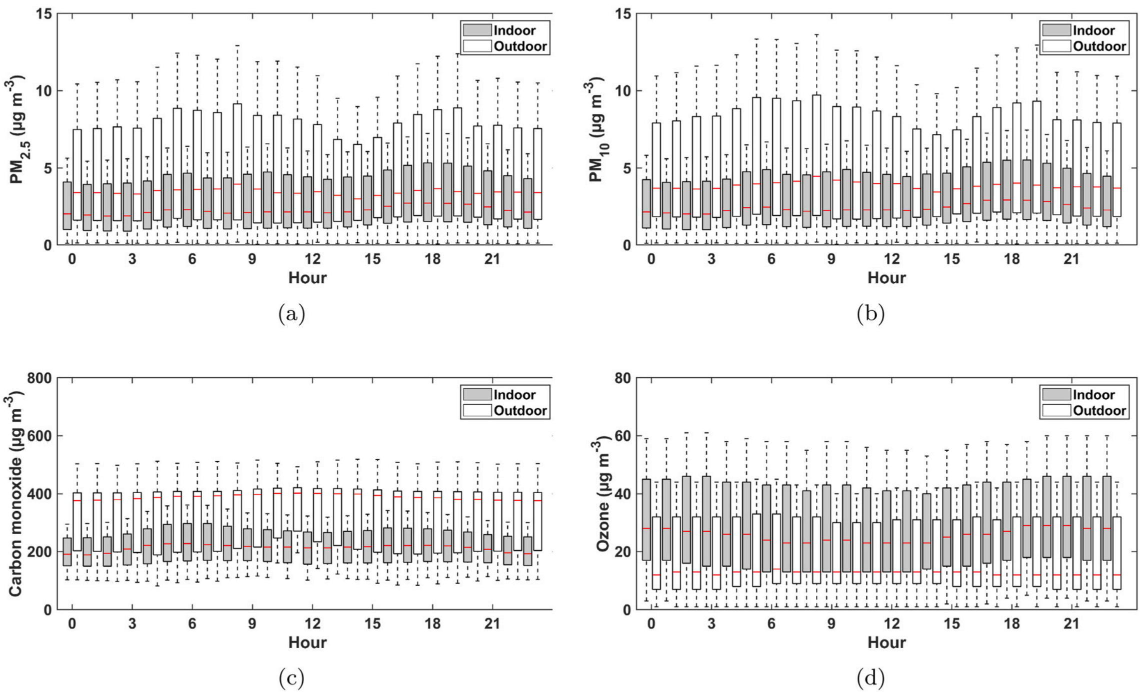

Fig. 4. Indoor vs outdoor concentrations of (a) $PM_{2.5}$, (b) PM_{10}, (c) CO, and (d) O_3 variables in the Pakila district.

types of aerosol increases during rush hours – i.e. 7 AM–9 AM in the morning and 4:30 PM - 18:00 PM in the afternoon – when people use their vehicles to go and return from work. Coarse particles of dimension 10 μm, i.e., PM_{10}, are formed due to dust from heavy traffic, smoke, or construction sites, and can cause eye irritation, lung and throat infections, and lung cancer (CDC). Same goes for fine particulate matters, i.e., $PM_{2.5}$, which are formed mainly due to combustion emission, are even more dangerous as they can reach lungs and even the blood stream due to their small dimensions of less than 2.5 μm. To the contrary, indoor concentrations in the Pakila district of $PM_{2.5}$ and PM_{10} are lower than outdoors, although they follow the same patterns and reach their peaks during the busiest hours of the day. In fact, indoors we are more shielded by the causes of particle pollution. However, there are several infiltration factors such as poor insulation of buildings and opening of windows that cause outdoor pollution to transport indoors (Lv et al., 2017). For instance, as much as 30%–75% of indoor $PM_{2.5}$ pollution is due to outdoor environment (Dockery & Spengler, 1981; Jenkins, 1996; Xiong et al., 2004).

