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Review

State-of-the-Art Low-Cost Air Quality Sensors, Assemblies, Calibration and Evaluation for Respiration-Associated Diseases: A Systematic Review

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Abstract: Indoor air quality and respiratory health have always been an area of prime interest across the globe. The significance of low-cost air quality sensing and indoor public health practices spiked during the pandemic when indoor air pollution became a threat to living beings, especially human beings. Problem Definition: Indoor respiration-associated diseases are hard to diagnose if they are due to indoor environmental conditions. A major challenge was observed in establishing a baseline between indoor air quality sensors and associated respiratory diseases. Methods: In this work, 10,000+ articles from top literature databases were reviewed using six bibliometric analysis methods (Lorenz Curve of Citations, Hirch's H-Index, Kosmulski's H2-Index, Harzing's Hl-Norm-Index, Sidoropolous's HC-Index, and Schrieber's HM-index) to formulate indoor air quality sensor and disease correlation publication rubrics to critically review 482 articles. Results: A set of 152 articles was found based on systematic review parameters in six bibliometric indices for publications that used WHO, NIH, US EPA, CDC, and FDA-defined principles. Five major respiratory diseases were found to be causing major death toll (up to 32%) due to five key pollutants, measured by 30+ low-cost sensors and further optimized by seven calibration systems for seven practical parameters tailored to respiratory disease baselines evaluated through 10 cost parameters. Impact: This review was conducted to assist end-users, public health facilities, state agencies, researchers, scientists, and air quality protection agencies.

Keywords: respiratory diseases; low-cost air quality sensors; air quality assessment; sensing technologies (STs); measurement; configurations; sensor assemblies; gas sensor calibration systems (GSCSs)

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1. Introduction

It is widely accepted that air pollution leads to major health problems, costing economies billions of dollars per year in terms of health care costs and loss of productivity. Various studies around the world have linked many chronic diseases to air pollution. The recent WHO (24 February 2024) respiratory disease mortality statistic of 129,308 deaths for those aged 75 and above (only in America [1]) were alarming. Additionally, in work [2], it was anticipated that household air pollution caused 3.2 million fatalities annually, including approximately 237,000 deaths of children under the age of 5. Each year, 6.7 million premature deaths are attributed to the consequences of ambient and home air pollution. Living with chronic obstructive pulmonary disease (COPD), lung cancer, ischemic heart disease, stroke, and other non-communicable illnesses is made worse by household air pollution [3]. The term "Air Quality" refers to a gas assessment mechanism that can be used as a standard unit variable to govern acceptable pollution reciprocally as defined by the

World Health Organization (WHO), the U.S. Environmental Protection Agency (US-EPA), and the United Nations Environment Programme (UNEP) [4].

Air quality is monitored using low-cost mobile sensors and reference instrumentation, which face many challenges. An air quality gas sensor is an electronic or electrochemical instrument that can measure the ratio of gas particles in a given volume of air, usually in units of part per million (ppm), through some sensing element. Air quality gas sensors may also have a variety of other applications [4–6]. Indoor pollutants' detection threshold or resolution, range, and linearity are critical challenges in atmospheric sensor systems. The pollutant sensor's resolution becomes critical when detecting low-concentration pollutants like VOCs and Radon. In 1815, the first gas detector system, known as the Davy lamp, was invented by Sir Humphry Davy (of England) to detect the presence of methane (firedamp) in underground coal mines [7]. The first gas sensor was invented by Dr. Oliver Johnson that originated from the catalytic combustion (LEL) sensor [8]. Clark and Lyons utilized the strategy of the electrochemical detection of oxygen or hydrogen peroxide to measure glucose in biological samples [9]. The ubiquity of impedance is mainly leveraged to realize gas transducers [10]. Optical sensors are passive, i.e., require an external field excitation source to inject some energy into the observation specimen for measurement [11–13]. The feedback of this energy can have many numerical relationships with the induced signal, termed as the working response (refractive coupling) [14]. In this work, we focus on surveying sensors and instrumentation used in air quality measurement as well as associated diseases. The research hierarchy of this work is presented in Figure 1.

