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Application of the low-cost sensing technology for indoor air quality monitoring: A review

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ABSTRACT

In recent years, low-cost air pollution technologies have gained increasing interest and, have been studied widely by the scientific community. Thus, these new sensing technologies must provide reliable data with good precision and accuracy. Accordingly, this review aimed to evaluate and compare the low-cost sensing technology against other instruments used for comparison by various studies from the scientific literature to monitor indoor air quality in different indoor environments. After exclusions, a total of 42 studies divided into two subsections (11 laboratory studies and 31 field studies) were analysed considering their aim, location, study duration, sampling area, pollutant(s) evaluated, sensor/device and instrument used for comparison, performance indexes and main outcomes.

The reviewed studies aimed to assess different low-cost sensors/devices to monitor indoor air quality against other instruments used for comparison. The vast majority of the studies took place in USA. The laboratory studies were mainly conducted in a controlled chamber, and field studies were performed in homes, offices, educational buildings, among others. In both cases, particulate matter was the most assessed pollutant, either with commercial devices (e.g.: Speck, Dylos, Foobot) or sensors (e.g. Sharp GP2Y1010AU0F). In general, based on statistical parameters, the air quality low-cost sensors/devices tested presented moderate correlations with the instruments used for comparison, revealing sufficient precision for monitoring air quality in indoor microenvironments, especially for qualitative analysis. Thus, low-cost sensing technology to monitor indoor air quality is encouraged, but not waiving the relevance of high quality instruments (mainly reference instruments).

Contents

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1. Introduction

Clean air is one of the most fundamental principles of life quality and well-being. As people spend a large part of their time indoors, such as homes, offices, schools, health care facilities, or other private and public buildings (Bluyssen, 2013), indoor air quality (IAQ) has gained an increasing concern worldwide (Kumar et al., 2016b). According to the World Health Organization (WHO), in 2012 (WHO, 2014), household air pollution led to more than 4 million premature deaths among children and adults. Moreover, indoor air pollution (IAP) was responsible for more than 1.5 million deaths and 2.7% of the global burden of disease (WHO, 2007), and most recently, it was placed as the 9th most considerable Global Burden of Disease risk (Forouzanfar et al., 2015).

Among the most relevant and most widely considered reference documents, the World Health Organization (WHO) published IAQ-specific guidelines for the protection of public health from risks related to the exposure to selected pollutants commonly found indoors, particularly particulate matter ($PM_{2.5}$ and PM_{10}), ozone (O_3), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon monoxide (CO) (WHO, 2021) and benzene, formaldehyde, naphthalene, benzo[a]pyrene, radon, trichloroethylene and tetrachloroethylene (Sérafin et al., 2021; WHO, 2010). Therefore, it is clear the need to monitor IAQ in real-time, detecting these pollutants, and thus avoiding the development of adverse health effects from its inhalation (Moreno-Rangel et al., 2018). Conventionally, the methodologies adopted to measure indoor air pollutants are based on: (i) passive sampling, that requires long sampling periods (usually few weeks) followed by later laboratory analysis; and/or (ii) continuous sampling, which generally is bulky and expensive, generating noise and vibration, preventing its deployment in many places at the same time, leading to a limited spatiotemporal coverage (Caron et al., 2016). Thus, alternative methodologies have been sought and studied due to many constraints found in IAP characterisation. As such, low-cost air pollution monitoring technologies emerge as a promising revolutionary advance in IAQ monitoring, providing either answers to scientific questions or applications for end-users (through massive increases in spatial and temporal data resolution) (Morawska et al., 2018).

Low-cost technology has advanced quickly, with new research, developments and applications, being already published several studies that have tested this type of technology in ambient air monitoring (Fishbain et al., 2017; Lewis et al., 2018; Liu et al., 2020a; Mead et al., 2013; Miskell et al., 2017; Schneider et al., 2017; Spinelle et al., 2017b; Ye et al., 2021; Zheng et al., 2018). More recently, due to the fast-growing sensing technology, an extensive range of low-cost air quality devices or sensor modules was made available in the market for indoor measurement purposes. These technologies are easy to use and, in their majority, provide quantitative information of pollutant concentrations of different indoor air quality parameters (Chojer et al., 2020; Fanti et al., 2021; Howard et al., 2022; Kang et al., 2021b; Zhang and Srinivasan, 2020).

Rai et al. (2017) in a comprehensive review of the scientific literature, recognised the need of providing scientific guidance to choose appropriate low-cost sensors and assessed the performance of several commercially available low-cost sensors for measuring particulate matter and gaseous pollutants (CO, O_3, NO_2 and SO_2) in outdoor environments. Although many studies indicated that IAQ is affected by outdoor air (Kang et al., 2021a; Leung, 2015; Shrestha et al., 2019; Tofful et al., 2021; Yang et al., 2015), it should be noted that there are significant differences between indoor and outdoor air qualities, what should be considered for monitoring (Han et al., 2016). In addition, there are numerous sources of pollutants detected indoors, which depend on the particularity of each indoor space (Soreanu et al., 2013). Moreover, some review articles focused on low-cost technology for indoor air pollution sensing (Kumar et al., 2016a,b; Schieweck et al., 2018), while Jovašević-Stojanović et al. (2015), Morawska et al. (2018) and Kang et al. (2022) saw the need for a review including the indoor and outdoor application of this technology. However, none of them systematically reviewed studies that compared low-cost sensing technology against other instruments to monitor IAQ in different indoor spaces (such as homes, offices, schools, among others). This is highly important because the conditions under which sensors are calibrated in the laboratory do not often overlap with the full range of conditions encountered in an indoor environment (Morawska et al., 2018; WMO, 2020). Therefore, to understand the application of the low-cost sensing technology for indoor air monitoring, the present review focused on studies that simultaneously used low-cost sensors/devices and other instruments for comparison at indoor environments, including laboratory studies simulating indoor conditions.

2. Methodology of this review

The review was conducted considering the following online scientific databases: *Science Direct*, *Scopus*, *PubMed* and *Google Scholar*, using the main keywords "low-cost sensors" and "indoor air quality" simultaneously. Although no language restriction criteria were applied, all the referred studies in this review were published in English. Moreover, except for the non-peer-reviewed literature, all the other scientific written publications were considered. Furthermore, the present review refers to the studies published from 2013 (once the first study dates to that year) to 2021. A total of 176 publications were identified and reduced to 127 after duplicate removal. After that, titles and abstracts were examined for relevance. The publications were collected and organised in the EndNote library (version X8).

Detailed air pollution sensing methods/technologies to determine IAQ, as well as its development, characteristics, challenges and applications, are beyond the scope of this review and have already been addressed in other reviews (Jovašević-Stojanović et al., 2015; Kumar et al., 2016a,b; Morawska et al., 2018; Schieweck et al., 2018). Thus, this review includes studies that have compared low-cost sensing technology costing less than 2000€ for a multi-sensor and/or 500€ for a single sensor device with other instruments: (i) in the laboratory, simulating the conditions of indoor spaces; and/or (ii) in the field, i.e., in settings as homes, educational buildings, offices, among others, evaluating IAQ or indoor environment quality (IEQ). Note that the instruments used for comparison with low-cost sensors/devices varied from study to study, with most of them being instruments scientifically validated, from now on defined as research-grade instruments. However, in some cases, they were reference instruments in the legally binding sense of the term (instruments that use federal reference methods and equivalents). In turn, the term low-cost sensor refers to the sensor module themselves. In contrast, low-cost devices correspond to either commercially available or self-developed devices for monitoring IAQ (usually include at least one sensor module, power system, electronic hardware, components for data transmission, storage, and retrieval in a protective box). Moreover, studies that: (i) evaluated at least one type of pollutant (not considering those that evaluated only comfort/meteorological parameters); (ii) used either individual module sensors (usually integrated in a prototype built by the authors) or commercially available devices; and (iii) performed measurements in both indoor and outdoor environments were also included. Studies that did not use an instrument for comparison simultaneously with the low-cost sensors/devices were excluded. Also, devices that used passive sensors were not considered, which despite using low-cost technology, were not within the scope of this review. After applying these criteria, 48 publications corresponding to 42 studies (some of them corresponding to the same study/project) were selected. These studies contain information about the use and application of low-cost sensing technology in indoor environments, of which (i) 11 were performed in the laboratory; and (ii) 31 have tested this technology in different indoor environments, evaluating IAQ or IEQ, being considered field studies. Fig. 1 presents the flowchart of the bibliographic review process.

3. Results and discussion

Table 1 summarises the main characteristics of the reviewed studies using low-cost technology to monitor the air in indoor environments (including study duration, sampling area, measured parameters, sensor/device, the instruments used for comparison and performance indexes). Additional information about the studies (such as the aim, location and main outcomes) can be found in Supplementary Material — Table S1.

3.1. Study design

The greater number of publications were reported in most recent years (Table 1). In addition to the growing interest in the use of low-cost sensors/devices to monitor IAQ (Morawska et al., 2018), this trend can be justified by the recent increase in the availability and reliability of this technology.

According to the purpose of this review, all the selected studies had the main aim of evaluating different low-cost sensors to monitor IAQ or IEQ (Tiele et al., 2018) against instruments used for comparison (inclusion criteria for the studies' selection), such as reference and research-grade instruments. Specific and detailed aims of each study can be found in Table S1 (Supplementary Material).

Fig. 2 shows the geographical distribution and the respective number of studies considered in this review. As can be seen (Fig. 2 and Table S1), most of the reviewed studies were performed in the United States of America. The quality of indoor air is directly and indirectly influenced by different factors, such as geographic and topography, meteorological conditions (wind, precipitation and climate), population density, traffic, industry, human activities, among others (Karimi et al., 2016). In addition, the lack of indoor air quality data in some regions makes it difficult to estimate air pollution exposure and predict future air quality trends (Singh et al., 2021). Thus, different locations should be considered a target of interest to evaluate the performance of low-cost sensors/devices.

It was possible to verify that most of the studies were performed during a short-term, with some of them for a few minutes (Dacunto et al., 2013, 2015; Demanega et al., 2021; He et al., 2021; Semple et al., 2013). However, the short-term performance (minutes/hours) presented a considerable limitation because it did not cover all periods of the day, which can prevent the detection of concentration variations that may occur and, consequently, it is not known how well they describe peak and background values. Contrarily, the long-term performance of the sensors can be useful for tracking pollution sources (Sun et al., 2019), and it will determine how extensively they can be used in the future (Liu et al., 2020b). Also, elements such as their robustness, sensitivity, stability and drift with time can be addressed (Liu et al., 2020b). Although the long-term durability of low-cost sensors is not well characterised, and many of them do not have a long lifetime under polluted conditions, long-term assessment is necessary to categorise bias and assess data quality after field use (Malings et al., 2019). However, long-term studies are rarely reported in the literature, even though many low-cost

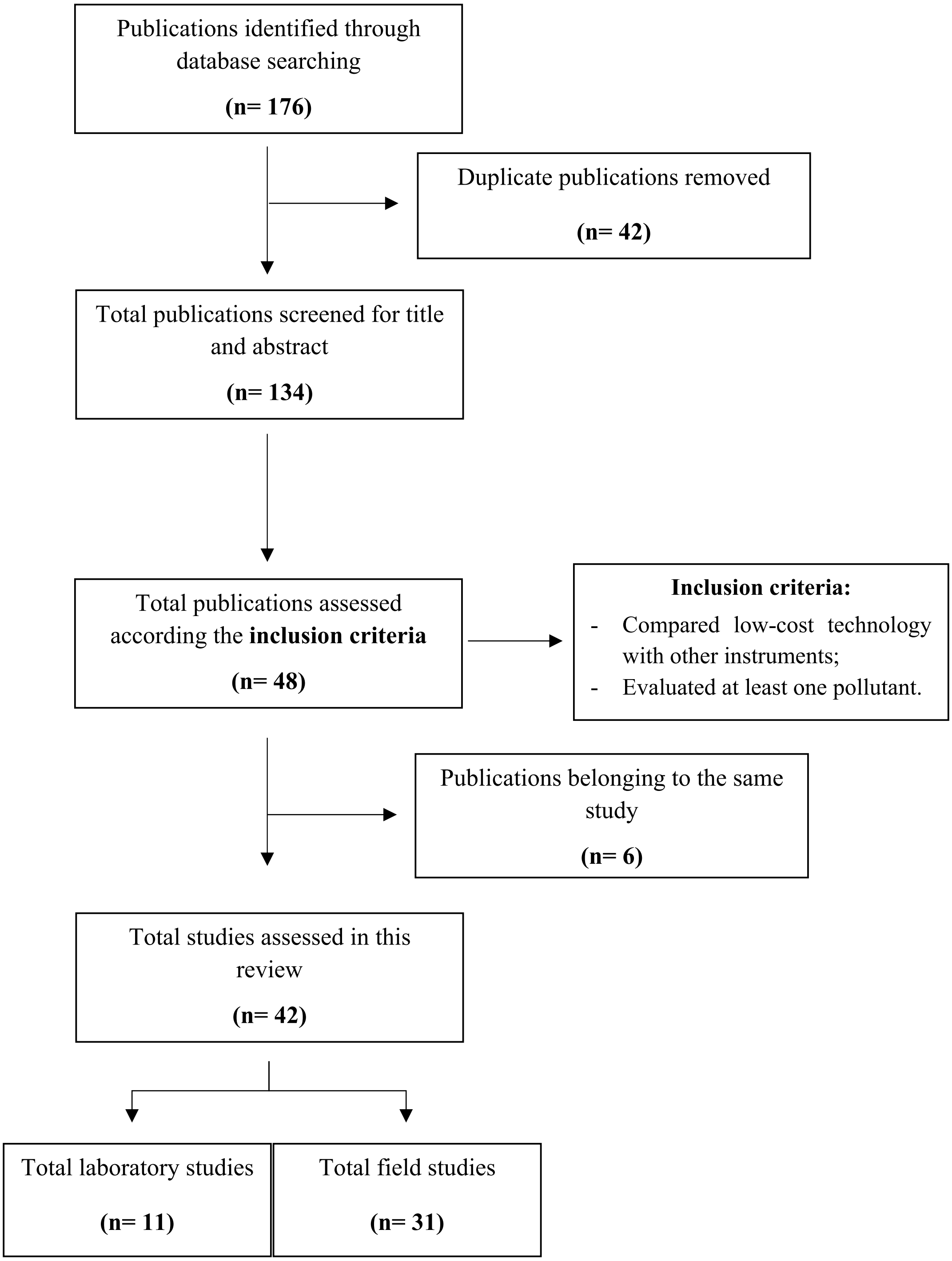

Fig. 1. Flowchart of the bibliographic review process.

