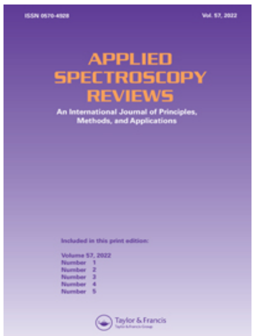

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REVIEW

Review of low-cost sensors for indoor air quality: Features and applications

Milagros Ródenas García[a], Andrea Spinazzé[b], Pedro T.B.S. Branco[c,d], Francesca Borghi[b], Guillermo Villena[e], Andrea Cattaneo[b], Alessia Di Gilio[f], Victor G. Mihucz[g], Elena Gómez Álvarez[h], Sérgio Ivan Lopes[i], Benjamin Bergmans[j], Cezary Orłowski[k], Kostas Karatzas[l], Gonçalo Marques[m], John Saffell[n], and Sofia I.V. Sousa[c,d]

[a]EUPHORE Labs., Fundación Centro de Estudios Ambientales del Mediterráneo (CEAM), Paterna, Valencia, Spain; [b]Risk Assessment for Human Health (RAHH) Research Group, Department of Science and High Technology, University of Insubria, Como, Italy; [c]LEPABE – Laboratory for Process Engineering, Environment, Biotechnology and Energy, Faculty of Engineering, University of Porto, Porto, Portugal; [d]ALiCE – Associate Laboratory in Chemical Engineering, Faculty of Engineering, University of Porto, Porto, Portugal; [e]Department of Physical and Theoretical Chemistry, Faculty of Mathematics and Natural Sciences, University of Wuppertal, Wuppertal, Germany; [f]Department of Biology, University of Bari, Bari, Italy; [g]Institute of Chemistry, ELTE – Eötvös Loránd University, Budapest, Hungary; [h]Department of Edaphology, School of Agricultural Engineering, University of Cordoba, Córdoba, Spain; [i]ADiT-LAB – Applied Digital Transformation Laboratory, Polytechnic Institute of Viana do Castelo, Viana do Castelo, Portugal; [j]ISSEP – Institut Scientifique de Service Public, Liege, Belgium; [k]IBM Centre for Advanced Studies, Faculty of Computer Science and New Technologies, WSB University in Gdańsk, Gdansk, Poland; [l]Environmental Informatics Research Group, School of Mechanical Engineering, Aristotle University of Thessaloniki, Thessaloniki, Greece; [m]Polytechnic of Coimbra, ESTGOH, Oliveira do Hospital, Portugal; [n]NosmoTech Ltd, Cambridge, UK

ABSTRACT

Humans spend the majority of their time indoors, where they are potentially exposed to hazardous pollutants. Within this context, over the past few years, there has been an upsurge of low-cost sensors (LCS) for the measurement of indoor air pollutants, motivated both by recent technological advances and by increased awareness of indoor air quality (IAQ) and its potential negative health impacts. Although not meeting the performance requirements for reference regulatory-equivalent monitoring indoors, LCS can provide informative measurements, offering an opportunity for high-resolution monitoring, emission source identification, exposure mitigation and managing IAQ and energy efficiency, among others. This article discusses the strengths and limitations that LCS offer for applications in the field of IAQ monitoring; it provides an overview of existing sensor technologies and gives recommendations for different indoor applications, considering their performance in the complex indoor environment and discussing future trends.

KEYWORDS

Low-cost sensors; indoor air quality; pollutants; particulate matter; sensing technology; monitoring

CONTACT Milagros Ródenas García mila@ceam.es EUPHORE Labs., Fundación Centro de Estudios Ambientales del Mediterráneo (CEAM), Charles R. Darwin, 14, Parque Tecnológico, 46980 Paterna, Valencia, Spain.

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1. Introduction

The concern about the negative impacts of indoor air quality (IAQ) on human health has fueled a growing awareness, even though most air quality (AQ) regulations and atmospheric chemistry research have historically focused on outdoor air. Humans spend more than 90% of their time indoors in developed countries[1] and poor IAQ has been estimated to be the ninth-largest factor of disease risk.[2] The World Health Organization (WHO) states that, nowadays, household air pollution is one of the main causes of premature death and disease in the developing world, attributing >3.8 million premature deaths per year to household exposure to smoke from inefficient cooking practices and fuels indoors[3] compared to 4.2 million deaths attributed to ambient (outdoor) air pollution. The mixture of indoor air pollutants derives from outdoor infiltration and from indoor source emissions (such as furniture and paintings, cleaning products, indoor activities, etc.[4]). The concentrations of those pollutants, which include a variety of particulate matter, biological pollutants and around 400 gas compounds, are ruled by multiple indoor and outdoor factors.[5,6]

The awareness of AQ related problems has developed in parallel with rapid technological advances, which have evolved to offer low-cost sensors (LCS) and sensor systems capable of satisfying the interest of citizens, who demand online and real-time information concerning air pollution, as part of their digital ecosystem. This demand is in line with the characteristics of LCS, which can provide high-density spatiotemporal pollution data, which motivated their rapid dissemination over the last years. There is still no universally agreed definition of LCS.[7]

A chemical sensor, in general, is a device that converts chemical data into an analytically useful signal.[8] The WMO reports[9,10] state that a sensor system is defined as an integrated device consisting of one or more sensor elements and other supporting components needed to make a fully functional and autonomous detection system. Other names have been given to sensor systems in the literature, like IoT (Internet of Things) AQ sensors, environmental sensors, low-cost sensors, air sensors, among others.[11] Two definitions are adopted in this work:[9,12] i) *sensor element*: the fundamental transduction mechanism able to respond to the presence of a gas or particle and that generates a measurable signal, such as electrical, ii) *sensor system*: a fully functional and autonomous detection system which includes one or several sensor elements and its assorted signal processing hardware. It can include remote data transfer and data processing steps. Although some definitions are available,[13,14] a general description accepted by the scientific community is that they have significantly lower costs than reference-grade instrumentation, which allows for deployment with a high degree of spatial resolution. Low-cost, easy-to-use air pollution monitoring technologies have recently emerged and have advanced quickly in IAQ monitoring.

More in detail, to date, there are open and challenging questions over LCS that have to be addressed, e.g., regarding their purpose, their performance, lack of established and standardized criteria and procedures on their use and of intrinsic quality assurance tools, among others. LCS generally do not meet performance requirements of regulatory equivalent reference instrumentation indoors.[9] Nevertheless, the recently published Standard CEN/TS 17660-1:2021[15] has set the criteria established by the Directive 2008/50/EC[16] for the equivalence of sensor systems used outdoors to those instruments for indicative measurements and objective estimation (Directive 2008/50/EC).[16] To date, there is no similar standard for indoor measurements, but it is a step forward in the reliability of LCS in general. Their use to characterize the subtle changes in the indoor environment is challenging due to the sensitivity, accuracy and time response that they present. However, a range of common indoor air pollutants can be measured with these devices, offering an excellent opportunity for the indoor community, like the identification of possible emission sources in different parts of a household, management and mitigation of IAQ issues, real-time warning systems, personal exposure, as well as building control to optimize energy efficiency and for health risk assessment purposes.[9] Kumar et al.[17] discussed how real-time sensing could bring a paradigm shift in managing the concentration of important air pollutants at high spatiotemporal resolution in billions of urban houses worldwide. LCS deployed in large numbers and accessed through wireless links throughout the internet can provide an extraordinary opportunity to manage and control the new generation of buildings,[18] empowering citizens to control their environments. Despite their drawbacks, their use has been encouraged due to their advantages (e.g., lower costs, portability, lower electricity consumption, etc.).[7,14,17,19–22,131,132]

Within this context, and from the upsurge use of LCS to characterize the air quality outdoors, the IAQ community has considered their use with caution, but also with expectation. However, there are significant differences between the contaminants found in both environments, the environments themselves, and the purpose for which LCS are used, which imply that LCS used indoors have their own specificities.[14,23,24]

This review discusses the possibilities offered by LCS for indoor use and also their limitations. It revisits the variety of LCS that are used for measuring indoor contaminants and discusses their use for a suite of purposes, including the different technologies employed and considering their performance, advantages and disadvantages. This study is devoted to a wide audience that includes the academic community, AQ experts, architects, building managers, decision-makers, the public and, in general, those interested in the AQ of indoor environments and in exploring the prospects of using LCS for this purpose. The main contribution of this review paper is to discuss the current state of the art of LCS technologies for IAQ-related purposes while highlighting potential limitations and challenges.

2. Use of LCS for indoor air quality applications

LCS can be used for purposes related to the IAQ, indoor comfort index and energy optimization in buildings. A recent publication from Chojer et al.[7] systematically reviewed in detail 35 projects, corresponding to 41 publications reporting the development of LCS indoors. All were published from 2014 onwards, and the majority were published in the previous three years (2017–2019), thus evidencing a growing subject. Buildings or general indoor environment monitoring were the intended application in most of the reviewed projects, while other specific applications were also found, such as IAQ monitoring of classrooms, hospitals, personal monitoring, and asthma trigger assessment. These authors observed that other relevant IAQ applications were missing, like households in low-income countries, museums or airports, although this does not mean that such applications have never been tested in other studies.

Due to their low cost, ease of installation, and low power consumption, LCS are increasingly used in system networks to provide an increased spatial measurement density of real-time concentrations. They can measure a series of common indoor air pollutants,[25] such as carbon monoxide (CO), ozone (O_3), nitrogen dioxide (NO_2) and airborne particulate matter (PM) along with carbon dioxide (CO_2) for controlling ventilation levels indoors. Chojer et al.[7] observed that most of the reviewed projects included only temperature (T), relative humidity (RH) and CO_2 sensors, while CO was measured in 43% of the studies, volatile organic compounds (VOCs) in 37%, and $PM_{2.5}$ and PM_{10}, at a lower extent than expected. Other pollutants were also considered sporadically (formaldehyde (HCHO), O_3, NO_2, ammonia, benzene, toluene and nitrogen oxides (NO_x)).

LCS open a new era in monitoring the concentration of indoor pollutants in indoor environments worldwide.[17] Nevertheless, LCS show limitations as they do not give a reliable absolute measure, for which they cannot be used as a substitute for reference instruments for monitoring purposes.[9] For the same reason, LCS cannot currently be used in IAQ monitoring for toxicological or legal thresholds compliance, nor should they be used for IAQ audits. Still, their relative output, under certain conditions, can be used to generate metrics or indicators that allow qualitative and cost-effective IAQ management.[26]

LCS can also be used for AQ awareness and identification of pollution hotspots. Standalone LCS and LCS networks have a great potential for performing diagnostics of air contamination events from emitting sources and occupants' activities. IAQ data can be used to correlate the occupant's diseases with their living environment quality. Furthermore, source apportionment analyses of indoor pollutants (e.g., VOCs) could become possible, and the impact of various building materials on IAQ could be also evaluated.[27] For instance, Shen et al.[28] used a network of LCS to disentangle the contribution of different sources (infiltration from outdoors vs cooking) to the time-resolved concentrations in the various premises of a residential home. Among others, this approach avoids the uncertainties linked to the effect of sampling location on the variability of air concentrations.[29]

Personal monitoring in the breathing zone is the gold standard for the exposure assessment to air pollutants, whenever the inhalation pathway is predominant. Compact, light, economical, and energy-efficient LCS have a great potential for application in large-scale risk assessment or epidemiological studies.[30]

LCS make now possible the involvement of the local communities in IAQ measurements to increase consumer awareness of the importance of reducing indoor exposure to toxic chemicals and making informed behavioral choices (e.g., smoking, using or not a fume hood during cooking) for an effective IAQ control. The use of IoT nodes can lead to improvements in the process of data acquisition and processing as well as to enhanced applications for data consulting and notifications. It also enables the creation of real-time health and wellbeing monitoring systems to plan effective strategies and real-time mitigation interventions to improve IAQ management in smart living environments. These goals could be also achieved in citizen-science projects, making sure that participants would be correctly advised by experts on the correct use (e.g., calibration, maintenance, etc.) of LCS, data analysis and interpretation of results. As a matter of fact, one of the open challenges is the quality control, data pre-processing and analysis of such a large amount of data.[20] Naturally, a great increase in data coverage will emphasize the need for skilled staff to treat LCS (big) data (i.e., a high volume of data of different nature, generated with high velocity) and turn it into correct and useful information.[14,31]

The use of LCS for management of energy and IAQ in urban and commercial buildings has been reviewed in the literature.[20,32] Low-cost and smart devices can be used to change the way people interact with buildings and use their facilities, as well as manage their own exposure. LCS can contribute to the buildings to become smarter, healthier, more comfortable and more energy-efficient. Networks of IAQ sensor kits or systems can be useful to building managers and may be included in risk management programs for controlling indoor sources of air pollutants and building ventilation. More in general, LCS can be applied in intelligent and autonomous control systems equipped with complimentary wireless communication infrastructures for a real-time and long-term integrated and optimized management of IAQ, energy consumption and microclimate.[26,33] The augmented spatial and temporal coverage provided by LCS technologies in comparison with reference monitoring systems could also favor optimized management of heating, ventilation and air conditioning systems, preventing incorrect decisions and consequent health outcomes for the occupants.[34]

Williams and collaborators[35] identified 16 different air monitoring applications derived from 48 studies that included quantitative performance information. Among these, the most cited objective for monitoring air pollution was supplemental monitoring, followed by community near-source monitoring, public education, and hot-spot detection.

The lowering of costs of IAQ monitoring could imply a large-scale use of LCS in prevention programs for health protection. This could specifically benefit low-income households, for which indoor comfort, IAQ, health, and energy and environmental problems were evaluated.[36] At the same time, one should be very cautious in using LCS to test compliance of such measurements with IAQ legally binding thresholds or guidance values for the intrinsic disadvantages and limitations (lack in accuracy and long-term stability, cross-interferences, etc.) reported before. Moreover, the fact that the indoor environment itself can affect LCS performance should be also taken into due account.[37]

2.1. Advantages and disadvantages of LCS

Table 1 shows a list of the main technical advantages and limitations in the use of LCS indoors. Applications and non-recommended uses, which can be considered as advantages and disadvantages, respectively, have not been reported in this table as they have been discussed above.

