



# Recent advancements in low-cost portable sensors for urban and indoor air quality monitoring

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## Abstract

The spatiotemporal heterogeneity of the air pollutants complicates appropriate monitoring. The collective measures or crowdsensing is a promising approach to achieve a better air pollution assessment because it includes the local concentration of pollutants, as well as the position and mobility of people. Thus, compared to traditional static monitoring, the participatory sensing data by low-cost sensors can avoid the misclassification of exposition to air pollutants, enabling a comprehensive understanding of their health effects. This systematic review integrates each core part of what is required to achieve crowdsensing for air pollution: sensors, portable devices, and data models. Despite the limitations of sensors in terms of sensitivity and selectivity, it has been possible to use portable air monitors to determine pollution hotspots around the world. However, limited models for data processing, performance issues when using low-cost devices, in addition to lack of community engagement, are the challenges to overcome for the feasibility of air pollution assessment with portable monitors.

**Keywords** Crowdsensing air pollutants · Indoors and outdoors · Mobile air monitoring · Portable sensors

## Introduction

The New Urban Agenda published by the United Nations in 2017 emphasized the unprecedented growth of cities globally. The population living in urban areas is projected to double by 2050. Therefore, urbanization in the twenty-first century will be recognized as one of the significant trends that will generate more profound transformations in socio-urban dynamics and will result in major challenges to maintain sustainability in cities (Evans et al. 2016). The severity of the world's air pollution problem resulted in the

World Health Organization's agenda to include (a) actions to reduce the global epidemic of noncommunicable diseases and climate change, with the reduction of air pollution as a fundamental pillar; (b) a "Call for Urgent Action" by health and other sectors to reduce the 7 million deaths per year; (c) consensus to develop a "Global Clean Air Movement" with commitments by ministers, mayors, intergovernmental organizations, and non-state actors to achieve air quality levels in line with the WHO 2030 Air Quality Guidelines; and (d) improved evidence on the health impacts of air pollution, acute episodes along with new tools to estimate the impacts and related costs, and benefits required to improve air quality (Loomis et al. 2013).

Air pollution is one of the main challenges to urban health and environmental sustainability. It is defined as the presence in the air of one or more substances at a concentration above natural levels, with the potential to produce an adverse impact on human and environmental health (Seinfeld and Pandis 2016). At present, according to the World Health Organization (WHO), approximately 91% of the world's population lives in places where air quality exceeds the limits established as safe. The Global Burden of Diseases, Injuries, and Risk Factors Study 2015 included air pollution as one of the main causes of the increase in global morbidity, mainly in developing countries (Cohen et al. 2017). The

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costs of pollution are myriad, but the most damaging economic cost is represented by the premature mortality toll.

Concentrations of outdoor air pollutants vary across time and geographical space depending on source characteristics, causing varying degrees of air pollutants exposure, which is defined as the contact between a person and a chemical, physical, or biological agent carried by air (Kampa and Castanas 2008). A typical urban area is affected predominantly by environmental background pollutants in the surrounding region, which has derived from a variety of anthropogenic and natural processes. The increase in pollutant concentrations in a region is related to urban activities and their diverse emissions, characteristic of highly populated areas, causing high levels of a variety of pollutants depending on the size of the city (Loomis et al. 2013). In addition to the mixing of pollutants in urban areas, locally elevated levels of pollutants emitted on site occur at smaller scales (from zero to hundreds of meters). Specific locations affected by high levels of air pollution include sites near and on roadways (also in vehicle cabins), industrial plants, or fire plumes. On the local scale, large exposure gradients around factories and industrial complexes can also occur. In contrast, plumes from power plants and fires can extend tens or thousands of kilometers around. Another example is dust, which has impacts at multiple scales; locally generated dust can have an impact in limited areas, in contrast, dust storms can lead to intercontinental transport (Jonson et al. 2018).

Personal air pollutant exposures are a critical link between air pollution and negative human health effects and therefore a key variable to conduct epidemiologic studies. However, estimating personal exposures and identifying their sources present significant challenges due to exposure variability (Snyder et al. 2013). It is well known that both the pollutant emission sources and the physical or chemical processes affect pollutant concentrations. However, factors such as location, human activities, or behavior can heavily affect the levels of people exposure (Dias and Tchepel 2018). Thus, proper assessment of the air pollution impact on individuals is limited by the availability of reliable public data, the cost and time of high-resolution data collection, data privacy and confidentiality issues, and the management of communication and computational data. Alternatively, a collective participation system in which individuals measure local air pollution conditions via mobile devices can be employed. This type of collaborative contribution, also known as crowdsensing, is a promising approach to achieve greater accuracy in the assessment of air quality and its heterogeneity (Guo et al. 2015). Nevertheless, Yoo et al. mention that recording the activity of individuals using portable monitoring devices or travel diaries remains impractical as it is time-consuming and subject to the inaccuracy of measurement and is therefore not suitable for epidemiological studies with large sample sizes (Yoo et al. 2015). Thus,

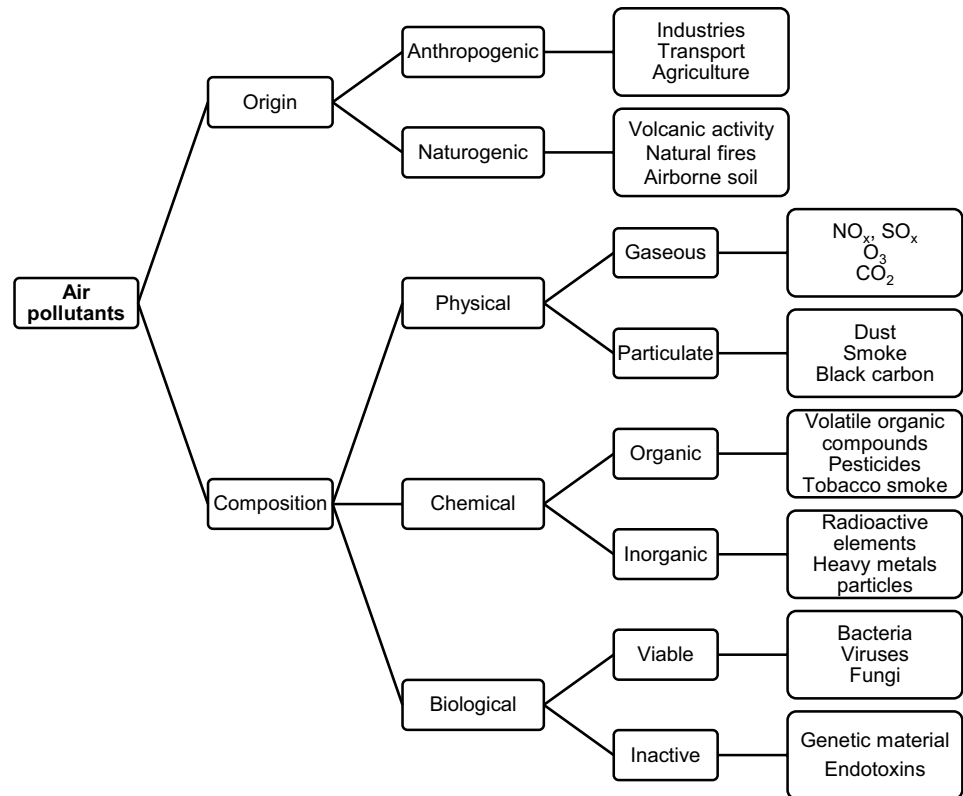
comprehensive studies on air quality are vital to understanding the problems associated with it. Previous reviews have clearly highlighted a relationship between a realistic air quality measure and the sensor quality, mode of transport, local exposure, and big data analysis (Cepeda et al. 2017; Commodore et al. 2017; Thompson 2016). Nevertheless, the rapid development of sensors for mobile devices and epidemiological studies based on crowdsensing data make necessary a summary concerning all the recent advances. Thus, the aim of this review is the presentation of an up-to-date and comprehensive panorama of the progresses on air monitoring for personal exposure assessment, considering aspects ranging from sensor operation principles and data treatment to future challenges in air pollution measurement.

## Methodology

The systematic review was conducted using scientific databases, including Scopus, PubMed, and Google Scholar. Only papers in the English language and published in peer-reviewed journals were considered. Congress proceedings were not contemplated. Due to the accelerated developments in the field of crowdsensing of air pollutants, the search was limited to publications from 2015 to the date of submission of this review. The keywords used in databases were “air pollution crowdsensing,” “portable sensors air monitoring,” and “personal sensing air quality pollutants.” Multiple publications of the same project were consolidated or only the most relevant of them were included.

