Sensors for Airborne Pollutants

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Contributor: Giacomo Fanti

In the last years, the issue of exposure assessment of airborne pollutants has been on the rise, both in the environmental and occupational fields. Increasingly severe national and international air quality standards, indoor air guidance values, and exposure limit values have been developed to protect the health of the general population and workers; this issue required a significant and continuous improvement in monitoring technologies to allow the execution of proper exposure assessment studies. One of the most interesting aspects in this field is the development of the "next-generation" of airborne pollutants monitors and sensors (NGMS). The principal aim of this review is to analyze and characterize the state of the art and of NGMS and their practical applications in exposure assessment studies. A systematic review of the literature was performed analyzing outcomes from three different databases (Scopus, PubMed, Isi Web of Knowledge); a total of 67 scientific papers were analyzed.

Keywords: low-cost sensors ; citizen science ; miniaturized monitors ; exposome ; mobile app ; wearable monitors

1. Introduction

To better explain the meaning of the terminology used in this review, the authors would like to clarify the definition of some terms that should not be taken for granted. This is needed to avoid misunderstandings while reading the following text. In the context of this review, a "sensor" is a component of a measuring instrument; more specifically, it is the sensing component that allows the performance of the measurement of the airborne concentration of pollutants, typically by relating a chemical–physical property of an airborne pollutant with a signal that can be detected by the instrument, related to the concentration of the pollutant, and then made available and interpreted by the evaluator. A "monitor" (also referred to as a "sensor system") is an integrated device, i.e., a measuring instrument for pollutants airborne concentrations, which is equipped with one (single-parameter monitor) or more (multi-parameter monitor) measuring sensors, as well as with sub-components and other supporting components (e.g., battery, case, GPS (global position system) module, display, Bluetooth module) needed to create a fully functional and autonomous detection system. A sensor system can also include components that reside remotely from the physical sensor and include remote data transfer and data processing steps [1]. The goal of this review is to characterize what the authors intend to call "next generation" monitors and sensors (NGMS): this term refers to "miniaturized" and/or "low-cost" and/or "wearable" sensors and/or monitors. Concerning the definition of "miniaturized monitors" (MMs), in this study, the authors refer to a previous study [2] which identified MMs as those devices with a greater dimension smaller than 20 cm. The proposed dimensional criterion is not always strictly applied in the scientific literature, but it was an arbitrary subdivision with a certain level of subjective decisions. In any case, MMs are those devices having significantly lower dimensions than reference-grade instrumentation. Among MMs, a particular category of sensors and monitors are wearable monitors (WMs), i.e., small, lightweight monitors being used as wearables to provide real-time personal exposure measurements [3][4]. There is still a lack of a universally agreed upon definition of low-cost monitors (LCMs) [5]. Although some different definitions are available [6][7], the scientific community generally defines them as those having significantly lower costs than reference-grade instrumentation [4], in such a way that the acquisition of a single unit has a minimal impact on the budget for monitoring activities. For the purpose of this study, an LCM is defined as a monitor, the cost of which does not exceed the order of magnitude of a few hundreds of dollars [7][8].

2. Current Insights

2.1. Sensors for Selected Pollutants

In 2008, the WHO recommended and targeted values for main air pollutants [9][10]. Among those proposed, this review focused on the following pollutants: nitrogen dioxide (NO_2), ozone (O_3), carbon monoxide (CO), volatile organic compounds (VOCs) and airborne particulate matter (PM) with an aerodynamic diameter below 2.5 µm ($PM_{2.5}$) and below 10 µm (PM_{10}) (the coding "PM" was applied to categorize NGMSs that can simultaneously analyze more than one fraction of particulate matter) (**Table 1**). After the full-text reading step, it was outlined that some pollutants were poorly investigated and the available evidence did not allow for an extensive discussion: for this reason, NGMSs for NO [9][11][12][13][14][15], NO_x [16][17], CO_2 [15][18][19][20], SO_2 [21][22], and BC [23] were not discussed in this review. As a first result, we found that the most commonly used sensors to monitor the selected air pollutant gases are those produced by Alphasense (www.alphasense.com; accessed on 22 April 2021; Great Notley, Essex, UK). These sensors are categorized as electrochemical (EC) sensors, based on an amperometric principle of operation for the quantification of nitrogen dioxide (NO_2), ozone (O_3) and carbon monoxide (CO) [13]. Furthermore, concerning the monitoring of VOCs, what emerged from the literature is that the most common instruments used for this scope are produced by Sensirion (SGP30 and SGPC3) [24][25]. Regarding the measurement of different-sized fractioned PM particles, the most used sensors are those produced by Plantower (PMS3003; PMS5003) and Sharp Electronics (GP2Y1010AU0F) probably also due to their low dimensions and costs. These sensors are based on physical light scattering (LS) processes. Due to the interaction of a light beam with PM, the beam is diffused partially and randomly in all the directions of space. The detection of the intensity and wavelength of scattered light contains information about particle size and/or volume [26]. In these NGMSs, the incident light source is usually a laser and light detection devices (photodiodes) are placed at specific angles to the incident direction. Temperature (T) and relative humidity (RH) sensors were also considered because NGMSs performance may vary significantly with the variation of these factors [21][27][28][29]. For example, when the RH is high, condensed particles and fog are detected and reported by particle monitoring instruments that do not have drying systems at the sample inlets, thus interfering with the measurement performance. This effect should be considered when using low-cost sensors [30][31][32] at the same as it was considered in past studies using time-resolved monitors [33][34][35]. Temperature is a key factor that has an impact on the reaction rate and gas vapor pressure. It could be observed that the QTF (quartz tuning fork) gas sensors' (mass sensitive piezoelectric resonators) sensitivity decreases with increasing environmental temperatures. Therefore, the temperature-dependent sensitivity behavior needs to be accounted for in the QTF sensors calibration protocol to consider different real free-living environmental scenarios [36]. Regarding the sensors used to acquire T and RH data, there is no evidence that one sensor is preferred and/or more used than others, but the most selected brand is Sensirion. The investigated T and RH sensors are all based on the principle of capacitive sensing (CS) to measure RH values and on silicon band gap (SBG) semiconductors to measure T values. Finally, regarding the acquisition data about GPS information, very poor information were found: only 2 of 67 papers explain which sensor models are used in the respective studies (G.TOP FGPMMOPA6H [11] and Adafruit Ultimate GPS chip [37]). This is probably due to the fact that GPS sensors have a high energy consumption so it is preferred to use mobile phone-integrated GPS modules to save battery consumption (e.g., [38]).