sensors are intended to be deployed in the field with minimal maintenance over a long period (Bai et al., 2020). Regarding the studies reviewed, Gillooly et al. (2019) conducted a study for a longer period (9 weeks over 18 months), making a six-month calibration procedure to overcome drifts, while Zamora et al. (2020) carried out a study over 12 months (using the instrument for comparison during 1 week each month). Similarly, Kang et al. (2022) performed weeklong measurements (5 to 9 days) quarterly between 2017 and 2020. However, even with short-term measurements, failure and malfunction

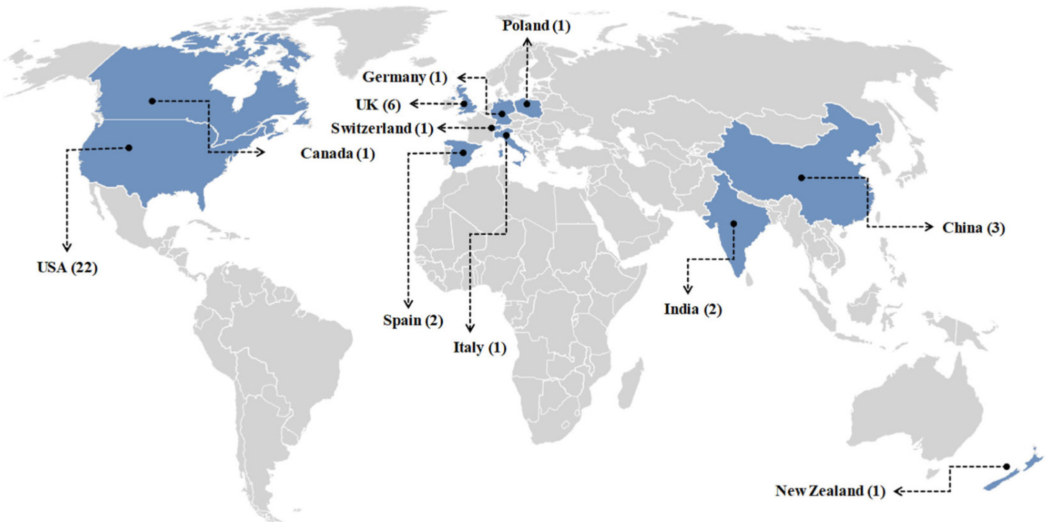

Fig. 2. Geographical distribution and the respective number of studies considered in this review. Note: Three studies are not included in this figure because they do not identify the location.

rate of low-cost sensors/devices were one of the identified problems of the air quality low-cost devices (Alavi-Shoshtari et al., 2013), and they were detected among different low-cost units evaluated (Curto et al., 2018).

The most studied sampling areas were offices and homes (kitchen and bedrooms being the most reported) (Table 1). From the point of view of public health and exposure to IAP, homes and workplaces are crucial indoor environments since people spend there about 90% of their time (Khajehzadeh and Vale, 2017; Morawska et al., 2017; Spiru and Simona, 2017). However, there is a need to conduct studies using low-cost sensing technology in other indoor environments of equal relevance, such as: (i) hospitals and health care facilities since high-risk groups often frequent them (usually most vulnerable to IAP) (Leung and Chan, 2006); (ii) vehicles and transports, due to the high health risks associated to in-cabin air quality for some pollutants, although people spend only an average of about 5.5% of time daily in transport (Xu et al., 2016); and (iii) gyms and sports facilities due to the significant inhalation rate caused by the physical activity even for a short period of exposure (Ramos et al., 2014), among others. A very recent study from the current review reinforced the importance of monitoring IAQ in oncology units where high air quality standards must be ensured to protect the health of patients, concluding that low-cost sensors had great potential for inexpensive, real-time monitoring and detection of pollution events (Palmisani et al., 2021). Furthermore, although not evident in the articles of this review, there is a notorious interest in using low-cost sensing technology in educational premises (Basińska et al., 2019; Branco et al., 2014; Chen et al., 2020; Jovanović et al., 2014; Kaduwela et al., 2019; Kalimeri et al., 2016; Nunes et al., 2016; Oliveira et al., 2019; Sá et al., 2017; Wang et al., 2018). In addition to the indoor sampling areas, some measurements with low-cost sensing technology were also carried out outdoor (Casey et al., 2018; Hojaiji et al., 2017; Krause et al., 2019; Zikova et al., 2017).

The vast majority of the selected studies focused on particulate matter (about 59%), mainly in the $PM_{2.5}$ fraction, followed by CO_2 (11 studies, 18%) and then CO (5 studies, 8%). Pollutants such as VOC/TVOC and ozone were notoriously less studied (4 studies each, 6%), while only 2 studies evaluated NO_2 (3%). The great interest in PM study by the scientific community can be due to the recognition of PM as one of the main pollutants in indoor (and outdoor) environments (Morawska et al., 2017) and supported by the well-known relationship of PM_{10} and $PM_{2.5}$ exposure with adverse health effects on human health (Dominici et al., 2006; Gillooly et al., 2019; Shah et al., 2013). Respirable particles (with aerodynamic diameter $\leq$10 μm) are accounted for approximately 2.7% of the global burden of diseases (Hetland et al., 2000). Beyond this, many easy to use and almost reliable PM low-cost sensors are available on the market, which may have contributed to the highest incidence in the study of this pollutant (Jayaratne et al., 2020). Besides, the technology used by all the sensors is also well known, which facilitate particle measurement. However, many assumptions and approximations were implemented in the sensors or devices (particles vary in size, composition and concentration). Furthermore, so far, PM composition cannot be determined with low-cost sensors, which would be challenging. On the other hand, devices containing gaseous sensors (such as CO, NO_2, VOC) tend to be more expensive than PM devices. Moreover, electrochemical sensors are more susceptible to environmental interference and are cross-sensitive to other gases (Afshar-Mohajer et al., 2018). In particular, VOC sensors have additional limitations since they usually measure a total mixture of several VOC (referred to as TVOC) instead of identifying individual chemicals, which could lead to a variation in its response and not represent a real result (Thakor et al., 2021). In addition, VOC sensors have a too high limit of detection and quantification and poor selectivity properties, which could also compromise the measurements (Spinelle et al., 2017a; Szulczyński and Gębicki, 2017).

Table 1
Summary of the main characteristics of the reviewed studies using low-cost sensors in indoor environments.

Laboratory studies	Reference	Study duration	Sampling area	Measured Parameters	Sensor/Device	Instrument used for comparison[a]	Performance indexes
	Demanega et al. (2021)	15 min to 1 h (each experiment)	Environmental chamber, V = 63.3 m^3 (where were emitted eight common indoor sources simulating both cold and warm season)	$PM_{2.5}$, CO_2 and TVOC	**Devices:** AirVisual Pro, Kaiterra Laser Egg ($PM_{2.5}$, CO_2); Awair 2nd Edition, Foobot, uHoo ($PM_{2.5}$, CO_2, TVOC); Clarity Node ($PM_{2.5}$); Netatmo (CO_2) **Sensors:** Sensirion SPS30, Alphasense OPC-N3, Alphasense OPC-R1 ($PM_{2.5}$); NovaFitness SDS018 ($PM_{2.5}$, PM_{10}); Sensirion SCD40, CO2 metre K30 (CO_2,)	Grimm Mini WRAS Model 1371 ($PM_{2.5}$) LI-COR 850 Biosciences gas analyser (CO_2) GrayWolf AdvancedSense Pro with an IQ-610 Probe and Aeroqual Photoionization Detector (TVOC)	$r_{PM2.5}$ = 0.533 – 0.997; r_{CO2} = 0.975 (AirVisual) $r_{PM2.5}$ = 0.662 – 0.998; r_{CO2} = 0.998; r_{TVOC} = 0.96 (Awair) $r_{PM2.5}$ = 0.632 – 0.997 (Clarity) $r_{PM2.5}$ = 0.224 – 0.982; r_{CO2} = 0.360; r_{TVOC} = 0.88 (Foobot) $r_{PM2.5}$ = 0.373 – 0.995; r_{CO2} = 0.999 (Kaiterra) $r_{PM2.5}$ = 0.297 – 0.957; r_{CO2} = 0.999; r_{TVOC} = 0.86 (uHoo) r_{CO2} = 0.812 (Netatmo) $r_{PM2.5}$ = 0.124 – 0.998 (OPC-N3) $r_{PM2.5}$ = 0.958 – 0.998 (OPC-R1) $r_{PM2.5}$ = 0.737 – 0.998 (SPS30) $r_{PM2.5}$ = 0.578 – 0.901 (SDS018) r_{CO2} = 0.994 (SCD40) r_{CO2} = 0.986 (K30)

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Table 1 (*continued*).

	Zou et al. (2020, 2021a,b)	*n.d.*	Chamber, V = 1.65 m^3 (controlled experiments including incense, burnt toast smoke, etc.)	$PM_{2.5}$	**Devices:** AirThinx, AirBeam2, Dylos DC1100 Pro, TSI BlueSky, Purple Air II **Sensors:** Honeywell HPMA115S0 Sharp GP2Y1010AU0F Plantower PMS5003	TSI SMPS Model 3938 TSI APS Model 3321	$R^2_{incence}$ = 0.39 – 1.00; R^2_{toast} = 0.18 – 0.99 (AirThinx) $R^2_{incence}$ = 0.23 – 1.00; R^2_{toast} = 0.70 – 0.99 (AirBeam2) $R^2_{incence}$ = 0.48 – 0.90; R^2_{toast} = 0.54 – 0.96 (Dylos) $R^2_{incence}$ = 0.21 – 0.99; R^2_{toast} = 0.57 – 0.99 (BlueSky) $R^2_{incence}$ = 0.60 – 0.99; R^2_{toast} = 0.59 – 0.99 (PA-II) $R^2_{incence}$ = 0.16 – 0.95; R^2_{toast} = 0.25 – 1.00 (Honeywell) $R^2_{incence}$ = 0.39 – 0.96; R^2_{toast} = 0.21 – 1.00 (Sharp) $R^2_{incence}$ = 0.33 – 0.99; R^2_{toast} = 0.21 – 0.99 (Plantower)
	Wang et al. (2020)	A few hours (per 24 experiments over 10 days)	Laboratory, V = 120 m^3 (where particles from typical residential activities were generated[b])	$PM_{2.5}$ and PM_{10}	Air Quality Egg 2018, AirVisual Pro, Awair 2nd Edition, Kaiterra Laser Egg 2, PurpleAir Indoor and Ikair	Thermo Scientific TEOM 1405-DF with FDMS Grimm Mini WRAS Model 1371. Met One BT-645 and Thermo pDR-1500	R^2_{TEOM} = 0.75 – 0.80 $R^2 \geq$ 0.83 (mineral sources) $R^2 \geq$ 0.98 (incense and mosquito coil) $R^2 \geq$ 0.95 (candle experiments)

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Table 1 (*continued*).

Wang et al. (2019b)	Five to six hours (per experiment)	Laboratory, V = 30 m^3 (where cigarette was generated to simulate urban indoor particle)	$PM_{2.5}$	Hike HK-B3	MicroPEM	R^2 = 0.87 – 0.98
Singer and Delp (2018)	16 days (warm season 2017)	Laboratory, V = 120 m^3 (where particles from typical residential activities were generated[b])	$PM_{2.5}$	AirBeam, AirVisual Pro, Foobot, PurpleAir PA II, Air Quality Egg, Awair and Speck (2–3 units each) Thermo pDR-1500 and Met One BT-645[c]	Thermo Scientific TEOM 1405-DF with FDMS Grimm Mini WRAS Model 1371	*n.d.*
Sousan et al. (2017)	*n.d.*	Test chamber (simulation of three polydisperse aerosols[d])	$PM_{2.5}$	Foobot, Speck and AirBeam Thermo pDR-1500[e]	Thermo pDR-1500[e] TSI APS 3321 and Grimm SMPS-C 5.402	Comparison with TSI and Grimm: r = 0.99; CV = 5%–8% (Foobot) r = 0.91–0.99; CV = 8%–25% (Speck) r = 0.70–0.96; CV = 2%–9% (AirBeam) r = 0.99 (pDR-1500) Comparison with pDR-1500: r = 0.99 (Foobot) $r = 0.92 - 0.99$ (Speck) $r = 0.66 - 0.97$ (AirBeam)
Hojaiji et al. (2017)	Several hours (varying T and RH to detect real time variations) Few days (to test the reliability and accuracy of the sensor against Dylos)	Controlled chamber (simulation of indoor – cooking and walking on the carpet and outdoor – natural changes in wind, humidity, and temperature conditions)	$PM_{2.5}$	2 Sharp GP2Y1010AU0F	Dylos DC1100 Pro and Alphasense OPC-N2	Comparison between Sharp and Dylos: r = 858 ± 0.026 (outdoor) r = 0.667 ± 0.002 (indoor) Comparison with OPC-N2: r_{Sharp} = 0.972 (outdoor); r_{Sharp} = 0.969 (indoor); r_{Dylos} = 0.963 ± 0.05

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Table 1 (*continued*).