## Air pollution composition

Initially, air pollution was conceived as a local problem in urban areas, but due to the growth of industrial and residential areas, the burning of biomass, and the increase in transportation demand, it has evolved from a regional to a global problem. The wide diversity of contaminants makes difficult their classification that can be performed by considering their origin, size, composition, etc. For example, Fig. 1 presents a diagram with a general classification of air pollutants, which can be extended to more detailed subgroups. WHO has identified the pollutants with the most evidence of public health concern which include particulate matter (PM), ozone, nitrogen dioxide, carbon monoxide, and sulfur dioxide. There is increasing evidence of the health effects associated with air pollution from the particulate matter of less than 10 ( $PM_{10}$ ) and 2.5 ( $PM_{2.5}$ ) microns in diameter. The particles, as they are small enough, can penetrate lung tissues and reach the bloodstream, causing cardiovascular, cerebrovascular, and respiratory events. Even the high concentration of PM per day has been associated with an increased

**Fig. 1** Air pollutants classification and examples

risk of ischemic stroke (Kampa and Castanas 2008). Studies suggest a deeper impact of traffic pollution on human health, rather than the one given by the natural contaminants (Yitshak Sade et al. 2015). According to the World Health Organization (WHO), outdoor air pollutant exposure is a major cause of death and disease globally. Health problems are reflected in an increase in medical attention and hospital admissions for pollution-related illnesses, as well as an increased risk of premature death. Ambient air pollution is associated with heart disease, stroke, and other lung conditions, resulting in an estimated 4.2 million premature deaths worldwide (Organization 2016).

According to the United States Environmental Protection Agency (EPA), the common air pollutants named “criteria air pollutants” are the ground-level ozone (O<sub>3</sub>), particulate matter (PM), carbon monoxide (CO), lead (Pb), sulfur dioxide (SO<sub>2</sub>), and nitrogen dioxide (NO<sub>2</sub>). Unfortunately, exposure to particulate matter is currently regulated in PM standards that only discriminate between particle size but not between the composition or origin of the particulate matter (Silva et al. 2020). Nevertheless, as methods of analysis and epidemiological studies improve, new compounds will be added, for example, the black carbon (BC) which is a fraction of the PM related to combustion processes (Dekoninck et al. 2015). Indoors, for example, in homes or workplaces, where there are no apparent sources of air pollutant emissions, a variety of chemicals are emitted from a wide range

of sources, such as building materials, paints, air conditioning or fans, cosmetics, pesticides, personal care products, cooking, and other everyday household products (Kruza et al. 2020). Thus, a spatial classification of air pollution can be divided into outdoor and indoor air.

## Personal air monitoring

Most fixed monitoring stations continuously monitor air pollution in urban areas and provide highly accurate measurements. They consist of instruments based on very precise instrumental techniques specific for analyzing a wide variety of contaminants (Magno et al. 2016). However, monitoring stations present certain disadvantages, for example, the large infrastructure for their installation (expensive and heavy instruments, large areas, etc.), rigorous protocols for their operation, and, finally, the excessive costs of periodic maintenance and calibration. These drawbacks limit the number of air pollution monitoring stations deployed on the territory. Consequently, a sparse number of stations in large cities is inadequate to detail the microenvironments of the millions of people who live in the area (Bales et al. 2019; Bashir Shaban et al. 2016).

The concentration of atmospheric pollutants depends on the location, and therefore, also the time and space of the pollutant concentration are important to avoid dangerous

exposures of humans (Magno et al. 2016). For this reason, the individual pollution exposure measured through a personal monitoring device is indispensable; this approach generally enables to compute instantaneous concentration measurements leading to pollutant exposure time series (or exposure profile). Using this methodology, the profile of each individual can be summarized through comprehensible data in order to estimate a target population exposure distribution. Characterizing the exposure of individuals who move in different environments is a difficult task. The composition of pollutants in the air is not entirely defined and only the most abundant ones are considered in routine measurements. Many trace contaminants are simply taken as part of a certain class of pollutants, for example, organic compounds or particulate matter (Cohen et al. 2017).

Therefore, two different approaches to assessing human exposure to air pollutants can be used. The first is a direct approach where exposure levels are measured for each individual through the personal monitoring or by using biological markers. The second approach is indirect, as exposure levels are usually estimated or modeled from environmental measurements, exposure models, and surveys. Additional methods for assessing exposure may include measurement at a specific site or only where exposure occurs in the individual (a specific area of the body), reconstruction of internal exposure by using internal indicators (such as biomarkers) after exposure has taken place, and estimation of contaminant concentrations considering scenarios from models that consider exposure time. There are other less commonly used models for personal exposure because they consider all individuals indistinguishable and the concentration of contaminants homogeneous (Dias and Tchepel 2018).

In general, three types of variability can be identified: (a) spatial variability that can occur both at regional (macro-scale) and local (micro-scale) levels; (b) temporal variability, which refers to variations over time whether short or long term; and (c) interindividual variability which can be either human characteristic and human behaviors/preferences. Individual locations, activities, or behaviors are not necessarily independent of variations in pollutant-specific emissions or processes. For example, pollutant concentrations and personal activities at a specific location may vary according to weather conditions or between weekdays and weekends (Gao et al. 2020). It is also possible to rely on additional information that is predictive of instantaneous exposure. Such information is provided by covariates, like location, activity, and behavior. Covariates can be used to stratify an individual's instantaneous exposure, where each stratum can be identified as a specific microenvironment. For example, the location of an individual can be used to define microenvironments such as outdoor not in transit, outdoor biking, and outdoor in the park.

This methodology should ensure that the use of sensors is non-intrusive, allowing their integration into everyday objects and environments, for example, in cars, bicycles, or offices and homes. A desirable approach is that sensors are combined or communicated with other everyday portable devices (smartphones, tablets, and laptops) providing instantaneous and easily understandable information readings. An advantage for sensor development would be to contain as many contaminant detectors as possible at the same time, resulting in a challenge for most of the currently developed sensors and integrated platforms, due to the rapidly increasing size and complexity of both hardware and software instruments required to operate the different technologies (Oluwasanya et al. 2019).

Personal air monitoring is not only limited to determine the concentration of pollutants but it has also been recognized as useful to change the habits and behaviors of users, allowing an improvement in lifestyle (Heydon and Chakraborty 2020). Hence, new air pollutant detection technologies can revolutionize health epidemiological studies by providing reliable exposure data at a well-defined level of geospatial resolution to investigate the underlying mechanisms of air pollution health effects (Chatzidiakou et al. 2019).

### Sensors for air quality

Measuring atmospheric pollutants is challenging. Some of the difficulties in the analysis of air pollutants are their low concentration, complex chemical composition, and the presence of mixtures of compounds in the air. Standard monitoring devices applied to calculate pollutant exposure use a variety of measurement methods depending on the class of pollutants being measured. For instance, particulate matter concentrations are measured through gravimetric analysis and light-scattering devices. Light-scattering (LS) monitors use a laser beam to shine particles located in a chamber. A light detector then measures the scattered light which depends on the concentration and size of the particles; then, a constant air flow to feed particles into the chamber is required to produce reliable estimates (Chen et al. 2018b). Although the LS monitors measure the size and number of the particles with high accuracy, it does not measure their mass directly, and an additional estimation is required. As an alternative, the microbalance method has been proposed as a low-cost sensor for quantifying the mass concentration of PM, where the resonance frequency of a piezo transducer is changed due to particle deposition (Qin et al. 2019).

The identification and quantification of volatile organic compounds are sometimes necessary through traditional analytical techniques such as gas chromatography (GC) and mass spectrometry (MS), which provide high sensitivity, chemical specificity, and a wider range of chemicals

detected. However, these high-resolution analytical systems have high manufacturing and operating costs, as well as large size and weight, and their application in mobile air quality monitoring is not feasible (Fung et al. 2019). On the other hand, the same techniques could be applied through the miniaturization of the sensor, resulting in a practical device with low energy consumption (Dong et al. 2016; Tryner et al. 2019).