Gases. Fig. 4(c) and (d) present the concentrations of CO and O_3 variables as diurnal cycle in the form of boxplots in indoor (grey) and outdoor (white) environments, respectively. As expected, the CO concentration, produced mainly by an incomplete combustion of carbon-containing fuels, is higher outdoors than indoors (Li et al., 2018). The mean concentration remains mostly in the higher end of the boxplot edge, at around 370 $\mu g/m^3$. Its variation during the day is not significant, though it reaches its highest values between 8AM and 5PM, during which time there is a higher density of traffic. The indoor CO concentration, however reaches its maximum values early in the morning, and then again later in the afternoon. This is a direct consequence of the fact that many fuel-based appliances and lanterns, as well as wood-burning stoves and grills emit CO in the air due to their incomplete combustion. Such appliances are needed for heating and cooking and are switched off when people leave for work, thus causing a decrease in indoor concentration levels during working hours. In fact, Pakila district features a high number of traditional Finnish saunas that rely on wood burning, as opposed to electricity, to generate heat (Tarkoma et al., 2019). Similarly, the average apartment size in Pakila is among the highest in Helsinki, with most buildings being older than 50 years. As such, a considerable proportion of homes, especially detached houses, use wood for additional heating or saunas (Levander & Bodin, 2014). Fig. 4(d) shows the indoor and outdoor concentration level of O_3. The outdoor concentration levels are higher during the morning and late afternoon hours. Although O_3 is not emitted directly from automobiles, the compound is the outcome of NO_x (nitrogen oxides) and hydrocarbons reacting with sunlight in the atmosphere (Zaidan et al., 2019a). However, due to the low sun intensity in Finland during winters, the concentration levels during the day show no accentuated variations and remain at around 32 $\mu g/m^3$. The indoor concentration, however, varies between 38 and 46 $\mu g/m^3$ and shows clear diurnal variations (Weschler, 2000). Though initially counter-intuitive, indoor O_3 pollution can reach higher values than outdoor due to a multitude of factors such as air purifiers and different air cleaners that release O_3 as a by-product, as well as office equipment such as