	Manikonda et al. (2016)	*n.d.*	Laboratory chamber (considering cigarette smoke and Arizona Test Dust as PM sources)	$PM_{2.5}$ and PM_{10}	2 Speck, 1 Dylos1100 Pro, 1 Dylos 1700, 3 TSI AirAssure and 1 UB AirSense	Grimm 1.109, TSI APS 3321 and TSI FMPS 3091	Comparison with APS 3321: $R^2_{Speck\_CS} = 0.92–0.95$; $R^2_{Speck\_ATD} = 0.96$ $R^2_{Dylos\_CS} = 0.86–0.96$ $R^2_{Dylos\_ATD} = 0.76–0.95$ $R^2_{AirAssure\_CS} = 0.42–0.99$ $R^2_{AirAssure\_ATD} = 0.94–0.98$ $R^2_{UBAS\_CS} = 0.85$ Comparison with Grimm 1.109 and FMPS 3091: $R^2_{Speck\_CS} = 0.87–0.97$ $R^2_{Dylos\_CS} = 0.87–0.97$ $R^2_{AirAssure\_CS} = 0.84–0.99$ $R^2_{UBAS\_CS} > 0.90$ Comparison with FMPS 3091: $R^2_{Speck\_ATD} = 0.58$; $R^2_{Dylos\_ATD} > 0.70$ $R^2_{AirAssure\_ATD} > 0.70$
	Wang et al. (2015)	2.5 h for each experiment	Test chamber, V = 94.2 dm^3 (where incense burning, atomised NaCl, sucrose, and NH_4NO_3 particles and atomised polystyrene latex spheres were generated)	PM_1	Shinyei PPD42NS, Samyoung DSM501A and Sharp GP2Y1010AU0F	SidePak AM510 TSI AirAssure	Comparisons with SidePak: $R^2_{PPD} > 0.945$ $R^2_{DSM} > 0.891$ $R^2_{GP2Y} > 0.983$ Comparisons with AirAssure: $R^2_{GP2Y} = 0.996$

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Table 1 (*continued*).

	Austin et al. (2015)	*n.d.*	Airtight box, V = 1 dm^3	$PM_{2.5}$	4 Shinyei PPD42NS	TSI APS 3321	Comparison for concentrations below 50 $\mu g/m^3$: $R^2_{0.75\mu m} = 0.66$ $R^2_{1.00-3.00\mu m} = 0.99$ $R^2_{6.00\mu m} = 0.86$
	Semple et al. (2013)	591 min (14 experiments of 30–60 min each)	Controlled chamber V = 3.63 m^3 (where various concentrations of second-hand smoke (SHS) were generated)	$PM_{2.5}$	Dylos DC1700	SidePak AM510	*n.d.*
Field studies	Kang et al. (2022)	Weeklong measurements (5 to 9 days) on a quarterly basis between 2017 and 2020	40 homes	O_3 and NO_2	Aeroqual SM-50 (O_3) Aeroqual S500 (NO_2) (8 devices of each)	2B Technologies Model 211 (O_3) 2B Technologies Model 405 (NO_2)	R^2 = 0.39 – 0.99 (O_3) R^2 = 0.55 – 1.00 (NO_2)
	He et al. (2021)	85 to 120 min	Two laboratory environments: (i) chamber V = 1 m^3 with generation of polystyrene latex (PSL) spheres of 0.72 and 2.00 μm and Arizona Road Dust (ARD); (ii) room-size chamber V = 25 m^3 with generation of nanosilver-based surface cleaner One residential apartment with generation of particles created by a cooking event	$PM_{2.5}$, CO_2	Foobot and AirVisual Node (AV)	TSI DustTrak DRX Model 8534 ($PM_{2.5}$) Grimm Mini-WRAS ($PM_{2.5}$) TSI Indoor Air Quality Meter Model 7545 (CO_2)	Chamber V = 1 m^3 – $PM_{2.5}$ r = 0.78 – 0.98; R^2 = 0.60 – 0.95 (Foobot) r = 0.92 – 0.99; R^2 = 0.85 – 0.98 (AV) Chamber V = 1 m^3 – CO_2 r = 0.09 – 0.56; R^2 = 0.01 – 0.31 (Foobot) r = 0.99 – 1.00; R^2 = 0.98 – 0.99 (AV) Room-size chamber V = 25 m^3 – $PM_{2.5}$ r = 0.68 – 0.96; R^2 = 0.46 – 0.91 (Foobot) r = 0.55 – 0.84; R^2 = 0.30 – 0.71 (AV) Residential apartment – $PM_{2.5}$ r = 0.98 – 0.99; R^2 = 0.97 (Foobot) r = 0.98; R^2 = 0.96 – 0.97 (AV)
	Palmisani et al. (2021)	4 days in laboratory and 5 h in field (Italy) 72 h (Spain)	Oncology hospitals	$PM_{2.5}$	Speck	FAI – Model OPC – Multichannel Optical Particle Counter Monitor and Grimm Model EDM180	R^2 = 0.34 – 0.66

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Table 1 (*continued*).

Tryner et al. (2021)	1 week (8th to 15th October 2020)	Kitchen of an occupied home	$PM_{2.5}$, PM_{10}, CO_2, CO, NO_2 and O_3	**Home Health Boxes (HHB):** Plantower PMS5003 (PM) Sensirion SCD30 (CO_2) Alphasense CO–B4 (CO) Alphasense NO2–B43F (NO_2) Alphasense OX-B431 (O_3)	Thermo Scientific TEOM 1405 (PM) LI-820 CO2 Gas Analyser (CO_2) QTrak Model 7575-X (with 982 probe) (CO) Thermo Environmental Instruments Model 42C (NO_2) and Model 49C (O_3)	r = 0.96 – 0.97 ($PM_{2.5}$) r ≥ 0.97 (CO_2) r = 0.83 – 0.97 (CO) r = 0.89 – 0.97 (NO_2) r = 0.48 – 0.78 (O_3)
Baldelli (2021)	90 to 300 min in laboratory 7 days in field: 31st March to 6th April 2019 (O_3) 14th October to 20th October 2019 ($PM_{2.5}$, CO_2 and O_3)	Residential building	$PM_{2.5}$, CO_2 and O_3	uHoo Device considering: Shinyei Kaisha PPD42-60 ($PM_{2.5}$), ELT Sensor T-110-3V (CO_2) and SGX Sensortech MICS-2714 (O_3)	TSI Optical Particle Sizer Model 3330 ($PM_{2.5}$) Vaisala GMP222 (CO_2) 2B Technologies Model 106-L (O_3)	Laboratory: $R^2 = 0.980$; $\rho = 0.982$ ($PM_{2.5}$) $R^2 = 0.972$; $\rho = 0.985$ (CO_2) $R^2 = 0.816$; $\rho = 0.571$ (O_3) Field: $\rho = 0.765{-}0.894$ ($PM_{2.5}$) $\rho = 0.721 - 0.863$ (CO_2) $\rho = 0.523 - 0.622$ (O_3)
Shen et al. (2021)	50h of calibration in living room immediately prior to the experiment (14th to 24th March 2020)	Indoor spaces from a typical apartment (kitchen, living room, study room, bedrooms and entrance) and outside of a window on the balcony connected to the living room	$PM_{2.5}$	PM-Model-II from Green Built EnvMent (Plantower PMS3003)	Thermo Scientific Model FH 62 C14	$R^2 = 0.85$ – 0.94
Coulby et al. (2021)	Multiple sample periods were conducted between 1st to 30th November 2020	Office	CO_2, $PM_{2.5}$, Temperature, RH, Light	Winsen MH-Z19B (CO_2) Plantower PMSA003i ($PM_{2.5}$) Bosch BME280 (Temperature, RH) Rohm BH1750 (Light)	Onset HOBO MX1102 (CO_2, T, RH) Onset HOBO MX1104 (T, RH, light) Air Visual Pro ($PM_{2.5}$)	r = 0.95 – 0.97 (CO_2) r = 0.23 – 0.24 ($PM_{2.5}$) r = 0.94 – 0.97 (Temperature) r = 0.98 – 0.99 (RH) r = 0.93 – 0.95 (light)

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Hegde et al. (2020)	20th to 25th May 2016 (Home I) 15th to 21st October 2016 (Home II)	Two homes	$PM_{2.5}$	Utah Modified Dylos Sensor (UMDS) based on Dylos DC100 Pro AirU (Plantower PMS3003 sensor)	Grimm 1.109, DustTrak II Aerosol Monitor 8530 and Airmetrics MiniVol	$R^2 = 0.48 - 0.98$ (AirU) $R^2 = 0.54 - 0.99$ (UMDS)
Kaliszewski et al. (2020)	28th March to 1st April 2020 (4 days)	A high occupancy living room in a flat	$PM_{2.5}$	Alphasense OPC-N3	TSI AeroTrak Handheld Particle Counter 8220	$r = 0.744 - 0.995$
Zamora et al. (2020)	12 weeks over 12 months	Home (occupied and non-smoking)	$PM_{2.5}$	AirVisual Pro, Speck and AirThinx	Thermo pDR-1200	Comparisons with Thermo pDR-1200: $R^2 = 0.89 - 0.90$ (AirVisual Pro) $R^2 = 0.27 - 0.50$ (Speck) $R^2 = 0.92 - 0.93$ (AirThinx) Comparisons between devices: $R^2 = 0.99$ (AirVisual Pro) $R^2 = 0.17$ (Speck) $R^2 = 1.00$ (AirThinx)
Manibusan and Mainelis (2020)	7 days	Three homes	$PM_{2.5}$	Air Quality Egg 2 (AQE2), BlueAir Aware, Foobot and Speck	Thermo pDR-1000, DustTrak DRX Monitor 8534 and Personal Modular Impactors (PMI)	Comparisons with pDR-1000: $R = 0.31 - 0.89$; $\rho = 0.32 - 0.50$ (AQE2) $R = 0.52 - 0.95$; $\rho = 0.33 - 0.87$ (BlueAir) $R = 0.75 - 0.99$; $\rho = 0.36 - 0.86$ (Foobot) $R = 0.45 - 0.96$; $\rho = 0.21 - 0.64$ (Speck) Comparisons with DRX: $R = 0.15 - 0.90$; $\rho = 0.32 - 0.43$ (AQE2) $R = 0.49 - 0.97$; $\rho = 0.18 - 0.82$ (BlueAir) $R = 0.56 - 0.99$; $\rho = 0.51 - 0.82$ (Foobot) $R = 0.25 - 0.99$; $\rho = 0.22 - 0.63$ (Speck) Comparisons with PMI: $R = -0.59$ (AQE2); $R = 0.91$ (BlueAir) $R = 0.94$ (Foobot); $R = 0.70$ (Speck)

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Wang et al. (2019a)	Indoor: 5 days Outdoor: 2 days	Laboratory (indoor) Nearby roadside (outdoor)	$PM_{2.5}$ and PM_{10}	5 Plantower PMS 7003	Thermo Scientific TEOM and Grimm 1.108	Comparisons with reference instruments: $R^2 = 0.90 - 0.97$ (indoor) $R^2 = 0.43 - 0.78$ (outdoor) Comparisons between Plantowers: $R^2 = 0.91 - 0.99$ (indoor) $R^2 = 0.64 - 0.92$ (outdoor)
Thomas et al. (2019)	From 10 min to 24 h	Two offices (one mechanically and one naturally ventilated) and one laboratory (containing CO_2 levels reaching 3000 ppm)	CO_2	Winsen MHZ16	Rotronic CL11	*n.d.*
Collingwood et al. (2019)	20–57 min (calibration) 2–8 months (operation inside a home or an office)	Home or office (where particles were generated by removing detritus from the bag of a vacuum cleaner and manually spread it)	$PM_{2.5}$ and TSP	25 Utah Modified Dylos Sensor (UMDS) based on Dylos DC100 Pro	Grimm 1.109	$R^2_{PreC\_PM2.5} = 0.72 - 0.80$ $R^2_{PosC\_PM2.5} = 0.72 - 0.99$ $R^2_{CC\_PM2.5} = 0.83 - 1.00$ $R^2_{PreC\_TSP} = 0.74 - 0.80$ $R^2_{PosC\_TSP} = 0.76 - 0.99$ $R^2_{CC\_TSP} = 0.83 - 0.99$
Krause et al. (2019)	7 days	3 home's living room	$PM_{2.5}$	PAM Model AS520	Grimm 1.108	$R^2 = 0.96$ (indoor) $R^2 = 0.64$ (outdoor)
Gillooly et al. (2019)	1 week — laboratory tests 9 weeks over 18 months — field tests	Various homes (in two environmental justice communities)	$PM_{2.5}$	Alphasense OPC-N2	SidePak AM510 and MicroPEM	For laboratory testing: $R^2_{OPC-N2\_SidePak} = 0.47$ $RMSE_{OPC-N2\_SidePak} = 2.94$ mg/m^3 $RMSE_{OPC-N2\_MicroPEM} = 0.52$ mg/m^3 For field testing: $R^2_{OPC-N2\_MicroPEM} = 0.82$ $RMSE_{OPC-N2\_MicroPEM} =$ 3.52 mg/m^3