2.2. LCS vs reference instruments

Since the monitoring of IAQ involves using reference-grade methods or equivalent, LCS should ideally exhibit sensitivity, selectivity, good accuracy and robustness.[22]

Table 1. List of main advantages and disadvantages of LCS, (excluding application aspects).

Advantages
Low-cost
Low size, low weight, portable
Allows real-time and high temporal and spatial coverage (possibility of installing sensor networks)
Emerging market, with growing number of companies now commercializing LCS
Growing scientific literature reporting evaluations of the performance of LCS vs reference measurements
(big) Data that can be accessed online and in real-time (IoT, mobile apps) by citizens
Suitable for citizen-science projects

Disadvantages
Often affected by cross-sensitivities with compounds and atmospheric variables*
Frequent calibration needed, although not between service intervals
Relatively short lifetime (1–2 years)
Long term drift and, in some cases, poor data quality
Many studies do not report the analysis method used
Lack of standardization of procedures for calibration and data analysis
Concern about data access and data protection

*Less important indoors than outdoors due to lower variability of RH and T.

Nonetheless, due to the affordability and accessibility of low-cost sensors, their validity and reliability deserve attention. The WMO reports[9,10] highlight that LCS can not substitute reference instruments, especially for mandatory monitoring. A recent systematic review[38] evaluating 31 studies performed in indoor environments and 11 in laboratory conditions, evidenced that the reliability of LCS for qualitative AQI analysis was adequate. However, a consistent on-field calibration between the LCS and a reference instrument is highly recommended. Besides, a future trend for this technology is the application of an intelligent algorithm able to continuously calibrate the sensors from the data measurements. In this regard, it should be noted that to date such a process is not totally independent because reference instruments are still needed for validation and calibration purposes.

In general, LCS exhibit moderate correlations with reference-grade instruments, revealing sufficient precision for monitoring IAQ, especially for qualitative analysis. Overall, using LCS to monitor IAQ is encouraged, but not waiving the relevance of high-quality instruments.[22,38] For these reasons, currently, LCS cannot replace reference-grade measurement techniques in applications such as IAQ monitoring for toxicological or legal thresholds compliance, nor should they be used for IAQ audits. Still, these authors state that their relative output, under certain conditions, can allow qualitative and cost-effective IAQ management. In this regard, the major purpose of using LCS in IAQ assessment has been their successful use as a complementary tool of the reference techniques, as a qualitative source of atmospheric composition data, followed by community near-source monitoring, public education and hot-spot detection.[35] According to the work of these authors, the preference for regulatory monitoring is the achievement of high accuracy, selectivity and precision. Although these parameters are still important for non-regulatory monitoring purposes, high spatial density and low cost are given priority. The uncertainty associated with the LCS data is usually higher than that of reference monitors.[39] Compared to these, LCS tend to be less sensitive, less precise, and less selective to measure a specific compound or variable of interest. Another key finding of the WMO reports[9,10] is that LCS should be operated under established quality assurance and quality control protocols that guarantee to meet or exceed the objectives of the research

Table 2. Comparability of LCS for indoor measurements and reference instrumentation.

Concept	Low-cost sensor	Reference-grade instrument
Cost (indicative range)	100–2500 €	10000–75000 €
Operating cost	Relatively inexpensive	Expensive
Location	Portable or fixed (also organized in sensors network)	Typically fixed location
Staff Training	Little or none (monitor) Some training (research)	Some training (monitor) High training (instrument)
Analysis skills	None (if data are provided by the sensor system) High (research)	None (monitor) High skills (instrument)
Data quality	Depends on sensor and analysis procedure. Not complying with AQ directive (Directive 2008/50/EC)	Known and stable. Repeatable and reliable, complying with AQ directive (Directive 2008/50/EC)
Selectivity	May suffer from interferences with environmental parameters and other contaminants	High selectivity
Lifetime	1–2 years + drift	> 10 years
Development degree	Research	Advanced
Accessibility to data	In real-time	In real-time (monitor) Usually not in real-time (instrument)
Area coverage	High	Low
IoT applications	Yes	No
For regulatory monitoring	No	Yes
End user	Research, policymakers, building managers	Local government, citizens

application. Until very recently, despite the number of reviews published in the scientific literature, there was no standard protocol for comparing and evaluating the agreement between sensor systems and reference observations. Under these conditions, the use of sensors for monitoring purposes, i.e., demanding compliance with the requirements of grade instruments, or beyond their possibilities, has plaid against their credibility, leading to mistrust of LCS. Some of the aspects discussed above have been addressed by the Standard CEN/TS 17660-1:2021,[15] which regulates the procedures and requirements of sensor systems for monitoring gas contaminants in outdoor measurements at fixed sites. An adapted regulation for indoor applications is still pending.

Table 2 compares a generic LCS device with its corresponding reference-grade instrument (i.e., a reference instrument with a certification from an official regulating body), measuring (indoor air) pollutants according to a predefined methodology and providing data that meets regulatory requirements.[10] Detailed evidence about performance comparison of LCS with reference-grade instruments area is also available in recently published studies.[22,38]

2.3. Technical aspects

The use of LCS for IAQ assessment purposes, when compared to outdoor environments, demand for increased repeatability and accuracy, due to LCS operation across a wide range of levels, particularly at low concentrations. Another critical element common to LCS used both indoors and outdoors is handling, processing, and analysis of the huge amount of data that can be obtained from all these sensors, which still present a significant challenge and associated cost. Still, Sá et al.[38] concluded that the use of LCS to monitor IAQ should be encouraged, because of the advantages described above.

Besides, even though a sensor network can be deployed at a relatively low cost, the labor to maintain the network and process the data is likely to quickly exceed the cost of the hardware. It is also imperative to consider the cost of field calibration, additional hardware requirements, setup and installation costs in the total budget. Thus, the future of sensor networks for IAQ purposes or its integration in existing BEMS (Building Energy Management System) lies not only in the improvement of the sensor's technology but also in the availability of accessible and affordable services for data processing and sensor-network maintenance.

Saini et al.[11] stated that the major problem is solving the tradeoff between quality and cost. Sensor calibration requirements and accuracy are key parameters for the developer's community. Solving limitations associated with frequent calibration requirements is a considerable challenge. Consequently, it is critical to design sensors for remote monitoring applications that are easy to maintain. The plug-and-play sensors with IoT capabilities present a significant opportunity for future applications and reduce additional hardware requirements. Additionally, clear criteria for selecting appropriate sensors according to their specific use (awareness, hot spot detection, etc.,) and place of installation (schools, hospitals, restaurants, residential housing) are needed. The industry has to address these applications and respond to the LCS community by designing cost-efficient solutions, which can be also useful for developing smart cities with sustainable buildings that ensure healthy IAQ conditions for occupants.

Aging of LCS produces drift, which affects their long-term stability and their performance, eventually leading to shortening their lifetime.[40,41] In PM LCS, degradation of the electrical components of the sensor and dust accumulation are generally believed to be the causes of drift.[42,43] Besides, most sensor packages cannot provide reliable information, since they still have limitations regarding their selectivity. In a study on the control of IAQ in smart homes, Zhang and Srinivasan[44] did not consider this technology sufficiently advanced to be applied for regulatory purposes on a large scale, because of their limited robustness, repeatability, and lack of a widely accepted protocol for sensor validation, testing and deployment. Sensor performance will need to be tested under a wide range of environmental conditions[10,11] before being deployed on a large scale. Also, the own continuous and fast development of LCS can be challenging for the evaluation of LCS by researchers, as several versions of the same type of sensor with different states of evolution and performance can coexist in the same study framework.

Regarding PM LCS, to date, it is unlikely that the current generation of these sensors will be able to effectively detect so many details and subtle variations in the indoor environment, but with the rapid development of the technology, this will likely change. For example, currently available LCS are not suitable for measuring ultrafine/nanoparticles ($<$100 nm in diameter).[26] Another weakness of LCS is their signal-to-noise ratio which defines their limit of detection (LOD), making them less useful in low pollution environments. This can be solved to some extent by recording for longer periods and averaging the results, collocating several sensors and taking an average and using digital filters to remove high-frequency noise.[133]

2.3.1. Implementation

Depending on their operating principle, there are different technologies used by the sensor elements to react to the presence of the pollutant, namely electrochemical (EC),[46] metal oxide semiconductors (MOS)[45] photoionization detectors (PID),[47] non-dispersive infrared (NDIR)[48] and light scattering[49] among others. According to Chojer et al.,[8] the most recurrent sensing technologies were thermistors (temperature), capacitive sensor technology (RH), non-dispersive infrared – NDIR (CO_2), particle scattering (PM), and Metal Oxide Semiconductor – MOS (CO, VOC and formaldehyde). A description of sensor technologies is provided in the **Supplementary Material S1.** Only sensors for determining pollutants are considered here, therefore, environmental parameters, e.g., RH and T, are not included in this work.

Regarding hardware integration, two platform types have recently emerged with high applicability for the development of low-cost IAQ systems, namely Generic Platforms and Sensor Platforms, whose main part is a microcontroller. Generic platforms are general-purpose computing platforms with multiple functionalities. Sensor platforms are specific-based platforms that integrate built-in capacities and environmental LCS for AQ applications. Moreover, the reduced size of these low-cost sensor platforms allows for new capabilities to evaluate health risks from indoor air pollution exposure.[39]

It is a common practice to use these platforms to collect data for IoT applications, to control actuator devices, and to perform certain data processing tasks. IAQ systems based on IoT can incorporate sensors to monitor different parameters such as CO_2, CO, PM, VOCs, O_3, NO_2 and SO_2[11]. The most popular platforms are the ESP32, Arduino, Raspberry Pi boards, and Waspmote. To connect these boards (and their sensors) to the internet, usually, wireless communication technologies are preferred, e.g., the WiFi network, which has an extensive and accessible infrastructure. However, other communication technologies for data transmission are used by some IAQ systems based on IoT, such as Bluetooth, due to its compatibility and low cost, and Ethernet.[50] If the required range is small and the needed bandwidth is low, Zigbee should be considered. LoRa enables long-range transmissions with very low power consumption.[51]

The introduction of wireless technologies allowed the use of sensor networks, which are defined as a group of devices distributed over a specific area. A sensor network consists of nodes each of them including one or several sensors, data transmission module, a microcontroller and a power source.[52] Their purpose is to analyze a specific functionality, e.g., monitor the AQ in different indoor activities.[11,53] The whole network can be considered as a class of measuring instruments, and can also integrate additional data from reference nodes or instrument, in such a way that by using computational intelligence, the measurement uncertainty and the number of LCS nodes needed can be reduced.[54,55]

2.3.2. Calibration and data analysis methods

One of the most critical challenges associated with LCS technology is the level of data reliability. The process of guaranteeing that the data measured with a sensor is consistent with the same data from a standard measurement is also often called quality assurance (QA).[10] These authors state that this is often performed using calibration techniques where a sensor is compared with a reference-grade instrument and, certainly, the current research to improve the data reliability of LCS focuses on developing calibration models. By applying a suitable calibration to any device, QA ensures that a sensor produces robust and accurate data. Sensors need to be calibrated by collocating them with reference instruments, which may be considered to provide the "ground truth," and within the environment in which they will operate. Although this is less critical indoors than outdoors due to the lower variability of T and RH indoors, sensors must be calibrated under conditions as close as possible to those at which the measurements will be done.[10,11] Thus, the LCS measurement is used as input to the modeling procedure, together with other data (typically measurements of additional pollutants as well as of ambient environment conditions like T and RH). Then, a model is developed, trained, tested and validated, resulting in an output that is as close as possible to the ground truth. This procedure has been shown to improve not only the basic statistical indices of sensor performance but also to be able to drastically improve the relative expanded uncertainty of the measurement. It renders the LCS as appropriate for uses not previously foreseen (i.e., as complementary measurements to official instruments under certain assumptions), according to the Directive 2008/50/EC[16] and to the Standard CEN/TS 17660-1:2021[15] for AQ.[55]

While linear models have been more commonly used in calibrations, recently, non-linear machine learning (ML) models are emerging as a promising advancement that have improved the data results in outdoor studies, being able to better account for environmental effects and cross-sensitivities.[56–58] The number and type of interfering contaminants indoors imply that extrapolating the application of these advanced methods from sensors used outdoors to indoors is not straightforward, it should be taken with caution and suggests the need for further discussion and research. In general, considering indoor environments, more studies are needed as only a few have been published.

Another aspect is the lack of standard procedures to calibrate the data from LCS. In their review of 40 studies, Saini et al.[11] stated that 31 studies (77.5%) did not report calibration procedure details, and the accuracy specification was absent in 39.4% of them. The authors indicated that numerous sensors (pre-calibrated and field-calibrated models) demand recurrent calibration, almost after every 6 months, to maintain reliable and accurate performance. Repeated calibration can be a serious challenge when remote monitoring is the focus. It is also critical to implement frequent calibration in real-time because the calibration procedures may be too complex for the end-user. Chojer et al.[7] concluded that only 12 out of 35 reviewed LCS development projects evaluated sensor performance, including calibration and/or validation outcomes of the sensors, thus showing that most of the developers still merely apply the factory datasheets information. These authors also evidenced a lack of standardized practice and therefore that calibration and validation methods varied significantly with each project. With just two studies testing the long-term stability and only one study checking the cross-sensitivity of the sensors, the authors concluded that more studies are needed, especially those conducted with a thorough check of device performance to ensure data reliability from the LCS. Finally, a recent review[22] examined the LCS for AQ measurement: results of the analysis suggested that LCS exhibited improved performances in the experiments with stable environmental settings, in the comparison against non-designated reference instruments. However, methodological factors in experimental design (such as the pollutant attribute and sensor original equipment manufacturer specification) resulted in contradictory results. Mean Normalized Bias (MNB) and Coefficient of Variation (CV) (i.e., two measures that US-EPA recommends for determining the suitable application tier of AQ sensors,[59]) varied significantly among published experiments due to the discrepancy in experimental design.