Table 1. Pollutants and other parameters (temperature—T; relative humidity—RH) investigated, relative NGMSs used (only those available), relative technologies (EC—electrochemical; MOS—metal oxide semiconductor; LS—light scattering; CS—capacitive sensing; Th—thermistor; SBG—silicon band gap; n.a.—not available) and the number of involved papers in which sensors were made explicit and used. Monitors are marked by "*" to distinguish them from the sensors. Technical features of the selected sensors are summarized in Tables S2 and S3 (Supplementary Materials).

Pollutants	Sensor Name/Models	Sensor Technology	Available Papers	References
NO_2	**Alphasense NO2-A1**	**EC**	**1**	[14]
	Alphasense NO2-A43F	**EC**	**4**	[12][13][15][39]
	Alphasense NO2-B43F	**EC**	**5**	[9][16][18][19][20]
	e2V MiCS-2710	**MOS**	**2**	[40][41]
	*** Sailbri Cooper Inc SCI-608**	**n.a.**	**1**	[42]
	SGX SensorTech MiCS 2714	**MOS**	**1**	[43]
	SGX SensorTech MiCS-4514	**MOS**	**3**	[11][37][44]
O_3	**Alphasense OX-A431**	**EC**	**5**	[12][13][15][39][45]
	Alphasense OX-B431	**EC**	**5**	[9][18][19][46][47]
	Nissha FIS SP-61	**MOS**	**1**	[19]
	*** Sailbri Cooper Inc SCI-608**	**n.a.**	**1**	[42]
	SGX Sensortech MICS 2614	**MOS**	**3**	[24][16][43]
	Winsen MQ-131	**MOS**	**1**	[48]

Pollutants	Sensor Name/Models	Sensor Technology	Available Papers	References
CO	Alphasense CO-A4	EC	2	[13][45]
	Alphasense CO-AF	EC	1	[14]
	Alphasense CO-B41	EC	4	[9][18][46][47]
	e2V MiCS-5525	MOS	1	[49]
	Figaro TGS 2442	MOS	1	[43]
	* Sailbri Cooper Inc SCI-608	n.a.	1	[42]
	SGX SensorTech MiCS-4514	MOS	3	[11][37][44]
	Winsen MQ-7	MOS	1	[48]
VOC	Sensirion SGP30	MOS	1	[25]
	Sensirion SGPC3	MOS	1	[24]
PM	Honeywell HPMA115S0	LS	1	[50]
	Nova Fitness SDS-011	LS	1	[20]
	Plantower PMS3003	LS	3	[11][32][51]
	Plantower pms5003	LS	3	[37][52][53]
	Sharp Electronics GP2Y1010AU0F	LS	3	[46][48][54]
	* TSI OPS3330	LS	1	[55]
$PM_{2.5}$	Alphasense OPC-N2	LS	1	[56]
	Plantower pms3003	LS	4	[15][32][57][58]
	* RTI International MicroPEM	LS	1	[59]
	* Sailbri Cooper Inc SCI-608	LS	1	[42]
	Sharp DN7C3CA006	LS	2	[47][60]
	Shinyei PPD42NS	LS	1	[61]
	Shinyei PPD60PV- T2	LS	2	[35][62]
PM_{10}	* Sailbri Cooper Inc SCI-608	LS	1	[42]
Other Parameters				
T–RH	Adafruit AM2302	CS–TH	1	[46]
	Aosong Electronics DHT22	CS-TH	1	[37]
	CMOS sensor (HTU-21D)	CS-TH	1	[39]
	Cozir AH-1	ND	1	[15]
	* Sailbri Cooper Inc SCI-608	ND	1	[42]
	Sensirion SCD30	CS-SBG	1	[20]
	Sensirion SHT15	CS-SBG	2	[32][58]
	Sensirion SHT31	CS-SBG	1	[51]
	Sensirion SHT75	CS-SBG	1	[45]
	SST sensing CO2S-A	ND	1	[18]
	Texas Instruments HDC1080	CS-TH	1	[11]
GC	G.TOP FGPMMOPA6H	GPS	1	[11]
	Adafruit Ultimate GPS chip	GPS	1	[37]