Since Jonathan E. Thompson published a great review of the state-of-the-art of sensors for air quality studies (Thompson 2016), new advances have been made in the last years. For this reason, here we present the new technologies and proposals of sensors for air monitoring. Table 1 enlists the most recent developments in portable sensors. Depending on the pollutant, the principle of detection can be either chemical or physical, but the predominance of electrochemical techniques is noted, as they are very sensitive, selective, and do not require complex electrical circuits. The chemoresistors commonly are based on metal oxide semiconductors, where the change in conductivity or resistance caused by chemical-adsorption of gas molecules at the surface of the semiconductor is measured at high temperatures, requiring a high energy consumption (Güntner et al. 2016; Yu et al. 2017). As an alternative, graphene-based materials have been proposed due to the electrical conductivity of graphene is sensitive to adsorption of gas molecules down to ppb level even at low temperatures (Kim et al. 2016; Magno et al. 2016; Melios et al. 2018; Oluwasanya et al. 2019). The sensing mechanism of chemosensors on graphene is dominated by sorption-based swelling; the sorption of a given target analyte onto the sensing film is modulated by surface and edge defects that affect film conductivity and sensor performance. However, the detailed mechanism of the interactions between the gases and the nanosensor has not yet been described (Patel et al. 2018). Electromechanical sensors are another interesting proposal for low-cost sensors because they do not need a power supply to work and the contaminants are detected through physical changes perceptible to the naked eye (Fraiwan et al. 2016; Qin et al. 2020).

Due to the growing use of smartphones in the world population, these devices are ideal as a basic tool for implementing all kinds of sensors. For example, the smartphone camera can be used as a simple color detector (Salcedo and Sevilla 2017), to measure mechanical shifts (Qin et al. 2020), or even to detect radiation (Keller et al. 2019). Nevertheless, to facilitate the widespread use of portable and low-cost gas sensors, some challenges must still be overcome. The broad types of pollutants in the air complicate the full characterization because, despite the selectivity of the sensors, the presence of certain compounds can interfere with the measurements. Relative humidity and temperature are the first challenges for reliable measurements, and calibration or adjustments must be necessary to obtain accurate

readings (Manikonda et al. 2016). Technological advancements on accurate sensors might improve personal air pollution exposure assessment. Even if the technology is not available, plants can be used as monitors of air pollutants, for example, tobacco and recently muscades and lichens (Cocozza et al. 2016; Van der Wat and Forbes 2015). Perhaps in the future, biological sensors will be much more efficient and accurate so that they can coexist with urban environments helping to purify and monitor the air.

## Mobile monitors

Urban areas generally have national air pollution monitoring stations which are expensive and scarce due to the high-precision instrument required and their size (Lin, Chi and Lin 2020). Air pollution monitoring using traditional fixed measurement stations is severely limited by the availability of land and high maintenance costs (~\$30,000 per year), making it difficult to obtain measurements of air pollution concentrations with sufficient resolution to distinguish the most polluted points in a large urban area (Liu et al. 2019). Therefore, many sites with potentially high concentrations of air pollutants remain outside the coverage of the monitoring network. Direct measurements of fine-grained air pollution can provide fidelity and accuracy unbeatable by other methods, but the measurement requires a large number of air monitors.

The accuracy of mobile monitors of air pollutants remains in discussion. Coefficients of determination ( $R^2$ ) are used to assess the strength of correlations (linear or not) between a tested device and a certificate professional monitor. For example, a mobile monitoring platform called SentinAir, which measures CO<sub>2</sub>, NO<sub>2</sub>, and O<sub>3</sub>, was evaluated in real outdoors and indoors resulting in an effective monitor plug-and-play for local environments, but the validation shows  $R^2$  values as low as 0.507 for NO<sub>2</sub> (Suriano 2020). Although there is a good correlation in laboratory tests, it decreases during in-field experiments (Jerrett et al. 2017; Zimmerman et al. 2018). For example, five portable sensors namely Speck, Dylos 1100Pro/Dylos 1700, AirAssurePM<sub>2.5</sub> IAQ Monitor, and AirSense were tested (Manikonda et al. 2016). Experiments were carried out in an indoor chamber, with constant temperature, relative humidity, and particle source. In these ideal conditions, all monitors correlated coefficients near to 1, although in some cases the correlation was not linear. In contrast, the real in-field conditions, such as daylight hours with sunshine, affect measurements performed by the electronics housed inside the low-cost monitor, providing readings with higher values, most probably due to the solar radiation heating the enclosure components (N. Genikom-sakis et al. 2018). It has also been shown that bias caused by heat stress can be more notable than those ones induced by cold stress (Gillooly et al. 2019). In a study involving the



**Table 1** Novel sensors for portable air pollution detectors

Sensor type	Characteristic	Pollutants	Observations	Space tested	Ref
Electromechanical	Paper-based/smartphone camera	Hydrocarbons	Humidity interferes in measures	Laboratory	Qin et al. (2020)
Electromechanical	Swellable thin polymers on paper	Methanol, ethanol, acetone, and THF	Low cost, detection by the naked eye	Saturated atmosphere	Frairan et al. (2016)
Electromechanical	Photoacoustic cell	NO <sub>x</sub>	Long-running stability	Nitrogen atmosphere	Dong et al. (2016)
Electromechanical	Ferrite nanoparticles	Benzene, toluene, and xylene	Sensitive and selective	Laboratory air-controlled mixtures	Matatagui et al. (2019)
Electromechanical	Acoustic resonator covered with carbon nanotubes	Formaldehyde	Reproducible and selective	Closed test box	Wang et al. (2018a)
Chemoresistance	Porous-doped SnO <sub>2</sub> films	Formaldehyde	Stable responses and reliable at a high relative humidity	Simulated breath	Güntner et al. (2016)
Chemoresistance	Nb <sub>2</sub> O <sub>5</sub> nanorods	NO <sub>2</sub>	Sensible and stable at high temperatures	Dry synthetic air	Yu et al. (2017)
Chemoresistance	Carbon nanotube field-effect transistors	Fungal particles	Detect two different fungal species simultaneously	Residential areas	Kim et al. (2016)
Chemoresistance	WO <sub>3</sub> and Ag layers	NO	Inexpensive and selective	Closed test box	Shimizu et al. (2018)
Chemoresistance	Graphene on 6H-SiC	NO <sub>2</sub>	Selective, temperature stable	Synthetic air	Melios et al. (2018)
Chemoresistance	Polymeric field-effect transistor	Ammonia and amines	Selective, low driving voltages	Laboratory air-controlled mixtures and spoilage of meat	Wang et al. (2018b)
Chemoresistance	Carbon nanotubes gas sensors	NO <sub>2</sub>	Low-power detector	Energy consumption in theoretical scenarios	Magno et al. (2016)
Chemoresistance	Ionic liquid	CO <sub>2</sub>	Selective, low-power consumption, reusable	Nitrogen atmosphere	Bhude et al. (2020)
Chemoresistance	Carbon nanotubes	CO <sub>2</sub>	Reliable in low humidity environments	Laboratory air-controlled mixtures	Guo et al. (2020)
Chemoresistance	Graphene and SnO <sub>2</sub> or WO <sub>3</sub> nanoparticles	Benzene, toluene, and xylene	Selective, continuous monitoring	Laboratory air-controlled mixtures	Behi et al. (2020)
Chemoresistance	rGO–In <sub>2</sub> O <sub>3</sub> film	Aniline	Selective, adaptable to the environmental conditions	Laboratory	Chang et al. (2020)
Chemoresistance	SnO <sub>2</sub> nanowires	H <sub>2</sub> S	Good sensitivity and repeatability	Laboratory and outdoors	Thai et al. (2020)
Chemoresistance	Separation column coupled to Pd-doped SnO <sub>2</sub> nanoparticles sensor	Methanol	Humidity and temperature dependents	Laboratory	van den Broek et al. (2019)
Chemoresistance	Metal nanoparticles layers on a silicon chip	H <sub>2</sub> S, H <sub>2</sub> , and NO <sub>2</sub>	Selective, low-power consumption	Laboratory air-controlled mixtures	Fahad et al. (2017)
Chemoresistance	Graphene carboxymethylcellulose print	NO <sub>2</sub> , PM	Selective multi-sensor platform	Laboratory air-controlled mixtures	Oluwasanya et al. (2019)
Chromatographic/spectroscopic	Polymer tube and UV LED	Benzene, toluene, ethylbenzene, and xylene	Sensitive, portable, low-volume samples	Nitrogen atmosphere	Khan et al. (2020)
Colorimetric	Selective reaction change color	CO	Selective, reusable, humidity dependent	Laboratory air-controlled mixtures	Lin et al. (2018)

Table 1 (continued)