3. Quality of the data measured by LCS in indoor environments

3.1. Indicators of performance

At present, the main limitation of LCS is that they are generally characterized by worse performance in terms of accuracy than the commonly used standard techniques.[30] Previous studies have tested several LCS investigating their measurement performance. Concerning this issue, the European Union Air Quality Directive indicates that uncertainty should be the main indicator for the evaluation of the data quality objective of air pollution measurement methods.[16]

The performances of LCS must be evaluated in order to validate the data collected. Nevertheless, there is a lack of uniformity in the metrics used in the reported validation results (R^2, percentage errors, MAE – Mean Absolute Error, etc.) and in the parameters to study (linearity, precision, etc.). In fact, it is important to harmonize the metrics used to evaluate the quality of the data, which includes both the calibrations and the analysis. Significant efforts and initiatives have and are being carried out in this line, which aim at standardizing the use and testing procedures of LCS, and at setting certification schemes based on the uncertainty of the measurement, which will allow better use of LCS and a better evaluation of their performance. The most common technique is to make a preliminary evaluation under laboratory conditions, using LCS paired with golden standard methods and evaluate their performances. Usually, LCS performance is evaluated using different methods or reliability indicators,[60–62] e.g.,:

- **Precision**: evaluation of uncertainty between collocated LCS by means of uncertainty analysis and linear regression, as reported by Watson et al.[63]
- **Comparison with reference methods**: using Mann-Whitney test, Spearman's correlation (rho) and regression analysis according to the indications described by Watson et al.[63] Accordingly, linear regression analysis may be used to evaluate the level of agreement between two methods (in this case LCS and reference method). Moreover, as reported in the literature,[63] equation parameters (R, slope, and intercept) can be used as indicators of the comparability and/or predictability between the two methods.
- **Linearity**: using linear regression analysis to describe the agreement between the concentration measured via LCS under examination and the reference technique. The y-intercept and the slope of regression, as well as the coefficient of determination, may be used for the evaluation of the agreement.
- **Error trends**: using the Bland-Altman plot method[64,65] and evaluating the absolute and relative errors.
- **Uncertainty**: uncertainty between a couple of LCS can be calculated following the guidance (EC Working Group for demonstration of equivalence). Both classical and artificial intelligence methods are used for assessing uncertainty.[54]

However, the evaluation of this metric is not included in most sensor studies.[66] The most commonly used statistical indicators used with sensor elements and sensor systems in relation to reference instruments are reported in Table S1 as derived from recent studies.[66–68] Rai et al.[69] published an exhaustive literature review on this topic where performance was assessed for PM, O_3 and NO_2 by considering the values of the coefficient of determination (R^2), compared with reference instruments. Most studies considered the parameters repeatability, reproducibility, stability and limit of detection.[66,67,70,71] The most common metric informed either in field, laboratory or indoor intercomparisons against reference data is R^2, which can be interpreted as an indicator of how well measurements obtained by means of a tested sensor fit with those obtained from the corresponding "reference" instrument.

Another important parameter in LCS performance evaluation is that of the Relative Expanded Uncertainty (REU), as this is the criterion for their classification in a way that is consistent with the requirements for indicative measurements and objective estimation defined in Directive 2008/50/EC.[16] The REU is used for this purpose by the recently adopted ISO standard CEN/TS 17660-1:2021.[15]

During the last ten years, several intercomparisons have been carried out for gases and particulate matter, in the laboratory,[72,73] in the field,[60,66–68,74,75] and also in indoor environments.[37,76] Some of these intercomparisons were carried out using sensor systems and others using only the sensor elements. A recent review[22] examined the indicators used to evaluate the performance of AQ LCS from a total of 112 articles. Figures of R^2, Root Mean Square Error (RMSE), MNB, and CV were extracted for a detailed analysis. It was observed that R^2 or its square root (R, Pearson Correlation Coefficient) were commonly adopted to describe how well the response of LCS correlated to that of reference instruments. Besides, RMSE, MAE, MNB, Mean Bias Error (MBE), Standard Error of Estimate (SEE), and Mean Normalized Error (MNE) to evaluate the measurement error of the LCS. RMSE and SEE provided more weighting to the most significant errors, while MAE treated each error equally. MBE and MNB described the deviation from the reference instrument. CV was used to assess the intra-model variability in 20 studies. Williams et al.[59] proposed to use MNB and CV to determine the performance of AQ sensors. In Table S2 it is possible to observe the variation of the different metrics commonly used for different gases.

3.2. Certification and testing initiatives

Unlike reference instrumentation subjected to comprehensive regulatory standards and processes for evaluation and certification, few standards and certifications exist for LCS. This has led to confusion in the market, as new buyers are unaware of the performance of their sensors, how to operate (e.g., calibrate) them, and how well they need to perform for a given purpose. Some protocols developed by research centers and national standardization institutes are emerging to provide quality indicators (quantitative performance requirements).

Saini et al.[11] pointed out that there is a significant lack of scientific validation and testing activities following systematic approaches to validate the performance of LCS when compared with calibrated instruments. These studies should consider different indoor environments and different stages of the sensor's life quality.

Unfortunately, the calibration of the sensors in the laboratory do not often overlap with the full range of conditions in an indoor environment. Tests in laboratories or simulation chambers are suitable to study cross-sensitivities with a number of gaseous species[77] and dependence on relative humidity and temperature. Nevertheless, they cannot cover the suit of variability of gaseous species existing indoors and ever-evolving aerosol physical and optical properties, all of which are known sources of error for LCS measurements, reason why it is recommended that the calibration of the sensors is done in a real environment.

There have been various initiatives for developing a structured and repeatable LCS testing procedure. Some of those include (indicative list):

- The Environmental Protection Agency of the USA, providing the US EPA Air Sensor Toolbox (US-EPA[78]) on sensor use, sensor testing protocols, LCS use guidelines and best practices, etc., for laboratory and field environments.
- The Air Quality Sensor Performance Evaluation Center (AQ-SPEC[79]) program of the California South Coast area, provides installation guides and information on laboratory as well as on the field tests for outdoor environments.
- The AIRLAB Microsensors Challenge (AIRLAB[80]) organized by Airparif, France, testing approx. 55 devices using 20 metrics, including indoor and outdoor evaluation sites.
- ASTM D8405-21 (ASTM International[81]) , and standard method for evaluating $PM_{2.5}$ sensors in indoor air applications.
- AIREAMOS,[82] a Spanish initiative promoting the measurement of CO_2 levels as an indicator of COVID-19 infection risk, carried out one of the few systematic tests of CO_2 LCS indoors and in simulation chambers (EUPHORE[83]), elaborating a guide with the evaluation of different commercial sensors versus a reference.

An important initiative is the publication of the already briefly introduced above Standard CEN/TS 17660-1:2021[16] by the Technical Committee CEN/TC 264, Working Group 42 on AQ, entitled "Performance evaluation of air quality sensor systems – Part 1: Gaseous pollutants in ambient air" for sensor systems used to monitoring gas contaminants in fixed sites outdoors, i.e., not indoors. A second part of PM LCS is being prepared. The specifications are based on total uncertainty of the Data Quality Objectives (DQOs), similar to the quantitative absolute values usually provided for reference instrumentation.[17] It requires both laboratory and field trial validation and sets a certification scheme that, for the first time, defines 3 classes of sensors, based on the uncertainty of the measurement, as follows: *Class 1 sensor system:* sensors consistent with indicative methods; *Class 2 sensor system*: sensors consistent with objective estimations methods and *Class 3 sensor system*: sensors not formally associated with any mandatory target. It also defines procedures and requirements for the evaluation of the performance of LCS.

In addition to the above, there have been initiatives for developing Laboratory Test Methods for Low-Cost Indoor Air Quality Sensors (e.g., by the Office of Energy Efficiency & Renewable Energy,[84] which has already produced tangible results.

3.3. Performance of LCS by pollutant

A description of the performance of different types of sensors grouped by the species they determine is given in this work. The selection has been done based on the key pollutants pointed out by the WHO document on IAQ guidelines[3] for the protection of public health from risks associated with exposure to pollutants indoors and considering their relevance to the IAQ. Therefore, some are important from the toxicological and health point of view, for their use as indicators of occupancy control and comfort, for source identification, or because of their interest as reactive species. A common limitation of LCS is the lack of appropriate evaluations in conditions relevant to the indoor environment in order to define the performance and the effect of typically expected interferences. Whenever available, reference has been made here to studies conducted indoors and, were not possible due to the limited number of studies under such conditions, information from outdoor studies has been included. While manufacturers claim that LCS can be used in both environments, extrapolations from outdoor to indoor must be taken with caution. In summary, some LCS have a higher potential to provide at least good quality estimations of some indoor air pollutants, within certain limits of tolerance. That information could be deemed quite useful for the monitoring of certain indoor pollutants such as CO or CO_2. Regarding other LCS, e.g., NO_2 or O_3, advancements in the technology and in the analysis algorithms have improved their performance, although their use to obtain accurate indoor measures is still challenging.

3.3.1. Nitrogen dioxide (NO_2)

NO_2 LCS can be used in source identification, e.g., fire detection, and can be used as a parameter to calculate the so-called AQ Index (AQI) together with concentrations of CO_2, t-VOCs and PM. In the market, the technologies used for NO_2 sensors are Metal Oxide Semiconductor (MOS) and Electrochemical (EC), with typical limit of detection (LoD) of 2 ppbv and 2–5 ppbv, respectively. Both are cross sensitive to O_3, but in the case of EC sensors it, has been reduced by including an O_3 filter. MO sensors baseline resistance drifts with time and have strong sensitivity to RH, therefore, they are difficult to calibrate. Di Carlo and Falasconi[85] have attributed the MOS sensor drift to different structural and morphological variations of the sensor. Hence, EC sensors are preferred over MO. However, EC sensors also show high sensitivity to T and RH and recent papers[70] have presented algorithms that attempt to correct this. Lewis et al.[77] identified interferences with other compounds such as CO_2 which, at atmospheric concentrations, might be significant compared to the signal generated by NO_2. This interference might be due to high concentrations of CO_2 changing the gas diffusion rate of NO_2 (and of other gases). To face this dependency on atmospheric parameters, these authors proposed supervised learning algorithms to improve the accuracy of the data reported by sensors. Spinelle et al.,[86] reported interferences against O_3 in certain NO_2 sensors, which can be diminished by applying supervised learning techniques. Karagulian et al.[66] found in a review of comparison tests in the field that those algorithms reported R^2 of 0.91–0.94 versus multi-linear regression algorithms with R^2 of 0.81. However, R^2 varied from nearly 0 to 0.998 depending if it was calculated using data measured in laboratory or field conditions (Table 3) which points out that sensors must

Table 3. Performance parameters of NO_2 sensors in laboratory and field studies.

Device	Sensor (type)	Coefficient of Det. (R^2) – Lab	Coefficient of Det. (R^2) – Field	Interferences
SGX MiCS 2710	MOS	>0.998[a]	0.02–0.74[b-d]	O_3[b]
Alphasense NO_2-A1	EC	0.97b–0.99[e]	0.89–0.92[e]	SO_2[a], O_3[e]
CairPol CairClip NO_2 ANA	EC	0.99[f]	0.01–0.74[b,g]	NH_3[f], O_3[b]
Alphasense NO_2-B4	EC	0.96–0.99[b,h,i]	0.04–0.90[b,c,h,i]	O_3[b], CO_2[k]
Citytech NO_2_3E50	EC	> 0.99[f]	0.00–0.89[b,c]	NH_3[f], O_3[b]
Aeroqual AQYv1.0	EC	0.60–0.77[l]	0.60–0.88[l]	n.d.
Aeroqual S500	EC	n.d.	**0.55–1.00**[m]	n.d.
Alphasense NO2–B43F	EC	n.d.	**0.89–0.97**[n]	n.d.

Coefficient of determination (R^2). [a]Williams et al.[59]; [b]Spinelle et al.[86]; [c]Borrego et al.[67]; [d]Jiao et al.[138]; [e]Mead et al.[46]; [f]Spinelle et al.[86]; [g]Duval et al.[97]; [h]Castell et al.[39]; [i]Sun et al.[139]; [k]Lewis et al.[77]; [l]AQ-SPEC[79]; [m]Kang et al.[22], [n]Tryner et al.[87] Field indoor measurements in bold letters.

Table 4. Performance parameters of O_3 sensors in laboratory and field studies.

Device	Sensor (type)	Coefficient of Det. (R^2) – Lab	Coefficient of Det. (R^2) – Field	Interferents
2bTech POM	UV	0.995[a]	0.99[a]	n.d.
Aeroqual AQY	MOS	0.975[a]	0.96[f]	n.d.
Aeroqual S-500	MOS	0.991a	0.94–0.98[d]	n.d.
Alphasense O3B4	EC	>0.99[b]	0.02–0.70[f]	NO_2
Alphasense OX-B421	EC	0.99[c]	0.01–0.66[a]	NO_2, NO, CO_2
Unitec	MOS	0.897[a]	0.77[a]	n.d.
Aeroqual SM-50	MOS	n.d.	**0.39–0.99**[f]	n.d.
Alphasense OX-B431	EC	n.d.	**0.48–0.78**[g]	n.d.
SGX Sensortech MICS-2714	MOS	0.816[h]	**0.52–0.62**[h]	n.d.

Coefficient of determination (R^2). [a]Collier-Oxandale et al.[68]; [b]Spinelle et al.[86]; [c]Castell et al.[39], [d]Masey et al.[140], [f]AQ-SPEC,[79] [g]Kang et al.,[22] [h]Tryner et al.,[87] [i]Baldelli.[25] Field indoor measurements in bold letters.

be calibrated under conditions as close as possible to those at which the measurements will be done.[10,11] Nevertheless, these figures have to be taken with caution since they correspond to laboratory and urban environments. Only a few studies include NO_2 measurements indoors with LCS, which could be related to the measurement's complexity.[38] Among those, measurements in kitchens using NO_2 sensors (NO_2-B43F, Alphasense) reported R^2 of 0.79–0.94[87] and a comprehensive campaign in 40 homes using the Aeroqual S500 Sensor System showed R^2 values of 0.55–1.00.[22]

3.3.2. Ozone (O_3)

The most used techniques for O_3 detection are MOS and EC sensors. Both techniques perform very well under laboratory conditions where all degrees of freedom are controlled (Table 4). O_3 sensors have shown good repeatability in laboratory evaluations,[86] but in the real-world other parameters affect the data quality.