2.2. Mobile Apps

A crucial role to improve the user interaction with the devices is played by mobile apps specifically developed for some of the NGMSs. In the last few years, this aspect has played an increasing role, especially as regards the storage and transfer of measurement data. The most important role in this sense has been played by technologies that allow the cableless (wireless personal area network) transfer of measurement data from the device (where they are temporarily stored in special data-loggers or memory slots) to the mobile app platform, where they can be viewed, processed, managed, and shared, if necessary. As said in Borghi et al. (2017) [2], the way to communicate and share scientific data is changing and some aspects are particularly interesting such as (i) communication and data transfer via wireless and (ii) data communication via web or smartphone applications. This generally saves time and is more practical than more laborious methods that require manual data download and subsequent processing. The most widely used method is Bluetooth technology, which is further improved with the development of Bluetooth low-energy technology (BLE) [63]. It allows easy and stable communication between NGSMs and a smartphone in which the mobile app is supported. In this review, 23 articles [24][11][16][19][21][22][23][35][36][41][45][52][54][62][64][65][66][67][68][69][70][71] out of 67 reports information about the use of any mobile app supporting NGMSs; most of those (13 apps) were developed on the Android platform [6][19][21][22][25][35][38][45][66][69][71][72][73], only one was developed on the iOS platform [66], and the remaining were not specified. As reported by Kanjo et al. [74], using a mobile phone to collect data can bring many advantages, especially related to the fact that (i) a large percentage of the population carries around mobile phones; (ii) many kinds of data can be processed, stored, and transferred easily by mobile phones; (iii) the collection of data should be more power-efficient because the acquired information are sent directly to the mobile phone. Due to these advantages, the use of mobile apps is considered one of the aspects that is sensibly improving exposure assessment studies, shortening and filling the distance between citizens and researchers. Different kinds of outputs are returned by the smartphone application, such as the concentrations of the investigated pollutants, date, time, and position; these outputs are generally reported in a user-friendly interface. All of these data can be plotted in real time on a graphical interface that allows users to immediately share important information such as exposition peaks, mean concentrations, limit values (e.g., AirCasting app by HabitatMap Inc. [35]). In future developments, to describing sensors and apps, it will be recommended to also investigate communication transmission technologies and common platforms/websites applied to these low-cost sensors, such as 4G, 5G, or Wi-Fi. For the platform, for example, the Edimax Airbox (https://airbox.edimaxcloud.com/ (accessed on 22 April 2021)) and LASS location-aware sensing system in Taiwan are used.

2.3. Applications in Environmental Monitoring and Exposure Assessment

As already discussed, NGMSs cannot totally replace traditional approaches in environmental exposure assessment regarding data reliability, but they can fill other gaps, such as improving data in terms of spatial and temporal resolution. However, although reliable measurements through reference instruments are (and will remain) fundamental, other features of NGMSs may outweigh some of their drawbacks, including lower measurement reliability. Traditional measurement methods require bulky instrumentation. Instead, thanks to their low weight and dimensions, NGMSs are generally miniaturized and/or wearable, which can minimize the interference on subjects' normal activities. For all these reasons, innovative studies for environmental exposure assessment will probably need to exploit both traditional methods and NGMSs, or a combination of them, to allow the investigation of a wide range of different scenarios and subjects' categories or populations [34]. A range of low-cost air quality sensors are now available on the market, thanks to the fast-growing field of sensing technology. Most of these monitors provide quantitative information of pollutant concentrations, in addition to being generally quite easy to use [17][62]. The performance of these low-cost miniaturized sensors must be evaluated, especially in-field. Moreover, their comparability (compared to reference methods [75]) should be carefully evaluated. Using these miniaturized sensors as a support to fixed air quality monitoring networks, both in indoor and outdoor environments [34], it should be possible to obtain a more representative characterization of the subject's exposure and achieve a wider spatial coverage. With the continuous improvement of these technologies, it could be possible to develop and use ubiquitous networks of NGMSs, by different subjects and entities (i.e., governments, municipalities, or individuals). Furthermore, many end-user applications shall be available. These applications can be installed and used by anyone, not only by experts in air pollution monitoring, who can also select the right type of NGMSs for the right purpose and to obtain the data needed. Nevertheless, the data interpretation by non-experts could introduce issues that may affect the validity of the results [6]. This concept refers to the already introduced citizen science approach, defined as scientific research conducted, in whole or in part, by amateur (or non-professional) scientists. The application of these technologies is set to grow and the conversations with communities are expanded by the current low-cost sensing technologies, which also supplement the routine ambient air monitoring networks [6]. Through the use of machine learning, Chew et al. (2019) [38] have been able to demonstrate that by using monitors for the evaluation of personal pollutant exposure, equipped with accelerometers, it is possible to identify periods of biking through the subjects day. Since personal exposure data is related to the respiration rate [38], thanks to the finding mentioned above, the estimation of the dose of potential pollutants inhaled has become possible applying the use of NGMs in exposure assessment studies. Sinaga et al. (2020) [57] outlined that, thanks to the advent of NGMSs, nowadays it is easier to investigate the daily exposure of citizens that live in developing countries, even if they usually do not have many resources to perform these evaluations. In their study, the most contributive factors of PM exposure were identified as mosquito coil burning and factory smoke and it has been taken as reference information to formulate policies and guidelines that aim to reduce citizen exposure and improve health protection [57]. Obtaining expensive instrumentation to monitor air quality is not always foregone, especially in developing or industrializing areas, but NGMSs can solve this problem due to their low cost and easy applicability [61]. Win-Shwe et al. (2020) [76] indicated that continuous assessment of personal exposure level is possible using the NGMS developed in their study, also matching NGMS with mobile sensing technologies. The authors are planning to give health education to the public regarding lifestyle in microenvironments with the scope to reduce indoor air pollution [76]. Barkjohn et al. (2020) [58], using several NGMSs, have pointed out that reducing the infiltration of outdoor air in homes and decreasing pollution at the city or country level can reduce the personal exposure of citizens. The project conducted by Chen et al. (2020) [42] investigated the personal exposure of students to $PM_{2.5}$ wearing NGMSs during school hours in a two-month campaign. The personal exposure of the students can be influenced by outdoor pollution, caused by nearby sources, and it must be evaluated also monitoring air quality outside the school building. The monitoring campaign outcomes showed that short-term and acute events (e.g., resuspension of particles due to students' movements) are more significant in terms of contributing to exposure than outdoor air pollution. The suspended particle characteristics significatively influence the exposure of the subjects due to their high inhomogeneity, which contributes to increment its variability [42].