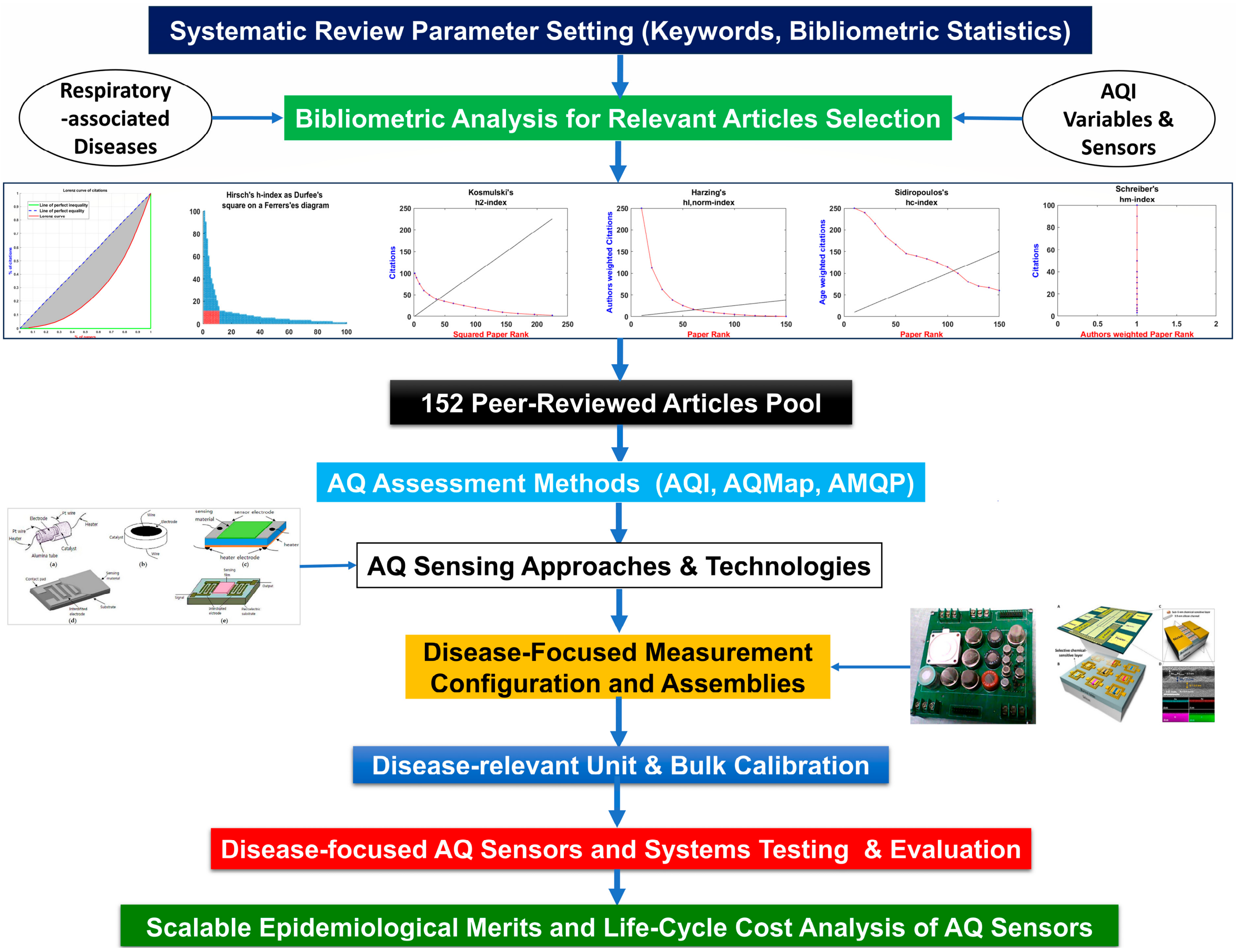


Figure 1. Indoor respiration-assisted disease-focused systematic review hierarchy [1–152].

The existing practices lead to a lack of transparency and conceptual challenges that can make it difficult to recognize the similarities and differences between indoor diseases and existing gas sensing systems and the contributions of new techniques. The contributions of this paper are chronologically comprehended as being indoor epidemiology-focused: (1) bibliometric analysis of IAQ and indoor epidemiology correlation; (2) air quality assessment (AQA) frameworks; (3) AQ sensor types and technologies; (4) AQ sensors, configurations, and topologies; (5) AQ sensor calibration and testing systems; (6) AQ measurement systems; (7) indoor epidemiology and diseases; (8) practical considerations in the real-world deployment of low-cost AQ Sensors for indoor respiratory conditions and disease diagnosis; and (9) future recommendations and research directions. The articles selected and the exclusion workflow is presented in Figure 2 below.

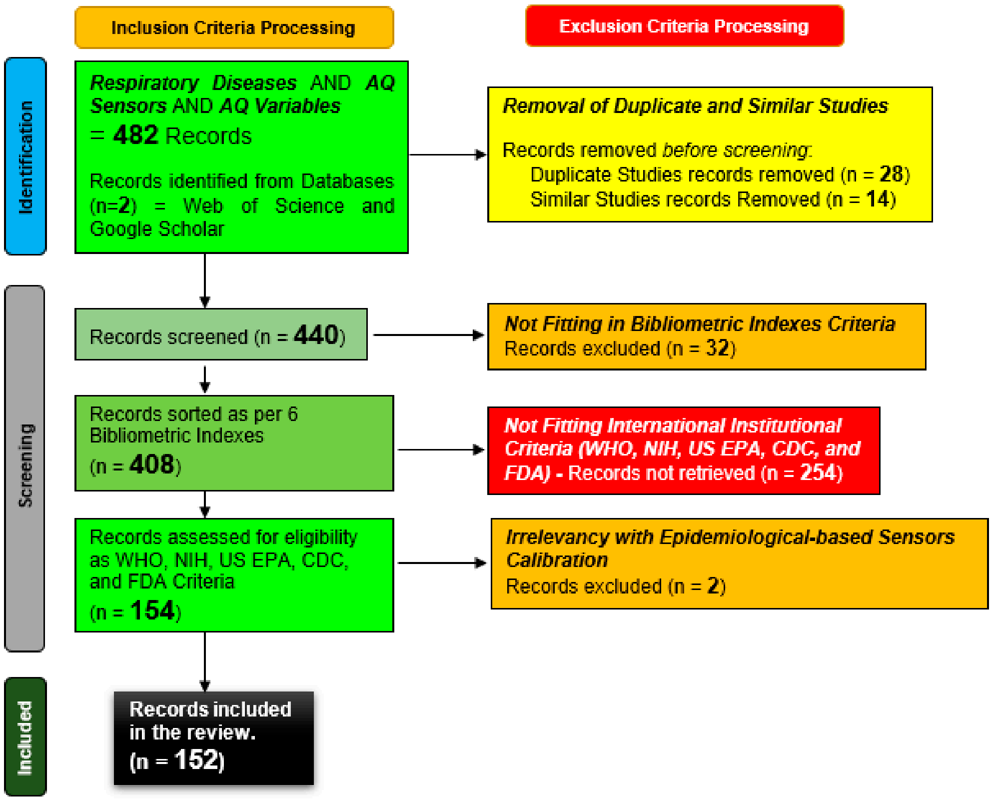


Figure 2. PRISMA diagram of workflow for inclusion of articles based on literature search and their applied exclusion criteria to scope in the focus of sensors and respiratory diseases.

Since low-cost AQ is a huge domain and has a plethora of terminologies, Table 1 presents the key acronyms and abbreviations used in this research.

Table 1. Key terms used in this Work.