Field assessments have generally shown O_3 sensors performance as being encouraging. MOS O_3 sensors tend to exhibit slow response times, non-linear relationships with reference data, limits of detection of several ppbV, limited interferences with other gases and some sensitivity to temperature and humidity.[59,86] Typical R^2 values range between 0.12 and 0.77 for O_3 sensors reported in the AQ-SPEC evaluations.[67,79,88] MOS sensors show more long-term drift than EC sensors. These authors also stated that EC sensors show very fast response times with minimal rise and lag times which suggests potential use for continuous or near-continuous environmental monitoring, linear response and appropriate detection limits for ambient applications. These authors, among others, observed O_3 sensors interference from NO_2 and NO_2 sensors interference from O_3.

MOS sensors for O_3 are typically SnO_2, but better performance is achieved with WO_3. Careful control of ambient air temperature and RH can lead to good MOS results.[59] EC sensors remain the most common sensor, since, like NO_2 sensors, they are selective, responding only to other strong oxidants (including NO_2 and halides). However, although NO_2 sensors can remove O_3, it is much more difficult for O_3 sensors to remove NO_2 and often the O_3 sensor signal is actually the combination of NO_2 plus O_3, then, the NO_2 concentration must be measured and subtracted from the total concentration to derive the O_3 concentration. According to Williams et al.,[89] WO_3 MOS sensors are better at excluding NO_2.

Both O_3 and NO_2 are toxic and the limit value set by WHO for NO_2 is 10 $\mu g\ m^{-3}$ for annual average and 20 $\mu g\ m^{-3}$ for 24 h-exposure, and the limit values of O_3 for human health protection, which can be applied to indoor air, are 100 $\mu g\ m^{-3}$ for an average 8-hours exposure.[3] These low thresholds put very low error levels for these two gases: if we assume a +/−25% error of the LV then measuring these species is a challenge for LCSs.

3.3.3. Carbon Dioxide (CO_2)

Most CO_2 sensors are based on the NDIR technology, some of them include built-in temperature and RH sensors for output compensation. This technology is very accurate and selective as the detection is done in a narrow wavelength band, avoiding absorption from other molecules. However, sensors must be individually calibrated for temperature and humidity dependence.[9] Typically, CO_2 LCS report accuracies of either ±30 ppm or ±50 ppm (±3% or ±5% of the measured value), which is an acceptable error for most indoor applications (i.e., evaluation of the occupancy level and ventilation rates in a room). Recently, with the COVID-19 pandemic, the use of these sensors has experienced a huge growth as CO_2 levels have been proposed to be used as an indicator for estimating the ventilation rate and, indirectly linked, the airborne infection risk.[48,90]

NDIR CO_2 sensors are different in their design and the resultant performance. The first to note is size and form factor: a standard cylindrical shape is common, while others offer a variety of designs, mostly based on optical moldings on top of an electronic board. One important difference is the use of single or dual path optics: dual path is more expensive but provides a reference channel to correct for drift in the optical components (e.g., SCD30 from Sensirion, which includes T and RH compensation). The optical design is also important: the simplest design is a straight path, but this makes the sensor housing larger, so folded optics, integrating spheres and focused systems are available. The light source is the major power requirement. Tungsten lamps are low-cost but typically require 300 mA when operating. LEDs are now becoming available at 4 to 4.4 µm emission wavelengths, which dramatically reduces the power requirements. Likewise, the detector has traditionally been either a thermopile or pyroelectric, but photovoltaic and photoacoustic detectors are now on the market, each with different costs, power requirements and performances. Three important performance

Table 5. Performance parameters of NDIR CO_2 sensors.

Sensor System	NDIR SENSOR (Company)	Dual/Single channel	Coefficient of Det. (R^2) – Office	Accuracy
Aranet	SUNRISE (Sensair)	n.d.	0.99a	±30ppm +3% of reading
Sanity Air	SCD-30 (Sensirion)	Doble	0.99a	±30ppm +3% of reading
Stand alone sensor	IRC-A1 (Alphasense)	n.d.	0.91–0.93c	±50ppm
SignCO_2	COZ-IR (G.S.S.)	Single	0.97a	±30ppm +3% of reading
Dioxcare	CM1116 (Cubic)	Single	0.99a	±50ppm + 5% of reading

[a]AIREAMOS[82]; [c]Suriano et al.[141]

issues should also be considered. NDIR CO_2 sensors are linearly dependent on the ambient pressure, and its correction is a lesser one but desirable. If the CO_2 LCS does not include a pressure sensor, then ±3% weather driven barometric pressure variations will change the observed CO_2 concentration by an additional ±3%. A second problem is shock resistance. If a LCS uses a tungsten light bulb as the infrared source, then shock can shift the tungsten filament in the light bulb, significantly shifting the reading. A third issue is warm up and response time. To get the required accuracy, the optical system should be thermally stable. If the light source is thermal and requires more than 10mW power then heat will be generated and the entire optical sensor must be thermally stable to achieve the quoted accuracy, taking typically 15 to 30 minutes. Once stable, the optics respond in milliseconds, but the sensor response time depends on the rate of CO_2 diffusion into the optical cell, so LCS response time is diffusion-limited and depends on the mechanical design.

To warn the users, it is worth mentioning that there are other options in the market to measure CO_2 using a t-VOC sensor, which indirectly measures the so-called equivalent CO_2 (eCO_2). This option lacks transparency not only on what an eCO_2 is but also on how the conversion to CO_2 is done, which makes these sensors a non-recommended option.[91] These authors also point out that these kinds of issues are likely contributing factors to mistrust of LCS in general. On the contrary, the NDIR technology is recommended. Studies on the behavior of the sensor's output along with working time are critical for reliable validation of LCS. A standard method is being drafted, ASTM WK74360 (ASTM International, 2020[92]), for evaluating CO_2 sensors in indoor air applications. Table 5 shows a summary of the performances of some of some NDIR sensors when compared with reference instruments.

3.3.4. Carbon Monoxide (CO)

CO is mostly measured with EC sensors, with detection limits lower than 10 ppb. However, there are a couple of studies related with MOS. Piedrahita et al.[93] stated that the response of the sensor MICS-5525 decreased linearly when the temperature was increased from 19 °C to 40 °C during chamber testing. Furthermore, R^2 ranged from 0.38 and 0.60. Spinelle et al.[94] tested the MiCS 4514 under field conditions. R^2 between the sensor and the reference data ranged from 0.76 to 0.78 during the calibration period but after 4.5 months validation phase, $R^2<0.1$. Regarding EC sensors, Borrego et al.[67] tested four different sensor systems (AQMesh, CAM_11, ENEA/AirSensorBox, NanoEnvi) with the same sensor element (Alphasense CO-B4) in a field campaign and the R^2 ranged from 0.53 to 0.87 pointing out that not only the sensor element itself is important but also the implementation and the algorithm applied in the calculations. Also, evaluations of CO sensors showed good linearity with reference measurements and few interferences. For example, Gillooly et al.[95] reported R^2 of 0.99 and RMSE of 0.018 ppm, and Casey et al.[96] $R^2 \geq 0.96$ and RMSE $\leq$ 0.1 ppm in indoor studies. Tryner et al.[76] obtained R^2 from 0.63 to 0.94 using an Alphasense CO-B4 in studies carried out in kitchens. In chambers studies, an excellent agreement between EC sensors and reference data with R^2>0.99[39,46] was found. Sun et al.[97] reported that the sensor element Alphasense CO-B4 was unaffected by humidity and temperature changes during chamber studies. However, in a laboratory study, Lewis et al.[77] found that the sensor's response increased by 0.201 $mV \cdot ppb^{-1}$ per percentage point increase in humidity. If analyzed with machine learning or modeling corrections, low-cost CO detection techniques resulted in a high degree of correlation (R^2 = 0.95–0.99), with uncertainty in the 10–15% range as reported in an outdoor study.[57] However, CO sensors may be linear over a limited concentration range, therefore the CO sensor should be chosen according to the concentration range for which it will be used.[98]

3.3.5. Total volatile organic compounds (t-VOC):

LCS determine VOC as an operational metric defined as "total VOC" that covers a large group of individual substances. An air sample can contain 100–200 types of VOCs with diverse chemical structures. VOCs are present at different levels of concentration indoors. The continuous and direct-reading monitoring of the concentration of VOCs from these sensors is used to better understand AQ changes related to pollutant activities in the home and to identify sources of pollution such as off-gassing from building materials or furniture[99] or leaks from technological installations. t-VOC LCS cannot give a chemical speciation, but instead, they can provide well-resolved time and spatial information.[77]

PID-based sensors are mostly used for VOC monitoring, but also MOS-based sensors,[47] EC amperometric sensors and gas-sensitive field effect transistors (GasFETs) exist.[100] A critical downside of the available sensors is the varying (and often unknown) response factor to certain substance groups. The response factors may vary considerably for e.g., PID sensors[101] or certain MOS sensors.[102] This can lead to significant inaccuracies especially in complex mixtures of 20 or more substances, when even critical substances may be entirely missed or false-positive may interfere with the evaluation.

MOS and EC sensors show overall high sensitivity even at sub-ppb levels and specificity to individual VOCs or families of them. However, studies conducted both in laboratories and on-field to evaluate the performance of these devices revealed that the sensor response was affected by chemical interference and the sensor sensitivity changed with environmental parameters (temperature and humidity).[37] On the contrary, PIDs were less selective than MOS and EC sensors but they are more sensitivity and can measure from sub-ppb to ppm.[103] Although PID sensors are generally used for the real-time monitoring of t-VOCs concentration, the selection of specific photon energies of different UV lamps may also allow the ionization and detection of specific chemical classes e.g., aromatic hydrocarbons.[100] Therefore, in the context of the development of

MOS and EC sensors, PID sensor's availability as portable detectors of VOCs have progressively increasing in the last few years.

PIDs are valuable tools for the detection of VOCs but their performance in terms of sensitivity, levels of detection and ability to detect many different compounds strictly depend on PID design features. To detect VOCs, several ultraviolet light sources with different energies can be used: 10,6, 9.6, 10.0 and 11.7 eV. The most commonly used lamp emits energy at 10.6 eV. The 11.7 eV lamp can detect many compounds, but it has a relatively short lifetime (about 500 hours of continuous operation), thus requiring frequent lamp changes, driving up maintenance time and cost. Since the photoionization technique is not selective, the measurements are quoted as total VOCs (t-VOCs). Nevertheless, more selective data can be done using lamps at 9.8 or 10 eV, allowing some selective detection of aromatic VOCs, including for example benzene, toluene and xylenes.

In addition to the UV source, other design features of a PID could allow an effective and reliable detection of VOCs. Since temperature can affect the sensor performance, the compensation over typical operating temperature range (0 to 40° C) by internal software should be a must for reliable PID. As regards humidity, at higher non-condensing relative humidity conditions it can produce a small background signal on the order of several ppb. Moreover, water molecules could block UV light from the gas of interest and reduce the span reading by up to 50%. However, thanks to an optimized detector cell geometry these effects can be minimized (up to 10%). In addition, it is advisable to keep the sensor temperature a few degrees above the dewpoint temperature to avoid condensation. Finally, in order to face the non-linearity of output at higher concentration levels due to self-quenching (also known as the rollover effect), a synthetic span gas, such as the isobutylene, is used as standard calibration gas and to determine the response factors, which are a measure of the sensitivity of a PID to a particular gas compared to the standard used. Moreover, it is also possible to attach a pre-filter tube to allow detection and selective measurement of a single VOC component (e.g., benzene).[100]

In a MOS, the sensing element is a semi-conductor (a common metal oxide is SnO_2). Commercial screen-printed ceramic MOS sensors achieve detection limits down to sub-ppb levels due to the well-known grain boundary effect.[104] The voltage across the sensor layer is usually maintained at values lower than 1 V to prevent electromigration in the layer leading to sensor drift. However, the affinity of the pollutants and the sensitivity of the sensors depend on the working temperature of the sensor and thus these sensors have to be integrated with heating systems. MOS response is not linear and t-VOCs concentrations can be overestimated.[105,106] Also, MOS sensors are cheap, and combining various sensors with different reactive layers can be useful to allow getting a signature of the mixture of VOCs present in the room as a function of specific activities, e.g., cooking, cleaning, ventilation, etc.

t-VOC sensors respond to changes in the home activities and to emissions of VOCs, while their speciation is challenging. Some LCS are specifically produced to monitor single VOCs, such as formaldehyde, benzene or ethanol, but the collection of reliable data is still an open task. In particular, cross-sensitivity still remains a critical issue associated with these miniaturized devices. VOC sensors are good indicators for the purpose of indoor monitoring, awareness and identification of hazardous substance leaks.[107] Demanega et al.,[37] one of the few studies in the literature using t-VOC sensors, tested different types in a laboratory under the conditions set by the ASTM D72974-14 Standard Practice for Evaluating Residential Indoor Air Quality[108] and found R^2 from 0.74 to 0.92. These authors highlighted the potential to identify high pollutant exposures and to provide data at high spatiotemporal frequency. Values of R^2 from 0.68 to 0.75 were reported from a comparison of t-VOC sensors in homes with a reference instrument, while for the intercomparison among sensors R^2 varied from 0.79 to 0.94.[109]

3.3.6. PM_1, $PM_{2.5}$, PM_{10}

Most LCS for particulate matter measurement are based on optical methods (laser scattering) and determine $PM_{2.5}$, and hence large particles typically generated by mechanical processes (e.g., dust resuspension). PM LCS do not detect small particles, which are originated from several typical indoor activities such as combustion processes, cooking, cleaning (terpenes + O_3), with the majority of them of diameters $< 0.1\,\mu m$ (ultrafine particles, UFP).[110] Indeed, LCS cannot detect UFP,[32] of paramount interest in the indoor environment.[111,112] On the other hand, their small size and limitations in air flow to sample coarse particles, lead to PM_{10} underestimation in some cases and, in many LCS, PM_{10} is typically inferred from the $PM_{2.5}$ concentration by internal calculations.