Sensor type	Characteristic	Pollutants	Observations	Space tested	Ref
Colorimetric	Nylon-6 nanofibrous membrane	Fumigants	Naked-eye detectable color	Laboratory air-controlled mixtures	Tang et al. (2018)
Colorimetric	Paper-based enzyme sensor	Bisphenol A	Preactivation with water, naked-eye detectable color	Domestic indoors	Alkasir et al. (2015)
Colorimetric	(CuI)/polystyrene composite	Gaseous Hg <sup>0</sup>	Detection with a smartphone camera	Laboratory air-controlled mixtures	Salcedo and Sevilla (2017)
Microbalance	Micro quartz tuning fork	PM <sub>2.5</sub>	High sensitivity, continuous monitoring	Controlled flow and concentration, and outdoors	Qin et al. (2019)
Optical	Liquid waveguide capillary cell/optical detector	SO <sub>3</sub> and SO <sub>4</sub> <sup>2-</sup>	Continuous monitoring	Firecracker day	Tian et al. (2018)
Optical	Griess – Saltzman method coupled to an optical detector	NO <sub>2</sub>	Continuous monitoring	Urban air	Tian et al. (2017)
Optical	Light-scattering sensor	PM <sub>2.5</sub>	Low-cost sensor with an active filter sampler	Laboratory aerosol chamber	Tryner et al. (2019)
Photodiode	Silicon-based diode	Radioactivity	Low-cost and smartphone compatibility	Common sources of radiation	Keller et al. (2019)

test of O<sub>3</sub> sensors at a different relative humidity and flow rate, it was observed that when the changes were abrupt, the sensors did not provide accurate measurements (Pang et al. 2017). However, if the change in RH or flow rate is slow enough, a simple correction in the calibration model is sufficient to obtain an accurate reading. In general terms, it can be considered that the error affecting the personal air monitoring is significantly smaller than the error introduced when estimating personal exposure based on sparsely distributed outdoor fixed monitoring stations (Chatzidiakou et al. 2019). Nevertheless, frequent calibrations constitute the necessary maintenance, which costs are in addition to the study expenses, without including the personnel effort required to conduct ongoing maintenance and evaluation.

Modifications or interventions to improve the performance of commercial devices are also a viable possibility. For example, while the commercial device Aeris sensor is currently not a replacement for the most sensitive research-grade instrumentation available, it remains useful for monitoring formaldehyde in specific conditions (Shutter et al. 2019). Even though there are commercially available devices for air pollution monitoring such as AirBeam, there are still limitations to overcome, such as sensitivity, cost, or portability. Sensor modules are typically characterized for their small and light weight, relatively short response time, and low-power consumption. With the development of mobile tracking and sensing technologies (e.g., global positioning systems (GPS) and portable air pollution sensors), the acquisition of accurate, high-resolution data on individual movement, and personal exposure to air pollution has been driven (Park and Kwan 2017). However, low-cost sensors are often sensitive to environmental conditions and exhibit interferences when the contaminant mixture is complex, which historically have not been accounted for in laboratory calibrations, limiting their usefulness for monitoring (Park and Kwan 2017). The heterogeneous calibration models performed around the globe make difficult the standardization of air monitoring; however, it must be guaranteed the application of the recommendations to achieve the minimum data quality for personal exposure measurement (Zimmerman et al. 2018). In particular, frequent calibrations are needed for the newly developed sensors (Apte et al. 2017).

Although the determination coefficient is the most used method for the validation of personal monitors, other statistical methods can also be used such as Pearson, Kendall, and the Spearman correlation coefficients. Depending on the linear or non-linear behavior of the data, a specific coefficient could be more adequate. A comparison between the different functions in field studies is available (Fishbain et al. 2017).

In terms of energetic consumption, mobile devices are generally powered by batteries, which should provide sufficient energy autonomy for field studies. Adding a higher capacity battery increases the cost and weight of the device,

so alternatives have been studied to lower their power consumption. This result can be achieved by utilizing an optimized data acquisition process, for example, a quality-driven sensor management function to continuously select the best sensors for a predefined sensing task, avoiding the acquisition of non-useful data (Marjanović et al. 2016). There are cases in which continuous measurements are not necessary, in these circumstances, a duty-cycling powering scheme that periodically turns on and off the sensors, could save up to 90% energy as compared to the continuous operating mode (Burgués and Marco 2018). Thus, a toolbox for air pollution monitoring must include hardware: sensors, transmitters, displays, and software (data analysis and collection) (Karami et al. 2018).

The mobile devices for air pollution monitoring can be very useful to ensure the safety of workers with high exposure to contaminants such as welders (McManus and Haddad 2019) or firefighters (Amorim et al. 2016). In this case, the monitor implementation is technically challenging even with small, portable instruments because it must not compromise the comfort and safety of the protective equipment. The monitoring of air pollutants with mobile devices has also been used to study the risk to people working on industrial fracking sites over extended periods, finding marked elevations of BC and NO<sub>2</sub> concentrations in downwind proximity to diesel engine exhaust emissions from fracking equipment (Ezani et al. 2018).

There are still some aspects that need to be considered in air monitoring through mobile devices to more realistically assess air pollution. For example, considering each person's inhaled dose would be ideal to inform each individual of their exposure risk. Air pollutant absorption tends to be higher during intense individual physical activity; therefore, the use of inhaled dose as an exposure metric is necessary for environmental epidemiology studies (Dons et al. 2017). Devices with replaceable parts or modular plug-and-play sensors can make the epidemiological studies with this device more convenient and user-friendly (Deng et al. 2016; Yi, Leung and Leung 2017). Alternatively, measurements with mobile monitors can be made using sensor networks mounted on robots configured to find PM hot spots (Cashikar et al. 2019).

## Data analysis

The development of reliable air pollution models applicable to different environments provides an accurate estimate of the impact of air pollution on human health (Manekiya, Donelli and Donelli 2019). Currently, measurements of air pollution zones are limited to data collection but do not give a clear view of the degree of exposure for individuals. Thus, it results necessary to develop a framework to collect real-time pollution data related to the main aspects related to

the issue: traffic conditions, emissions, ambient pollutant concentration, and human exposure (El Alaoui El Abdal-laoui et al. 2019).

The use of mobile computing, machine learning, and artificial intelligence tools has experienced an increased presence in air pollution exposure modeling (Messier et al. 2018). The process of air quality assessment involves not only the acquisition of data, but also its proper analysis and processing. Having a source of big data through mobile air quality sensors enhances exposure models. This has made it possible to determine significant variabilities over short distances and time due to the non-uniform distribution of emission sources, dilution, and weather conditions. For example, data mining techniques considering spatial variables have been used to explore the determinants of spatial patterns in air pollution levels and distribution (Kamel Boulos et al. 2019). The implementation of fast air pollution sensors can address the problems of variability and improve spatiotemporal accuracy by achieving a spatial resolution in the order of meters. This approach provides a spatial precision of 4–5 orders of magnitude higher than those ones possible with current central site ambient monitoring systems (Messier et al. 2018). Schemes based on a social cooperative inference to determine environmental conditions can be complemented with modified non-Bayesian social for data integration in mobile crowdsensing to allow users to exchange information with their neighbors and cooperatively infer pollution rates, which is the goal of the crowdsensing task, otherwise not measurable directly (Meng et al. 2018). In addition to measuring pollution levels, the use of mobile devices can help to understand the factors that influence air pollutants. A study based on multivariate models found that the combination of traffic, urban design, and meteorological variables mainly impacted air quality. However, the limitation in capturing and modeling all existing variables results in 40% unexplained variability (Miskell et al. 2018). Therefore, more studies in this field are necessary for air quality prediction and the consequent adoption of preventive measures in a reliable way.

On the other hand, validation of portable sensors must be performed with the correct processing data to establish quantitative relationships between readings from portable air pollution monitors and reference measurements. In some cases, the response of the portable device is not necessarily linear with respect to the reference and must be adjusted through mathematical models (Lin et al. 2017; Suriano 2020). To facilitate the calibration process, the category-based calibration approach (CCA) for air monitoring sensors has been proposed (Wang et al. 2020b). Unlike traditional calibration approaches where single models are employed, the CCA adopts multiple regression models based on pollutant type and concentration. In the calibration process, the responses of the various sensors are classified and then



calibrated using the appropriate regression models that are selected according to the appropriate weighting based on the type of contaminant. This approach allows the instrument to learn and adjust the sensor readings to ensure data quality.