2.4. Applications in Occupational Hygiene

As reported above, most of the papers analyzed in this review showed that the use of NGMSs is widespread in environmental exposure and environmental health studies, some of which also directly and actively involved citizens in exposure measurements. NGMSs are used to support the reference-grade monitoring instruments and environmental health policy and strategies. To date, the use of NGMSs in occupational hygiene applications is less frequent, mainly because policy- and legislation-based decisions have the strictest performance requirements for precision, accuracy, completeness, and detection limit of data [77]. Nevertheless, NGMSs sensing devices can offer new opportunities in the field of occupational safety and health management [4][78][26][30][46][47][79][80][81][82][83]. Some of the most interesting applications of NGMSs are reported hereafter. NGMSs were applied in physically demanding and hazardous construction settings [81] with the aim to mitigate the high risks associated to these work tasks. Even though that is not the focus of this review, various smart bracelets, wristbands, and smartwatches incorporate numerous sensors that allow to track health and exercise and combine the capabilities of a smartphone with a wristwatch. The purpose is to exploit the capabilities of wearables to change the way workers interact with their environment and enable them to monitor critical, environmental, and physiological data and process it to gain situational awareness. Data acquired by conventional sampling becomes available weeks after sampling and wearables usually provide a single measurement of one hazard, typically integrated over a single work shift. In the last decades, industrial hygienists have been using direct reading instruments (DRIs) and real-time monitors for gas/vapor and PM monitoring. NGMSs also provide measurements that are immediately available for actions and interpretations providing continuous monitoring of several hazards throughout the workplace. NGMSs are still smaller, lighter, and more powerful and connected than the instrumentation of recent decades. The identification of several sources of hazards has been possible thanks to these measurements, which are also used to formulate strategies for improved control and continuously evaluate their effectiveness. A shift to comprehensive exposure assessment is possible thanks to this departure from the conventional sampling usually adopted until nowadays and the priority that workers are adequately protected from workplace hazards will undoubtedly be improved. Once matched with a position tracking system, in the future, these data will also be used to evaluate the personal exposure of a single worker and can be modeled while they move through the workplace [47]. The application of NGMSs may have several advantages for workers regarding workplace safety monitoring [84]. For example, integrating real-time data with machine-learning models, a subset of artificial intelligence that is concerned with creating systems that learn or improve their performance based on the data they use, can exponentially raise the probability of preventing and limiting the potential risks associated with the industrial environment [80]. Moreover, the development of newer software toolkits and microprocessor platforms is powering the WSN systems. A WSN is a network of several sensors that can communicate with each other and with a central controlling unit that collects all the information coming from all the devices. By modelling this information, it could be possible to create plant risk maps, and consequently manage the risk at each workplace, with the aim of improving the occupational health and safety system [46]. As suggested by Goede et al., 2020 [78], high-resolution data from real-time/direct-reading instrument sensors can be used to enrich estimates from models that predict exposure to chemicals in the workplace. By modeling the information acquired by the sensors, recalibrating, refining, and validating existing (time-integrated) models, scientists will be able to improve worker's security and health in the workplace. New approaches such as "occupational dispersion models" (e.g., interpolation/computational fluid dynamic models, and assimilation techniques), paired with sensor data, will be specifically useful. Through early warning systems, source finding, and improved control design, these techniques may be used to develop site-specific personal exposure maps which could significantly support the aim to mitigate worker exposure [78]. It is also necessary to elaborate on the meaning of "exposure assessment" because it is not obvious that its intrinsic meaning could be directly applied in occupational hygiene applications when using NGMSs. For example, when NGMSs are not only used to monitor the workers' exposure (i.e., for exposure assessment purposes), but also to conditionate the behavior of the workers (i.e., by providing real-time warning to the worker experiencing high exposure conditions and therefore suggesting a change in the performance of the job task to reduce the level of exposure). The result of this kind of application will not only be that of having a representative measure of the exposure of the worker in real conditions, but rather an "exposure-based real-time risk management" in which the behavior (and consequently the exposure) of the worker is modified in real-time, thus also providing a sort of exposure-driven risk management.

2.5. Overall Discussion

In summary, NGMSs could provide substantial benefits (including lower efforts at lower cost) when applied to the monitoring of exposure to airborne pollutants in both general environments (i.e., for general populations) and occupational settings (i.e., workers' occupational exposure), if compared to traditional exposure assessment methods, which rely on sampling devices (i.e., by means of sampling pumps or diffusion methods), sampling substrates (e.g., sampling filters, adsorbent substrates), and on the subsequent analytical phase (e.g., gravimetric determinations, chemical characterizations). In more detail, one of the advantages of NGMSs is to provide new insights on exposure dynamics due to their ability to collect data at greater spatiotemporal resolutions (i.e., direct-reading methods) [61]. Furthermore, NGMSs can report and process the data as soon as they are collected and while the instrument is still deployed (i.e., real-time analysis). Therefore, due to their features (i.e., reduced cost, ease of deployment, direct reading capabilities together with the wireless network ability and the possibility of integrating them with other exposure estimation methods), new ways of collecting and sharing environmental and occupational exposure information has become possible using NGMSs [4][78]. For these reasons, both in environmental and occupational hygiene, not only is the need for accurate evaluation of human exposure to airborne pollutants confirmed and reiterated, but a step forward is required as regards the methods, techniques, and technologies to be used for this purpose.