Most direct-reading PM sensors categorize measurements into three-dimensional fractions: PM_1, $PM_{2.5}$ and PM_{10}. LCS for PM measurement calculate particle numbers and diameters, then convert them into particle mass as $\mu g/m^3$. A sensor measuring single particles is called optical particle counter (OPC) while a sensor measuring total scattered light intensity is a nephelometer or photometer.[113] The performance of PM sensors is limited by various physical and sensing "challenges":

- Unlike reference PM analyzers that control airflow rates, cheaper pumps used in LCS PMs struggle to control flow rate even if any variation in the flow rate will lead to bias errors because the number of particles passing the light beam will vary with flow rate.
- OPCs and Nephelometers measure the optical diameter of particles and infer the particle mass by assuming a density and refractive index of the particles being measured to calculate particle mass as PM,[42] which may lead to over/underestimation of the concentration.
- PM measurements by LCS can be impacted by the environmental conditions as well as gaseous cross-sensitivities for PM and gaseous sensors, respectively.[69] The effect of relative humidity (RH) must be considered: different studies have reported the influence of RH on different particle properties, such as: i) particle volume; ii) shape; iii) refractive index; and, consequently, iv) light scattering properties.[49,60] A number of correction algorithms and strategies have been proposed.[114,115,134,135] This problem is not linear: it is negligible below typically 65% RH but then grows rapidly as water vapor approaches 100% RH, leading to optical oversizing of the particles by the Nephelometer or OPC and hence overestimation of the particle mass.

- Inability to detect very small particles: LCS struggle to measure below 250 to 400 μm, depending on the unit, and cannot detect UFPs, which must be estimated. UPFs are the most numerous of the spectrum of particles, frequently exceeding 10,000 cm^3, but they do not have an equivalent contribution to the total mass since mass is dependent on diameter. Several studies highlighted LCS variable response depending on PM size and composition and lack of sensitivity to particles with diameter lower than 0.3 μm.[7,42,103] Nephelometers have a better chance of estimating UFPs (with the correct algorithm) because they measure the total scattering from an ensemble of particles, not just one particle. Not yet at the price of a LCS, initiatives to develop cost-effective, miniature UFP-sizers based on electrical-mobility-based techniques are being explored.[116]
- Nephelometers do not measure single particle diameters, so the calculation of PM_1, $PM_{2.5}$ and PM_{10} must include assumptions of the particle size distribution. Further, the definition of particle diameter is not universal. The optical particle diameter is different from the aerodynamic and electrical mobility diameters for non-spherical particles. Tapered element oscillating microbalance, beta attenuators and optical PM sensors all measure different particle diameter/mass and do not align exactly with the reference method, which is gravimetric (EN 12341:2015).

Despite the disadvantages related to the instruments' performances, these devices are continuously being improved, and their use is becoming increasingly widespread both in outdoor and indoor monitoring campaigns. PM LCS may monitor from low PM concentration (clean rooms) to pollution levels up to 2,000 μg/m^3. Previous studies indicate that the optical PM LCS is more suitable to be used in environments where the presence of larger particles (and therefore particle mass) is more significant. It has also been suggested that this is more the case for particles in the accumulation and coarse mode, where aerosols have had sufficient time to coagulate and condensate and form accumulation mode particles.[113,117]

LCS have been successfully used to track indoor variations in PM concentrations associated with home activities and have been compared to research-grade instruments. The largest PM concentrations were observed when measuring during several activities (cooking and spraying aerosol products) in different rooms (kitchen and bedroom).[118] The authors pointed out that estimating the mass concentration in the presence of the wide variety of PM sources existing indoors is challenging. However, PM LCS can help to manage personal exposure. There have been a number of comparative studies of LCS PM sensors.[60,73] Tables 6, S3 and S4 summarize performance parameters of LCS to determine PM_1, $PM_{2.5}$ and PM_{10}, respectively, in indoor and laboratory studies.

3.3.7. Radon

Radon is the largest contributor to the radiation exposure of populations in indoor environments since, at normal atmospheric conditions, radon appears on the earth's surface in the gas form, and easily accumulates indoors. Radon assessment can be obtained using active detectors.[121] These have a power supply, have the capacity for

Table 6. Performance parameters in $PM_{2.5}$ sensors. Adapted from Sá et al.[38]

References	Sampling area	Device SENSOR	Performance indexes
Palmisani et al.[103]	Oncology hospitals	Speck	$R^2 = 0.34–0.66$
Tryner et al.[87]	Kitchen of an occupied home	Plantower PMS5003	$R^2 = 0.92–0.94$
Baldelli[25]	Residential building	Shinyei Kaisha PPD42-60	$\rho = 0.765-0.894$
Shen et al.[28]	Spaces in appartment (kitchen, living room, study room, bedrooms and entrance) and outside	Plantower PMS3003	$R^2 = 0.85-0.94$
Coulby et al.[91]	Office	Plantower PMSA003i	$R^2 = 0.052–0.058$
Hegde et al.[118]	Two homes	Modified Dylos DC100Pro, Plantower PMS3003	$R^2 = 0.54–0.99$ $R^2 = 0.48–0.98$
Kaliszewski et al.[76]	A high occupancy living room in a flat	Alphasense, OPC-N3	$R^2 = 0.55–0.99$
Zamora et al.[119]	Home (occupied and non-smoking)	AirVisual Pro, Speck, AirThinx	$R^2 = 0.89–0.90$ $R^2 = 0.27–0.50$ $R^2 = 0.92–0.93$
Manibusan and Mainelis[120]	Three homes	Air Quality Egg 2 AQE2, BlueAir Aware, Foobot, Speck	$R^2 = 0.023–0.81$ $R^2 = 0.24–0.94$ $R^2 = 0.31–0.98$ $R^2 = 0.06–0.98$

Coefficient of determination (R^2). Spearman correlation (ρ). Only indoor field studies from the year 2020 onwards have been included.

storing data, can include wireless communications and can operate for short-term and long-term exposure assessment.

This type of detector is designed to detect alpha radiation, and typically, LCS implementations use ionization chambers[122–124] or alpha spectrometry.[125–127] Ionization chambers establish an electrical field between two or more electrodes, and the air is allowed to diffuse into the chamber, being the ionization caused by the decay of radon which emits alpha particles. The ionized particles are then accelerated and collide into the electrodes, generating electrical pulses that are then detected and counted for specific time intervals.[128] Alpha spectrometry can also be used to analyze the air that passes through a passive diffusion chamber and perform inexpensive radon detection based on PIN photodiodes.[129,130] Currently, there are several commercially available LCS for radon assessment. A recent pioneer study[131] has evidenced that LCS can be used in short-term radon monitoring, being promising tool for actively reducing exposure to indoor radon concentrations.

3.3.8. Sulfur dioxide (SO_2)

SO_2 can be monitored with EC and MOS sensors. It is not normally measured by LCS, for which they are often ineffective due to their low detection limit, very at the edge of the typical concentrations of SO_2 found indoors, which vary from 0 to 8 ppb.[132] A study outdoors found low correlations with reference at levels below 5 ppb.[67]

3.3.9. Hydrogen sulfide (H_2S)

EC hydrogen sulfide sensors show sensitivity down to a few ppb due to their high electroactivity. These EC sensors will also measure thiols/mercaptans but with lower sensitivity and hence higher LoD, which aligns with the human detection limits.

4 Conclusions

The increased awareness of AQ due to its health effects and the rapid technological advances in the field, have motivated an upsurge of LCS, which can bring a paradigm shift in IAQ. LCS can give data in near-real time, at a relatively low cost and with easy deployment, allowing a high temporal and spatial data frequency. To date, LCS generally do not meet regulatory equivalent monitoring requirements and are not a substitute of reference-grade measurement techniques indoors. Their sensitivity, time response and accuracy make their use to characterize the subtle changes in the indoor environment challenging. However, they offer an excellent opportunity for the IAQ community in uses like the identification of emission sources in different parts of a household, mitigation of IAQ issues, real-time warning systems, personal exposure, and in controlling buildings from the energy efficiency point of view.

Still, sensors systems with real-time readings can open a new era in high resolution of spatiotemporal IAQ sensing, empowering individuals to control their own environments and with several expected benefits including i) real-time characterization of indoor concentrations, ii) increased spatial resolution, iii) reduced uncertainty, iv) identification of emitting sources from indoor activities, v) air supply data, vi) improved IAQ management and vii) health benefits. Advancements in technology promise to revolutionize IAQ monitoring and allow for much-improved exposure assessment opportunities. Nevertheless, many challenges need to be addressed, including data reliability and accuracy. Improving portability and reducing the cost of sensors for measuring gaseous pollutants and PM without compromising selectivity and sensitivity are currently the main challenges in IAQ. The development of sensors for ultrafine/nanoparticle measurement is another future requirement.

There are still many open questions, mainly related to the lack of openness and standardization of calibration and analysis procedures, evaluation of performance, handling and quantification of interferences. Significant efforts and initiatives have been, and are being carried out in this line, which aim at standardizing the use and testing procedures of LCS, which will allow better use of LCS and a better evaluation of their performance. This question has been already addressed for sensor systems used outdoors, with a certification scheme based on the uncertainty of the measurement which is a step forward and opens a new era in the use of LCS in general. An adapted regulation for the measurements with LCS indoors is necessary too. To date, this is precisely a field subject of important efforts through different initiatives to standardize procedures. In parallel, calibration and analysis algorithms are continuously being reported with a lack of uniformity in the metrics used in the reported validation results (R^2, percentage errors, MAE, etc.) and in the parameters to study (linearity, precision, etc.), putting an important limitation on the comparison of device performance, and consequently difficulties in understanding this field's developments. Moreover, these results are mostly reported for outdoor environments. Nevertheless, as discussed in this work, there are significant differences between the type and number of contaminants found indoors and outdoors, along with the environmental conditions, relative humidity and temperature, the latter less variable indoors, and the purpose for which LCS are used, aspects that must be considered.

While physical and data solutions are being improved in LCS, further studies are needed in indoor sites, with an effort to compare LCS against reference instruments to characterize performance, interferences, sensor-to-sensor variability, temporal drift, etc. An assessment and discussion on the suitability and extrapolation of procedures applied and evaluation of performance obtained outdoors to indoors is also desirable. A field to explore in the use of LCS is the remote calibration and the data processing of the entire network of LCS versus the individual analysis, which initial studies have found to be a promising procedure. Besides, their use in wearable devices demands easy to deploy sensors and sensor networks and, by extension, reliable and lower-power wireless communication. Other technological future developments should be aimed to improve the selectivity and long-term stability of the sensors, which will clearly result in better reliability. Also, the specific problem of the indoor environment demands a higher selectivity to discern among VOCs at ppb concentrations and measurement of ultrafine particles.

Even though LCS are not a replacement of more advanced techniques, and their use has to be taken with caution, their low cost and characteristics make them useful as a complement to those for specific purposes, generally as a qualitative source of information. Low-cost sensor technology is continuously evolving. The interest by the scientific community and in citizen science in LCS predicts that this evolution will continue toward more accurate and selective sensors, likely improving their performance and reliability, and therefore becoming a common instrument in IAQ assessment and management.

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ORCID

Milagros Ródenas García http://orcid.org/0000-0002-6136-3660
Andrea Spinazzé http://orcid.org/0000-0003-0371-3164
Pedro T.B.S. Branco http://orcid.org/0000-0002-4163-0936
Francesca Borghi http://orcid.org/0000-0003-3452-2803
Guillermo Villena http://orcid.org/0000-0002-1867-1879
Andrea Cattaneo http://orcid.org/0000-0002-2962-7259
Alessia Di Gilio http://orcid.org/0000-0001-9951-4498
Victor G. Mihucz http://orcid.org/0000-0002-5320-669X
Elena Gómez Álvarez http://orcid.org/0000-0001-5235-9806
Sérgio Ivan Lopes http://orcid.org/0000-0001-6944-7757
Benjamin Bergmans http://orcid.org/0000-0002-4324-449X
Cezary Orłowski http://orcid.org/0000-0001-7716-5522
Kostas Karatzas http://orcid.org/0000-0002-1033-5985
Gonçalo Marques http://orcid.org/0000-0001-5834-6571
John Saffell http://orcid.org/0000-0002-9844-2063
Sofia I.V. Sousa http://orcid.org/0000-0002-4139-673X

References

1. Zomorodian, Z.-S.; Tahsildoost, M.; Hafezi, M. Thermal Comfort in Educational Buildings: A Review Article. *Renew. Sustain. Energy Rev*. 2016, *59*, 895–906. doi:10.1016/j.rser.2016.01.033
2. Forouzanfar, M. H.; Alexander, L.; Anderson, H. R.; Bachman, V. F.; Biryukov, S.; Brauer, M.; Burnett, R.; Casey, D.; Coates, M. M.; Cohen, A.; et al. Global, Regional, and National Comparative Risk Assessment of 79 Behavioural, Environmental and Occupational, and Metabolic Risks or Clusters of Risks in 188 Countries, 1990 – 2013: A Systematic Analysis for the Global Burden of Disease Study. *Lancet*. 2015, *386*, 2287–2323. doi:10.1016/S0140-6736(15)00128-2
3. WHO. 2021. *WHO Global Air Quality Guidelines: Particulate Matter ($PM_{2.5}$ and PM_{10}), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*. WHO: Geneva, Switzerland. https://apps.who.int/iris/handle/10665/345329. (eletronic version).
4. Edwards, R.-D.; Jurvelin, J.; Koistinen, K.; Saarela, K.; Jantunen, M.; Askyl, J. VOC Source Identification from Personal and Residential Indoor, Outdoor and Workplace Microenvironment Samples in EXPOLIS-Helsinki, Finland. *Atmos. Environ*. 2001, *35*, 4829–4841. doi:10.1016/S1352-2310(01)00271-0
5. González-Martín, J.; Kraakman, N.-J.-R.; Pérez, C.; Lebrero, R.; Muñoz, R. A State-of-the-Art Review on Indoor Air Pollution and Strategies for Indoor Air Pollution Control. *Chemosphere*. 2021, *262*, 128376. DOI: 10.1016/J.CHEMOSPHERE.2020.128376.
6. Villanueva, F.; Rodenas, M.; Ruus, A.; Saffell, J.; Gabriel, M.-F. Sampling and Analysis Techniques for Inorganic Air Pollutants in Indoor Air. *Appl. Spectrosc. Rev*. 2021, 1–49. doi:10.1080/05704928.2021.2020807
7. 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 Quality Monitoring Devices: Recent Advancements. *Sci Total Environ*. 2020, *727*, 138385. doi:10.1016/j.scitotenv.2020.138385