It is important to note that although the quantitative performance and validation of portable monitors can be accurately tested under controlled laboratory conditions, the performance of the monitors must also be validated in the field. A comparison between portable monitors using a site-specific calibration proved that the variables and environmental conditions must be considered for proper calibration (Zusman et al. 2020). In some cases, an unacceptable baseline drift and a variable correlation coefficient were observed in a large fraction of acquisitions performed through portable monitors. These issues must be addressed to obtain reliable data (Sagona et al. 2018; Zhang et al. 2018). For example, the relationship between the measurements by the QT-50 light-scattering  $PM_{2.5}$  monitor and by the parallel gravimetric measurements was used to establish a field calibration method for low-cost optical sensors (Larcombe et al. 2017). However, even when the QT-50 instrument was calibrated with respect to the gravimetric method and considering temperature and relative humidity, it was observed that the QT-50 measurements overestimated the concentration levels. In the case of the Aeroqual 500 series monitors with  $O_3$  sensors, the application of correction models, including ambient temperature and RH influence, was sufficient to reproduce the values obtained from a standard monitor (Masiol et al. 2018). Universal software has been developed to acquire data and to perform the calibration of heterogeneous devices, sensors, or instruments allowing remote and real-time control (Zheng et al. 2016). Some calibration models are summarized in the literature (Maag et al. 2018). Detailed reviews about the promising hardware of IoT architectures and technologies and models of air pollution monitoring systems are proposed in (Alvear et al. 2018) and (Idrees and Zheng 2020) respectively.

Data transmission is also an important feature to improve personal detection. To achieve the best performance, the air sensing information needs to be transmitted and processed in time. Thus, low-power wide area (LPWA) technology based on machine-to-machine (M2M) communications can be used to provide ubiquitous coverage, low-power consumption, and costs for devices that send or receive messages infrequently and with limited data rates (Masiol et al. 2018). On the other hand, a modulated scattering technique adapted to the sensors has been proposed to operate in the X band at 10 GHz, to guarantee a reasonable compromise between device dimensions and costs, in comparison with the wireless sensor networks (Manekiya, Donelli and Donelli 2019).

The impact of the sampling strategies on prediction accuracy is under active research. A combination of the sampling and modeling strategies to improve the accuracy

of pollutant exposure assessment could be a feasible, cost-saving solution in cohort studies (Zhu et al. 2019). Although sampling and calibration designs improve predictions and reduce the uncertainty of the low-cost sensors, they are inevitably limited to the quality and number of sensors (Yoo et al. 2020). A study comparing four types of monitors showed that only two, the microAeth BC and Aeroqual  $O_3$  monitors, were most consistent in instrument response, achieving the stability of calibration (Lin et al. 2017). In an other study using the MicroPEM monitor, hourly averages of measurements showed a strong correlation with the standard monitor, but they were featured by slopes less than 1. The average personal  $PM_{2.5}$  level in most enclosed spaces like buses, restaurants, and subway stations was higher than the outdoor ones, at least during non-hazy days (Zhang et al. 2017). Water vapor can cause interference when measuring PM, as it condenses on the suspended particles making them grow hygroscopically. On this basis, an algorithm based on Köhler's theory has been proposed to generate a correction that significantly improves the performance of the sensor and preserves fundamental information about the composition of the particles (Di Antonio et al. 2018).

In order to inform the public of air pollutant measurements, it is necessary to establish a simple and easily identifiable scale. Currently, the Air Pollution Index (API) is used as a reference number to communicate to the public the current or predicted level of air pollution. The API is useful for non-expert users to identify the degree of air pollution or pollution criteria; it is foreseen that its use will spread more and more. Ideally, all air quality monitoring devices should have the ability to notify users of current air quality through an intuitive display (colors, numbers, single adjectives) that can indicate the level of air quality in real-time (Gunawan et al. 2018; Tiele et al. 2018). As an alternative to communicating the air quality, a web page on an open-source cloud platform has been proposed to display and analyze the air quality data from the sensors and an e-mail can be sent when the air composition is in an unhealthy state (Zakaria et al. 2018).

Many Internet of Things (IoT) applications have been proposed for monitoring the values of API either indoor or outdoor (Karar et al. 2020). The framework of IoTs has been implemented using 1176 portable air quality  $PM_{2.5}$  sensors called "AirBox" (Lin, Chi and Lin 2020). The spatiotemporal distribution between the AirBox sensors and the local stations was different, requiring data fusion and correlation. The model for spatiotemporal estimation of the AirBoxes was based on the theory of Optimal Linear Data Fusion and integrated with a Kriging method of multiple time steps. This model showed that combining the  $PM_{2.5}$  concentration data from the low-cost AirBoxes improved the spatiotemporal  $PM_{2.5}$  concentration estimation.

Measurements of personal exposure to air pollution through wearable devices can be attached to wristbands, belts, and backpacks for continuous recording of air quality during daily activities. Thus, spatial big data collected by wearables can be processed and analyzed with data science methods and incorporated into epidemiological studies focused on disease prevention. Non-linear associations and integration of multiple sources of spatial big data can be improved using machine learning, improving predictive performance. For example, using random forest models or neural networks, multiple predictors (mobile sensors, fixed stations, satellite images) can be included to predict environmental pollution from previously defined categories (traffic, urban pollution, weather, UV radiation) (Kamel Boulos et al. 2019).

Crowdsensing must guarantee user privacy and data authenticity. Quality of information (QoI) in mobile crowdsensing is key to obtain reliable data and requires the development of models that ensure the correct detection of valid data (Restuccia et al. 2017). Although there is not much discussion on the subject, a block-chain structure to collect the data in collective measurements has been proposed (Kolumban-Antal et al. 2020). This improves the security and privacy of data, processing, and transmission time have to be optimized, preventing any form of data manipulation.

## Crowdsensing of air pollution

Measurements from atmospheric monitoring stations are frequently used as a measure of exposure in epidemiological studies on the health effects of air pollution. However, these fixed stations do not provide spatial and temporal resolution of pollutants. Consequently, traditional measurements often mask the variability of exposure in the population studied and are therefore not optimal for obtaining representative exposures of individuals or groups with health problems (Bell et al. 2020).

It is clear that air pollution levels change continuously over space and time. As individuals also move through space, the level of an individual's exposure to ambient air pollution is also conditioned by the mobility of the person, resulting in air pollution exposure levels that not only change across space, but can also change between hours or even minutes. This is important to take into account in order to correctly weigh spatiotemporal variations and dynamic interactions between pollutants and humans at a high resolution (Yoo et al. 2015). Hence, it is more useful to monitor air pollution at short intervals of time compared to a daily or monthly average. By adopting this strategy, vulnerable people would have more reliable information to make decisions on their spatiotemporal behaviors and minimize their exposure in different microenvironments

(Park and Kwan 2017). Based on the above elements, we can conclude that air pollution monitoring with traditional techniques has practical limitations since it assumes a homogeneous distribution of people; in addition to this element, we must consider that contamination levels are equal in the surroundings and for long periods (Chen et al. 2018a).

For example, Roy et al. studied the statistical relationships between fungal spore concentration and different climatic factors (Roy et al. 2017). After prolonged sampling, a significant correlation was observed between fungal spore concentration, air pollutants, and allergic manifestation. Improved estimates of personal exposure can potentially enhance environmental epidemiology studies (which often rely on data from fixed ambient air monitoring stations). The conjunction of air pollution sensors, physiological sensors, and location (GPS) sensors can establish a stronger connection between a person's exposure environment and health indicators (Snyder et al. 2013).

Consequently, the low spatial coverage of air pollutant measurements and the oversimplification of hypotheses about the mobility of people do not allow visualizing the spatial complexity and the temporal dynamic characteristics of personal exposure, affecting the reliability of epidemiological studies (Yoo et al. 2015). Therefore, estimates among individuals may be similar despite differences in their mobility, which is incorrect (Ma et al. 2019). Even for the naturogenic pollutants, it is necessary the personal exposure monitoring. For example, the estimation of population exposure to PM<sub>2.5</sub> has been proposed considering the population distribution, but not the air pollution variation at a personal scale (Liu et al. 2019). Then, social intermediaries should be the most valuable tool to achieve more realistic epidemiological research.

Mobile crowdsensing is an unprecedented technique that enables the collection of sensing data on a large scale (e.g., in a community or city). Modern mobile devices used by many people (e.g., smartphones) can be equipped with multiple sensors or software to collectively capture and share data (Liu et al. 2019). Crowdsensing is a complex process that requires a variety of tools. Figure 2 shows an overview of everything that is needed for crowdsensing. To implement the crowdsensing, high-precision sensors are needed, and they must be assembled in devices sufficiently small to be easily transported; then, measurements of the local environment are completed, and the data is processed on remote servers. Finally, users, through a friendly interface, can know about the air quality in their environment. The fundamental part of crowdsensing is based on encouraging people to participate in the acquisition of useful information for the study of various phenomena by providing real-time measurements combined with contextual information such as location and temperature (El Alaoui El Abdallaoui et al.