References

1. Kant, R.; Bhattacharya, S. Sensors for Air Monitoring. In Environmental, Chemical and Medical Sensors; Springer: Sing apore, 2018; pp. 9–30.
2. Borghi, F.; Spinazzè, A.; Rovelli, S.; Campagnolo, D.; Del Buono, L.; Cattaneo, A.; Cavallo, D.M. Miniaturized monitors f or assessment of exposure to air pollutants: A review. Int. J. Environ. Res. Public Health 2017, 14, 909.
3. Zhang, Q.; An, C.; Fan, S.; Shi, S.; Zhang, R.; Zhang, J.; Li, Q.; Zhang, D.; Hu, X.; Liu, J. Flexible gas sensor based on graphene/ethyl cellulose nanocomposite with ultra-low strain response for volatile organic compounds rapid detection. Nanotechnology 2018, 29, 285501.
4. Ruiter, S.; Kuijpers, E.; Saunders, J.; Snawder, J.; Warren, N.; Gorce, J.-P.; Blom, M.; Krone, T.; Bard, D.; Pronk, A.; et al. Exploring Evaluation Variables for Low-Cost Particulate Matter Monitors to Assess Occupational Exposure. Int. J. En viron. Res. Public Health 2020, 17, 8602.
5. Chojer, H.; Branco, P.T.B.S.; Martins, F.G.; Alvim-Ferraz, M.C.M.; Sousa, S.I.V. Development of low-cost indoor air quali ty monitoring devices: Recent advancements. Sci. Total Environ. 2020, 727, 138385.
6. Morawska, L.; Thai, P.K.; Liu, X.; Asumadu-Sakyi, A.; Ayoko, G.; Bartonova, A.; Bedini, A.; Chai, F.; Christensen, B.; Du nbabin, M.; et al. Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: Ho w far have they gone? Environ. Int. 2018, 116, 286–299.
7. Rai, A.C.; Kumar, P.; Pilla, F.; Skouloudis, A.N.; Di Sabatino, S.; Ratti, C.; Yasar, A.; Rickerby, D. End-user perspective of low-cost sensors for outdoor air pollution monitoring. Sci. Total Environ. 2017, 607–608, 691–705.
8. Zhang, H.; Srinivasan, R.; Ganesan, V. Low cost, multi-pollutant sensing system using raspberry pi for indoor air quality monitoring. Sustainability 2021, 13, 370.
9. Topalović, D.B.; Davidović, M.D.; Jovanović, M.; Bartonova, A.; Ristovski, Z.; Jovašević-Stojanović, M. In search of an o ptimal in-field calibration method of low-cost gas sensors for ambient air pollutants: Comparison of linear, multilinear an d artificial neural network approaches. Atmos. Environ. 2019, 213, 640–658.
10. Krzyzanowski, M. WHO air quality guidelines for Europe. J. Toxicol. Environ. Health Part A Curr. Issues 2008, 71, 47–5 0.

11. Becnel, T.; Tingey, K.; Whitaker, J.; Sayahi, T.; Le, K.; Goffin, P.; Butterfield, A.; Kelly, K.; Gaillardon, P.E. A Distributed L ow-Cost Pollution Monitoring Platform. IEEE Internet Things J. 2019, 6, 10738–10748.
12. Castell, N.; Dauge, F.R.; Schneider, P.; Vogt, M.; Lerner, U.; Fishbain, B.; Broday, D.; Bartonova, A. Can commercial lo w-cost sensor platforms contribute to air quality monitoring and exposure estimates? Environ. Int. 2017, 99, 293–302.
13. Chatzidiakou, L.; Krause, A.; Popoola, O.; Di Antonio, A.; Kellaway, M.; Han, Y.; Squires, F.; Wang, T.; Zhang, H.; Wang, Q.; et al. Characterising low-cost sensors in highly portable platforms to quantify personal exposure in diverse environ ments. Atmos. Meas. Tech. 2019, 12, 4643–4657.
14. Mead, M.I.; Popoola, O.A.M.; Stewart, G.B.; Landshoff, P.; Calleja, M.; Hayes, M.; Baldovi, J.J.; McLeod, M.W.; Hodgso n, T.F.; Dicks, J.; et al. The use of electrochemical sensors for monitoring urban air quality in low-cost, high-density net works. Atmos. Environ. 2013, 70, 186–203.
15. Liu, M.; Barkjohn, K.K.; Norris, C.; Schauer, J.J.; Zhang, J.; Zhang, Y.; Hu, M.; Bergin, M. Using low-cost sensors to mo nitor indoor, outdoor, and personal ozone concentrations in Beijing, China. Environ. Sci. Process. Impacts 2020, 22, 13 1–143.
16. Barcelo-Ordinas, J.M.; Garcia-Vidal, J.; Doudou, M.; Rodrigo-Munoz, S.; Cerezo-Llavero, A. Calibrating low-cost air qu ality sensors using multiple arrays of sensors. In Proceedings of the 2018 IEEE Wireless Communications and Network ing Conference (WCNC), Barcelona, Spain, 15–18 April 2018; pp. 1–6.
17. Chatzidiakou, L.; Krause, A.; Han, Y.; Chen, W.; Yan, L.; Popoola, O.A.M.; Kellaway, M.; Wu, Y.; Liu, J.; Hu, M.; et al. U sing low-cost sensor technologies and advanced computational methods to improve dose estimations in health panel st udies: Results of the AIRLESS project. J. Expo. Sci. Environ. Epidemiol. 2020, 30, 981–989.
18. Zimmerman, N.; Presto, A.A.; Kumar, S.P.N.; Gu, J.; Hauryliuk, A.; Robinson, E.S.; Robinson, A.L.; Subramanian, R. A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monit oring. Atmos. Meas. Tech. 2018, 11, 291–313.
19. Suriano, D.; Cassano, G.; Penza, M. Design and Development of a Flexible, Plug-and-Play, Cost-Effective Tool for on-F ield Evaluation of Gas Sensors. J. Sens. 2020, 2020.
20. Frederickson, L.B.; Lim, S.; Russell, H.S.; Kwiatkowski, S.; Bonomaully, J.; Schmidt, J.A.; Hertel, O.; Mudway, I.; Barrat t, B.; Johnson, M.S. Monitoring excess exposure to air pollution for professional drivers in London using low-cost senso rs. Atmosphere 2020, 11, 749.
21. Yi, W.Y.; Leung, K.S.; Leung, Y. A modular plug-and-play sensor system for urban air pollution monitoring: Design, impl ementation and evaluation. Sensors 2018, 18, 7.
22. Fletcher, R.R.; Oreskovic, N.M.; Robinson, A.I. Design and clinical feasibility of personal wearable monitor for measure ment of activity and environmental exposure. In Proceedings of the 2014 36th Annual International Conference of the I EEE Engineering in Medicine and Biology Society, Chicago, IL, USA, 26–30 August 2014; pp. 874–877.
23. Nieuwenhuijsen, M.J.; Donaire-Gonzalez, D.; Rivas, I.; De Castro, M.; Cirach, M.; Hoek, G.; Seto, E.; Jerrett, M.; Sunye r, J. Variability in and agreement between modeled and personal continuously measured black carbon levels using nov el smartphone and sensor technologies. Environ. Sci. Technol. 2015, 49, 2977–2982.
24. Mallires, K.R.; Wang, D.; Tipparaju, V.V.; Tao, N. Developing a Low-Cost Wearable Personal Exposure Monitor for Stud ying Respiratory Diseases Using Metal-Oxide Sensors. IEEE Sens. J. 2019, 19, 8252–8261.
25. Dessimond, B.; Annesi-Maesano, I.; Pepin, J.L.; Srairi, S.; Pau, G. Academically produced air pollution sensors for pers onal exposure assessment: The canarin project. Sensors 2021, 21, 1876.
26. Du, Z.; Tsow, F.; Wang, D.; Tao, N. A Miniaturized Particulate Matter Sensing Platform Based on CMOS Imager and Re al-Time Image Processing. IEEE Sens. J. 2018, 18, 7421–7428.
27. Balanescu, M.; Suciu, G.; Dobrea, M.A.; Balaceanu, C.; Ciobanu, R.I.; Dobre, C.; Birdici, A.C.; Badicu, A.; Oprea, I.; Pa sat, A. An algorithm to improve data accuracy of PMs concentration measured with IoT devices. Adv. Sci. Technol. Eng. Syst. 2020, 5, 180–187.
28. Balanescu, M.; Oprea, I.; Suciu, G.; Dobrea, M.A.; Balaceanu, C.; Ciobanu, R.I.; Dobre, C. A study on data accuracy fo r IoT measurements of PMs concentration. In Proceedings of the 2019 22nd International Conference on Control Syste ms and Computer Science (CSCS), Bucharest, Romania, 28–30 May 2019; pp. 182–187.
29. Duvall, R.M.; Long, R.W.; Beaver, M.R.; Kronmiller, K.G.; Wheeler, M.L.; Szykman, J.J. Performance evaluation and co mmunity application of low-cost sensors for ozone and nitrogen dioxide. Sensors 2016, 16, 1698.
30. Lin, C.; Xian, X.; Qin, X.; Wang, D.; Tsow, F.; Forzani, E.; Tao, N. High Performance Colorimetric Carbon Monoxide Sen sor for Continuous Personal Exposure Monitoring. ACS Sens. 2018, 3, 327–333.