8. Hulanicki, A.; Glab, S.; Ingman, F. Chemical Sensors Definitions and Classification. *Pure Appl. Chem*. 1991, *63*, 1247–1250. doi:10.1351/pac199163091247
9. Lewis, A., Von Schneidemesser, E.; and Peltier, R. *Low-Cost Sensors for the Measurement of Atmospheric Composition: Overview of Topic and Future Applications*; WMO: Geneva, Switzerland, 2018.
10. Peltier, R.-E.; Castell, N.; Clements, A.L.; Dye, T.; Hüglin, C.; Kroll, J.-H.; Lung, S.-C.-C.; Ning, Z.; Parsons, M.; Penza, M.; Reisen, F.; Schneidemesser, E. *An Update on Low-Cost Sensors for the Measurement of Atmospheric Composition, December 2020*; WMO: Geneva, Switzerland, 2021.
11. Saini, J.; Dutta, M.; Marques, G. Sensors for Indoor Air Quality Monitoring and Assessment through Internet of Things: A Systematic Review. *Environ. Monit. Assess*. 2021, *193*, 1–32. doi:10.1007/s10661-020-08781-6
12. NRC – National Research Council. *Expanding the Vision of Sensor Materials*; The National Academies Press: Washington, D.C., 1995. pp. 73–88. doi:10.17226/4782
13. Snyder, E. G.; Watkins, T. H.; Solomon, P. A.; Thoma, E. D.; Williams, R. W.; Hagler, G. S. W.; Shelow, D.; Hindin, D. A.; Kilaru, V. J.; Preuss, P. W.; et al. The Changing Paradigm of Air Pollution Monitoring. *Environ. Sci. Technol*. 2013, *47*, 11369–11377. doi: 10.1021/es4022602 SNYDER, 2013
14. Howard, J.; Murashov, V.; Cauda, E.; Snawder, J. Advanced Sensor Technologies and the Future of Work. *Am. J. Ind. Med*. 2022, *65*, 3–11. doi:10.1002/ajim.23300
15. Standard CEN/TS 17660-1:2021: Air Quality—Performance Evaluation of Air Quality Sensor Systems—Part 1: Gaseous Pollutants in Ambient Air. https://standards.iteh.ai/catalog/standards/cen/5bdb236e-95a3-4b5b-ba7f-62ab08cd21f8/cen-ts-17660-1-2021 (accessed May 19, 2022).
16. Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on Ambient Air Quality and Cleaner Air for Europe Europe (CAFE). *Offi J Eur Union*. 2008, *1*, 1–44.
17. Kumar, P.; Skouloudis, A. N.; Bell, M.; Viana, M.; Carotta, M. C.; Biskos, G.; Morawska, L. Real-Time Sensors for Indoor Air Monitoring and Challenges Ahead in Deploying Them to Urban Buildings. *Sci. Total Environ*. 2016b, *560-561*, 150–159. doi:10.1016/j.scitotenv.2016.04.032
18. Kumar, P.; Morawska, L. Energy-Pollution Nexus for Urban Buildings. *Environ Sci Technol*. 2013, *47*, 7591–7592. doi:10.1021/es402549p
19. Morawska, L.; Thai, P. K.; Liu, X.; Asumadu-Sakyi, A.; Ayoko, G.; Bartonova, A.; Bedini, A.; Chai, F.; Christensen, B.; Dunbabin, M.; et al. Applications of Low-Cost Sensing Technologies for Air Quality Monitoring and Exposure Assessment: How Far Have They Gone? *Environ Int*. 2018, *116*, 286–299. doi:10.1016/j.envint.2018.04.018
20. Fanti, G.; Borghi, F.; Spinazzè, A.; Rovelli, S.; Campagnolo, D.; Keller, M.; Cattaneo, A.; Cauda, E.; Cavallo, D.-M. Features and Practicability of the Next-Generation Sensors and Monitors for Exposure Assessment to Airborne Pollutants: A Systematic Review. *Sensors*. 2021, 2021, *21*, 4513. doi:10.3390/s2113
21. Jovašević-Stojanović, M.; Bartonova, A.; Topalović, D.; Lazović, I.; Pokrić, B.; Ristovski, Z. On the Use of Small and Cheaper Sensors and Devices for Indicative Citizen-Based Monitoring of Respirable Particulate Matter. *Environ Pollut*. 2015, *206*, 696–704. doi:10.1016/j.envpol.2015.08.035
22. Kang, Y.; Aye, L.; Ngo, T. D.; Zhou, J. Performance Evaluation of Low-Cost Air Quality Sensors: A Review. *Sci Total Environ*. 2022, *818*, 151769. doi:10.1016/j.scitotenv.2021.151769
23. Han, Y.; Li, X.; Zhu, T.; Lv, D.; Chen, Y.; Hou, L.; Zhang, Y.; Ren, M. Characteristics and Relationships between Indoor and Outdoor PM2.5 in Beijing: A Residential Apartment Case Study. *Aerosol Air Qual. Res*. 2016, *16*, 2386–2395. doi:10.4209/aaqr.2015.12.0682
24. Carslaw, N. Chemical Reactions in the Indoor Atmosphere. In *Indoor Air Pollution*, Harrison, R. M., Hester, R. E., Eds.; Royal Society of Chemistry: Cambridge, 2019; 105–126 doi:10.1039/9781788016179-00105

25. Baldelli, A. Evaluation of a Low-Cost Multi-Channel Monitor for Indoor Air Quality through a Novel, Low-Cost, and Reproducible Platform. *Measure Sens*. 2021, *17*, 100059. doi:10.1016/j.measen.2021.100059
26. Kumar, P.; Martani, C.; Morawska, L.; Norford, L.; Choudhary, R.; Bell, M.; Leach, M. Indoor Air Quality and Energy Management through Real-Time Sensing in Commercial Buildings. *Energy Build*. 2016a, *111*, 145–153. doi:10.1016/j.enbuild.2015.11.037
27. Poulhet, G.; Dusanter, S.; Crunaire, S.; Locoge, N.; Kaluzny, P.; Coddeville, P. Recent Developments of Passive Samplers for Measuring Material Emission Rates: Toward Simple Tools to Help Improving Indoor Air Quality. *Build Environ*. 2015, *93*, 106–114. doi:10.1016/j.buildenv.2015.02.034
28. Shen, H.; Hou, W.; Zhu, Y.; Zheng, S.; Ainiwaer, S.; Shen, G.; Chen, Y.; Cheng, H.; Hu, J.; Wan, Y.; Tao, S. Temporal and Spatial Variation of PM2.5 in Indoor Air Monitored by Low-Cost Sensors. *Sci Total Environ*. 2021, *770*, 145304. doi:10.1016/j.scitotenv.2021.145304
29. Ciuzas, D.; Prasauskas, T.; Krugly, E.; Sidaraviciute, R.; Jurelionis, A.; Seduikyte, L.; Kauneliene, V.; Wierzbicka, A.; Martuzevicius, D. Characterization of Indoor Aerosol Temporal Variations for the Real-Time Management of Indoor Air Quality. *Atmos. Environ*. 2015, *118*, 107–117. doi:10.1016/j.atmosenv.2015.07.044
30. Borghi, F.; Spinazzè, A.; Rovelli, S.; Campagnolo, D.; Del Buono, L.; Cattaneo, A.; Cavallo, D.-M, Luca Del Buono. Miniaturized Monitors for Assessment of Exposure to Air Pollutants: A Review. *IJERPH*. 2017, *14*, 909. doi:10.3390/ijerph14080909
31. Cauda, E.; Snawder, J.; Spinazzè, A.; Cattaneo, A.; Howard, J.-C.-D. The Challenge for Industrial Hygiene 4.0. A NIOSH Perspective on Direct-Reading Methodologies and Real-Time Monitoring in Occupational Environments. *The Synergist*, 2022. https://synergist.aiha.org/202202-new-stage-ih?utm_source=aiha&utm_medium=email&utm_content=february-digital-edition&utm_campaign=sdigital22 (accessed April 20, 2022).
32. Kumar, A.; Gurjar, B.-R. Low-Cost Sensors for Air Quality Monitoring in Developing Countries – a Critical View. *AJW*. 2019, *16*, 65–70. doi:10.3233/AJW190021
33. Cattaneo, A.; Spinazzè, A.; Cavallo, D. M. Indoor Air Quality in Offices. In *Handbook of Indoor Air Quality*, Zhang, Y., Hopke, P. K., Mandin, C., Eds. Springer: Singapore, 2022, doi:10.1007/978-981-10-5155-5_77-1
34. Kim, M.; Liu, H.; Kim, J.-T.; Yoo, C. Evaluation of Passenger Health Risk Assessment of Sustainable Indoor Air Quality Monitoring in Metro Systems Based on a non-Gaussian Dynamic Sensor Validation Method. *J Hazard Mater*. 2014, *278*, 124–133. doi:10.1016/j.jhazmat.2014.05.098
35. Williams, R.; Nash, D.; Hagler, G.; Benedict, K. Peer Review and Supporting Literature Review of Air Sensor Technology Performance Targets. *US Environmental Protection Agency. Office of Research and Development. National Exposure Research Laboratory*, 2018. EPA/600/R-18/324. www.epa.gov/research.
36. Kolokotsa, D.; Santamouris, M. Review of the Indoor Environmental Quality and Energy Consumption Studies for Low Income Households in. *Europe. Sci. Total Environ*. 2015, *536*, 316–330. doi:10.1016/j.scitotenv.2015.07.073
37. Demanega, I.; Mujan, I.; Singer, B.-C.; Anđelković, A.-S.; Babich, F.; Licina, D. Performance Assessment of Low-Cost Environmental Monitors and Single Sensors under Variable Indoor Air Quality and Thermal Conditions. *Build Environ*. 2021, *187*, 107415. doi:10.1016/j.buildenv.2020.107415
38. Sá, J. P.; Alvim-Ferraz, M. C. M.; Martins, F. G.; Sousa, S. I. Application of the Low-Cost Sensing Technology for Indoor Air Quality Monitoring: A Review. *Environ. Technol. Innov*. 2022, *28*, 102551. doi:10.1016/j.eti.2022.102551
39. Castell, N.; Dauge, F.-R.; Schneider, P.; Vogt, M.; Lerner, U.; Fishbain, B.; Broday, D.; Bartonova, A. Can Commercial Low-Cost Sensor Platforms Contribute to Air Quality Monitoring and Exposure Estimates? *Environ Int*. 2017, *99*, 293–302. volumeISSN 0160-4120,doi:10.1016/j.envint.2016.12.007