2019). Unfortunately, collective participation is limited by time consumption and privacy issues. Several proposals have been made to improve citizen participation, such as the payment of an incentive (Haddad and de Nazelle 2018; Restuccia et al. 2017; Yang et al. 2019). Comfort is another point to consider since the noise or weight of the devices can be a disadvantage for volunteers (Sagona et al. 2018).

An example that shows that crowdsensing is not an easy process is the project of Taiwan's Environmental Protection Administration, a nationwide project where large-scale distributed sensors were deployed to effectively monitor and manage the emission of pollutants (Chen and Liu 2020). However, the methods used to optimize sensor distribution were inadequate for deploying thousands of sensors because geographic features were not considered. Due to the significant challenges to estimating personal exposures described above and the practical limitations of existing personal monitors, epidemiological studies often rely on pollutant concentrations as the primary basis for exposure estimation. Only rarely these methodologies are specifically designed for exposure assessment (Cepeda et al. 2017; de Bont et al. 2020; Wu et al. 2020b).

At the same time, it is important that projects using mobile air quality sensors consider the potential effects of their use on the attitudes and behaviors of volunteers, as they are generally not experts. One study suggests that participation where people are holding the sensors, compared to traditional monitoring, generates greater motivation among participants. In addition, sensor use generates interest in learning more about air pollution and risk perception (Oltra et al. 2017).

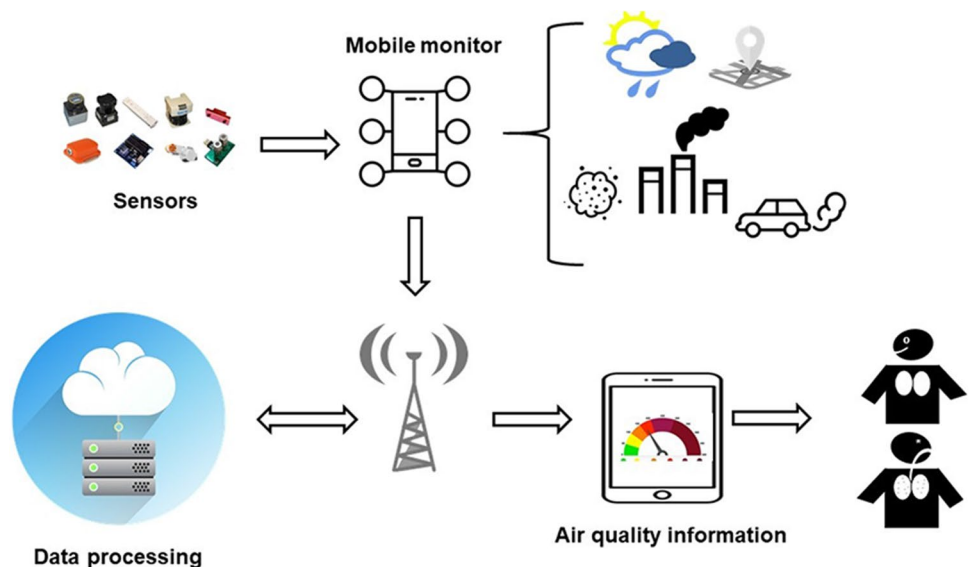
Epidemiological research has continually required more reliable estimates of human exposures. The higher the level of refinement in contaminant characterization, the more

accurate and useful the information from exposure estimates. For example, exposure indicators could be improved by implementing the use of mobile monitors among people in order to increase the spatial resolution of measurements within an area typically covered by a central site monitor or by increasing data acquisition at specific times where central site measurements are not available (Chen et al. 2018a; Park and Kwan 2017). Although several options have been considered for monitoring air pollution in urban settings, crowdsensing is an emerging technique of great interest; the implementation of this technique could become widespread in the short term (Ma et al. 2019).

### Urban and intraurban areas

Individual exposure to air pollution is a dynamic process consisting of several iterations between the person and the urban environment, which depend on both the spatiotemporal distribution of air pollutants and the daily activities of the individual. Consequently, the configuration and functioning of urban spaces are closely related to the manner in which a person is exposed to airborne pollutants. For example, urban environments affected by heavy traffic (urban mobility) and the lack of walking streets could result in high pollutant exposures for pedestrians as has been shown in Ma et al. (2019) and reviewed by Cepeda et al. (2017). For these reasons, a quantitative and qualitative understanding of urban dynamics is an important piece of evidence to design epidemiologic studies of outdoor air pollution. Furthermore, a proper understanding of the urban dynamics and air pollution could help the development of actions to palliate the negative effects of pollution on human health through regeneration and urban acupuncture techniques (Dekoninck et al. 2017).

**Fig. 2** Crowdsensing elements and process



Epidemic models based on stationary air pollutant monitor recordings are susceptible to give unreliable and even erroneous results because the mobility of people is not considered. Most people move to areas outside residential areas to carry out their daily activities; therefore, each person is exposed to different contexts despite living in the same neighborhood. Therefore, mobility to sites with higher pollution must be carefully weighed for the assessment of exposure to poor air quality. For example, employees and young people, in contrast to pensioners and older people, will have higher exposure due to their higher levels of daily mobility (Alvear et al. 2017; Liang et al. 2019). Thus, participatory sensing data can avoid underestimation of exposure to pollutants.

Kwan et al. have identified two major methodological problems that are particularly relevant when assessing individual exposure to air pollution: the uncertain geographic context problem (UGCoP) and the neighborhood effect averaging problem (NEAP) (Kim and Kwan 2020). The UGCoP is the problem that using different delineations of spatiotemporal contexts could lead to different research results of the health effects of environmental influences on individuals and the NEAP results when the mobility of individuals and their exposures to nonresidential contexts is ignored, causing biased estimates of personal exposure.

Thus, spatiotemporal variability of air pollution and individual daily movement patterns in exposure and health risk assessment is fundamental to perform a realistic epidemiologic model (Ma et al. 2019). Kwan et al. conducted a study on air pollution in California by considering individual-level movement patterns, participants' residential locations, hourly air pollution levels, and daily pollution averages (Park and Kwan 2017). In this study, they illustrate from 3D geovisualization how air pollution levels are spatiotemporally dynamic and how potential health effects are likely to vary as a function of mobility through the day. Although they did not measure individual air pollution or consider indoor air pollution, the influence of the spatiotemporal variable and people's mobility is evident.

The latest published projects in local exposure to air pollution are listed in Table 2. Although most mobile monitoring is focused on citizen use, motorized vehicles (Frederickson et al. 2020; Söderena et al. 2020; Zhang et al. 2020) or bicycles (Dekoninck et al. 2015; Ueberham et al. 2019; Wu et al. 2020a) have been successfully implemented as a mobile medium, which avoids requesting consent from individuals.

In a preliminary study, using three portable sensors, it was possible to demonstrate that these devices are useful to distinguish different environments such as commuting trips or indoor environments (Languille et al. 2020). For another study, an app was developed to obtain environmental, position, and mobility data with more than 1500 participants

(Ottaviano et al. 2019). This approach enabled the large-scale collection of citizen science data with higher data spatial resolution, providing predictive analytic solutions to empower citizens with urban, environmental, and health recommendations. The accuracy of mobile monitors is rarely discussed in field studies; however, Chatzidiakou et al. demonstrated that the errors of portable devices for measuring air pollutants is significantly lower than the error introduced when estimating personal exposure from measurements from sparsely distributed fixed outdoor monitoring stations (Chatzidiakou et al. 2019). Thus, it is possible to use portable monitoring devices to achieve reliable exposure metrics that would allow extending their use even for domestic use as a health prevention tool to avoid unnecessary exposures.

The core problem for the assessment of air pollutants lies in the complex variety of chemical components. These affect individuals differently (depending on inhalation rates, lung volumes, and physical activity, combined with the enormous spatiotemporal variability of external exposure) making the correlation of their health effects significantly more complicated. The ensemble of various disciplines could correlate multiple weighted factors to refine air pollution studies (Yoo et al. 2015). Thus, the study of the effects of poor air quality on people should be interdisciplinary enough to be able to quantify individual differences in exposure, to motivate participants to be constantly informed, and to track the temporal variability of pollutant concentrations at the local level that can be related to traffic conditions, road types and meteorology, etc. (Kim and Kwan 2020; Liu et al. 2020).