31. Jayaratne, R.; Liu, X.; Thai, P.; Dunbabin, M.; Morawska, L. The influence of humidity on the performance of a low-cost air particle mass sensor and the effect of atmospheric fog. Atmos. Meas. Tech. 2018, 11, 4883–4890.

32. Huang, R.; Lal, R.; Qin, M.; Hu, Y.; Russell, A.G.; Talat, M.; Afrin, S.; Garcia-menendez, F.; Neill, S.M.O. Application and Evaluation of a Low-cost PM Sensor and Data Fusion with CMAQ Simulations to Quantify the Impacts of Prescribed Burning on Air Quality in Southwestern Georgia, USA Application and Evaluation of a Low-cost PM Sensor and Data Fusion with CMA. J. Air Waste Manag. Assoc. 2021.

33. Zieger, P.; Fierz-Schmidhauser, R.; Weingartner, E.; Baltensperger, U. Effects of relative humidity on aerosol light scattering: Results from different European sites. Atmos. Chem. Phys. 2013, 13, 10609–10631.

34. Spinazzè, A.; Fanti, G.; Borghi, F.; Del Buono, L.; Campagnolo, D.; Rovelli, S.; Cattaneo, A.; Cavallo, D.M. Field comparison of instruments for exposure assessment of airborne ultrafine particles and particulate matter. Atmos. Environ. 2017.

35. Borghi, F.; Spinazzè, A.; Campagnolo, D.; Rovelli, S.; Cattaneo, A.; Cavallo, D.M. Precision and accuracy of a direct-reading miniaturized monitor in PM2.5 exposure assessment. Sensors 2018, 18, 3089.

36. Deng, Y.; Chen, C.; Tsow, F.; Xian, X.; Forzani, E. Unraveling fabrication and calibration of wearable gas monitor for use under free-living conditions. In Proceedings of the 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, USA, 16–20 August 2016; pp. 4897–4900.

37. Hegde, S.; Min, K.T.; Moore, J.; Lundrigan, P.; Patwari, N.; Collingwood, S.; Balch, A.; Kelly, K.E. Indoor household particulate matter measurements using a network of low-cost sensors. Aerosol Air Qual. Res. 2020, 20, 381–394.

38. Chew, R.; Thornburg, J.; Jack, D.; Smith, C.; Yang, Q.; Chillrud, S. Identification of bicycling periods using the MicroPEM personal exposure monitor. Sensors 2019, 19, 4613.

39. Dong, Q.; Li, B.; Downen, R.S.; Tran, N.; Chorvinsky, E.; Pillai, D.K.; Zaghloul, M.E.; Li, Z. A Cloud-Connected NO2and Ozone Sensor System for Personalized Pediatric Asthma Research and Management. IEEE Sens. J. 2020, 20, 15143–15153.

40. Magno, M.; Jelicic, V.; Chikkadi, K.; Roman, C.; Hierold, C.; Bilas, V.; Benini, L. Low-Power Gas Sensing Using Single Walled Carbon Nano Tubes in Wearable Devices. IEEE Sens. J. 2016, 16, 8329–8337.

41. Huck, J.J.; Whyatt, J.D.; Coulton, P.; Davison, B.; Gradinar, A. Combining physiological, environmental and locational sensors for citizen-oriented health applications. Environ. Monit. Assess. 2017, 189, 114.

42. Chen, L.-W.A.; Olawepo, J.O.; Bonanno, F.; Gebreselassie, A.; Zhang, M. Schoolchildren's exposure to PM2.5: A student club–based air quality monitoring campaign using low-cost sensors. Air Qual. Atmos. Health 2020, 13, 543–551.