Acronyms	Description	References
IAQ	Indoor Air Quality	[1–152]
AQA	Air Quality Assessment	[14–43]
AQMap	Air Quality Mapping	[29–33,132,133]
AQMP	Air Quality Management Plan	[30–41]
API	Air Pollution Index	[21,27]
AQ-GS	Air Quality Gas Sensor	[6–13,18–113]
OGS	Optical Gas Sensor	[44,49–51]
ECS	Electrochemical Gas Sensor	[44,52–55]
AGS	Acoustic Gas Sensor	[44,64–67]

Table 1. *Cont.*

Acronyms	Description	References
CGS	Capacitive Gas Sensor	[44,56,57]
NDIR	Non-dispersion Infra-red	[49–51]
CMGS	Calorimeter Gas Sensor	[44,58]
SOI	Silicon on Insulator	[86–94,109–111]
SoM	System on Module	[35,56,80–86,101–112]
LoC	Electrode on Chip	[35,56–58,80–95]
GSAs	Gas Sensing Arrays	[102–113]
GSGs	Gas Sensing Grids	[106–111]
MFCs	Mass-Flow Controllers	[109–117]

2. Bibliometric Analysis of IAQ and Indoor Epidemiology Correlation

For this analysis, 10,000+ articles from the past 50 years were selected from the Web of Science (WoS), Google Scholar, SCOPUS, CrossRef, and Dimensions research databases. The bibliometric analysis was performed in MATLAB using six statistical indices: (a) Lorenz Curve of Citations; (b) Hirch's H-Index; (c) Kosmulski's H2-Index; (d) Harzing's Hl-Norm-Index; (e) Sidoropolous's HC-Index; and (f) Schrieber's HM-index. The biblio-statistical parameter settings are presented in Table 2 below.

Table 2. Biblio-statistical parameters settings for 10,000+ articles.

#	Description	References
1	Keywords	Indoor air quality, indoor respiratory diseases, indoor pollutants, indoor epidemiology, epidemiology-focused sensors, epidemiology-focused air quality methods, epidemiology-focused systems.
2	Citations (5–2000)	[2000 1850 1475 1290 1050 800 590 482 440 408 254 232 5]
3	Years (50)	2000 + [1 3 6 9 12 15 18 21 22]
4	Authors per paper (1–15)	[1 3 4 5 6 7 8 9 10 11 12 13 14 15]
5	Operators	WHO, NIH, CDC, US EPA, Methods, Policies, Rules, Approaches, Cases, Reports
6	Respiratory Diseases	Asthma, Chronic Obstructive Pulmonary Disease (COPD), Ischemic heart disease, Stroke, Pneumonia and Lower Respiratory Infections (LRIs), Lung Cancer, Sick Building Syndrome (SBS).

The BibTex files for each search were segregated as a single file from all four databases and that resulted in 8 unique files from four unique databases and 32 files in total, with 38,019 articles. The repeated articles were filtered using BibTex Script processor and the resulting archive contained 18,971 articles. The maximum number of citations selected was 2000 and above, with the minimum as 5 citations. Figure 3 presents a detailed summary.

These indices resolved the 482-article pool for this study, of which 152 articles are referred to in this work that define respiratory disease-focused indoor air quality assessments, sensors, and calibration practices based on Figure 2's workflow.