## Indoor areas

People tend to spend most of their time indoors; therefore, an evaluation of risk factors solely on the basis of exposure to outdoor air pollutants is erroneous. The distribution and amount of pollutants in indoor environments can be very different from that of outdoor environments, as it depends on factors specific to indoor environments, such as ventilation, air conditioning, and concentrations of harmful substances from sources such as tobacco smoke and, in general, combustion-related activities (cooking or heating) (Ma et al. 2019). Because the study of indoor air quality is more complicated by privacy issues, epidemiological research on indoor air pollution is scarce. However, current scientific studies show that the time spent in a given place is a determining factor in correctly assessing the effects of air pollutants on people's health (Park and Kwan 2017).

Table 3 shows indoor air quality studies based on personal or mobile sensors. In general, the highest exposure to air pollution on a quotidian day is not from vehicle emission but from the use of air conditioning systems, air fresheners, cooking, etc. (Sinaga et al. 2020). Indoor air quality (IAQ) is directly related to the number of people in the household, to

**Table 2** Studies on air pollution exposure in outdoors at the local scale

Pollutant	Location	Participants	Personal sensing and data	Ref
PM <sub>2.5</sub> and PM <sub>10</sub> , CO <sub>2</sub> , NO <sub>2</sub>	London, UK	14	Low-cost air pollution sensor nodes fitted in waste removal trucks, hospital vans, and taxis	Frederickson et al. (2020)
PM <sub>2.5</sub> , PM <sub>10</sub> , NO <sub>x</sub> , and VOCs	Sheffield, England	45	Plume Labs “Flow” air quality monitor	Heydon and Chakraborty (2020)
PM <sub>2.5</sub> , PM <sub>5</sub> , PM <sub>10</sub> , and CO <sub>2</sub> CO, NO <sub>2</sub> , O <sub>3</sub>	China	36 shared bikes	UbiAir and IoT box	Wu et al. (2020a)
		29	Sensor board connected to Android smartphone	Bales et al. (2019)
PM, CO, NO, NO <sub>2</sub> , and O <sub>3</sub> CO, NO <sub>2</sub> , and O <sub>3</sub>	UK and China	400	Low-cost sensors/GPS	Chatzidiakou et al. (2019)
	Paris, Singapore, Birmingham, Barcelona, New York, Pavia, and Keelung	1500	2 developed sensors/PulsAir mobile app	Ottaviano et al. (2019)
NO <sub>2</sub> and VOCs	London, UK	22	Sensor and smartphone app	Haddad and de Nazelle (2018)
PM, NO <sub>2</sub> , and black carbon	Paris, France	15	3 commercial devices tested	Languille et al. (2020)
PM <sub>2.5</sub>	Los Angeles, USA	18	AirBeam portable air monitor	Johnston et al. (2019)
PM <sub>2.5</sub>	Beijing, China	112	Portable air pollutant sensor/smartphone GPS	Ma et al. (2019)
PM <sub>2.5</sub>	New York, USA	43	Local air monitoring stations/GPS by smartphone app	Yoo et al. (2015)
PM	Beijing, China	50	TE-STR portable monitor and CHO platform	Liang et al. (2019)
PM	Leipzig, Germany	66 cyclists	Particle number counts device	Ueberham et al. (2019)
NO <sub>x</sub> , O <sub>3</sub>	California, USA	2737	Diary activity-travel/co-kriging model	Kim and Kwan (2020)
NO <sub>2</sub> , O <sub>3</sub>	Beijing, China	6	Multiple alphasense sensors in a backpack	Liu et al. (2020)
NO <sub>2</sub> , O <sub>3</sub>	Montreal, Canada	76 sites	Aeroqual sensors	Deville Cavellin et al. (2015)
NO <sub>x</sub>	Finland	Four diesel passenger cars	Portable emissions Measurement system	Söderena et al. (2020)
NO <sub>x</sub>	China	31 vehicles	Portable emissions measurement system	Zhang et al. (2020)
NO <sub>2</sub>	Barcelona, Spain	12	Aeroqual sensor	Oltra et al. (2017)
O <sub>3</sub>	New Jersey, USA	10	Portable ozone monitor	Sagona et al. (2018)
Black carbon	Antwerp, Barcelona, and London	122	microAeth black carbon aerosol monitor	Dons et al. (2017)
Black carbon	Ghent, Belgium	209 trips by bicycle	Micro-aethalometer	Dekoninck et al. (2015)

the activities carried out in those places, and also to the variability concerning the heterogeneous daily activities of the inhabitants (Ghahramani et al. 2019). Poor air quality in the spaces we commonly use for daily activities is an important factor that directly affects our health. Fortunately, improving IAQ is possible by simply opening windows or ensuring good ventilation to reduce the concentration of pollutants retained in the enclosed environment. A study in common indoor places found that increase in PM<sub>10</sub> was due to movements of the occupants of the room, which caused the

re-suspension of coarse particles (Ragazzi et al. 2017). In the case of PM<sub>2.5</sub> and PM<sub>1</sub> concentrations, it was observed that they remained at high levels even at the end of the activities that generated them. CO<sub>2</sub> levels are closely related to the number of individuals and ventilation in concordance with other studies (Gall et al. 2016). When indoor ventilation is poor, CO<sub>2</sub> easily exceeds 1000 ppm, which is linked to low comfort of building occupants, headaches, drowsiness, and attention deficit (Ragazzi et al. 2017).



Among the activities commonly performed indoors is cooking, which produces the highest levels of PM<sub>2.5</sub> reaching levels of 100 µg/m<sup>3</sup> while cooking (Cao and Thompson 2017). The concentration of PM<sub>2.5</sub> is also related to the use of personal care products such as skin creams, hairsprays, and antiperspirants. A short-time increase of VOC occurs after working hours, which can be the result of the temporary existence of a contaminant source such as cleaning materials (Karami et al. 2018). The use of mosquito coils during the night causes exposure peaks during sleeping hours, being more common in wet seasons (Sinaga et al. 2020).

Homes are not the only indoor spaces where polluted air is a risk. Air monitoring has been implemented in workplaces where hazardous gas emissions are a risk. The monitor of nitrous oxide levels in the breathing zones of dental employees demonstrates that more than half of the measurements exceeded the maximum recommended concentrations (Cheng et al. 2019). In the case of healthcare personnel

and patients who undergo endoscopy procedures, they are exposed to unhealthy levels of CO<sub>2</sub> and VOCs (Bang et al. 2019).

The viability of the use of a low-cost monitor for indoor air quality was studied for PM measures. Six low-cost sensors were exposed to diverse indoor air pollutants, but only semi-quantitative responses were achieved due to the poor detection limit (Wang, Delp and Singer 2020). The measures are limited by the variability in the response due to the multiple sources of contaminants, which complicates their use for the quantitative assessment of indoor concentrations and exposures. Recently, a study of commercial portable sensors for air pollution was achieved to test their reliability inside a building (Goletto et al. 2020). The authors found that none of the devices commercially available to the mass public was able to meet the quantitative standard for indoor air pollution measures. Furthermore, a qualitative analysis of air pollutants is possible using domestic sensors. On the other hand,