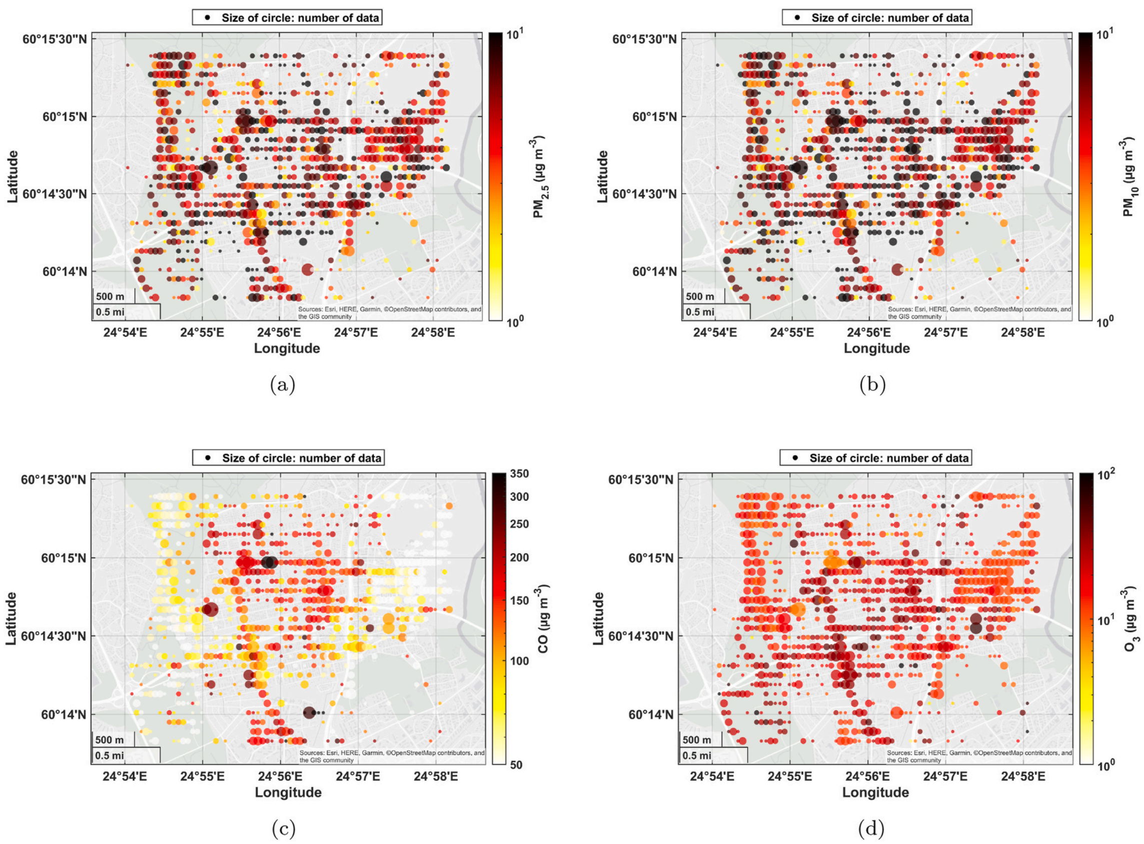

Fig. 5. Heatmaps of outdoor concentrations of (a) $PM_{2.5}$, (b) PM_{10}, (c) CO, and (d) O_3 variables in the Pakila district.

photocopiers (Health Canada and Residentia). In fact, home electric devices alone are a significant contributor of ozone indoors, with such equipment being used mainly in the morning before people go to work or in the late afternoon when they get back (Huang et al., 2019). The findings from our low-cost sensor data suggest that they can accurately support and complement existing measurements from high-end devices, though at a higher spatial and temporal resolution.

Pollution hotspots. Figs. 5 and 6 show the concentration levels of (a) $PM_{2.5}$, (b) PM_{10}, (c) CO, and (d) O_3 variables in the form of heatmaps outdoors and indoors, respectively. The size of the circle increases with the number of sensor readings in the given geographical (longitude and latitude) area, whereas the color gets darker with higher concentration levels of the pollutant. We have sensor data from almost the entire Pakila district, with fewer data only on the bottom right where a small park and sport arena are located. Fig. 5(a) and (b) as well as Fig. 6(a) and (b) show similar concentrations (as seen earlier in Fig. 4(a) and (b)). The pollution hotspots for both $PM_{2.5}$ and PM_{10} are spread almost uniformly over the area, though at a higher concentration along the main streets in the district. This finding emphasizes one more time how PMs originating from sources like traffic dust and wood burning spread fast, putting at risk the health of the people living in the area. The highest concentrations are located in the vicinity of the interchange and its left (where several schools and kindergartens are located), as well as along one of the main streets (Pakilantie) in the district. Although the indoor concentrations are lower, Fig. 6(a) and (b) demonstrate how indoor $PM_{2.5}$ and PM_{10} hotspots follow the pattern of those outdoors, proving that such pollutants can indeed transport in to our homes, offices, and schools, and thus putting our health at risk.

Figs. 5(c) and 6(c) show outdoor and indoor CO hotspots, respectively. We see that the sensor data distribution across the Pakila district is different, with more data points reported outdoors. That is, outdoor CO pollution measurements cover a wider area than that of indoor measurements. In fact, Fig. 5(c) shows various pollution hotspots in west Pakila, despite the vicinity of the green area on the left, suggesting that there are extra sources of outdoor CO emissions. We also see how strong outdoor pollution hotspots transfer indoors. Such is the case of pollution hotspots located at around N60°15′ E24°55′50″, N60°14′ E24°56′20″, and at N60°14′40″ E24°55′10″. Next, we show outdoor and indoor O_3 hotspots in Figs. 5(d) and 6(d), respectively. In both cases, the highest concentrations are around the main streets in Pakila, where most detached houses and apartment buildings are located, as well as in the vicinity of the interchange. As already reported in Fig. 4(d), the O_3 pollution hotspots are at higher concentration levels indoors, supporting our assumption that poor air ventilation (or massive use of air purifiers), wood burning, and usage of home electric equipment, for instance, are often-overlooked factors that lead to non-negligible indoor O_3 concentrations.