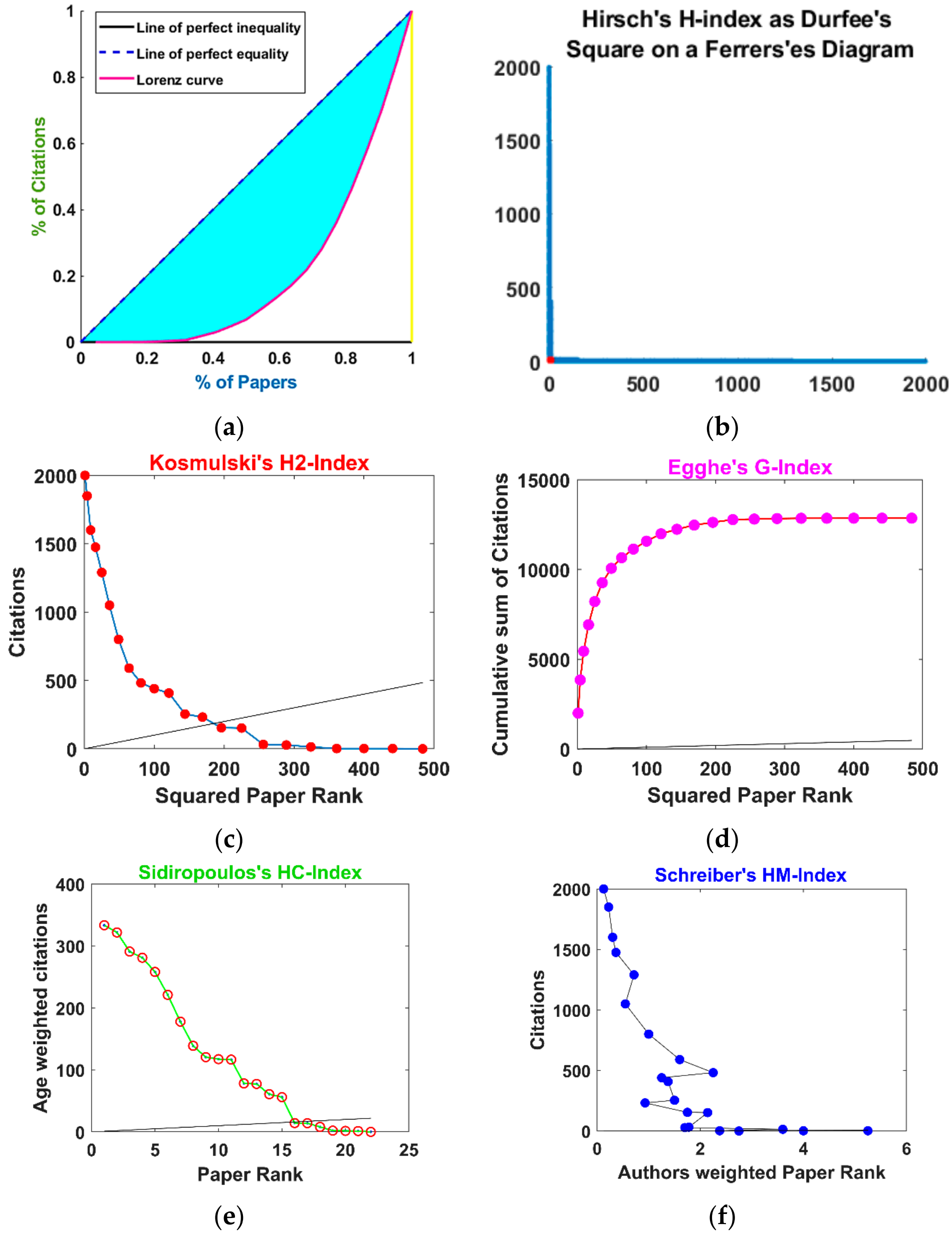


Figure 3. Statistical bibliometric indices for IAQ and indoor epidemiological relationship and public health baseline: (**a**) Lorenz Curve of Citations; (**b**) Hirch's H-Index; (**c**) Kosmulski's H2-Index; (**d**) Harzing's Hl-Norm-Index; (**e**) Sidoropolous's HC-Index; and (**f**) Schrieber's HM-index.

3. Indoor Air Quality Assessment for Indoor Epidemiology

In light of the indoor epidemiological guidance documented by the core environmental protection agencies, the WHO, NIH, CDC, US-EPA, EEA, and UNEP, air quality terminology refers to the entire legislative body of knowledge that involves analysis, methods, and criteria based on air quality [15–18]. The real-time AQA information from AQ sensors is used for environmental health and public safety. The major real-time methods used in this context are as follows:

1. Indoor air pollutant exposure limits;
2. Air Quality Standards;
3. Air quality mapping (AQMap);
4. Air Quality Management Plan (AQMP).

Each phase has its own clear and precise significance and contribution to the next phase. AQA and ACR involve the estimation of bio-tolerable gas thresholds [19,20] such as hazardous gas magnitudes and pollutant ratios in atmospheric volume; geospatial AQA to orchestrate regional AQM [21–23]; and the design of a model of regional air volume with effective and contributory variables to provide a mitigation plan [24].

3.1. Indoor Air Pollutant Exposure Limits

A very recent work by Sani et al. [25] based on the ISIAQ STC34 database covers all major global institutional guidelines (WHO IAQ 2010, US EPA, ASHRAE, etc.). Summing up the NIH, CEN Indoor Air Quality Standards, and Standards for IAQ GB/T 18883-2022, a comprehensive summary based on four parameters from the mentioned guidelines is presented below in Figure 4, also including indoor temperature and humidity limits.

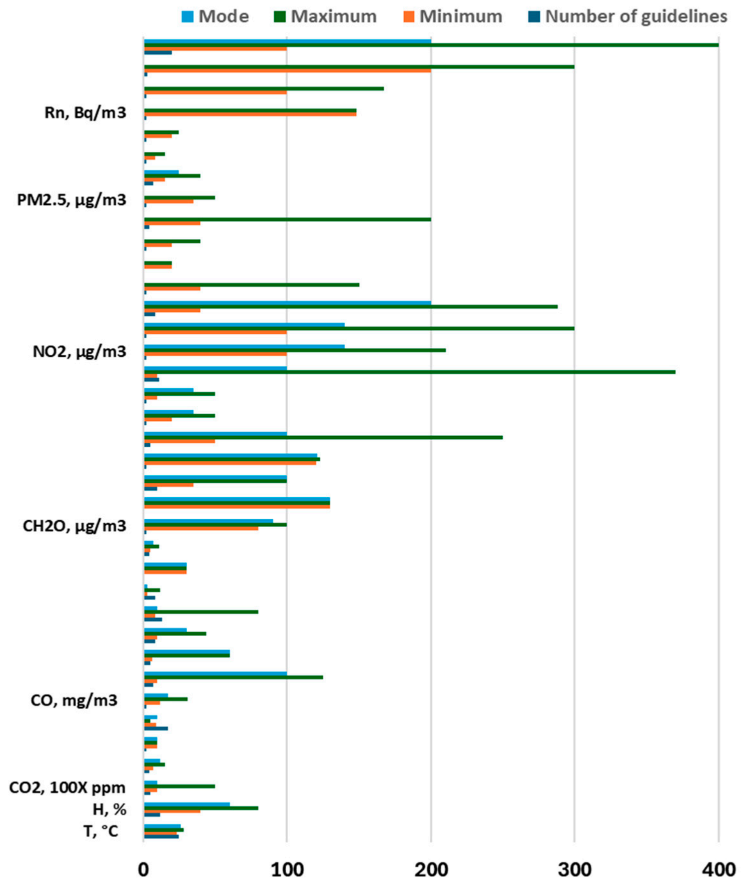


Figure 4. Summary of global institutional guidelines for indoor pollutant exposure limits as per WHO IAQ 2010, US EPA, ASHRAE, NIH, and CEN Indoor Air Quality Standards, Standards for IAQ GB/T 18883-2022 and ISIAQ STC34 Data.

In Figure 4, the CO_2 levels are at 100X to fit to the ranges of the chart (i.e., maximum = 50 means 5000 ppm and minimum = 10 means 1000 ppm) for better readability. Benzene is also mentioned in some standards but as a weak candidate. Indoor atmospheric chemistry is becoming more complex day by day, and additional pollutants like asbestos, lead, and PM1.0 need to be included in new IAQ standards globally, especially considering the pandemic strains.