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	Moreno-Rangel et al. (2018)	4 days	An occupied bedroom (floor area 10.5 m^2)	$PM_{2.5}$, CO_2 eq[f] and TVOC	5 Foobot	GrayWolf TG-502, GrayWolf IQ-410 and GrayWolf PC-3016A	Comparison with GrayWolf: r = 0.827 – 0.869 (TVOC) r = 0.397 – 0.525 (CO_2) r = 0.787 – 0.866 ($PM_{2.5}$) Comparison between Foobots: r = 0.892 – 0.974 (TVOC) r = 0.892 – 0.973 (CO_2) r = 0.576 – 0.843 ($PM_{2.5}$)
	Li et al. (2018)	*n.d.*	Woodworking shop	PM	8 Sharp GP2Y1010AU0F	SidePak AM510	Comparison with SidePak: R^2 = 0.990 – 0.997 Comparison between Sharps: R^2 = 0.993 – 0.999
	Curto et al. (2018)	5 days (Spain) and 1 week (India)	Homes (1 in Spain and 4 in India)	PM_1, $PM_{2.5}$, PM_{10} and CO	HAPEX (2 in Spain and 3 in India), TZOA-R (3 in Spain) and EL-USB-CO (3 in Spain and 3 in India)	TSI DustTrak DRX 8534 (PM_1, $PM_{2.5}$, PM_{10}) and TSI Q-Trak 7575 (CO)	Comparison with DRX: $\rho = 0.73$; CCC = 0.59[g] (HAPEX) $\rho = 0.89$; CCC = 0.62[g] (TZOA-R) $\rho = 0.68$; CCC = 0.66[h] (HAPEX) $\rho = 0.91$; CCC = 0.81[h] (TZOA-R) $\rho = 0.90$; CCC = 0.64[i] (TZOA-R) $\rho = 0.46$; $CCC_{TZOA-R} = 0.21$[j] (TZOA-R) Comparison Q-Trak/ EL-USB-CO: $\rho = 0.82$ – 0.89; CCC = 0.66 – 0.91[k] $\rho = 0.82$ – 0.94; CCC = 0.51 – 0.86[l]
	Casey et al. (2018)	3 days-outdoor co-location in CDPHE[m] Periods of 2–3 days – tests in each home 9 h – reference and U-Pod co-location	41 homes (in two communities)	CO	Alphasense CO-B4 in U-Pod sensor system	Thermo Scientific 48C CO analyser	Indoor sensor calibration: RMSE $\leq$ 0.1 ppm; $R^2 \geq 0.96$ Outdoor sensor calibration: RMSE $\leq$ 0.1 ppm; $R^2 \geq 0.80$

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Tiele et al. (2018)	*n.d.*	One office	$PM_{2.5}$, PM_{10}, TVOC, CO_2 and CO	HPMA115S0 (PM), CCS811 (TVOC), iAQ-Core C (TVOC), MiCS-VZ-89TE (TVOC), T6713 (CO_2) and LLC 110-102 (CO)	Extech CO210 (CO_2)[n]	*n.d.*
Wang et al. (2017, 2018) and Weyers et al. (2017)	2 days – calibration in a controlled environment office 3 days – calibration in an uncontrolled environment office 2 weeks - 2 classrooms in a school from Palmerston North 4 days - 3 classrooms in a school from Auckland	One office, V = 16.83 m^3 (controlled and uncontrolled environment) Two classrooms (1 school from Palmerston North) and three classrooms (1 school from Auckland)	$PM_{2.5}$, PM_{10} and CO_2	6 SKOMOBO units: Plantower PMS3003 (PM) and SenseAir K30 (CO_2)	2 TSI Q-Trak 7575 and 2 TSI DustTrak 8530	Controlled environment office: $R^2_{CO2} \geq 0.99$ $R^2_{PM2.5} = 0.82 – 0.90$ $R^2_{PM10} = 0.68 – 0.89$ Uncontrolled environment office: $R^2_{CO2} = 0.89 – 0.94$
Patel et al. (2017)	*n.d.*	Kitchen and adjoining parts of the home	$PM_{2.5}$	Sharp GP2Y1010AU0F	SidePak AM510	$R^2 = 0.713$
Zikova et al. (2017)	Indoor: 3 days Outdoor: 2 and 3 days	One home (indoor and outdoor)	$PM_{2.5}$	66 Speck	Grimm 1.109	When exposed to pulsed PM source: $R^2_{indoor} = 0.3$ (1 min) $R^2_{outdoor} = 0.1 – 0.2$ (1 min) $R^2_{outdoor} < 0.5$ (1 h) $R^2_{alldata} = 0.29$ (indoor) $R^2_{CO=0ppm} = 0.33$ (indoor) $R^2_{CO>0ppm} = 0.53$ (indoor) $R^2_{alldata} = 0.21$ (outdoor) $R^2_{CO=0ppm} = 0.06$ (outdoor) $R^2_{CO>0ppm} = 0.22$ (outdoor) Comparison between Specks: $R^2 > 0.90$ (indoor)

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	Jones et al. (2016)	Periods of 18 to 24 h (on 18 randomly selected days)	Two swine farrowing rooms	Respirable dust	Dylos DC1100	Thermo pDR-1200	$R^2 = 0.85$; $r = 0.92$ (raw) $R^2 = 0.72 - 0.74$; $r = 0.85 - 0.86$ (10-min) $R^2 = 0.62 - 0.63$; $r = 0.79$ (24-h gravimetrically)
	Ali et al. (2016)	One week for each sensor (co-location of sensors and instruments for comparison)	Laboratory and office in an educational building	CO_2	OSBSS platform[o]: SenseAir K-30	PP systems SBA-5 and Telaire 7000 series	$R^2_{CO2} = 0.969$ (lab); $R^2_{CO2} = 0.877$ (office)
	Abraham and Li (2014, 2016)	*n.d.*	*n.d.*	CO_2, VOC, CO and O_3	MG811 (CO_2), TGS2602 (VOC), MQ7 (CO) and MQ131 (O_3)	GrayWolf Direct Sense IAQ 610	*n.d.*
	Taylor and Nourbakhsh (2015)	*n.d.*	Medium-sized kitchen (cooking test); Small room (incense test)	$PM_{2.5}$	5 Speck	HHPC-6 and HHPC-6+	Comparison with HHPC-6/ HHPC-6+: $R^2 \geq 0.175$; $R^2 \geq 0.142$ (0.3 µm) $R^2 \geq 0.547$; $R^2 \geq 0.478$ (0.5 µm) $R^2 \geq 0.950$; $R^2 \geq 0.850$ (1 µm) $R^2 \geq 0.926$; $R^2 \geq 0.928$ (2 µm) $R^2 \geq 0.715$; $R^2 \geq 0.639$ (5 µm) Comparison between Specks: $R^2 \geq 0.902$
	Semple et al. (2015)	24 h	34 Homes (17 smoking and 17 non-smoking)	$PM_{2.5}$	Dylos DC1700	Sidepak AM510	$R^2 = 0.86$
	Dacunto et al. (2013, 2015)	47 to 1352 min	64 experiments in: (a) a 47 m^3 room in a small modular building; (b) the 60 m^3 kitchen/living area of an apartment; (c) a home; and (d) a motel room	$PM_{2.5}$	Dylos DC1100	SidePak AM510	$R^2 = 0.98$ CF[p] $= 0.32 - 0.70$

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	Weekly et al. (2013)	29.5 h of calibration 7.8 h of experiment measuring	Corridor of a heavily used office area	$PM_{0.5}$, $PM_{1.0}$, $PM_{2.5}$	5 Samyoung DSM501A (PM_1, $PM_{2.5}$) and 3 Shinyei PPD-20V ($PM_{0.5}$)	Met One Instruments GT-526S	Comparison with GT-526S: r = −0.03; MBE = 4.7% (PPD-20V – $PM_{0.5}$) r = 0.28; MBE = 19.4% (DSM501A - PM_1) r = 0.49; MBE = 9.5% (DSM501A - $PM_{2.5}$)

n.d. – not defined.

r — correlation coefficient; CV — coefficient of variation; R^2 — coefficient of determination; ρ — Spearman correlation; ARD — Arizona Road Dust; ATD — Arizona Test Dust; PPD — Shinyei PPD42NS; DSM — Samyoung DSM501A; GP2Y — Sharp GP2Y1010AU0F; UMDS — Utah Modified Dylos Sensor; PreC — new UMDS pre-calibration equation; PosC — contaminated UMDS post-calibration equation; CC — cleaned UMDS clean calibration equation; CCC — concordance correlation coefficient; VOC — volatile organic compounds; SHS — second-hand smoke; TSP — Total Suspended Particles; UMDS — Utah Modified Dylos Sensor.

[a] Instruments used to compare with low-cost sensors/devices.

[b] Sources included recreational combustion (candles, cigarettes, incense), mineral sources (unfiltered ultrasonic humidifier, Arizona Test Dust, dust mop) and cooking activities (heating oil in a steel wok on gas or electric burners, frying bacon, toasting 4 slices of bread in a toaster oven, and stir-frying green beans in oil on a gas burner, heating water in a covered pot on a gas stove, heating a gas oven, cooking a pizza in the gas oven, cooking pancakes on a lightly oiled pan over medium heat, and toasting bread in a well-used electric toaster oven).

[c] Thermo pDR-1500 and MetOne BT-645 were considered research monitors that allowed to adjust the scaling factor that relates instrument response to mass concentration and were also compared with reference instruments.

[d] Polydisperse aerosols included salt, welding fume, and Arizona road dust at concentrations up to 8500 $\mu g/m^3$.

[e] Thermo pDR-1500 was considered as both low-cost device and instrument for comparison.

[f] CO_2 equivalent.

[g] 5-min correlations for $PM_{2.5}$.

[h] 1-h correlations for $PM_{2.5}$.

[i] 1-h correlations for PM_1.

[j] 1-h correlations for PM_{10}.

[k] 5-min correlations for CO.

[l] 1-h correlations for CO.

[m] CDPHE — Colorado Department of Public Health and the Environment.

[n] No instruments for comparison were used for TVOC and PM.

[o] OSBSS — Open Source Building Science Sensors.

[p] CF — calibration factor.

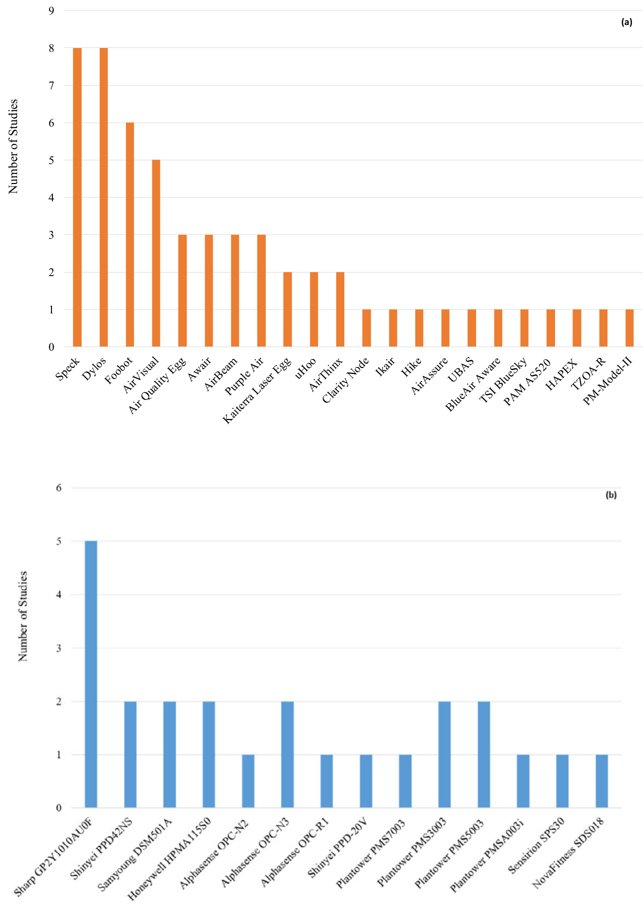

Fig. 3. Number of laboratory and field studies reviewed by: (a) low-cost PM devices (orange bars) and (b) low-cost PM sensors (blue bars). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The low-cost technologies available and applied are critically important, thus, distinct technologies (depending on the pollutant analysed) were identified in the 42 reviewed studies. Fig. 3 shows the number of laboratory and field studies reviewed by low-cost PM devices (orange bars) and PM sensors (blue bars). The same analysis (using a figure) was not performed for the remaining pollutants as they were not as representative as PM.

Regarding low-cost sensing technology for PM measurements, the reviewed studies (especially from the laboratory) tested mostly low-cost devices (entire developed unit with all components encompassed, usually commercially available for any end-user). According to Fig. 3, the older devices on the market, namely Speck and different versions of Dylos were the commercially available low-cost devices mostly used (with 8 studies each). In the same way, Sharp GP2Y1010AU0F (Sharp Corporation, Japan) was the low-cost sensor mostly used (by 5 studies). According to the commercially available device specifications, it was possible to establish some connections between PM devices and the chosen low-cost sensors. Accordingly, Sharp GP2Y1010AU0F was the sensor used by Foobot, AirAssure, UBAS and HAPEX, while different models of Plantowers were adopted in the manufacturing of AirQuality Egg, Kaiterra Laser Egg, PurpleAir, Clarity Node, TSI BlueSky and PM-Model-II. On the other hand, Dylos and AirVisual Pro produce their sensors in the devices.

Regarding the low-cost technology for evaluating other pollutants (gaseous), it was clear that all authors used sensors (instead of devices) and a wide range of them from various companies/manufacturers were chosen (e.g. Telaire, Figaro, Alphasense, among others). Also, few authors included TVOC/VOC, O_3 and NO_2, in their studies, which could be related to the measurements' complexity. Moreover, the low-cost device/sensor choice should be made carefully since some sensors do not precisely measure the pollutant they describe, and its concentration is inferred based on another pollutant (Moreno-Rangel et al., 2018).