40. Tancev, G. Relevance of Drift Components and Unit-to-Unit Variability in the Predictive Maintenance of Low-Cost Electrochemical Sensor Systems in Air Quality Monitoring. *Sensors*. 2021, *21*, 3298. doi:10.3390/s21093298
41. Kim, H.; Müller, M.; Henne, S.; Hüglin, C. Long-Term Behavior and Stability of Calibration Models for NO and NO2 Low-Cost Sensors. *Atmos. Meas. Tech*. 2022, *15*, 2979–2992. doi:10.5194/amt-15-2979-2022
42. Bulot, F. M. J.; Russell, H. S.; Rezaei, M.; Johnson, M. S.; Ossont, S. J. J.; Morris, A. K. R.; Basford, P. J.; Easton, N. H. C.; Foster, G. L.; Loxham, M.; Cox, S. J. Laboratory Comparison of Low-Cost Particulate Matter Sensors to Measure Transient Events of Pollution. *Sensors*. 2020, *20*, 2219. doi:10.3390/s20082219
43. Zimmerman, N. Tutorial: Guidelines for Implementing Low-Cost Sensor Networks for Aerosol Monitoring. *J. Aerosol Sci*. 2022, *159*, 105872. doi:10.1016/j.jaerosci.2021.105872
44. Zhang, H.; Srinivasan, R. A Systematic Review of Air Quality Sensors, Guidelines, and Measurement Studies for Indoor Air Quality Management. *Sustainability*. 2020, *12*, 9045. doi:10.3390/su12219045
45. Barsan, N.; Weimar, U. Fundamentals of Metal Oxide Gas Sensors. Book chapter at *Metal Oxide-based Gas Sensors VII*, 2012. doi:10.5162/IMCS2012/7.3.3
46. Mead, M.-I.; Popoola, O.-A.-M.; Stewart, G.-B.; Landshoff, P.; Calleja, M.; Hayes, M.; Baldovi, J.-J.; McLeod, M. W.; Hodgson, T.-F.; Dicks, J.; et al. The Use of Electrochemical Sensors for Monitoring Urban Air Quality in Low-Cost, High-Density Networks. *Atmos. Environ*. 2013, *70*, 186–203. doi:10.1016/j.atmosenv.2012.11.060
47. Agbroko, S. O.; Covington, J. Low-Cost, Portable PID Sensor for the Detection of Volatile Organic Compounds. *Sensor Actuat: B Chem*. 2018, *275*, 10–15. doi:10.1016/j.snb.2018.07.173
48. Di Gilio, A.; Palmisani, J.; Pulimeno, M.; Cerino, F.; Cacace, M.; Miani, A.; de Gennaro, G. CO2 Concentration Monitoring Inside Educational Buildings as a Strategic Tool to Reduce the Risk of Sars-CoV-2 Airborne Transmission. *Environ Res*. 2021, *202*, 111560. doi:10.1016/j.envres.2021.111560
49. Liu, L.-J.; Slaughter, J.-C.; Larson, T.-V. Comparison of Light Scattering Devices and Impactors for Particulate Measurements in Indoor, Outdoor, and Personal Environments. *Environ. Sci. Technol*. 2002, *36*, 2977–2986. doi:10.1021/es0112644
50. Marques, G.; Pitarma, R.-M.; Garcia, N.; Pombo, N. Internet of Things Architectures, Technologies, Applications, Challenges, and Future Directions for Enhanced Living Environments and Healthcare Systems: A Review. *Electronics*. 2019, *8*, 1081. doi:10.3390/electronics8101081
51. Lopes, S.-I.; Pereira, F.; Vieira, J.-M.-N.; Carvalho, N.-B.; Curado, A. Design of Compact LoRa Devices for Smart Building Applications. *GreeNets*. 2018, *269*, 1867–8211. doi:10.1007/978-3-030-12950-7_12
52. Li, J.; Li, H.; Ma, Y.; Wang, Y.; Abokifa, A.-A.; Lu, C.; Biswas, P. Spatiotemporal Distribution of Indoor Particulate Matter Concentration with a Low-Cost Sensor Network. *Build Environ*. 2018, *127*, 138–147. doi:10.1016/j.buildenv.2017.11.001
53. Jo, D.; Kim, G.-J. ARIoT: Scalable Augmented Reality Framework for Interacting with Internet of Things Appliances Everywhere. *IEEE Trans. Consumer Electron*. 2016, *62*, 334–340. doi:10.1109/TCE.2016.7613201
54. Cofta, P.; Orłowski, C.; Lebiedź, J. Trust-Based Model for the Assessment of the Uncertainty of Measurements in Hybrid IoT Networks. *Sensors*. 2020, *20*, 6956. doi:10.3390/s20236956
55. Bagkis, E.; Kassandros, T.; Karteris, M.; Karteris, A.; Karatzas, K. Analyzing and Improving the Performance of a Particulate Matter Low Cost Air Quality Monitoring Device. *Atmosphere*. 2021, *12*, 251. doi:10.3390/atmos12020251
56. Bigi, A.; Mueller, M.; Grange, S.-K.; Ghermandi, G.; Hueglin, C. Performance of NO, NO_2 Low Cost Sensors and Three Calibration Approaches within a Real World Application. *Atmos. Meas. Tech*. 2018, *11*, 3717–3735. doi:10.5194/amt-11-3717-2018

57. 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 Monitoring. *Atmos. Meas. Tech.* 2018, *11*, 291–313. doi:10.5194/amt-11-291-2018
58. Bagkis, E.; Kassandros, T.; Karatzas, K. Learning Calibration Functions on the Fly: Hybrid Batch Online Stacking Ensembles for the Calibration of Low-Cost Air Quality Sensor Networks in the Presence of Concept Drift. *Atmosphere*. 2022, *13*, 416. doi:10.3390/atmos13030416
59. Williams, R.; Kilaru, V.; Snyder, E.; Kaufman, A.; Dye, T.; Rutter, A.; Russell, A.; Hafner, H. *Air Sensor Guidebook*. EPA/600/R-14/159 (NTIS PB2015-100610); U.S. Environmental Protection Agency: Washington, DC, USA, 2014.
60. 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. doi:10.3390/s18093089
61. 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, *154*, 274–284. doi:10.1016/j.atmosenv.2017.01.054
62. Zikova, N.; Hopke, P.-H.; Ferro, A.-R. Evaluation of New Low-Cost Particle Monitors for PM2.5 Concentrations Measurements. *J. Aerosol Sci*. 2017, *105*, 24–34. doi:10.1016/j.jaerosci.2016.11.010
63. Watson, J.-C.; Chow, J.-C.; Moosmuller, H. 1998. Guidance for Using Continuous Monitoring in PM2.5 Monitoring Networks. EPA-454/R-98-012; Environmental Protection Agency, 1998.
64. Altman, D.-G.; Bland, J.-M. Measurement in Medicine: The Analysis of Method Comparison Studies. *Statistician*. 1983, *32*, 307–317. doi:10.2307/2987937
65. Bland, J.-M.; Altman, D.-G. Statistical Methods for Assessing Agreement between Two Methods of Clinical Measurement. *Lancet*. 1986, *327*, 307–310. doi:10.1016/S0140-6736(86)90837-8
66. Karagulian, F.; Barbiere, M.; Kotsev, A.; Spinelle, L.; Gerboles, M.; Lagler, F.; Redon, N.; Crunaire, S.; Borowiak, A. Review of the Performance of Low-Cost Sensors for Air Quality Monitoring. *Atmosphere-Basel*. 2019, *10*, 506. doi:10.3390/atmos10090506
67. Borrego, C.; Costa, A. M.; Ginja, J.; Amorim, M.; Coutinho, M.; Karatzas, K.; Sioumis, T.; Katsifarakis, N.; Konstantinidis, K.; De Vito, S.; et al. Assessment of Air Quality Microsensors versus Reference Methods: The Eunetair Joint Exercise. *Atmos. Environ*. 2016, *147*, 246–263. doi:10.1016/j.atmosenv.2016.09.050
68. Collier-Oxandale, A.; Feenstra, B.; Papapostolou, V.; Zhang, H.; Kuang, M.; Der Boghossian, B.; Polidori, A. Field and Laboratory Performance Evaluations of 28 Gas-Phase Air Quality Sensors by the AQ-SPEC Program. *Atmos. Environ*. 2020, *220*, 117092. doi:10.1016/j.atmosenv.2019.117092
69. 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. doi:10.1016/j.scitotenv.2017.06.266
70. Cross, E. S.; Williams, L. R.; Lewis, D. K.; Magoon, G. R.; Onasch, T. B.; Kaminsky, M. L.; Worsnop, D. R.; Jayne, J. T. Use of Electrochemical Sensors for Measurement of Air Pollution: correcting Interference Response and Validating Measurements. *Atmos. Meas. Tech*. 2017, *10*, 3575–3588. doi:10.5194/amt-10-3575-2017
71. Cordero, J.-M.; Borge, R.; Narros, A. Using Statistical Methods to Carry out in Field Calibrations of Low Cost Air Quality Sensors. *Sens. Actuators B Chem*. 2018, *267*, 245–254. doi:10.1016/j.snb.2018.04.021
72. Wang, Y.; Li, J.; Jing, H.; Zhang, Q.; Jiang, J.; Biswas, P. Laboratory Evaluation and Calibration of Three Low-Cost Particle Sensors for Particulate Matter Measurement. *Aerosol Sci. Technol*. 2015, *49*, 1063–1077. doi:10.1080/02786826.2015.1100710

73. Manikonda, A.; Zíková, N.; Hopke, P.-K.; Ferro, A.-R. Laboratory Assessment of Low-Cost PM Monitors. *J. Aerosol Sci.* 2016, *102*, 29–40. doi:10.1016/j.jaerosci.2016.08.010
74. Holstius, D.-M.; Pillarisetti, A.; Smith, K.-R.; Seto, E.-J.-A.-M.-T. Field Calibrations of a Low-Cost Aerosol Sensor at a Regulatory Monitoring Site in California. *Atmos. Meas. Tech.* 2014, *7*, 1121–1131. doi:10.5194/amt-7-1121-2014
75. Malings, C.; Tanzer, R.; Hauryliuk, A.; Kumar, S. P. N.; Zimmerman, N.; Kara, L. B.; Presto, A. A, R. Subramanian Development of a General Calibration Model and Long-Term Performance Evaluation of Low-Cost Sensors for Air Pollutant Gas Monitoring. *Atmos. Meas. Tech.* 2019, *12*, 903–920. doi:10.5194/amt-12-903-2019
76. Kaliszewski, M.; Włodarski, M.; Młyńczak, J.; Kopczyński, K. Comparison of Low-Cost Particulate Matter Sensors for Indoor Air Monitoring during COVID-19 Lockdown. *Sensors*. 2020, *20*, 7290. doi:10.3390/s20247290
77. Lewis, A. C.; Lee, J. D.; Edwards, P. M.; Shaw, M. D.; Evans, M. J.; Moller, S. J.; Smith, K. R.; Buckley, J. W.; Ellis, M.; Gillot, S. R.; White, A. Evaluating the Performance of Low Cost Chemical Sensors for Air Pollution Research. *Faraday Discuss.* 2016, *189*, 85–103. doi:10.1039/c5fd00201j
78. US EPA. Evaluation of Emerging Air Pollution Sensor Performance. Air Sensor Toolbox 2021. https://www.epa.gov/air-sensor-toolbox/evaluation-emerging-air-sensor-performance.
79. AQ-SPEC. Air Quality Sensor Performance Evaluation Center (AQ-SPEC).: http://www.aqmd.gov/aq-spec. (accessed March 5, 2022).
80. AIRLAB Microsensors Challenge. 2021 Edition. Airparif. https://airlab.solutions/en/projets/challenge-microcapteurs-edition-2021-90 (accessed May 24, 2022).
81. ASTM D8405-21. Standard Test Method for Evaluating PM2.5 Sensors or Sensor Systems Used in Indoor Air Applications. *ASTM International.* 2021. https://www.astm.org/d8405-21.html. (accessed May 2, 2022).
82. AIREAMOS. Promotion of ventilation for reducing the risk of COVID-19 infection (https://www.aireamos.org). Guide about Affordable CO2 detectors for COVID-19 Prevention, https://bit.ly/monitorsCO2.
83. Muñoz, A.; Borrás, E.; Ródenas, M.; Vera, T.; Pedersen, H.A. Atmospheric oxidation of a thiocarbamate herbicide used in winter cereals. *Environ. Sci. Technol.* 2018, ***52***, 9136–9144. https://doi.org/10.1021/acs.est.8b02157.
84. Office of Energy Efficiency & Renewable Energy. https://www.energy.gov/eere/buildings/downloads/development-laboratory-test-methods-low-cost-indoor-air-quality-sensors.
85. Di Carlo, S..; Falasconi, M. Drift Correction Methods for Gas Chemical Sensors in Artificial Olfaction Systems: techniques and Challenges. *Adv. Chem. Sensors*. 2012, ***2012***, 953–978.
86. Spinelle, L.; Gerboles, M.; Aleixandre, M. Performance Evaluation of Amperometric Sensors for the Monitoring of O_3 and NO_2 in Ambient Air at Ppb Level. *Procedian Eng.* 2015, *120*, 480–483. doi:10.1016/j.proeng.2015.08.676
87. Tryner, J.; Phillips, M.; Quinn, C.; Neymark, G.; Wilson, A.; Jathar, S. H.; Carter, E.; Volckens, J. Design and Testing of a Low-Cost Sensor and Sampling Platform for Indoor Air Quality. *J. Build Environ.* 2021, *206*, 108398. doi:10.1016/j.buildenv.2021.108398
88. Borrego, C.; Ginja, J.; Coutinho, M.; Ribeiro, C.; Karatzas, K.; Sioumis, T.; Katsifarakis, N.; Konstantinidis, K.; De Vito, S.; Esposito, E.; et al. Assessment of Air Quality Microsensors versus Reference Methods: The EuNetAir Joint Exercise – Part II. *Atmos. Environ.* 2018, *193*, 127–142. doi:10.1016/j.atmosenv.2018.08
89. Williams, D.-E.; Henshaw, G. S.; Bart, M.; Laing, G.; Wagner, J.; Naisbitt, S.; Salmond, J.-A. Validation of Low-Cost Ozone Measurement Instruments Suitable for Use in an Air-Quality Monitoring Network. *Meas. Sci. Technol.* 2013, *24*, 065803. doi:10.1088/0957-0233/24/6/065803
90. Bhagat, R.-K.; Wykes, M.-D.; Dalziel, S.-B.; Linden, P.-F. Effects of Ventilation on the Indoor Spread of COVID-19. *J. Fluid Mech.* 2020, *903*, F1-1–F1-18. doi:10.1017/jfm.2020.720