3.2. Indoor Air Quality Standards

A set of 31 global standards for CO_2, NO_2, CH_2O, CO, SO_2, PM2.5, PM10, O_3, and TVOCs was reviewed in the work [26] by Sabah et al. that covered Australia (NHMRC, National Occupational Health and Safety Commission), Belgium (AIVC), Canada (Health Canada), China (AQSIQ, SEPA), Hong Kong (HKEPD, HKIAQO, HKSAR), Denmark (DSIC), Europe (EC), Finland (iSIAQ), Germany (DFG/MAK), Japan (MHLW), Kuwait

(Kuwait EPA), Korea (KEITI), Malaysia (DOSH), Singapore (SIAQG, Institute of Environmental Epidemiology), and the US (ACGIH, ASHRAE, IDPH, OSHA, OEHHA, TDH, NIOS, U.S. EPA), as well as global coverage (WHO). AQI refers to a real-time structured chart with a bio-tolerable threshold of specific pollutants and bio-hazardous gases recommended by the EPA in the area under a specified border agency [19–27]. In a work [28] by Guanqiong Wei et al., 26 IAQ-relevant worldwide building standards and certifications were reviewed and classified into three levels (basic, green, health). The standards covered country-wise were China's (Hygienic standard series (GB/T series-1995-2001) Indoor Air Quality Standard (GB/T 18883-2002), Standard for Indoor Environmental Pollution Control of Civil Building Engineering (GB 50325-2020), Assessment Standard for Green Building (GB/T 50378-2019), Assessment Standard for Healthy Building (T/ASC 02-2016), and Assessment Standard for Healthy Building (T/ASC 02-2021); the US's Ventilation for Acceptable Indoor Air Quality (ANSI/ASHRAE Standard 62.1-2016), Ventilation for Acceptable Indoor Air Quality (ANSI/ASHRAE Standard 62.1-2019), Leadership in Energy and Environmental Design (LEED v4-2019), WELL Building Standard v2.2022.Q2, and the Building Research Establishment Environmental Assessment Method (BREEAM); France (Haute Qualité Environnementale (HQE)-2016); Germany (Deutsche Gesellschaft für Nachhaltiges Bauen (DGNB)-2020); Japan (Guide from MHLW-2000, Comprehensive Assessment System for Built Environment Efficiency (CASBEE)-2014); and the globe (Air quality guidelines global update 2005 (AQG 2005), WHO global air quality guidelines (AQG 2021), and WHO guidelines for indoor air quality: selected pollutants 2010). This work reviewed organic, non-organic, and particulate pollutants separately and concluded that Chinese standards were progressively stricter from the basic to health levels. A major gap of gradation or sorting the standards based on their strictness was found.

After a detailed study and review of the mentioned indoor AQ standards and building standards and certifications, the following gaps were found:

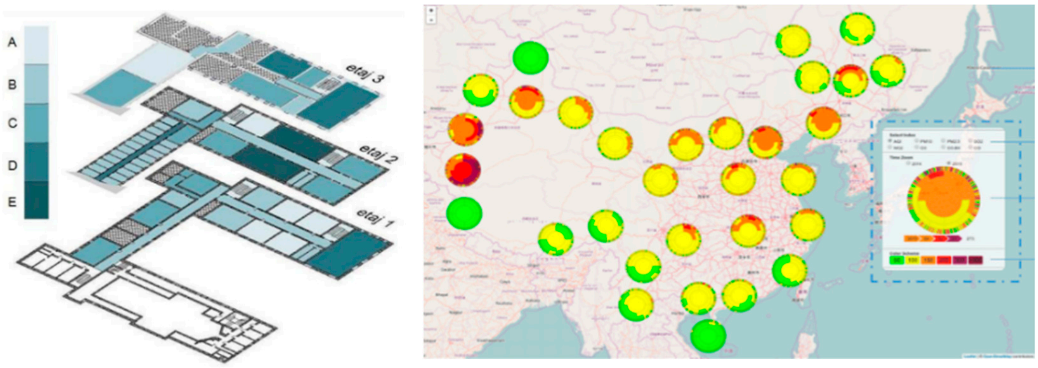
1. IAQ sensors must have range tables, magnitude specifications, and IAQ standard- and building certification-focused sampling rates to cover the respiratory disease exposure thresholds and probabilities.
2. Indoor pollutants in IAQ standards are not enough to cover indoor respiratory diseases. The toxins, allergens, and poisonous VOC exo-metabolites must be also measured with a dispersion probability for pollen, spores, molds, etc.

Another multi-parametric AQI innovation in assessment is the environmental performance index (EPI) by the Yale Center for Environmental Law and Policy [29], which can impact the exposure concerns in indoor AQ standards.

3.3. Air Quality Mapping (AQMap)

The geo-locations in the vicinity of AQ measurement using collective averaging and mean estimation procedures derive a real-time air quality map with an additional parameter: geographical positioning system (GPS) value [30,31]. The process of collection of all such points and orientating them geo-spatially is called AQMap [26–32]. There are two types of AQMap: (i) indoor air quality mapping (I-AQMap) and (ii) outdoor air quality mapping (O-AQMap) [33] (Figure 5).

Figure 5 shows that I-AQMap is building-wise and O-AQMap is region-wise. Different sets of gases and ratios of pollutants with different molecular sizes [34] use both approaches. The charting and graphing, as well as the typo-graphic presentation schemes available and their standardization process for AQMap based on their relative effectiveness, are mentioned in this work [35]. New studies must be introduced to fill the gaps of respiratory strain areas spatially. Additionally, extended research is needed that mathematically connects the indoor–ventilation–outdoor impact.