The spatial resolution of our heatmaps as well as the differentiation between indoor and outdoor concen-trations of a pollutant are

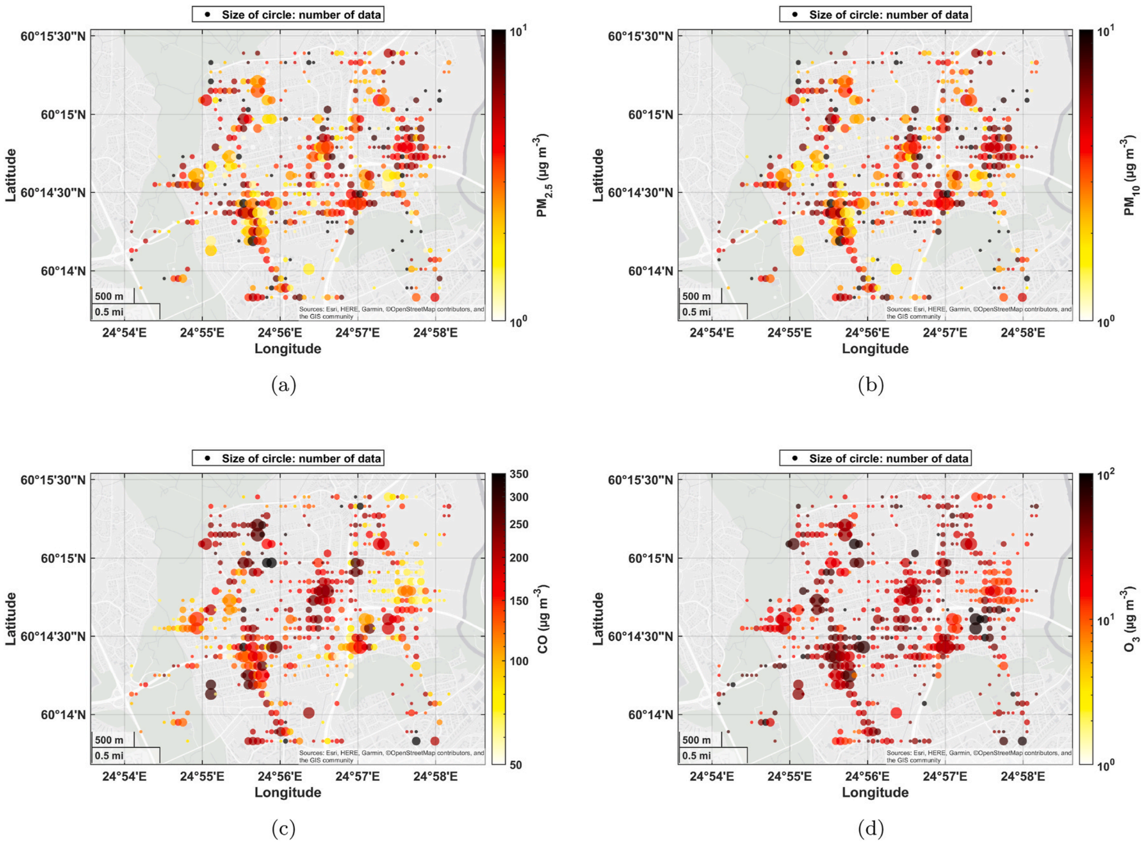

Fig. 6. Heatmaps of indoor concentrations of (a) $PM_{2.5}$, (b) PM_{10}, (c) CO, and (d) O_3 variables in the Pakila district.

primary indicators that pollution sources may be of different nature. As such, we are better capable of identifying them and taking actions at individual or regional or city level to improve air quality. To that end, our low cost sensors can complement existing expensive monitoring solutions (such as the Pirkkola monitoring station shown in Fig. 1(b)) that provide coarse-grained air quality data at a lower spatio-temporal resolution. In addition, they can contribute to the creation of air quality databases that are open to the public.