**Table 3** Indoor air monitoring using portable sensors

Pollutant	Location	Participants	Personal sensor	Ref
PM <sub>2.5</sub>	Apartment in Santa Clara, CA	1	Research-grade and low-cost air monitors	Cheng et al. (2019)
PM <sub>2.5</sub>	Pittsburgh	26	Speck sensor	Wong-Parodi (2018)
PM <sub>2.5</sub>	Bandung, Indonesia	50	AS-LUNG portable monitor	Sinaga et al. (2020)
PM <sub>2.5</sub>	Daily activities	2	Sharp PM2.5 dust sensor	Cao and Thompson (2017)
PM <sub>2.5</sub>	Residential (Baltimore)	One year of monitoring	3 low-cost sensors	Zamora et al. (2020)
PM <sub>2.5</sub>	3 residences	One week of monitoring	4 low-cost sensors	Manibusan and Mainelis (2020)
PM <sub>2.5</sub>	Quotidian environments	3 personal monitors	3 low-cost dust sensors	Agrawaal (2020)
PM <sub>10</sub> , PM <sub>2.5</sub>	Residential home	-	DC 1700 PM sensor	Han et al. (2016)
PM <sub>10</sub> and PM <sub>2.5</sub>	Inside of circulating cars	10 cities	Portable air quality and GPS	Kumar et al. (2021)
CO <sub>2</sub> , PM	Netherlands	280 classrooms	Wall-mounted stationary nodes	Palacios Temprano et al. (2020)
CO <sub>2</sub> , PM <sub>2.5</sub>	Living rooms and bedrooms	117	Two low-cost sensors	Dai et al. (2018)
CO <sub>2</sub> , PM	An office, a computer-room, and two bedrooms	-	GRIMM analyzer and Sensor-drone devices	Ragazzi et al. (2017)
CO <sub>2</sub>	Environmental climate chamber	41	2 wearable CO <sub>2</sub> sensor	Ghahramani et al. (2019)
CO <sub>2</sub>	Daily activities	16	Battery-operated sensor	Gall et al. (2016)
CO	Ghana	38 cooking areas	CO sensor/Bluetooth Low Energy (BLE) Beacon Technology	Piedrahita et al. (2019)
CO <sub>2</sub> , VOCs, PM <sub>2.5</sub> , NO <sub>2</sub> , CO, and O <sub>3</sub>	Gastrointestinal endoscopy unit	-	9 portable passive air quality monitoring sensors	Bang et al. (2019)
PM <sub>2.5</sub> and O <sub>3</sub>	Children's bedrooms	39	Plantower PM and Alphasense O <sub>3</sub> sensors	Barkjohn et al. (2020)
CO <sub>2</sub> , CO, PM <sub>10</sub> , NO <sub>2</sub>	Housing area	5 occupants	Sensors connected by Blynk IoT platform	Taştan and Gökozan (2019)
VOCs, CO <sub>2</sub> , PM <sub>2.5</sub>	Computer lab	-	Sensors connected to Arduino Uno boards	Karami et al. (2018)
N <sub>2</sub> O	7 dental operatories	18	2 commercial monitors	Hansen et al. (2019)
NO	Shipyard	43	Colorimetric detector tubes	McManus and Haddad (2019)

the validation of the portable sensor DC 1700 (Dylos) was well correlated with mass concentrations of  $PM_{2.5}$  measured using the reference monitor Grimm 11-R, resulting in a coefficient of determination of  $R^2 = 0.778$  for  $PM_{2.5}$  (Han et al. 2016). The portable sensor can be inaccurate because the complexity of the chemical composition of the measured aerosols cannot be properly analyzed, resulting in a poor correlation between the coarse PM readings of the portable monitor and the reference monitor. A proposed device for formaldehyde exposure monitoring at home or work was tested in real indoor air, resulting in excellent correlation with the reference; thus, this device can detect formaldehyde from different wood product emissions (van den Broek et al. 2019). A recent review about the characteristics of low-cost indoor air monitoring device development can be found in (Chojer et al. 2020).

Contamination and mobility mapping of people in indoor environments (schools, buildings, etc.) can be applied to track exposure hotspots. Fixed monitors are useful for spatial mapping of indoor air quality (discrete fixed points); however, a “Lagrangian” (mobile) monitoring method offers a way to measure continuous spatial profiles of concentration. An indoor positioning system (IPS) in combination with traditional activity recordings for personal exposure assessment would be useful to identify spontaneous location changes (e.g., leaving the kitchen temporarily while cooking) and provides more detailed exposure assessments despite not detecting emissions from sporadic sources (Cheng et al. 2019; Taştan and Gökozan 2019).

On the other hand, the use of wireless sensor networks in indoor areas can be useful to monitor air quality and additionally serve as a security alarm in case of a risk event such as a gas leak or fire (Jelicic et al. 2015). The benefit of including people in air quality studies is that the participants reach more action to reduce indoor air pollution after using the sensor. If low-cost, high-precision mobile air quality monitoring devices are successfully developed, they may be routinely used in the future to ensure patient health safety in hospitals, schools, and generally in enclosed spaces where people’s health may be compromised.

## Challenges and opportunities of mobile monitoring

The monograph published in 2016 by WHO’s International Agency for Research on Cancer (Humans 2016) has stated that “[...] studies of relationships between air pollution exposure and cancer require long periods of observation and large populations. Therefore, it is virtually impossible with currently available approaches to assess exposure via personal monitoring.” To the best of our knowledge, an integral, scalable, and cost-effective approach to reliably assess

exposure via personal monitoring to reveal health impacts of air pollution, acute episodes, and estimating impacts and the related cost is nonexistent.

Today, however, recent advances in mobile and cloud computing, ubiquitous computing, crowdsourcing/crowdsensing, machine learning, artificial intelligence, big data analysis, and sensor IoT technology open a promising avenue to measure individual exposure practically and cost-effectively. The application of these methodologies in this context was envisioned in The 2012 National Academy of Sciences report *Exposure Science in the 21st Century: A Vision and Strategy* (National Research Council 2012). This report identified “[...] ubiquitous sensors as one of the technologies that will likely substantially enhance exposure science and provide a more accurate and comprehensive personal exposure data. A more complete understanding of personal exposure to air pollution will support the development and implementation of air quality management policies.”

However, air pollution crowdsensing has still failed to address completely two main problems. First is the poor quality of measurements from commercial devices, which are limited to quantifying one or a few pollutants, are prone to interference between pollutants, and do not provide a convenient method for the user to perform recalibration or maintenance. Secondly, since not everyone is willing to cooperate with air quality data collection during their day-to-day activities, user privacy is a critical issue that we must pay attention to during implementation (Wang et al. 2020a; Yang et al. 2019).

To successfully achieve all the scopes of crowdsensing, it is necessary, in the first place, to increase people’s interest. To achieve that, it should not only involve rewards but efforts should also be made to ensure that information from monitoring devices can be easily interpreted by any user so that they might take actions that will help improve air quality. For example, communities may be less concerned about absolute concentrations and more about relative comparisons across sites. Since exposure levels are directly related to human dynamics, it is important to study and generate models for predicting the behavior of individuals from mobile crowdsensing. Ensuring the quality of the information is also a fundamental task in crowdsensing data collection. How to determine if the sensors are working properly or if the sensor is actually exposed to the outside air and not inside a backpack? These details will need to be considered for future studies using crowdsensing (Restuccia et al. 2017).

Regarding the state-of-the-art of the current sensor technology, although the number of commercially available sensors is increasing, the information on data quality and sensors performance compared to conventional analyzers on the field is limited. It is clear that the weather causes interference with low-cost sensors; hence, software and hardware development focused on automatic calibration is key

to achieve a reliable implementation of mobile devices for air monitoring. Because papers reporting negative results have low priority, only a few studies have been published concerning the stability and sensitivity issues (Lewis and Edwards 2016). On the other hand, portable monitor hardware is usually battery powered so that their limited energy budget presents a research and design challenge because reducing cost inevitably reduces the quality of the analysis.

Measuring air pollutants on a personal scale provides more realistic data on individual air quality. However, air pollutants' dosage also depends on increased physical activity, as it increases the amount of air inhaled. Therefore, measurements or models that take this into account would be much more accurate and useful for epidemiological studies (Cox 2021).

In the era of big data, crowdsourcing images would significantly enhance the existing remote sensing database. However, current progress has mostly been limited to small regions and objects. Large-scale data acquisition still relies on professional satellite and airborne platforms, where some challenges such as low-frequency observations and expensive high-resolution images still remain (Wang et al. 2020a). In summary, the ideal crowdsensing must contemplate, low cost (of acquisition, calibration, and maintenance), selectivity and sensitivity, weather influences (indoor and outdoor), and the mode of transport (pedestrian, vehicles, etc.). In parallel, the development of data transmission and storage, management, dissemination, and privacy, would also need to be addressed.

## Conclusions

The development of new sensors and portable devices for air pollutants has demonstrated that estimation of air quality with typical monitoring stations is not sufficiently accurate on an individual scale. The spatiotemporal variation of atmospheric pollutants requires the use of tools such as portable and low-cost sensors to obtain data at higher resolution, and citizen participation through crowdsensing offers a promising alternative for data acquisition. The latest research on air pollutant monitoring through crowdsensing shows that the exposure to pollutants not only depends on the area in which people live, but also depends directly on the work activities and their mode of transportation. The portable monitors have also allowed indoor air monitoring, being useful to know the sources of emission of pollutants and the possible alternatives to avoid them. However, in order to achieve an accurate mapping of air pollutants, it is necessary to continue developing more selective and energy-efficient sensors, devising models to guarantee the

robustness of the data and, above all, encouraging citizen participation.

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