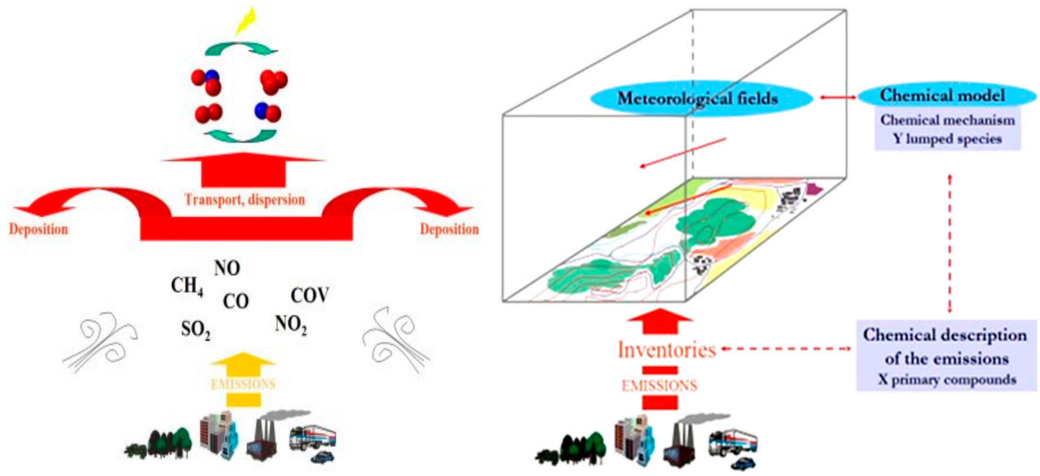


(**a**) (**b**)

Figure 5. Two fundamental approaches in real-time AQMap [26–32]. (**a**) Real-time indoor air quality mapping. (**b**) Real-time outdoor air quality mapping [33,34].

3.4. Air Quality Management Plan (AMQP)

The AQMP is based on the Brownian motion (Robert Brown), and the Brownian motion is defined as the random nature of particle dynamics in the air, presented in Figure 6 [36]. In the entire assessment of AQ, the most challenging and attention criteria is AQMP, especially air quality modeling [37,38]. Key work was accomplished by Dr. Gary Haq and Dr. Dieter Schwela in 2008 while modeling the toughest regions in Asia [39,40].



(**a**) (**b**)

Figure 6. Two-step AQMP methodology practices in AQM [36–42] (**a**) Air quality modelling [36]. (**b**) Air quality management implementation scheme [37,38].

Relating to the IAQ sections covered in the Clean Air Act Advisory Committee Meeting [41], Claudia et al. presented a very appreciable work on virtual pollution modeling using Bayesian network theory [42]. The AQMP (2012) presented by Dr. Bjarne Sivertsen and Alena Bartonova holds a landmark value in regional-level AQMP [43]. The INDAIR model and clean energy focused on bounded value models for a clear interpretation of decision-making AQMP parameters [44]. Future works are needed to cover the respiratory disease set of challenges that were not covered in these works.

3.5. Impact of Outdoor Air Quality on Indoor Air Quality and Associated AQIs

Indoor AQI is governed by outdoor AQI, as ventilation and human activities keep the air exchange process intact. The housing and ventilation procedures in every region are governed by outdoor AQI [45,46] and presented in Table 3.

Table 3. Global outdoor AQI limits.

Global Regulations	PM2.5 (μg/m^3)	PM10 (μg/m^3)	O_3 (ppb)	CO (ppm)	SO_2 (μg/m^3)	NO_2 (μg/m^3)
NAAQS [4]	12.0	150.0	70.0	9.0	75.0	53.0
US EPA [23]	12.0	150.0	70.0	9.0	75.0	53.0
EEA [21]	25.0	50.0	180.0	10.0	125.0	40.0
WHO [13,15]	10.0	20.0	100.0	4.0	20.0	40.0
CAQI [28]	25.0	50.0	180.0	10.0	125.0	40.0

A recent review by Murtaza et al. [46] surveyed several factors that affect the transfer of pollutants from outdoors to the inside environment. This work covered both experimental and modeling investigations and critically assessed several studies looking into the inter-environment variability and transmission; the findings are summarized in Table 4.

Table 4. Impact of outdoor pollutants on indoor pollution [47,48].

Outdoor Pollutants	Status	Indoor Atmosphere Impact
PM2.5	Varied concentrations based on location	Infiltration of PM may degrade indoor air quality, influencing the overall atmosphere.
NO_2	Variable levels near traffic and industry	NO_2 infiltration can alter indoor chemical composition, impacting the atmospheric milieu.
SO_2	Common near industrial sources	Infiltration introduces sulfur compounds, modifying indoor atmospheric conditions.
O_3	Variable levels of sunlight and pollutants	Ozone infiltration may lead to oxidative reactions, influencing indoor atmospheric chemistry.
VOCs	Emitted from various sources	VOC infiltration contributes to the overall composition, affecting odor and atmospheric makeup.

The study [48] concluded that long-term exposure evaluations can be better understood through experimental observations, and short-term spatial and temporal pollution transmission can be better visualized using CFD models. The review found that there was a lack of clarity regarding the relationship between determinant changes and the effects they have on transmission.

4. Indoor Epidemiology-Focused Air Quality Gas Sensor (AQ-GS) Technologies

In recent epidemiological studies focusing on key respiratory diseases as per the WHO [1,15] (ischemic heart disease, stroke, pneumonia, lower respiratory infections (LRIs), chronic obstructive pulmonary disease (COPD), and lung cancer), five sensing technologies were found to be relevant in the non-invasive diagnosis of these diseases and are presented in Figure 7 [49,50].

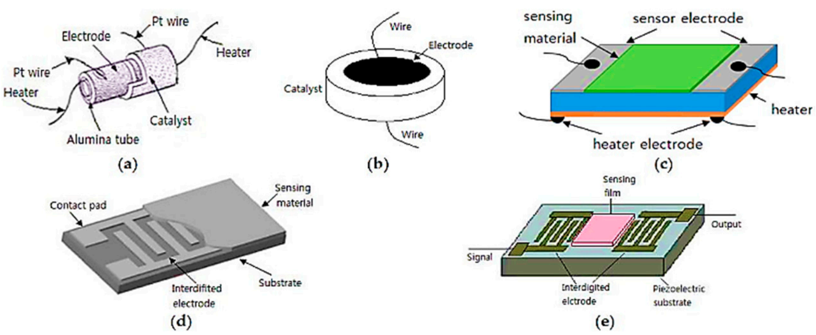
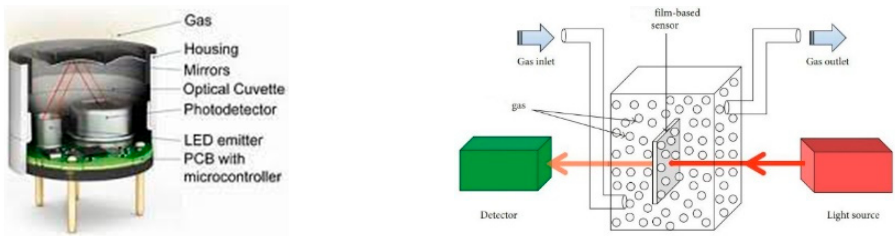


Figure 7. Five respiratory disease-relevant approaches in AQ gas sensor technologies [49].