5. Individual Exposure Monitoring

Particulate matter is a mixture of solid and liquid particles suspended in the air, whose size and chemical composition vary continuously in space and time (Kim et al., 2015; World Health Organization, 2013, pp. 6–7). The constituents of PM include compounds such as nitrates, sulfates, elemental and organic carbon, organic compounds (e.g., polycyclic aromatic hydrocar-bons), biological compounds (e.g., endotoxin, cell fragments), and various metals (e.g., iron, copper, nickel, zinc, and vanadium) (Kim et al., 2015). As such, its impact on human health is higher than that of other common pollu-tants such as carbon monoxide or ozone (Zaidan et al., 2019b). Moreover, PM is particularly harmful on human health (Peters et al., 2004) due to its very small dimensions, reaching lungs and blood stream. Its effects are related to the amount of pollution that reaches and stays in the body.

Lung-deposited dosage. The term refers to the total accumulated amount of PM pollution, also referred to in literature as *deposited dosage*, and depends on the breathing rate of individuals. For instance, commuters who often cycle or run, and thus have a faster breathing rate than a driver, are exposed to higher pollution levels (Zuurbier et al., 2010). Health effects such as decreased lung function, breathing difficulties, irrita-tion of airways and coughing, heart attacks, irregular heartbeat, and asthma have been directly linked to PMs (Cadelis et al., 2014; Fang et al., 2013; Kim et al., 2015). As such, it is of primary concern to provide people with estimates of PM pollution in the vicinity of their home, work place, and other sites of interest. This raises people's awareness toward the levels of pollution they are exposed to, and it nudges them to take action and commute via less-polluted paths.

Our air pollution exposure monitoring system provides the foundation for a real-time, personalized, and up-to-date exposure level system that could warn citizens when such levels are above recommended values. In fact, due to our *one-citizen – one-sensor* mapping, each citizen equipped with a low-cost air pollution sensor can learn about their daily exposure to PM pollutants, whether indoors or outdoors.

Individual exposure. We estimate an individual's level of exposure based on the average value of the $PM_{2.5}$ concentration in the air during the time of exposure. We do so by deriving the deposited dosage (DD) as the amount of $PM_{2.5}$ deposited in the respiratory tract during breathing, by means of the formula presented in (Hussein et al., 2015) and reported below.

$$DD = \int_{ti}^{tj} \int_{D_{pi}}^{D_{pj}} V_E \cdot D_F \cdot n_M^0 \cdot dlogD_p \cdot dt \tag{1}$$

Here V_E is the volume of air breathed per time (breathing rate) and D_F is the deposition fraction of aerosol particles in the respiratory system ($PM_{2.5}$ in this case). V_E depends on the body size, activity and status of the subject. D_F is different for different parts of the respiratory system (head/throat, tracheobronchial, and pulmonary/alveolar). It also depends on the physiology, status, and activity of the subject. In Equation (1), $n_M^0 = dM/dlog(D_p)$ is the lognormal particle number size distribution. Both D_F and n_M^0 are functions of *log* (D_p), where D_p is the particle diameter. The double integral is evaluated for an exposure time period $\Delta t = t_j - t_i$ based on any selected time resolution. Solving Equation (1) for inhalation of $PM_{2.5}$ during a period of $\Delta t = 1$ h, the deposited dosage of $PM_{2.5}$ is

$$DD = V_E \cdot D_F \cdot PM_{2.5} \cdot \Delta t, \tag{2}$$

where the values for V_E and D_F are based on (Hussein et al., 2013). More specifically, V_E are 0.51 m^3/h and 0.66 m^3/h for females and males, respectively; whereas the value for D_F is around 0.7 μm for both genders. Note that the unit of DD is (μg) and the unit of $PM_{2.5}$ is $\mu g/m^3$.

Table 4 presents the indoor and outdoor $PM_{2.5}$ dose deposited during 1 h for both male and female individuals. Specifically, the $PM_{2.5}$ concentration is reported by eight different low-cost sensors, and thus individuals. The highest deposited dosage happens outdoors, where factors such as road dust, traffic emissions, and dust from construction sites exacerbate $PM_{2.5}$ pollution. This holds valid for both males and females. In addition, we notice that women are more susceptible to $PM_{2.5}$ pollution for both indoor and outdoor environments. As expected, we notice that these values vary from sensor to sensor, strongly indicating that each individual is

Table 4
Indoor and outdoor deposited dose (DD) of $PM_{2.5}$ for a period of 1 h for male and female measured by eight low-cost portable sensors used in the campaign between October 30, 2019–January 15, 2020. The data is classified into indoors (in) and outdoors (out) by using a 20 °C as threshold.