43. SM, S.N.; Yasa, P.R.; Narayana, M.V.; Khadirnaikar, S.; Rani, P. Mobile monitoring of air pollution using low cost sensors to visualize spatio-temporal variation of pollutants at urban hotspots. Sustain. Cities Soc. 2019, 44, 520–535.

44. McKercher, G.R.; Vanos, J.K. Low-cost mobile air pollution monitoring in urban environments: A pilot study in Lubbock, Texas. Environ. Technol. 2018, 39, 1505–1514.

45. De Vito, S.; Formisano, F.; Agresta, A.; Esposito, E.; Massera, E.; Salvato, M.; Fattoruso, G.; Di Francia, G. A crowdfunded personal air quality monitor Infrastructure for Active Life Applications. In Proceedings of the 2017 IEEE International Workshop on Measurement and Networking (M&N), Naples, Italy, 27–29 September 2017; Volume 2, pp. 6–10.

46. Zuidema, C.; Stebounova, L.V.; Sousan, S.; Gray, A.; Stroh, O.; Thomas, G.; Peters, T.; Koehler, K. Estimating personal exposures from a multi-hazard sensor network. J. Expo. Sci. Environ. Epidemiol. 2020, 30, 1013–1022.

47. Thomas, G.W.; Sousan, S.; Tatum, M.; Liu, X.; Zuidema, C.; Fitzpatrick, M.; Koehler, K.A.; Peters, T.M. Low-cost, distributed environmental monitors for factory worker health. Sensors 2018, 18, 1411.

48. Dam, N.; Ricketts, A.; Catlett, B.; Henriques, J. Wearable sensors for analyzing personal exposure to air pollution. In Proceedings of the 2017 Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, USA, 28 April 2017; pp. 1–4.

49. Wen, T.H.; Jiang, J.A.; Sun, C.H.; Juang, J.Y.; Lin, T.S. Monitoring street-level spatial-temporal variations of carbon monoxide in urban settings using a wireless sensor network (WSN) framework. Int. J. Environ. Res. Public Health 2013, 10, 6380–6396.

50. Zou, Y.; Young, M.; Chen, J.; Liu, J.; May, A.; Clark, J.D. Examining the functional range of commercially available low-cost airborne particle sensors and consequences for monitoring of indoor air quality in residences. Indoor Air 2019, 30, 213–234.

51. Lung, S.C.C.; Tsou, M.C.M.; Hu, S.C.; Hsieh, Y.H.; Wang, W.C.V.; Shui, C.K.; Tan, C.H. Concurrent assessment of personal, indoor, and outdoor PM2.5 and PM1 levels and source contributions using novel low-cost sensing devices. Indoor Air 2020.

52. Tryner, J.; Quinn, C.; Windom, B.C.; Volckens, J. Design and evaluation of a portable PM2.5 monitor featuring a low-co st sensor in line with an active filter sampler. Environ. Sci. Process. Impacts 2019, 21, 1403–1415.

53. Mahajan, S.; Kumar, P. Evaluation of low-cost sensors for quantitative personal exposure monitoring. Sustain. Cities So c. 2020, 57, 102076.

54. Agrawaal, H.; Jones, C.; Thompson, J.E. Personal exposure estimates via portable and wireless sensing and reporting of particulate pollution. Int. J. Environ. Res. Public Health 2020, 17, 843.

55. Núñez, J.; Wang, Y.; Bäumer, S.; Boersma, A. Inline infrared chemical identification of particulate matter. Sensors 2020, 20, 4193.

56. Bulot, F.M.J.; Johnston, S.J.; Basford, P.J.; Easton, N.H.C.; Apetroaie-Cristea, M.; Foster, G.L.; Morris, A.K.R.; Cox, S. J.; Loxham, M. Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environ ment. Sci. Rep. 2019, 9, 1–13.

57. Sinaga, D.; Setyawati, W.; Cheng, F.Y.; Lung, S.C.C. Investigation on daily exposure to PM2.5 in Bandung city, Indones ia using low-cost sensor. J. Expo. Sci. Environ. Epidemiol. 2020, 30, 1001–1012.

58. Barkjohn, K.K.; Bergin, M.H.; Norris, C.; Schauer, J.J.; Zhang, Y.; Black, M.; Hu, M.; Zhang, J. Using low-cost sensors t o quantify the effects of air filtration on indoor and personal exposure relevant PM2.5 concentrations in Beijing, China. Aerosol Air Qual. Res. 2020, 20, 297–313.

59. Zhang, T.; Chillrud, S.N.; Ji, J.; Chen, Y.; Pitiranggon, M.; Li, W.; Liu, Z.; Yan, B. Comparison of PM2.5 exposure in hazy and non-hazy days in Nanjing, China. Aerosol Air Qual. Res. 2017, 17, 2235–2246.

60. Cao, T.; Thompson, J.E. Portable, Ambient PM2.5 Sensor for Human and/or Animal Exposure Studies. Anal. Lett. 2017, 50, 712–723.

61. Gao, M.; Cao, J.; Seto, E. A distributed network of low-cost continuous reading sensors to measure spatiotemporal vari ations of PM2.5 in Xi'an, China. Environ. Pollut. 2015, 199, 56–65.

62. Mazaheri, M.; Clifford, S.; Yeganeh, B.; Viana, M.; Rizza, V.; Flament, R.; Buonanno, G.; Morawska, L. Investigations in to factors affecting personal exposure to particles in urban microenvironments using low-cost sensors. Environ. Int. 201 8, 120, 496–504.

63. Liao, J.; McCracken, J.P.; Piedrahita, R.; Thompson, L.; Mollinedo, E.; Canuz, E.; De Léon, O.; Díaz-Artiga, A.; Johnso n, M.; Clark, M.; et al. The use of bluetooth low energy Beacon systems to estimate indirect personal exposure to hous ehold air pollution. J. Expo. Sci. Environ. Epidemiol. 2020, 30, 990–1000.