There are five unique technologies in low-cost air quality gas sensors (AQGSs): (a) optical gas sensors (OGSs); (b) electrochemical gas sensors (ECSs); (c) capacitive gas sensors (CGSs); (d) calorimetric gas sensors (CMGSs); and (e) acoustic gas sensors (AGSs) [49–83]. Nevertheless, their architectural and working principles are explained in detail in the respective sections, but in future developments, OEMs should consider incorporating the sensing features that are useful for respiratory disease occurrence probabilities.

4.1. Optical Gas Sensors (OGSs)

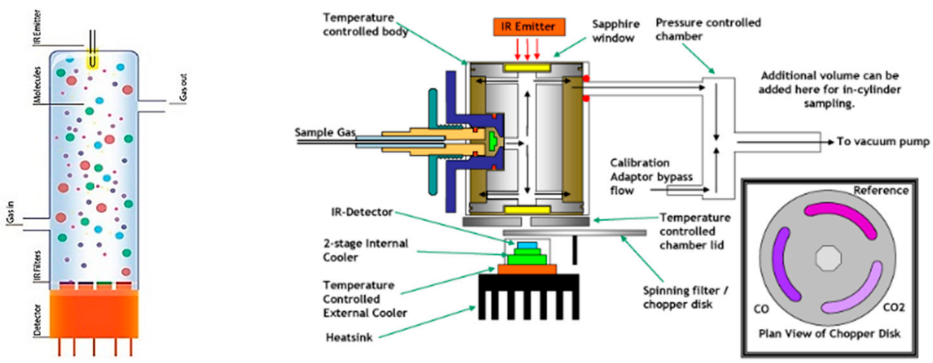
In OGSs, the entire identical or isometric coupling of optical diodes (transmitter (TX) and receiver (RX)) is a combination of transmitting and receiving modes [50]. In this case, a variable dielectric, like the human body, is introduced as exhibited in Figure 8 [51–54].



(**a**) (**b**)

Figure 8. Overview of OGS [50,53]. (**a**) Architecture. (**b**) Working principle.

In Figure 8, a light source transmits a light array through a file-based sensor that measures the impact of light on air particles and returns an analog voltage value for every unique gas which cycles through the micro-OGS chamber. The widely used OGS is a non-dispersive infra-red (NDIR) gas sensor that has a swift response and long lifetime, as this type does not use any consumables. The NDIR-GS is presented in Figure 9 below [55,56].



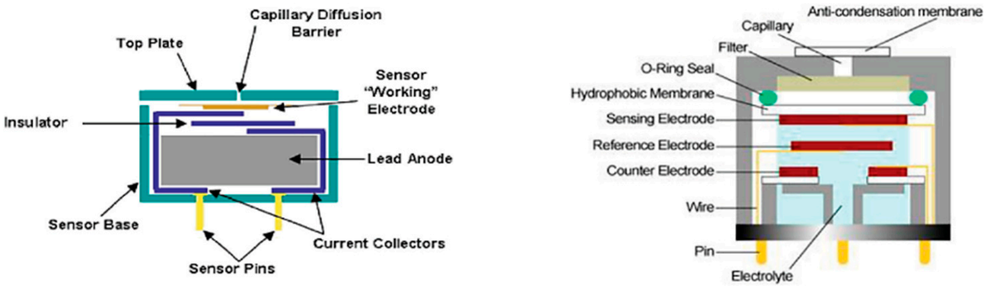
(**a**) (**b**)

Figure 9. Overview of NDIR-GS [55,56] (**a**) Architecture. (**b**) Working principle.

In the NDIR-GS presented in Figure 9, the same principle is used, i.e., light emission and reservation; the only difference is the IR nature of light that can sense up to 0.1 µm particles and needs air flow regulation by smart PWM fans for accuracy.

4.2. Electrochemical Gas Sensors (ECSs)

In ECSs, the receiver mode can possibly be made by making the working electrode a sensing element and the counter electrode an extension of the transmitting electrode to pick transmitted electrons through the electrolyte [52–54]. In this case, the working electrode acts as a multi-channel receiver for multi-variable sensing, as exhibited in Figure 10 below [57].



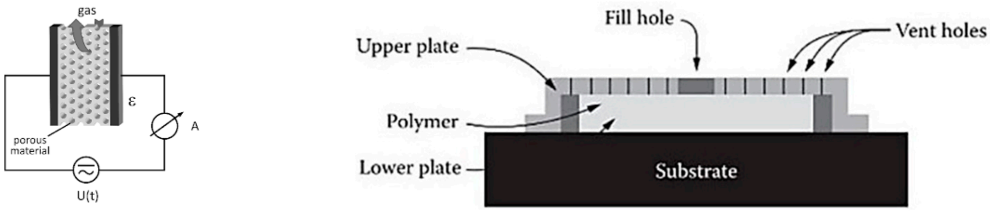
(a) (b)

Figure 10. Overview of ECS [56–58] (**a**) Architecture. (**b**) Working principle.

The ECS-GS presented in Figure 10 is a generic ECS architecture used by leading vendors in the gas sensor industry, i.e., FIGARO, SGX, and Honeywell. The faster response rates and solid-state architectures presented in [58,59] needed fabrication tendering to assess their mass production feasibility over existing technologies.