Deposited Dose (μg)	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
				Indoor (In)				
Male	0.770518	0.660556	0.942487	1.155383	1.976325	0.726582	1.619197	0.360656
Female	0.997141	0.854837	1.219689	1.495201	2.557597	0.940283	2.095431	0.466732
				Outdoor (Out)				
Male	2.958538	2.270792	0.947633	2.673501	1.610770	1.171055	3.227640	2.353517
Female	3.828697	2.938672	1.226349	3.459825	2.084526	1.515483	4.176946	3.045728

exposed to different levels of pollution which depend on their commute and the places they visit. This suggests that our low-cost sensors provide a realistic picture on how the deposited dose of a pollutant discriminates based on one's living conditions, vicinity (or not) to green areas, and their commute habits.

Fig. 7 shows the $PM_{2.5}$ deposited dosage for all our low-cost sensors. Female individuals deposit between 1 and 2.2 μg and between 2 and 4.2 μg of $PM_{2.5}$ pollutant indoors and outdoors, respectively; whereas these values amount to 0.8 and 1.9 μg and 1.7 and 3.2 μg for the male counterpart. While outdoor environments clearly pose a greater risk than indoor environments to people's health in terms of deposited dosage of $PM_{2.5}$, indoor environments and their sources of pollution (e.g., kitchen stoves and fire places) still account for a significant number of causes that affect human health. Such emphasizes the importance of indoor air quality monitoring, with more and more solutions focusing on *the home of the future* (Korhonen et al., 2003).

6. Discussion

The ubiquitous prevalence of hazardous compounds in the air, which more often than not originate from sources very close to us and about which we are not always aware of, renders us oblivious to them. In fact, low air quality constantly endangers human health. As such, air quality monitoring, both indoors and outdoors, is a cornerstone of any sustainable- and environment-oriented design. Its health benefits are visible even in heavily industrialized countries that easily are vulnerable to higher pollution levels (Li et al., 2016; Liang et al., 2019). For instance, the clean air action in China that took place over a period of two years reduced the mortality rate by around 9% (Zheng et al., 2017). Similarly, health benefits (e.g., reduction in cardiovascular disease morbidity and mortality) were seen during the COVID-19 pandemic in China as stringent traffic restrictions reduced pollutant concentrations (Chen et al., 2020).

In this article we focused on the Pakila district in Helsinki, which is renowned for its old residential buildings and a high presence of fireplaces, saunas and other wood-based sources of heat. Our work takes several mandatory steps toward *identifying the effects of air pollution on human health*. Specifically, our campaign contributed to: (i) data classification from low-cost portable sensors into indoor and outdoor, which paves the way to identify separate causes of air pollution for both environments, (ii) based on the individual findings, we link the presence of different pollutants to probable causes that vary in terms of time and space, and thus provide a detailed and fine-grained geolocation-specific pollution map, and (iii) correlate individuals' commute and routine with the amount of pollutant(s) deposited in the their body, and thus their individual exposure. Our findings from the air quality data collected by low-cost portable sensors regarding health risk assessment are summarized below.

Health effects (indoors). Wood smoke is a major contributor of air pollution inside detached houses. Specifically, they are source to multiple air pollutants such as $PM_{2.5}$, PM_{10} and black carbon (Jeong et al., 2019) which are hazardous to people's health. To protect people's health residing in such houses, the best option is to avoid using wood-burning stoves entirely, replace them with a non-burning option, or use a certified wood stove. Similarly, cleaner-burning natural gas or pellet appliances minimize air pollution, are more energy efficient, and provide better temperature control and healthier living environments. Moreover, the use of proper indoor ventilation systems reduces both PM and gaseous concentrations.