Besides, some authors built their own devices, integrating different air quality module sensors and other components as data acquisition hardware, wireless or Bluetooth communication, among others (Ali et al., 2016; Caron et al., 2016; Casey et al., 2018; Hegde et al., 2020; Tiele et al., 2018; Tryner et al., 2021; Weekly et al., 2013). Wang et al. (2017, 2018) and Weyers et al. (2017) established the SKOMOBO (SKOol MOnitoring BOx), a low-cost, low power consumption

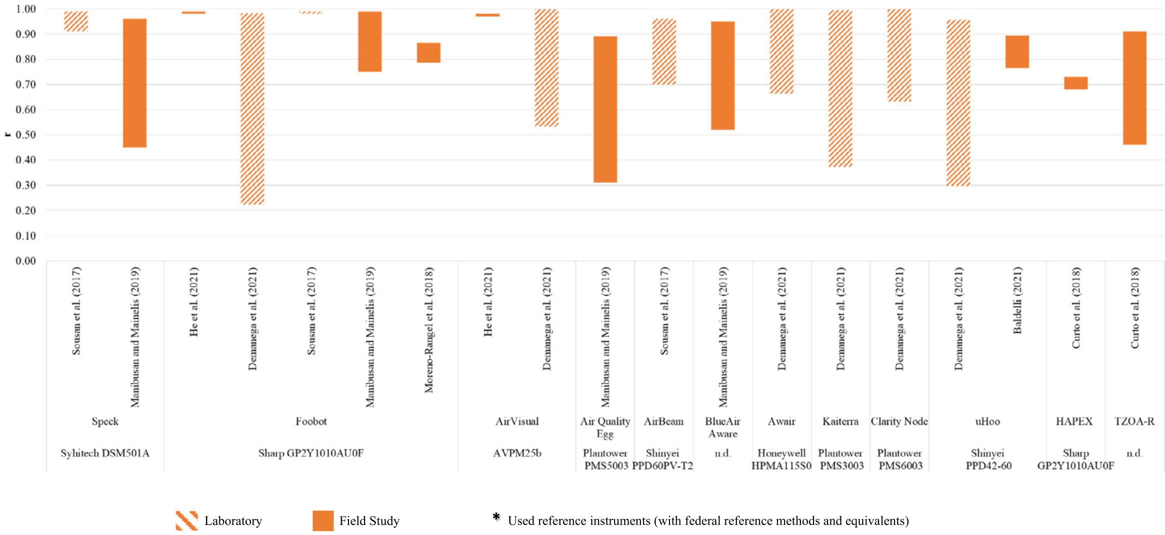

Fig. 4. Correlation coefficient (r) recorded by PM low-cost devices from the different studies (laboratory and field) included in the present review.

indoor environment monitoring device. In addition, Tryner et al. (2021) assembled a Home Health Boxes (HHB) to measure indoor pollutants concentrations using commercially low-cost modules, while a small custom printed circuit board with low-cost sensors (AirU), developed at the University of Utah, were tested by Hegde et al. (2020). Moreover, a low-cost wireless sensor network was also developed and deployed by Li et al. (2018), Hojaiji et al. (2017), Patel et al. (2017) and Abraham and Li (2014, 2016).

3.2. Sensors comparison

Different air quality instruments were used for comparison to evaluate the low-cost sensors/devices adopted in the reviewed studies. Still, according to the list provided by USEPA (2017) for instruments that use federal reference methods and equivalents, nine studies resorted to such equipment — Thermo Scientific TEOM (Singer and Delp, 2018; Tryner et al., 2021; Wang et al., 2019a, 2020), Grimm Model EDM180 (Palmisani et al., 2021) and Thermo Scientific Model FH 62 C14 (Shen et al., 2021) for PM, Thermo Scientific 48C CO analyser (Casey et al., 2018) for CO, 2B Technologies Model 211 (Kang et al., 2022), Thermo Environmental Instruments Model 49C (Tryner et al., 2021) and 2B Technologies Model 106-L (Baldelli, 2021) for O_3 and 2B Technologies Model 405 (Kang et al., 2022) and Thermo Environmental Instruments Model 42C (Tryner et al., 2021) for NO_2 . Besides, several other instruments adopted in these studies have been intensively used in air quality investigations, and have already been scientifically validated (research-grade instruments), such as a different version of Grimm, GrayWolf, TSI DustTrak and Q-Trak, SidePak, among others. Interestingly, some of the low-cost IAQ monitoring technologies mentioned by some authors were also used as instruments for comparison by others, namely the Dylos, Alphasense OPC-N2, TSI AirAssure, AirVisual Pro, MicroPEM and Personal Modular Impactors. Accordingly, there is a variation in both prices and quality of equipment, ranging from a few hundred (e.g. Rotronic CL11) to tens of thousands of euros (e.g. Thermo Scientific TEOM). There is no standard method or strategy to compare low-cost sensing technology with other, including regarding the type of instruments for comparison, but reference instruments (in the legally binding sense of the term) should preferably be used instead of research-grade instruments and low-cost sensing technology since their quality is not as high as the first one. Another consideration to be made is the lack of information on the characterisation of sensors and sensor system performance by the manufacturers (Lewis et al., 2018). The method used for the calibration is generally considered confidential information by the majority of low-cost sensors manufacturers, and scarce information can be found (Karagulian et al., 2019).

Figs. 4–7 show the correlation coefficient (r) and the coefficient of determination (R^2) recorded by the different studies (laboratory and field) in the present review using PM low-cost sensors/devices. Few studies did not report or reported other performance indexes, evaluating the low-cost sensor calibration mostly qualitatively (Table 1).

In general, it was possible to verify that the low-cost sensors/devices evaluated by the laboratory studies had high performance. Except for some devices and sensors evaluated by Zou et al. (2020, 2021a,b) and Demanega et al. (2021), which presented a wide range in their performance indexes, laboratory studies showed a correlation coefficient or R^2 higher than about 0.50 for both PM low-cost sensors and devices. Also, Baldelli (2021) presented better performance indexes between low-cost devices and instruments used for comparison in the laboratory than in the field. Furthermore, these conclusions were expected since laboratory conditions were controlled and, consequently, more likely to give better

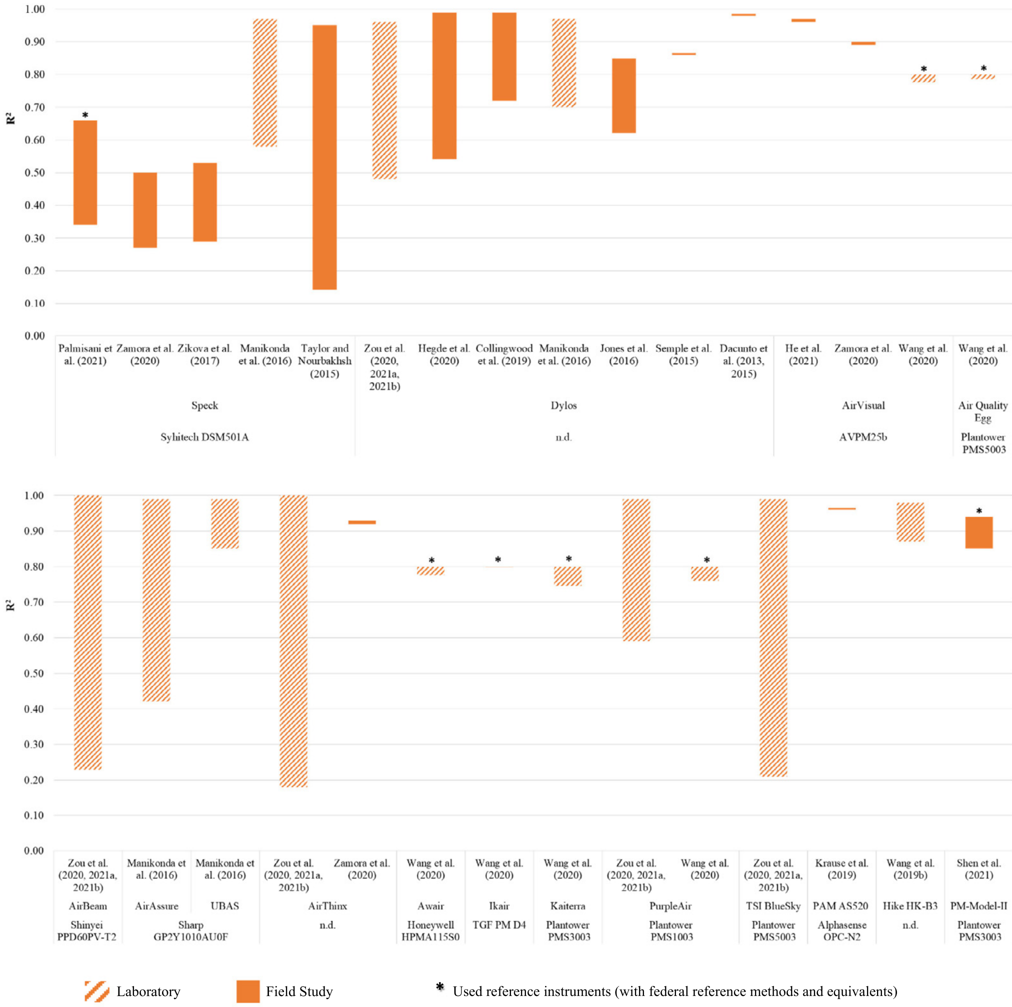

Fig. 5. Coefficient of determination (R^2) recorded by PM low-cost devices from the different studies (laboratory and field) included in the present review.

comparison results. However, opposite results were achieved by one study carried out in both field and laboratory that tested low-cost devices since better comparisons were observed in field measurements (He et al., 2020). These results could be explained by the fact that different sources of particulates were studied in the laboratory (polystyrene latex spheres, ARD, nanosilver-based surface cleaner) and field (cooking event). Nevertheless, these low-cost sensors/devices should be evaluated under real conditions since they might not behave similarly. Moreover, to improve their accuracy, Sousan et al. (2017) recommended a site-specific calibration and Hojaiji et al. (2017) and Manikonda et al. (2016) indicated the need for calibration under different temperature and relative humidity conditions.

In addition, field studies that also evaluated low-cost sensors/devices outdoors achieved the expected behaviour, having found higher performances for indoor measurements ($R^2 = 0.30 – 0.96$) than for those outdoors ($R^2 = 0.10 – 0.80$).

Regarding the comparison between sensors/devices, it was not possible to withdraw solid conclusions about the performance of those only studied by one author (e.g. AirAssure, UBAS, Ikair, Clarity Node, TSI BlueSky, HAPEX for PM devices and Plantower PMS7003, Alphasense OPC-N2, Shinyei PPD-20V for PM sensors). This achievement is even more evident in the studies that evaluated gaseous pollutants. Concerning those studied by more than one author, different results were obtained, most probably due to the different instruments used for comparison (from other low-cost devices to reference instruments), sampling area and study conditions. Nevertheless, Dylos, Foobot and AirVisual Pro (Figs. 4–5) presented moderate to high correlations (with fewer variations in r and R^2) in both laboratory and field studies. Moreover, it was found that different versions of Dylos can be valid instruments in providing instantaneous feedback and context on mass particle levels in home and work situations (Dacunto et al., 2013, 2015; Semple et al., 2015) and be a useful tool for air quality studies (Collingwood et al., 2019). However, Dylos presented a non-linear response, becoming less responsive to PM levels increases (Manikonda et al., 2016; Semple et al., 2013, 2015). Similarly, Foobot presented

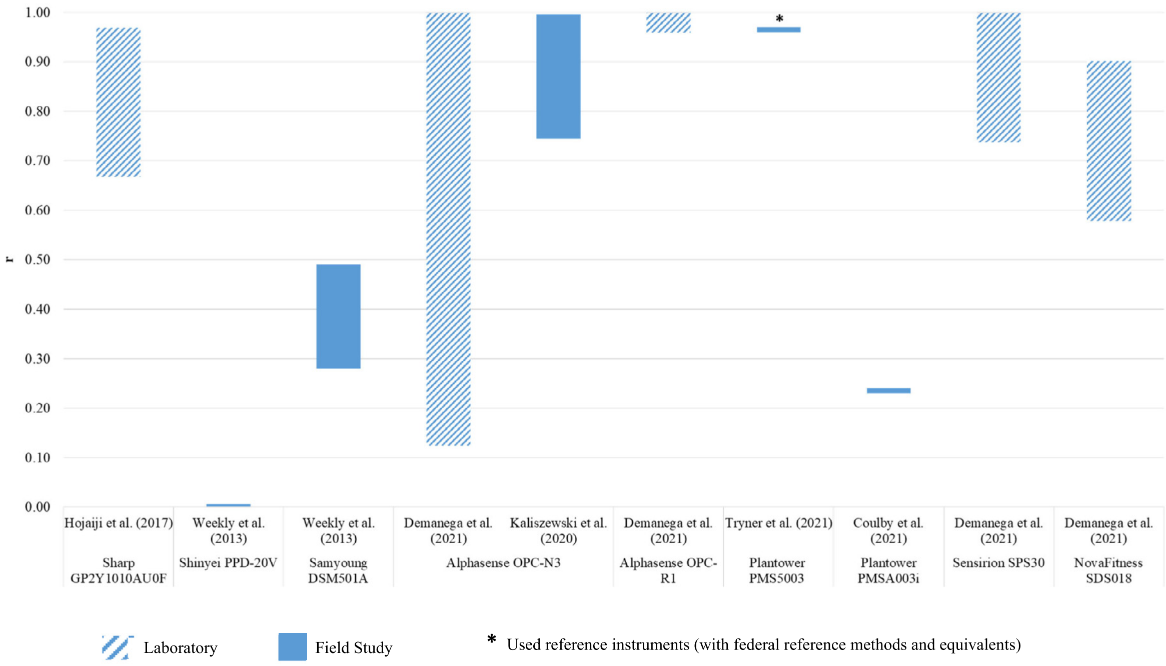

Fig. 6. Correlation coefficient (r) recorded by PM low-cost sensors from the different studies (laboratory and field) included in the present review.

promising results, especially when compared to the other devices evaluated by the same studies (Manibusan and Mainelis, 2020; Singer and Delp, 2018; Sousan et al., 2017). However, Moreno-Rangel et al. (2018) concluded that there was a significant agreement between Foobot and instrument used for comparison for TVOC (r = 0.827 – 0.869) and $PM_{2.5}$ (r = 0.787 – 0.866) data, but estimated misleading CO_2 concentrations (r = 0.397 – 0.525), which could have been due to the inferred CO_2 concentrations (through TVOC sensor; Foobot has no CO_2 sensor). AirVisual Pro exhibited high accuracy with minimal drift over the year period (Zamora et al., 2020) and the most consistent response across different residential sources (Wang et al., 2020). On the other hand, results with Speck were slightly worse than the other studied devices. Singer and Delp (2018) stated that Speck did not consistently respond to PM source emissions, while Zikova et al. (2017) suggested that this device appeared suitable for PM monitoring programmes, depending on the required performance to meet the goals of the study.