91. Coulby, G.; Clear, A.; Jones, J.; Godfrey, A. A Scoping Review of Technological Approaches to Environmental Monitoring. *IJERPH*. 2020, *17*, 3995. doi:10.3390/ijerph17113995
92. ASTM WK74360. New Test Method for Evaluating CO_2 Indoor Air Quality Sensors or Sensor Systems Used in Indoor Applications. *ASTM International*, 2020. https://www.astm.org/workitem-wk74360.
93. Piedrahita, R.; Xiang, Y.; Masson, N.; Ortega, J.; Collier, A.; Jiang, Y.; Li, K.; Dick, R.-P.; Lv, Q.; Hannigan, M.; Shang, L. The Next Generation of Low-Cost Personal Air Quality Sensors for Quantitative Exposure Monitoring. *Atmos. Meas. Tech*. 2014, *7*, 3325–3336. doi:10.5194/amt-7-3325-2014
94. Spinelle, L.; Gerboles, M.; Villani, M.-G.; Aleixandre, M.; Bonavitacola, F. Field Calibration of a Cluster of Low-Cost Commercially Available Sensors for Air Quality Monitoring. Part B: NO, CO and CO2. *Sens. Actuators B Chem*. 2017a, *238*, 706–715. doi:10.1016/j.snb.2016.07.036
95. Gillooly, S.-E.; Zhou, Y.; Vallarino, J.; Chu, M.-T.; Michanowicz, D.-R.; Levy, J.-I.; Adamkiewicz, G. Development of an in-Home, Real-Time Air Pollutant Sensor Platform and Implications for Community Use. *Env. Pollut*. 2019, *244*, 440–450. doi:10.1016/j.envpol.2018.10.064
96. Casey, G.-C.; Ortega, J.; Coffey, E.; Hannigan, M. Low-Cost Measurement Techniques to Characterize the Influence of Home Heating Fuel on Carbon Monoxide in Navajo Homes. *Sci. Total Environ*. 2018, *625*, 608–618. doi:10.1016/j.scitotenv.2017.12.312
97. Duvall, R.-M.; Long, R.-W.; Beaver, M.-R.; Kronmiller, K.-G.; Wheeler, M.-L.; Szykman, J.-J. Performance Evaluation and Community Application of Low-Cost Sensors for Ozone and Nitrogen Dioxide. *Sensors-Basel*. 2016, *16*, 1698. doi:10.3390/s16101698
98. Duvall, R. M.; Hagler, G. S. W.; Clements, A. L.; Benedict, K.; Barkjohn, K.; Kilaru, V.; Hanley, T.; Watkins, N.; Kaufman, A.; Kamal, A.; et al. Deliberating Performance Targets: Follow-on Workshop Discussing PM10, NO2, CO, and SO2 Air Sensor Targets. *Atmos. Environ*. 2021, *246*, 118099. doi:10.1016/j.atmosenv.2020.118099
99. Brown, S.-K.; Sim, M.-R.; Abramson, M.-J.; Gray, C.-N. Concentrations of Volatile Organic Compounds in Indoor Air–A Review. *Indoor Air*. 1994, *4*, 123–134. doi:10.1111/j.1600-0668.1994.t01-2-00007.x
100. Spinelle, L.; Gerboles, M.; Kok, G.; Persijn, S.; Sauerwald, T. Review of Portable and Low-Cost Sensors for the Ambient Air Monitoring of Benzene and Other Volatile Organic Compounds. *Sensors*. 2017b, *17*, 1520. doi:10.3390/s17071520
101. Hori, H.; Ishimatsu, S.; Fueta, Y.; Hinoue, M.; Ishidao, T. Comparison of Sensor Characteristics of Three Real-Time Monitors for Organic Vapors. *J Occup Health*. 2015, *57*, 13–19. doi:10.1539/joh.14-0146-OA
102. Herberger, S.; Herold, M.; Ulmer, H.; Burdack-Freitag, A.; Mayer, F. Detection of Human Effluents by a MOS Gas Sensor in Correlation to VOC Quantification by GC/MS. *Build Environ*. 2010, *45*, 2430–2439. doi:10.1016/j.buildenv.2010.05.005
103. Palmisani, J.; Di Gilio, A.; Viana, M.; de Gennaro, G.; Ferro, A. Indoor Air Quality Evaluation in Oncology Units at Two European Hospitals: Low-Cost Sensors for TVOCs, PM2.5 and CO2 Real-Time Monitoring. *Build. Environ*. 2021, *205*, 108237. doi:10.1016/j.buildenv.2021.108237
104. Schutze, A.; Baur, T.; Leidinger, M.; Reimringer, W.; Jung, R.; Conrad, T.; Sauerwald, T. Highly Sensitive and Selective VOC Sensor Systems Based on Semiconductor Gas Sensors: How to? *Environments*. 2017, *4*, 20. doi:10.3390/environments4010020
105. Yurko, G.; Roostaei, J.; Dittrich, T.; Xu, L.; Ewing, M.; Zhang, Y.; Shreve, G. Real-Time SensorResponse Characteristics of 3 Commercial Metal Oxide Sensors for Detection of BTEX and Chlorinated Aliphatic Hydrocarbon Organic Vapors. *Chemosensors*. 2019, *7*, 40. doi:10.3390/chemosensors7030040
106. Goletto, V.; Mialon, G.; Faivre, T.; Wang, Y.; Lesieur, I.; Petigny, N.; Vijapurapu, S. Formaldehyde and Total VOC (TVOC) Commercial Low-Cost Monitoring Devices: From

an Evaluation in Controlled Conditions to a Use Case Application in a Real Building. *Chemosensors*. 2020, *8*, 8. doi:10.3390/chemosensors8010008vocs
107. Szulczynski, B.; Gebicki, J. Currently Commercially Available Chemical Sensors Employed for Detection of Volatile Organic. *Environments*. 2017, *4*, 21–35.
108. ASTM D27297-21. Standard Practice for Evaluating Residential Indoor Air Quality Concern. *ASTM International*, 2014. https://www.astm.org/d7297-21.html (accessed April 4, 2022)
109. Moreno-Rangel, A.; Sharpe, T.; Musau, F.; McGill, G. Field Evaluation of a Low-Cost Indoor Air Quality Monitor to Quantify Exposure to Pollutants in Residential Environments. *J. Sens. Sens. Syst*. 2018, *7*, 373–388. doi:10.5194/jsss-7-373-2018
110. Wallace, L. Indoor Sources of Ultrafine and Accumulation Mode Particles: number Concentrations and Size Distributions. *Aerosol Sci. Technol*. 2006, *40*, 348–360. doi:10.1080/02786820600612250
111. Marval, J.; Tronville, P. Ultrafine Particles: A Review about Their Health Effects, Presence, Generation, and Measurement in Indoor Environments. *Build Environ*. 2022, *216*, 108992. doi:10.1016/j.buildenv.2022.108992
112. Bekö, G.; Weschler, C.-J.; Wierzbicka, A.; Karottki, D.-G.; Toftum, J.; Loft, S.; Clausen, G. Ultrafine Particles: Exposure and Source Apportionment in 56 Danish Homes. *Environ Sci Technol*. 2013, *47*, 10240–10248. doi:10.1021/es402429h
113. Kuula, J.; Kuuluvainen, H.; Rönkkö, T.; Niemi, J. V.; Saukko, E.; Portin, H.; Aurela, M.; Saarikoski, S.; Rostedt, A.; Hillamo, R.; Timonen, H. Applicability of Optical and Diffusion Charging-Based Particulate Matter Sensors to Urban Air Quality Measurements. *Aerosol Air Qual. Res*. 2019b, *19*, 1024–1039. doi:10.4209/aaqr.2018.04.0143
114. Pope, F. D.; Gatari, M.; Ng'ang'a, D.; Poynter, A.; Blake, R. Airborne Particulate Matter Monitoring in Kenya Using Calibrated Low-Cost Sensors. *Atmos. Chem. Phys*. 2018, *18*, 15403–15418. doi:10.5194/acp-18-15403-20182018
115. Malings, C.; Tanzer, R.; Hauryliuk, A.; Saha, P.-K.; Robinson, A.-L.; Presto, A.-A.; Subramanian, R. Fine Particle Mass Monitoring with Low-Cost Sensors: Corrections and Long-Term Performance Evaluation. *Aerosol Sci. Technol*. 2020, *54*, 160–174. doi:10.1080/02786826.2019.1623863
116. Liu, Q.; Liu, D.; Chen, X.; Zhang, Q.; Jiang, J.; Chen, D.-R. A Cost-Effective, Miniature Electrical Ultrafine Particle Sizer (Mini-eUPS) for Ultrafine Particle (UFP) Monitoring Network. *Aerosol Air Qual. Res*. 2020, *20*, 231–241. doi:10.4209/aaqr.2018.11.0427
117. Kuula, J. Opportunities and Limitations of Aerosol Sensors to Urban Air Quality Monitoring. PhD Dissertation, Aalto University, 2019a, 978–952. http://urn.fi/URN:ISBN:60-3843-8.
118. 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. doi:10.4209/aaqr.2019.01.0046
119. Zamora, M. L.; Rice, J.; Koehler, K. One Year Evaluation of Three Low-Cost PM2.5 Monitors. *Atmos. Environ*. 2020, *235*, 117615. doi:10.1016/j.atmosenv.2020.117615.
120. Manibusan, S.; Mainelis, G. Performance of Four Consumer-Grade Air Pollution Measurement Devices in Different Residences. *Aerosol Air Qual. Res.* 2020, *20*, 217–230. doi:10.4209/aaqr.2019.01.0045.
121. Elísio, S.; Peralta, L. Development of a Low-Cost Monitor for Radon Detection in Air. *Nucl. Instrum. Methods Phys. Res. A*. 2020, *969*, 164033. doi:10.1016/j.nima.2020.164033
122. Studnička, F.; Štěpán, J.; Šlégr, J. Low-Cost Radon Detector with Low-Voltage Air-Ionization Chamber. *Sensors*. 2019, *19*, 3721. doi:10.3390/s19173721
123. Pereira, F.; Lopes, S.-I.; Carvalho, N.-B.; Curado, A. RnProbe: A LoRa-Enabled IoT Edge Device for Integrated Radon Risk Management. *IEEE Access*. 2020, *8*, 203488–203502. doi:10.1109/ACCESS.2020.3036980
124. Alvarellos, A.; Gestal, M.; Dorado, J.; Rabuñal, J.-R. Developing a Secure Low-Cost Radon Monitoring System. *Sensors*. 2020, *20*, 752. doi:10.3390/s20030752

125. Carlo, D.; Lepore, C.; Gugliermetti, L.; Remetti, L. R. An Inexpensive and Continuous Radon Progeny Detector for Indoor Air-Quality Monitoring. *WIT Trans. Ecol. Environ*. 2019, *236*, 1743–3541. doi:10.2495/AIR190321
126. Gugliermetti, L.; Lepore, L.; Remetti, R.; Colarieti-Tosti, M. Alpha Spectrometry with the Inexpensive Open-Source Detector Alphaino. *Nucl. Instrum. Methods Phys. Res*. 2019, *928A*, 13–19. doi:10.1016/j.nima.2019.03.018
127. Morishita, Y.; Ye, Y.; Mata, L.; Pozzi, S.-A.; Kearfott, K.-J. Radon Measurements with a Compact, Organic-Scintillator-Based Alpha/Beta Spectrometer. *Radiat. Meas*. 2020, *137*, 106428. doi:10.1016/j.radmeas.2020.106428
128. Miles, J. Methods of Radon Measurement and Devices. 4th European Conference on Protection against Radon at Home and at Work Conference Programme and Session Presentations, 2004, 377.
129. Pronost, G.; Ikeda, M.; Nakamura, T.; Sekiya, H.; Tasaka, S. Development of New Radon Monitoring Systems in the Kamioka Mine. *Prog. Theor. Exp. Phys*. 2018, *9*, 093H01.
130. Martín-Martín, A.; Gutiérrez-Villanueva, J.-L.; Muñoz, J.-M.; García-Talavera, M.; Adamiec, G.; Íñiguez, M.-P. Radon Measurements with a PIN Photodiode. *Appl Radiat Isot*. 2006, *64*, 1287–1290. doi:10.1016/j.apradiso.2006.02.035
131. Sá, J.-P.; Branco, P.-T.-B.-S.; Alvim-Ferraz, M.-C.-M.; Martins, F.-G.; Sousa, S.-I.-V. Radon in Indoor Air: Towards Continuous Monitoring. *Sustainability*. 2022, *14*, 1529. doi: 10.3390/su14031529
132. Nazaroff, W.-W.; Weschler, C.-J. Indoor Acids and Bases. *Indoor Air*. 2020, *30*, 559–644. doi:10.1111/INA.12670
133. Schieweck, A.; Uhde, E.; Salthammer, T.; Salthammer, L. C.; Morawska, L.; Mazaheri, M.; Kumar, P. Smart Homes and the Control of Indoor Air Quality. *Renew. Sustain. Energy Rev*. 2018, *94*, 705–718. doi:10.1016/j.rser.2018.05.057
134. Benammar, M.; Abdaoui, A.; Ahmad, S.-H.; Touati, F.; Kadri, A. A Modular IoT Platform for Real-Time Indoor Air Quality Monitoring. *Sensors*. 2018, *18*, 581. doi:10.3390/s18020581
135. Lowther, S.-D.; Jones, K.-C.; Wang, X.; Whyatt, J.-D.; Wild, O.; Booker, D. Particulate Matter Measurement Indoors: A Review of Metrics, Sensors, Needs, and Applications. *Environ. Sci. Technol*. 2019, *53*, 11644–11656. doi:10.1021/acs.est.9b03425
136. Samad, A.; Melchor Mimiaga, F.-E.; Laquai, B.; Vogt, U. Investigating a Low-Cost Dryer Designed for Low-Cost PM Sensors Measuring Ambient Air Quality. *Sensors*. 2021, *21*, 804. doi:10.3390/s21030804
137. Di Antonio, A.; Popoola, O.; Ouyang, B.; Saffell, J.; Jones, R. Developing a Relative Humidity Correction for Low-Cost Sensors Measuring Ambient Particulate Matter. *Sensors*. 2018, *18*, 2790. doi:10.3390/s18092790
138. Jiao, W.; Hagler, G.; Williams, R.; Sharpe, R.; Brown, R.; Garver, D.; Judge, R.; Caudill, M.; Rickard, J.; Davis, M.; et al. Community Air Sensor Network (CAIRSENSE) Project: evaluation of Low-Cost Sensor Performance in a Suburban Environment in the Southeastern United States. *Atmos. Meas. Tech*. 2016, *9*, 5281–5292. doi:10.5194/amt-9-5281-2016
139. Sun, L.; Wong, K. C.; Wei, P.; Ye, S.; Huang, H.; Yang, F.; Westerdahl, D.; Louie, P. K.; Luk, C. W.; Ning, Z. Development and Application of a Next Generation Air Sensor Network for the Hong Kong Marathon 2015 Air Quality Monitoring. *Sensors*. 2016, *16*, 211. doi:10.3390/s16020211
140. Masey, N.; Gillespie, J.; Ezani, E.; Lin, C.; Wu, H.; Ferguson, N. S.; Hamilton, S.; Heal, M. R.; Beverland, I. J. Temporal Changes in Field Calibration Relationships for Aeroqual S500 O3 and NO2 Sensor-Based Monitors. *Sens. Actuators B Chem*. 2018, *273*, 1800–1806. doi:10.1016/j.snb.2018.07.087
141. Suriano, D.; Cassano, G.; Penza, M. Design and Development of a Flexible, Plug-and-Play, Cost-Effective Tool for on-Field Evaluation of Gas Sensors. *J. Sens*. 2020, *2020*, (1–20 pp.). doi:10.1155/2020/8812025