Health effects (outdoors). The use of our low-cost air quality sensors enables not only the identification of hotspots of dangerous pollutant, but also the creation of an ever-growing database that enables tracking of the air pollution over time. As such, it is possible to generate an *action road plan* toward the reduction of air pollution and study its efficacy. For instance, city planning can take full advantage of such data, and leverage its fine-grained and high spatio-temporal resolution to design smart solutions. In addition, our data enables *green route-alike* applications that recommend cleaner paths to the citizens.

Air pollution maps for citizens. Air quality data can be used to provide real-time air pollution maps to benefit people as part of *smart city* applications and services. These maps, which show pollution levels of different pollutants (as shown in Figs. 5 and 6), can be updated continuously and allow citizens to be aware of air pollution levels at different places; as such, citizens can properly plan their visit to a shopping mall or visit a park. Such pollution maps help mitigating health risk effects in rapidly-developing cities which are associated with people's allergy and asthma problems (Wang et al., 2021).

Citizen's mobility pattern. The data collected in our Pakila campaign contains accurate location infor-mation of our sensors (and thus citizens) over time. This allows us to generate ciziten's mobility patterns and identify common places of interest. This knowledge is extremely valuable during situations such as the ongoing COVID-19 pandemic to alert people about the transmission risk at given locations.

Challenges of our study. We faced several challenges during the campaign. Specifically, two sensor devices had to be replaced when users accidently dropped the sensors and they broke. Another two devices were replaced due to problems with soldered connectors that broke when the device got hit. This was fixed and the connectors were made more robust on the devices. Moreover, some users reported usability issues caused by a *too small* power switch. The users also received a weekly summary e-mail from the campaign staff with updates on the progress of the measurements, as well as aggregated results of the campaign area shown on a map. In addition, users got to see in details their own measurements via their own device page on our server. We also monitored the usage of the devices, and if the measurements stopped coming in, we sent a polite inquiry e-mail asking if there is a problem with the device or other reason.

7. Conclusions

We presented an indoor and outdoor air pollution monitoring system. Our citizen-based monitoring campaign relied on portable low-cost sensors to sense and report concentrations of different air pollutants in the Pakila district, Helsinki. Our low-cost sensors successfully reported accurate indoor and outdoor concentrations of various pollutants. The reported data was presented in the form of diurnal cycles and heatmap plots showing the distribution of such pollutants in space and time, and thus allowed us to decouple their

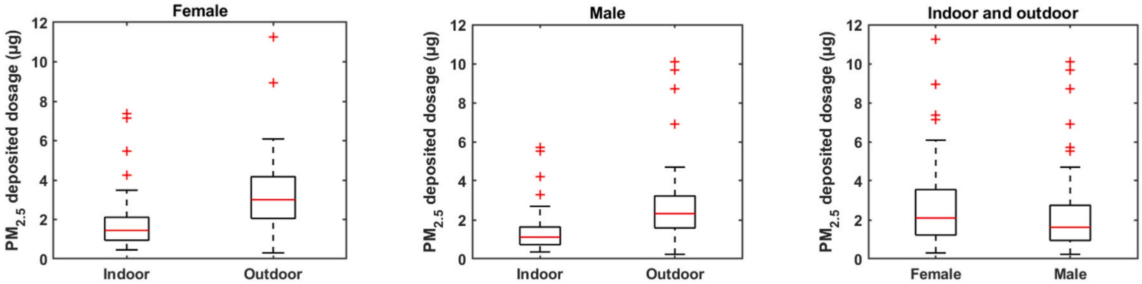

Fig. 7. From left to right: deposited dosage of $PM_{2.5}$ for female and male individuals in indoor and outdoor environments, as well as its cumulative value for both environments shown as boxplots with corresponding median value.

origin. Next, due to the *one-sensor – one-citizen mapping* property of our system, we showed how our low-cost sensors can be used to provide personalized information regarding exposure to a given pollutant on an individual scale. In addition, we showed how *green-route* applications can be build upon our data. The experimental results and lessons learned indicate that portable air quality monitors provide insights into personal pollution exposure and the micro-climates of the city. A usability study regarding the ease with which citizens carry our sensors would be highly beneficial to further increase the accuracy of the reported data. We leave such a task as future work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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