Regarding PM low-cost sensors (Figs. 6–7), data collected from Sharp GP2Y1010AU0F and Shinyei PPD42NS sensors in indoor environments agreed well with the measurements from the instruments used for comparison. Austin et al. (2015) stated that each sensor required an exclusive response curve and concluded that Shinyei PPD42NS modules without modifications might not be suitable for capturing the full range of higher indoor exposures in homes of smokers or where biomass is the primary source of energy for heating or cooking.

Summarising and analysing the studies that compared the performance of low-cost sensors/devices with reference instruments, it is possible to observe very good results ($R^2 = 0.90$–0.97, $R^2 = 0.75$–0.80 and r = 0.96–0.97) for Plantower PMS 7003 (Wang et al., 2019a), six low-cost commercially available devices (Wang et al., 2020) and Plantower PMS 5003 from HHB units (Tryner et al., 2021) with Thermo Scientific TEOM for PM, respectively; $R^2 = 0.34$–0.66 for Speck (Palmisani et al., 2021) with Grimm Model EDM180; $R^2 = 0.85$–0.94 for PM-Model-II (Shen et al., 2021) with Thermo Scientific Model FH 62 C14; $R^2 = 0.96$ between Alphasense CO-B4 and Thermo Scientific 48C for CO (Casey et al., 2018); $R^2 = 0.39$–0.99 for Aeroqual SM-50 and $R^2 = 0.55$–1.00 for Aeroqual S500 (Kang et al., 2022) with 2B Technologies Model 211 and 2B Technologies Model 405 respectively; $\rho = 0.523 - 0.622$ for uHoo (Baldelli, 2021) with 2B Technologies Model 106-L; and r = 0.48–0.78 for Alphasense OX-B431 and r = 0.89–0.97 for Alphasense NO2–B43F from HHB units (Tryner et al., 2021) with Thermo Environmental Instruments Model 49C and Model 42C, respectively).

3.3. Challenges, trends and future direction

From the main outcomes of the reviewed studies, it is possible to conclude that some low-cost sensors/devices showed good performances and can be used in indoor environments. However, the coefficient of determination (R^2) and the correlation coefficient (r - Pearson correlation and ρ - Spearman's correlation) were the performance indexes mainly used, reflecting the low-cost sensing technology precision but not necessarily the accuracy. Furthermore, information about the accuracy and precision of either low-cost sensors and devices or research-grade and reference instruments given by

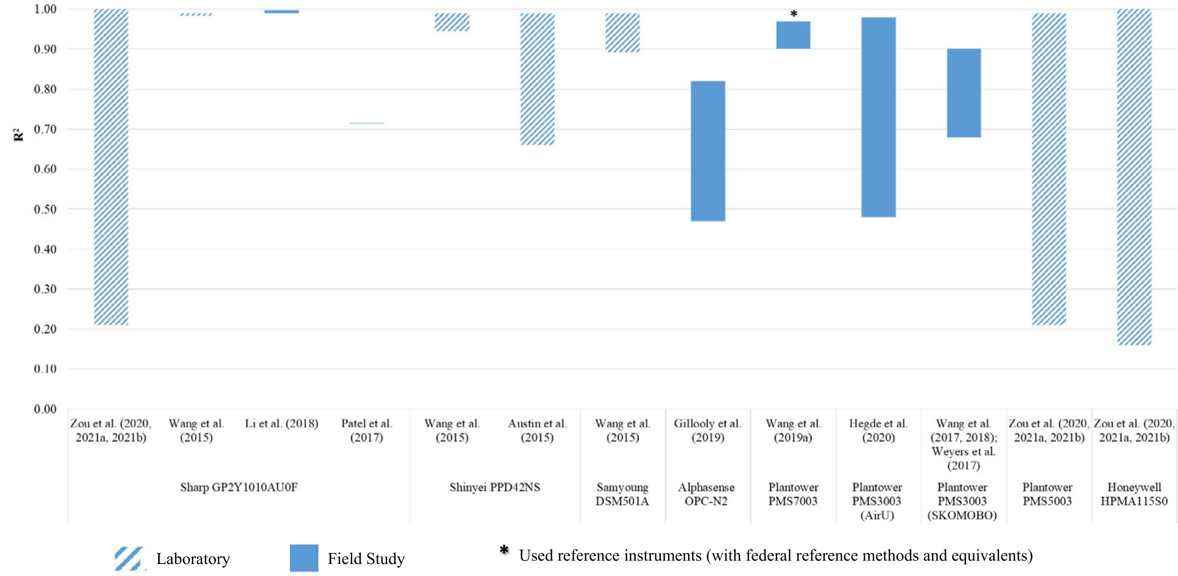

Fig. 7. Coefficient of determination (R^2) recorded by PM low-cost sensors from the different studies (laboratory and field) included in the present review.

the manufacturers was not always available and easy to find (Tables S2-S5 in Supplementary Material). Nevertheless, a significant part of the low-cost sensing technology evaluated by the reviewed studies can be used for qualitative air quality understanding, helping provide some context and valuable insights into indoor air and managing personal exposure (Hegde et al., 2020). Thus, it can be a ready-to-use, powerful and helpful tool by allowing the end-users to be aware of eventual high levels of pollutants, enabling them to apply simple mitigation measures. On the other hand, it can also be considered for quantitative analysis (based on the ranges) after applying calibration models (Baldelli, 2021; Shen et al., 2021). However, more studies using federal reference and equivalent methods (instead of other instruments) should be performed to evaluate their viability. In addition, caution is needed in its use because it is not yet able to achieve the same quality as the reference instruments and measure extreme levels. Therefore, one of the major limitations encountered that disabled the possibility of withdrawing solid conclusions regarding the sensors/devices used was the lack of a standard calibration methodology. Several different devices/sensors and instruments used for comparison, different study durations, performance indexes, settings and conditions in laboratory or field conditioned a clear interpretation. All these factors play a fundamental role in the performance of air quality monitoring technology (Zong et al., 2021). Moreover, Zhang and Srinivasan (2020) conducted a systematic review of air quality sensors, guidelines, and measurement studies for IAQ management and pointed out the differences in the equipment chosen by the studies and in the sampling protocols, along with the approach of analysing the data as the main causes for the lack of a uniform method for data quality and uncertainties control. Zamora et al. (2020) stated that, despite all these factors, data quality varies by brand and device, whereby an individual evaluation of each is essential. Thus, low-cost devices information must be the most clear, open and transparent as possible regarding the sensors encompassed, the calibrations performed, and under what conditions the calibrations should be done (Giordano et al., 2021). Furthermore, low-cost sensors must be calibrated regularly to maintain their reliability; otherwise, their measurements could drift and become less accurate over time (Tancev, 2021). Manibusan and Mainelis (2020) suggested that low-cost devices must be calibrated for particular locations and applications. Moreover, Gillooly et al. (2019) concluded that a trimonthly calibration is recommended for data interpretation, but exceeding this frequency could be challenging if not made simultaneously with the application of statistical methods to account for sensor degradation. In turn, Zamora et al. (2020) stated that monthly calibrations led to the highest accuracies, but almost the same level of accuracy could be achieved with one or two calibrations (depending on the device). Thus, a main conclusion that can be drawn is the need for regular on-field calibration between the low-cost sensing technology under study and the instrument used for comparison, even if a prior calibration has been done previously in the laboratory (simulating real conditions). Therefore, the bias possibly resulting from environmental factors could be quantified, helping the validation of the technology. In addition, to give robustness to the experiment, the instruments used for comparison should be, whenever possible, equipment that uses federal reference and/or equivalent methods for indoor air quality monitoring. Accordingly, Coulby et al. (2021) suggested increasing the accuracy of sensors resorting to reference instruments. Therefore, the definition of a standardised protocol for evaluation and calibration of low-cost sensors/devices after their purchase is of utmost importance. In short, the development and implementation of an intelligent and efficient model able to calibrate the devices continuously on-field learning from the data being measured presents a new future trend.

Another relevant point evidenced in this review is the need to design and choose the low-cost devices/sensors according to the purpose of each study since the indoor spaces, settings and environmental conditions influence their behaviour and performance. For the decision of the more appropriate low-cost sensing technology, different experiments in various scenarios should be considered whenever possible (Jiang et al., 2021). Thus, either scientific community or common end-users could make more conscious and targeted decisions regarding the sensor' selection.

4. Conclusions

There is a fair number of studies containing information about the use of low-cost sensor in indoor environments that compared them with research-grade or reference instruments. From 2013 until 2021, 42 studies were found (corresponding to 46 publications). The vast majority of the reviewed studies focused on evaluating PM, but other pollutants such as CO_2, TVOC, VOC, O_3, NO_2 and CO were also addressed. Nine studies reported using reference instruments (legally binding term) for comparison with low-cost sensing technology. In contrast, the remaining reviewed studies chose other instruments, either scientifically validated or even other low-cost devices.

Among the reviewed devices, Foobot, AirVisual Pro and different versions of Dylos were the most reliable. Regarding sensor modules, Sharp GP2Y1010AU0F was the option for most of the authors that evaluated PM, being reported a good agreement with the instruments used for comparison.

Moreover, the air quality low-cost sensors/devices tested presented adequate reliability, especially for qualitative air quality analysis in indoor sampling areas. However, it should be noted that the conditions under which each study was carried out and the instruments used for comparison were different, so their choice and use should be made with caution, considering the purpose and conditions under which the study will take place. In addition, a regular on-field calibration between the low-cost sensing technology and a reference instrument is highly recommended. Also, implementing an intelligent model able to calibrate the devices continuously with data learning presents a new future trend. The use of low-cost sensing technology to monitor IAQ is encouraged, as it has several advantages such as lower costs and, less noise, lower electricity consumption, among others. Also, the use of this technology is not yet totally independent because reference instruments are still needed for validation and calibration purposes. It is recommended to increase the number of studies, namely in other facilities and with new low-cost sensors/devices, that are arising with more frequency, as well as for a more extended measurement period and to understand if it is possible to apply a validation/calibration process to enable low-cost sensors/devices to work without the need of reference instruments.

CRediT authorship contribution statement

Juliana P. Sá: Methodology, Investigation, Data Curation, Writing - original daft, Visualization. **Maria Conceição M. Alvim-Ferraz:** Conceptualization, Writing - review & editing. **Fernando G. Martins:** Conceptualization, Writing – review & editing. **Sofia I.V. Sousa:** Conceptualization, Methodology, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eti.2022.102551.

References

Abraham, S., Li, X., 2014. A cost-effective wireless sensor network system for indoor air quality monitoring applications. Procedia Comput. Sci. 34, 165–171. http://dx.doi.org/10.1016/j.procs.2014.07.090.

Abraham, S., Li, X., 2016. Design of a low-cost wireless indoor air quality sensor network system. Int. J. Wirel. Inf. Netw. 23, 57–65. http://dx.doi.org/10.1007/s10776-016-0299-y.

Afshar-Mohajer, N., Zuidema, C., Sousan, S., et al., 2018. Evaluation of low-cost electro-chemical sensors for environmental monitoring of ozone, nitrogen dioxide, and carbon monoxide. J. Occup. Environ. Hyg. 15, 87–98. http://dx.doi.org/10.1080/15459624.2017.1388918.

Alavi-Shoshtari, M., Williams, D.E., Salmond, J.A., et al., 2013. Detection of malfunctions in sensor networks. Environmetrics 24, 227–236. http://dx.doi.org/10.1002/env.2206.

Ali, A.S., Zanzinger, Z., Debose, D., et al., 2016. Open Source Building Science Sensors (OSBSS): A low-cost Arduino-based platform for long-term indoor environmental data collection. Build. Environ. 100, 114–126. http://dx.doi.org/10.1016/j.buildenv.2016.02.010.

Austin, E., Novosselov, I., Seto, E., et al., 2015. Laboratory evaluation of the Shinyei PPD42NS low-cost particulate matter sensor. PLoS One 10, e0137789. http://dx.doi.org/10.1371/journal.pone.0137789.

Bai, L., Huang, L., Wang, Z., et al., 2020. Long-term field evaluation of low-cost particulate matter sensors in Nanjing. Aerosol Air Qual. Res. 20, 242–253. http://dx.doi.org/10.4209/aaqr.2018.11.0424.

Baldelli, A., 2021. Evaluation of a low-cost multi-channel monitor for indoor air quality through a novel, low-cost, and reproducible platform. Meas.: Sensors 17, 100059. http://dx.doi.org/10.1016/j.measen.2021.100059.

Basińska, M., Michałkiewicz, M., Ratajczak, K., 2019. Impact of physical and microbiological parameters on proper indoor air quality in nursery. Environ. Int. 132, 105098. http://dx.doi.org/10.1016/j.envint.2019.105098.

Bluyssen, P.M., 2013. The Healthy Indoor Environment: How to Assess Occupants' Well-Being in Buildings. Routledge, London, http://dx.doi.org/10.4324/9781315887296.