64. Deng, Y.; Chen, C.; Xian, X.; Tsow, F.; Verma, G.; McConnell, R.; Fruin, S.; Tao, N.; Forzani, E.S. A novel wireless wear able volatile organic compound (VOC) monitoring device with disposable sensors. Sensors 2016, 16, 2060.

65. Ueberham, M.; Schmidt, F.; Schlink, U. Advanced smartphone-based sensing with open-source task automation. Sens ors 2018, 18, 2456.

66. Alhakbani, N.; Alqahtani, A.; Al-Autibi, A.; Al-Sabti, R.; Al-Mogari, R.; Al-Sarhan, S. Air Pollution Measures in Riyadh City and Personal Exposure Level. In Proceedings of the 2015 International Conference on Cloud Computing (ICCC), Riyad h, Saudi Arabia, 26–29 April 2015; pp. 1–3.

67. Qin, X.; Xian, X.; Deng, Y.; Wang, D.; Tsow, F.; Forzani, E.; Tao, N. Micro Quartz Tuning Fork-Based PM 2.5 Sensor for Personal Exposure Monitoring. IEEE Sens. J. 2019, 19, 2482–2489.

68. Oluwasanya, P.W.; Alzahrani, A.; Kumar, V.; Samad, Y.A.; Occhipinti, L.G. Portable multi-sensor air quality monitoring pl atform for personal exposure studies. IEEE Instrum. Meas. Mag. 2019, 22, 36–44.

69. Arvind, D.K.; Mann, J.; Bates, A.; Kotsev, K. The AirSpeck Family of Static and Mobile Wireless Air Quality Monitors. In Proceedings of the 2016 Euromicro Conference on Digital System Design (DSD), Limassol, Cyprus, 31 August–2 Sept ember 2016; pp. 207–214.

70. Ueberham, M.; Schlink, U. Wearable sensors for multifactorial personal exposure measurements—A ranking study. En viron. Int. 2018, 121, 130–138.

71. Johnston, J.E.; Juarez, Z.; Navarro, S.; Hernandez, A.; Gutschow, W. Youth engaged participatory air monitoring: A 'day in the life' in urban environmental justice communities. Int. J. Environ. Res. Public Health 2020, 17, 93.

72. Gilmour, D.; Duong, K.M.; Gilmour, I.J.; Davies, M.W. NeoSTRESS: Study of Transfer and Retrieval Environmental Stre ssorS Upon Neonates via a Smartphone Application–Light. Air Med. J. 2020, 39, 97–102.

73. Yang, L.; Li, W.; Ghandehari, M.; Fortino, G. People-centric cognitive internet of things for the quantitative analysis of e nvironmental exposure. IEEE Internet Things J. 2018, 5, 2353–2366.

74. Kanjo, E.; Benford, S.; Paxton, M.; Chamberlain, A.; Fraser, D.S.; Woodgate, D.; Crellin, D.; Woolard, A. MobGeoSen: Facilitating personal geosensor data collection and visualization using mobile phones. Pers. Ubiquitous Comput. 2008,

12, 599–602.

75. Milton, R.; Steed, A. Mapping carbon monoxide using GPS tracked sensors. Environ. Monit. Assess. 2007, 124, 1–19.
76. Win-Shwe, T.T.; Thein, Z.L.; Aung, W.Y.; Yi, E.P.N.; Mating, C.; Nway, N.C.; Thant, Z.; Suzuki, T.; Mar, O.; Ishigaki, Y.; et al. Improvement of GPS-attached Pocket PM2.5 Measuring Device for Personal Exposure Assessment. J. UOEH 2020, 42, 307–315.
77. Schaefer, T.; Kieslinger, B.; Fabian, C.M. Citizen-Based Air Quality Monitoring: The Impact on Individual Citizen Scienti sts and How to Leverage the Benefits to Affect Whole Regions. Citiz. Sci. Theory Pract. 2020.
78. Goede, H.; Kuijpers, E.; Krone, T.; Feber, M.; Franken, R.; Fransman, W.; Duyzer, J.; Pronk, A. Future Prospects of Oc cupational Exposure Modelling of Substances in the Context of Time-Resolved Sensor Data. Ann. Work Expo. Health 2 021, 65, 246–254.
79. West, S.E.; Büker, P.; Ashmore, M.; Njoroge, G.; Welden, N.; Muhoza, C.; Osano, P.; Makau, J.; Njoroge, P.; Apondo, W. Particulate matter pollution in an informal settlement in Nairobi: Using citizen science to make the invisible visible. A ppl. Geogr. 2020, 114, 102133.
80. Iwawaki, A.; Otaka, Y.; Asami, R.; Ishii, T.; Kito, S.; Tamatsu, Y.; Aboshi, H.; Saka, H. Comparison of air dose and operat or exposure from portable X-ray units. Leg. Med. 2020, 47, 101787.
81. Cheriyan, D.; Choi, J.-H. Data on different sized particulate matter concentration produced from a construction activity. Data Br. 2020, 33, 106467.
82. Campero-Jurado, I.; Márquez-Sánchez, S.; Quintanar-Gómez, J.; Rodríguez, S.; Corchado, J.M. Smart helmet 5.0 for i ndustrial internet of things using artificial intelligence. Sensors 2020, 20, 6241.
83. Suciu, G.; Pasat, A.; Balanescu, M.; Poenaru, C. —Wearable Technologies for Monitoring Critical Situations in Hazardo us Environments. In Proceedings of the International Multidisciplinary Scientific GeoConference Surveying Geology an d Mining Ecology Management, SGEM, Sofia, Bulgaria, 14–22 August 2021; pp. 433–438.
84. Reid, M.; Reid, R.D.; Oswal, P.; Sullivan, K.; Bhartia, R.; Hug, W.F. NaDos: A real-time, wearable, personal exposure m onitor for hazardous organic vapors. Sens. Actuators B Chem. 2018, 255, 2996–3003.