Branco, P.T.B.S., Alvim-Ferraz, M.C.M., Martins, F.G., et al., 2014. Indoor air quality in urban nurseries at Porto city: Particulate matter assessment. Atmos. Environ. 84, 133–143. http://dx.doi.org/10.1016/j.atmosenv.2013.11.035.

Caron, A., Redon, N., Thevenet, F., et al., 2016. Performances and limitations of electronic gas sensors to investigate an indoor air quality event. Build. Environ. 107, 19–28. http://dx.doi.org/10.1016/j.buildenv.2016.07.006.

Casey, J.G., Ortega, J., Coffey, E., et al., 2018. Low-cost measurement techniques to characterize the influence of home heating fuel on carbon monoxide in Navajo homes. Sci. Total Environ. 625, 608–618. http://dx.doi.org/10.1016/j.scitotenv.2017.12.312.

Chen, L.W.A., Olawepo, J.O., Bonanno, F., et al., 2020. Schoolchildren's exposure to PM2.5: a student club–based air quality monitoring campaign using low-cost sensors. Air Qual. Atmos. Health http://dx.doi.org/10.1007/s11869-020-00815-9.

Chojer, H., Branco, P.T.B.S., Martins, F.G., et al., 2020. Development of low-cost indoor air quality monitoring devices: Recent advancements. Sci. Total Environ. 727, 138385. http://dx.doi.org/10.1016/j.scitotenv.2020.138385.

Collingwood, S., Zmoos, J., Pahler, L., et al., 2019. Investigating measurement variation of modified low-cost particle sensors. J. Aerosol Sci. 135, 21–32. http://dx.doi.org/10.1016/j.jaerosci.2019.04.017.

Coulby, G., Clear, A.K., Jones, O., et al., 2021. Low-cost, multimodal environmental monitoring based on the Internet of Things. Build. Environ. 203, 108014. http://dx.doi.org/10.1016/j.buildenv.2021.108014.

Curto, A., Donaire-Gonzalez, D., Barrera-Gómez, J., et al., 2018. Performance of low-cost monitors to assess household air pollution. Environ. Res. 163, 53–63. http://dx.doi.org/10.1016/j.envres.2018.01.024.

Dacunto, P.J., Cheng, K.-C., Acevedo-Bolton, V., et al., 2013. Real-time particle monitor calibration factors and PM 2.5 emission factors for multiple indoor sources. Environ. Sci.: Process. Impacts 15, 1511–1519. http://dx.doi.org/10.1039/c3em00209h.

Dacunto, P.J., Klepeis, N.E., Cheng, K.-C., et al., 2015. Determining PM 2.5 calibration curves for a low-cost particle monitor: common indoor residential aerosols. Environ. Sci.: Process. Impacts 17, 1959–1966. http://dx.doi.org/10.1039/c5em00365b.

Demanega, I., Mujan, I., Singer, B.C., et al., 2021. Performance assessment of low-cost environmental monitors and single sensors under variable indoor air quality and thermal conditions. Build. Environ. 187, 107415. http://dx.doi.org/10.1016/j.buildenv.2020.107415.

Dominici, F., Peng, R.D., Bell, M.L., et al., 2006. Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases. JAMA 295, 1127–1134. http://dx.doi.org/10.1001/jama.295.10.1127.

Fanti, G., Borghi, F., Spinazzè, A., et al., 2021. Features and practicability of the next-generation sensors and monitors for exposure assessment to airborne pollutants: A systematic review. Sensors 21, 4513.

Fishbain, B., Lerner, U., Castell, N., et al., 2017. An evaluation tool kit of air quality micro-sensing units. Sci. Total Environ. 575, 639–648. http://dx.doi.org/10.1016/j.scitotenv.2016.09.061.

Forouzanfar, M.H., Alexander, L., Anderson, H.R., et al., 2015. 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 2013. Lancet 386, 2287–2323. http://dx.doi.org/10.1016/S0140-6736(15)00128-2.

Gillooly, S.E., Zhou, Y., Vallarino, J., et al., 2019. Development of an in-home, real-time air pollutant sensor platform and implications for community use. Environ. Pollut. 244, 440–450. http://dx.doi.org/10.1016/j.envpol.2018.10.064.

Giordano, M.R., Malings, C., Pandis, S.N., et al., 2021. From low-cost sensors to high-quality data: A summary of challenges and best practices for effectively calibrating low-cost particulate matter mass sensors. J. Aerosol Sci. 158, 105833. http://dx.doi.org/10.1016/j.jaerosci.2021.105833.

Han, Y., Li, X., Zhu, T., et al., 2016. Characteristics and relationships between indoor and outdoor PM2.5 in Beijing: A residential apartment case study. Aerosol Air Qual. Res. 16, 2386–2395. http://dx.doi.org/10.4209/aaqr.2015.12.0682.

He, R., Han, T., Bachman, D., et al., 2020. Evaluation of two low-cost PM monitors under different laboratory and indoor conditions. Aerosol Sci. Technol. 55, 316–331. http://dx.doi.org/10.1080/02786826.2020.1851649.

He, R., Han, T., Bachman, D., et al., 2021. Evaluation of two low-cost PM monitors under different laboratory and indoor conditions. Aerosol Sci. Technol. 55, 316–331. http://dx.doi.org/10.1080/02786826.2020.1851649.

Hegde, S., Min, K.T., Moore, J., et al., 2020. Indoor household particulate matter measurements using a network of low-cost sensors. Aerosol Air Qual. Res. 20, 381–394. http://dx.doi.org/10.4209/aaqr.2019.01.0046.

Hetland, R.B., Refsnes, M., Myran, T., et al., 2000. Mineral and/or metal content as critical determinants of particle-induced release of IL-6 and IL-8 from A549 cells. J. Toxicol. Environ. Health A 60, 47–65. http://dx.doi.org/10.1080/009841000156583.

Hojaiji, H., Kalantarian, H., Bui, A.A.T., et al., 2017. Temperature and humidity calibration of a low-cost wireless dust sensor for real-time monitoring. In: 2017 IEEE Sensors Applications Symposium (SAS). IEEE Staff, United States. http://dx.doi.org/10.1109/SAS.2017.7894056, 2017.

Howard, J., Murashov, V., Cauda, E., et al., 2022. Advanced sensor technologies and the future of work. Am. J. Ind. Med. 65, 3–11. http://dx.doi.org/10.1002/ajim.23300.

Jayaratne, R., Liu, X., Ahn, K.-H., et al., 2020. Low-cost PM2.5 sensors: an assessment of their suitability for various applications. Aerosol Air Qual. Res. 20, 520–532. http://dx.doi.org/10.4209/aaqr.2018.10.0390.

Jiang, Y., Zhu, X., Chen, C., et al., 2021. On-field test and data calibration of a low-cost sensor for fine particles exposure assessment. Ecotoxicol. Environ. Saf. 211, 111958. http://dx.doi.org/10.1016/j.ecoenv.2021.111958.

Jones, S., Anthony, T.R., Sousan, S., et al., 2016. Evaluation of a low-cost aerosol sensor to assess dust concentrations in a swine building. Ann. Occup. Hyg. 60, 597–607. http://dx.doi.org/10.1093/annhyg/mew009.

Jovanović, M., Vučićević, B., Turanjanin, V., et al., 2014. Investigation of indoor and outdoor air quality of the classrooms at a school in Serbia. Energy 77, 42–48. http://dx.doi.org/10.1016/j.energy.2014.03.080.

Jovašević-Stojanović, M., Bartonova, A., Topalović, D., et al., 2015. On the use of small and cheaper sensors and devices for indicative citizen-based monitoring of respirable particulate matter. Environ. Pollut. 206, 696–704. http://dx.doi.org/10.1016/j.envpol.2015.08.035.

Kaduwela, A.P., Kaduwela, A.P., Jrade, E., et al., 2019. Development of a low-cost air sensor package and indoor air quality monitoring in a california middle school: Detection of a distant wildfire. J. Air Waste Manage. Assoc. 69, 1015–1022. http://dx.doi.org/10.1080/10962247.2019.1629362.

Kalimeri, K.K., Saraga, D.E., Lazaridis, V.D., et al., 2016. Indoor air quality investigation of the school environment and estimated health risks: Two-season measurements in primary schools in Kozani, Greece. Atmos. Pollut. Res. 7, 1128–1142. http://dx.doi.org/10.1016/j.apr.2016.07.002.

Kaliszewski, M., Włodarski, M., Młyńczak, J., et al., 2020. Comparison of low-cost particulate matter sensors for indoor air monitoring during COVID-19 lockdown. Sensors (Basel) 20, http://dx.doi.org/10.3390/s20247290.

Kang, Y., Aye, L., Ngo, T.D., et al., 2021b. Performance evaluation of low-cost air quality sensors: A review. Sci. Total Environ. 151769. http://dx.doi.org/10.1016/j.scitotenv.2021.151769.

Kang, K., Kim, T., Kim, H., 2021a. Effect of indoor and outdoor sources on indoor particle concentrations in South Korean residential buildings. J. Hard Mater. 416, 125852. http://dx.doi.org/10.1016/j.jhazmat.2021.125852.

Kang, I., McCreery, A., Azimi, P., et al., 2022. Indoor air quality impacts of residential mechanical ventilation system retrofits in existing homes in Chicago, IL. Sci. Total Environ. 804, 150129. http://dx.doi.org/10.1016/j.scitotenv.2021.150129.

Karagulian, F., Barbiere, M., Kotsev, A., et al., 2019. Review of the performance of low-cost sensors for air quality monitoring. Atmosphere 10 (506), http://dx.doi.org/10.3390/atmos10090506.

Karimi, H., Soffianian, A., Mirghaffari, N., et al., 2016. Determining air pollution potential using geographic information systems and multi-criteria evaluation: A case study in Isfahan Province in Iran. Environ. Process. 3, 229–246. http://dx.doi.org/10.1007/s40710-016-0136-4.

Khajehzadeh, I., Vale, B., 2017. How new zealanders distribute their daily time between home indoors, home outdoors and out of home. Kōtuitui: N. Z. J. Soc. Sci. Online 12, 17–31.

Krause, A., Zhao, J., Birmili, W., 2019. Low-cost sensors and indoor air quality: A test study in three residential homes in Berlin, Germany. Gefahrstoffe - Reinhalt. Luft 79, 87–92.

Kumar, P., Martani, C., Morawska, L., et al., 2016a. Indoor air quality and energy management through real-time sensing in commercial buildings. Energy Build. 111, 145–153. http://dx.doi.org/10.1016/j.enbuild.2015.11.037.

Kumar, P., Skouloudis, A.N., Bell, M., et al., 2016b. Real-time sensors for indoor air monitoring and challenges ahead in deploying them to urban buildings. Sci. Total Environ. 560–561, 150–159. http://dx.doi.org/10.1016/j.scitotenv.2016.04.032.

Leung, D.Y., 2015. Outdoor-indoor air pollution in urban environment: challenges and opportunity. Front. Environ. Sci. 2 (69), http://dx.doi.org/10.3389/fenvs.2014.00069.

Leung, M., Chan, A.H., 2006. Control and management of hospital indoor air quality. Med. Sci. Monit. 12, SR17–SR23.

Lewis, A., Peltier, W.R., von Schneidemesser, E., 2018. Low-cost sensors for the measurement of atmospheric composition: overview of topic and future applications.

Li, J., Li, H., Ma, Y., et al., 2018. Spatiotemporal distribution of indoor particulate matter concentration with a low-cost sensor network. Build. Environ. 127, 138–147. http://dx.doi.org/10.1016/j.buildenv.2017.11.001.

Liu, X., Jayaratne, R., Thai, P., et al., 2020a. Low-cost sensors as an alternative for long-term air quality monitoring. Environ. Res. 185, 109438. http://dx.doi.org/10.1016/j.envres.2020.109438.

Liu, X., Jayaratne, R., Thai, P., et al., 2020b. Low-cost sensors as an alternative for long-term air quality monitoring. Environ. Res. 109438. http://dx.doi.org/10.1016/j.envres.2020.109438.

Malings, C., Tanzer, R., Hauryliuk, A., et al., 2019. Fine particle mass monitoring with low-cost sensors: Corrections and long-term performance evaluation. Aerosol Sci. Technol. 1–15. http://dx.doi.org/10.1080/02786826.2019.1623863.

Manibusan, S., Mainelis, G., 2020. Performance of four consumer-grade air pollution measurement devices in different residences. Aerosol Air Qual. Res. http://dx.doi.org/10.4209/aaqr.2019.01.0045.

Manikonda, A., Zíková, N., Hopke, P.K., et al., 2016. Laboratory assessment of low-cost PM monitors. J. Aerosol Sci. 102, 29–40. http://dx.doi.org/10.1016/j.jaerosci.2016.08.010.

Mead, M.I., Popoola, O.A.M., Stewart, G.B., et al., 2013. The use of electrochemical sensors for monitoring urban air quality in low-cost, high-density networks. Atmos. Environ. 70, 186–203. http://dx.doi.org/10.1016/j.atmosenv.2012.11.060.

Miskell, G., Salmond, J., Williams, D.E., 2017. Low-cost sensors and crowd-sourced data: Observations of siting impacts on a network of air-quality instruments. Sci. Total Environ. 575, 1119–1129. http://dx.doi.org/10.1016/j.scitotenv.2016.09.177.

Morawska, L., Ayoko, G.A., Bae, G.N., et al., 2017. Airborne particles in indoor environment of homes, schools, offices and aged care facilities: The main routes of exposure. Environ. Int. 108, 75–83. http://dx.doi.org/10.1016/j.envint.2017.07.025.

Morawska, L., Thai, P.K., Liu, X., et al., 2018. Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? Environ. Int. 116, 286–299. http://dx.doi.org/10.1016/j.envint.2018.04.018.

Moreno-Rangel, A., Sharpe, T., Musau, F., et al., 2018. Field evaluation of a low-cost indoor air quality monitor to quantify exposure to pollutants in residential environments. J. Sensors Sensor Syst. 7, 373–388. http://dx.doi.org/10.5194/jsss-7-373-2018.

Nunes, R.A.O., Branco, P.T.B.S., Alvim-Ferraz, M.C.M., et al., 2016. Gaseous pollutants on rural and urban nursery schools in Northern Portugal. Environ. Pollut. 208 (Part A), 2–15. http://dx.doi.org/10.1016/j.envpol.2015.07.018.

Oliveira, M., Slezakova, K., Delerue-Matos, C., et al., 2019. Children environmental exposure to particulate matter and polycyclic aromatic hydrocarbons and biomonitoring in school environments: A review on indoor and outdoor exposure levels, major sources and health impacts. Environ. Int. 124, 180–204. http://dx.doi.org/10.1016/j.envint.2018.12.052.

Palmisani, J., Di Gilio, A., Viana, M., et al., 2021. 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. 205, 108237. http://dx.doi.org/10.1016/j.buildenv.2021.108237.

Patel, S., Li, J., Pandey, A., et al., 2017. Spatio-temporal measurement of indoor particulate matter concentrations using a wireless network of low-cost sensors in households using solid fuels. Environ. Res. 152, 59–65. http://dx.doi.org/10.1016/j.envres.2016.10.001.

Rai, A.C., Kumar, P., Pilla, F., et al., 2017. End-user perspective of low-cost sensors for outdoor air pollution monitoring. Sci. Total Environ. 607–608, 691–705. http://dx.doi.org/10.1016/j.scitotenv.2017.06.266.

Ramos, C.A., Wolterbeek, H.T., Almeida, S.M., 2014. Exposure to indoor air pollutants during physical activity in fitness centers. Build. Environ. 82, 349–360. http://dx.doi.org/10.1016/j.buildenv.2014.08.026.

Sá, J., Branco, P., Alvim-Ferraz, M., et al., 2017. Evaluation of low-cost mitigation measures implemented to improve air quality in nursery and primary schools. Int. J. Environ. Res. Public Health 14 (585), http://dx.doi.org/10.3390/ijerph14060585.

Schieweck, A., Uhde, E., Salthammer, T., et al., 2018. Smart homes and the control of indoor air quality. Renew. Sustain. Energy Rev. 94, 705–718. http://dx.doi.org/10.1016/j.rser.2018.05.057.
Schneider, P., Castell, N., Vogt, M., et al., 2017. Mapping urban air quality in near real-time using observations from low-cost sensors and model information. Environ. Int. http://dx.doi.org/10.1016/j.envint.2017.05.005.
Semple, S., Apsley, A., MacCalman, L., 2013. An inexpensive particle monitor for smoker behaviour modification in homes. Tobacco Control 22, 295–298. http://dx.doi.org/10.1136/tobaccocontrol-2011-050401.
Semple, S., Ibrahim, A.E., Apsley, A., et al., 2015. Using a new, low-cost air quality sensor to quantify second-hand smoke (SHS) levels in homes. Tobacco Control 24, 153–158. http://dx.doi.org/10.1136/tobaccocontrol-2013-051188.
Sérafin, G., Blondeau, P., Mandin, C., 2021. Indoor air pollutant health prioritization in office buildings. Indoor Air 31, 646–659. http://dx.doi.org/10.1111/ina.12776.
Shah, A.S.V., Langrish, J.P., Nair, H., et al., 2013. Global association of air pollution and heart failure: a systematic review and meta-analysis. Lancet 382, 1039–1048. http://dx.doi.org/10.1016/S0140-6736(13)60898-3.
Shen, H., Hou, W., Zhu, Y., et al., 2021. Temporal and spatial variation of PM2.5 in indoor air monitored by low-cost sensors. Sci. Total Environ. 770, 145304. http://dx.doi.org/10.1016/j.scitotenv.2021.145304.
Shrestha, P.M., Humphrey, J.L., Carlton, E.J., et al., 2019. Impact of outdoor air pollution on indoor air quality in low-income homes during wildfire seasons. Int. J. Environ. Res. Public Health 16 (3535), http://dx.doi.org/10.3390/ijerph16193535.
Singer, B.C., Delp, W.W., 2018. Response of consumer and research grade indoor air quality monitors to residential sources of fine particles. Indoor Air 28, 624–639. http://dx.doi.org/10.1111/ina.12463.
Singh, A., Gatari, M.J., Kidane, A.W., et al., 2021. Air quality assessment in three East African cities using calibrated low-cost sensors with a focus on road-based hotspots. Environ. Res. Commun. 3, 075007.
Soreanu, G., Dixon, M., Darlington, A., 2013. Botanical biofiltration of indoor gaseous pollutants–A mini-review. Chem. Eng. J. 229, 585–594.
Sousan, S., Koehler, K., Hallett, L., et al., 2017. Evaluation of consumer monitors to measure particulate matter. J. Aerosol Sci. 107, 123–133. http://dx.doi.org/10.1016/j.jaerosci.2017.02.013.
Spinelle, L., Gerboles, M., Kok, G., et al., 2017a. Review of portable and low-cost sensors for the ambient air monitoring of benzene and other volatile organic compounds. Sensors (Basel, Switzerland) 17 (1520), http://dx.doi.org/10.3390/s17071520.
Spinelle, L., Gerboles, M., Villani, M.G., et al., 2017b. Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. Part B: NO, CO and CO2. Sensors Actuators B 238, 706–715. http://dx.doi.org/10.1016/j.snb.2016.07.036.
Spiru, P., Simona, P.L., 2017. A review on interactions between energy performance of the buildings, outdoor air pollution and the indoor air quality. Energy Procedia 128, 179–186.
Sun, S., Zheng, X., Villalba-Díez, J., et al., 2019. Indoor air-quality data-monitoring system: Long-term monitoring benefits. Sensors (Basel, Switzerland) 19 (4157), http://dx.doi.org/10.3390/s19194157.
Szulczyński, B., Gębicki, J., 2017. Currently commercially available chemical sensors employed for detection of volatile organic compounds in outdoor and indoor air. Environments 4, 21.
Tancev, G., 2021. Relevance of drift components and unit-to-unit variability in the predictive maintenance of low-cost electrochemical sensor systems in air quality monitoring. Sensors (Basel, Switzerland) 21 (3298), http://dx.doi.org/10.3390/s21093298.
Taylor, M.D., Nourbakhsh, I.R., 2015. A low-cost particle counter and signal processing method for indoor air pollution. WIT Trans. Ecol. Environ. 198, 337–348. http://dx.doi.org/10.2495/AIR150291.
Thakor, G.S., Zhang, N., Santos, R.M., 2021. Sensing and delineating mixed-VOC composition in the air using a single metal oxide sensor. Clean Technol. 3, 519–533.
Thomas, D., Mistry, B., Snow, S., et al., 2019. Indoor air quality monitoring (IAQ): A low-cost alternative to CO2 monitoring in comparison to an industry standard device. In: Intelligent Computing - Proceedings of the 2018 Computing Conference, Vol. 858. pp. 1010–1027. http://dx.doi.org/10.1007/978-3-030-01174-1_77.
Tiele, A., Esfahani, S., Covington, J., 2018. Design and development of a low-cost, portable monitoring device for indoor environment quality. J. Sensors 2018, http://dx.doi.org/10.1155/2018/5353816.
Tofful, L., Canepari, S., Sargolini, T., et al., 2021. Indoor air quality in a domestic environment: Combined contribution of indoor and outdoor PM sources. Build. Environ. 202, 108050. http://dx.doi.org/10.1016/j.buildenv.2021.108050.
Tryner, J., Phillips, M., Quinn, C., et al., 2021. Design and testing of a low-cost sensor and sampling platform for indoor air quality. Build. Environ. 108398. http://dx.doi.org/10.1016/j.buildenv.2021.108398.
USEPA, 2017. List of Designated Reference and Equivalent Methods. United States Environmental Protection Agency (USEPA), North Carolina, United States.
Wang, Y., Boulic, M., Phipps, R., et al., 2017. Integrating open-source technologies to build a school indoor air quality monitoring box (SKOMOBO). Journal 21, 6–223. http://dx.doi.org/10.1109/APWConCSE.2017.00046.
Wang, K., Chen, F.-e., Au, W., et al., 2019a. Evaluating the feasibility of a personal particle exposure monitor in outdoor and indoor microenvironments in Shanghai, China. Int. J. Environ. Health Res. 29, 209–220. http://dx.doi.org/10.1080/09603123.2018.1533531.
Wang, Z., Delp, W.W., Singer, B.C., 2020. Performance of low-cost indoor air quality monitors for PM2.5 and PM10 from residential sources. Build. Environ. 171, 106654. http://dx.doi.org/10.1016/j.buildenv.2020.106654.
Wang, Y., Du, Y., Wang, J., et al., 2019b. Calibration of a low-cost PM2.5 monitor using a random forest model. Environ. Int. 133, 105161. http://dx.doi.org/10.1016/j.envint.2019.105161.
Wang, Y., Jang-Jaccard, J., Boulic, M., et al., 2018. Deployment issues for integrated open-source — Based indoor air quality school Monitoring Box (SKOMOBO). Journal 1–4. http://dx.doi.org/10.1109/SAS.2018.8336758.
Wang, Y., Li, J., Jing, H., et al., 2015. Laboratory evaluation and calibration of three low-cost particle sensors for particulate matter measurement. Aerosol Sci. Technol. 49, 1063–1077. http://dx.doi.org/10.1080/02786826.2015.1100710.
Weekly, K., Rim, D., Zhang, L., et al., 2013. Low-cost coarse airborne particulate matter sensing for indoor occupancy detection. Journal 3, 2–37. http://dx.doi.org/10.1109/CoASE.2013.6653970.
Weyers, R., Jang-Jaccard, J., Moses, A., et al., 2017. Low-cost indoor air quality (IAQ) platform for healthier classrooms in New Zealand: Engineering issues. Journal 20, 8–215. http://dx.doi.org/10.1109/APWConCSE.2017.00045.
WHO, 2007. Indoor Air Pollution : National Burden of Disease Estimates. World Health Organization, Geneva, Switzerland, https://www.who.int/airpollution/publications/nationalburden/en/.
WHO, 2010. WHO Guidelines for Indoor Air Quality: Selected Pollutants. In: European Series, World Health Organization. WHO Regional office in Europe, Copenhagen, Denmark.
WHO, 2014. Public Health, Environmental and Social Determinants of Health (PHE). World Health Organization, Geneva, Switzerland, https://www.who.int/phe/health_topics/outdoorair/databases/en/. Acessed in 08/04/2019.
WHO, 2021. WHO Global Air Quality Guidelines: Particulate Matter (PM2. 5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide. World Health Organization, Geneva, Switzerland, ISBN: 9240034226, https://apps.who.int/iris/handle/10665/345329 (eletronic version).

WMO, 2020. An Update on Low-Cost Sensors for the Measurement of Atmospheric Composition. World Meteorological Organization, Geneva, Switzerland, ISBN: 978-92-63-11215-6.

Xu, B., Chen, X., Xiong, J., 2016. Air quality inside motor vehicles' cabins: A review. Indoor Built Environ. 27, 452–465. http://dx.doi.org/10.1177/1420326X16679217.

Yang, F., Kang, Y., Gao, Y., et al., 2015. Numerical simulations of the effect of outdoor pollutants on indoor air quality of buildings next to a street canyon. Build. Environ. 87, 10–22.

Ye, Y., Wang, Q., Wang, J., 2021. Green city air monitoring and architectural digital art design based on IoT embedded system. Environ. Technol. Innov. 23, 101717. http://dx.doi.org/10.1016/j.eti.2021.101717.

Zamora, M.L., Rice, J., Koehler, K., 2020. One year evaluation of three low-cost PM2.5 monitors. Atmos. Environ. 235, 117615. http://dx.doi.org/10.1016/j.atmosenv.2020.117615.

Zhang, H., Srinivasan, R., 2020. A systematic review of air quality sensors, guidelines, and measurement studies for indoor air quality management. Sustainability 12, 9045.

Zheng, T., Bergin, M.H., Johnson, K.K., et al., 2018. Field evaluation of low-cost particulate matter sensors in high and low concentration environments. Atmos. Meas. Tech. 11, 4823–4846. http://dx.doi.org/10.5194/amt-11-4823-2018.

Zikova, N., Hopke, P.K., Ferro, A.R., 2017. Evaluation of new low-cost particle monitors for PM2.5 concentrations measurements. J. Aerosol Sci. 105, 24–34. http://dx.doi.org/10.1016/j.jaerosci.2016.11.010.

Zong, H., Brimblecombe, P., Sun, L., et al., 2021. Reducing the influence of environmental factors on performance of a diffusion-based personal exposure kit. Sensors 21, 4637.

Zou, Y., Clark, J.D., May, A.A., 2021a. Laboratory evaluation of the effects of particle size and composition on the performance of integrated devices containing Plantower particle sensors. Aerosol Sci. Technol. 55, 848–858. http://dx.doi.org/10.1080/02786826.2021.1905148.

Zou, Y., Clark, J.D., May, A.A., 2021b. A systematic investigation on the effects of temperature and relative humidity on the performance of eight low-cost particle sensors and devices. J. Aerosol Sci. 152, 105715. http://dx.doi.org/10.1016/j.jaerosci.2020.105715.

Zou, Y., Young, M., Chen, J., et al., 2020. Examining the functional range of commercially available low-cost airborne particle sensors and consequences for monitoring of indoor air quality in residences. Indoor Air 30, 213–234.