4.3. Capacitive Gas Sensors (CGSs)

In CGSs, the transmitter mode is made possible by making the sensor body an extension of the transmit electrode (or capacitor) to improvise the nearest transmitter-created electric fields [60,61]. In this case, a gap volume acts as a multi-impedance transmitter for multi-variable sensing receivers, as presented in Figure 11a below [62].



(a) (b)

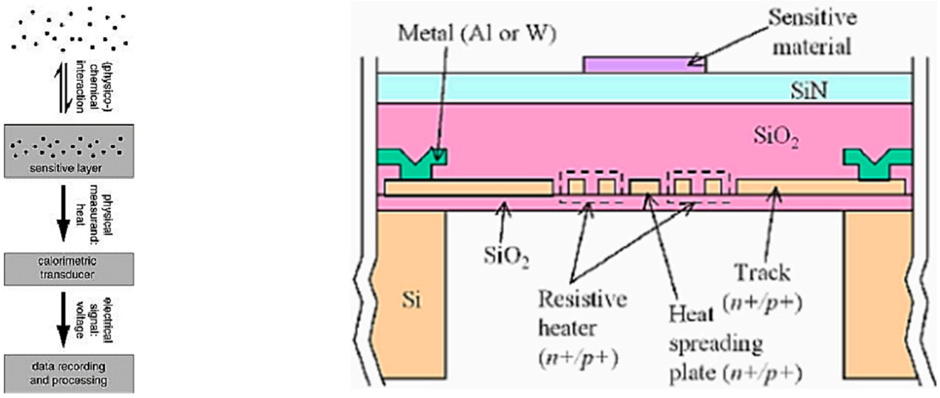
Figure 11. Overview of CGS [62]. (**a**) Architecture. (**b**) Working principle.

In Figure 11b, it is shown that the CGS is merely a capacitor in an isolated circuit where the electric flux between the plates is derived from the volume for gas measurement. The fill hole allows the air to enter the sensing zone and cycle back to the atmosphere through vents, and from a respiratory disease perspective, it should have a retention time for accurate pollutant chemistry assessment.

4.4. Low-Cost Calorimetric Gas Sensors (CMGSs)

In CMGSs, a displacement current flows through the body to the ground through a catalyst-loaded electrode gap [63]. A single electrode is utilized as a transmitter and receiver of flux as exhibited in Figure 12 below [63–65].

The finite element method (FEM) used by Mohamed Serry et al. [64] was a successful demonstration of a unique signal at different heater temperatures, which could be increased more than 23 times by increasing the heater voltage from 3.5 to 5.0 V. Also, selectivity for acetone vapors needed respiratory disease-mapped readouts in [66].

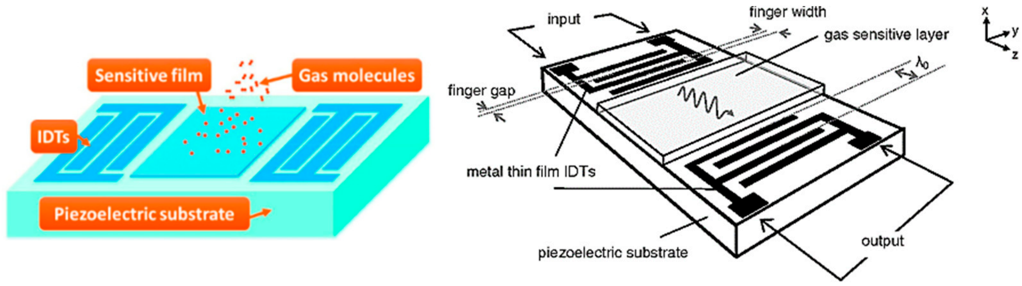


(**a**) (**b**)

Figure 12. Overview of CMGS [63–65]. (**a**) Architecture. (**b**) Working principle.

4.5. Low-Cost Acoustic Gas Sensors (AGSs)

In AGSs, a displacement or acoustic wave is transmitted through the gas, and the difference in the characteristics of the received wave from the original wave is converted into an equivalent AGS value [67]. A single electrode is utilized as a transmitter and receiver of flux, as exhibited in Figure 13 below.



(**a**) (**b**)

Figure 13. Overview of AGS [66,67]. (**a**) Architecture. (**b**) Working principle.

A new dimension of AGSs was explored in 2018 by Xueli Liu et al. [31,68]. According to Xueli et al., a typical surface acoustic wave (SAW) gas sensor, described in Figure 13, has a core element of thin-film coating along the SAW propagation path between the two interdigital transducers (IDTs). The absorption of the sensitive thin film modulates the SAW propagation by so-called mass loading; viscoelastic or acoustic–electric effects need to be optimized for respiratory disease-focused innovations.

4.6. Effectiveness of Gas Sensing Technologies and Respiratory Disease Approximation

The role of gas sensing technologies in respiratory disease approximation is a plethora of associated health condition proxies summarized in Figure 14 as a synopsis of works [49–66].

In Figure 14, the mentioned merits and capabilities can be enhanced by the fabrication approaches to exploit the material attributes and atmospheric chemistry resolution discussed in the next section.

Technology	Ischemic Heart Disease	Stroke	Pneumonia and LRI	COPD	Lung Cancer
OGS	Identification of specific gas biomarkers related to heart disease.	Detection of gas signatures linked to stroke-related conditions.	Exploration of unique optical signatures for pneumonia detection.	Monitoring optical changes associated with COPD biomarkers.	Identification of optical biomarkers specific to lung cancer (e.g., VOCs).
ECS	Sensing low concentrations of heart disease-related gases (ppb level).	Real-time monitoring of gases associated with stroke (ppm level).	Response to diverse biomarkers for pneumonia detection.	Continuous monitoring of COPD-related gases.	Detecting early-stage lung cancer biomarkers with sensitivity (ppb level).
CGS	Enhancing selectivity for heart disease markers (High selectivity).	Utilizing comprehensive datasets for stroke detection (Wide dynamic range).	Investigating dynamic range for pneumonia biomarkers (Variable sensitivity).	Optimizing for continuous COPD monitoring (Long-term stability).	Understanding response to early lung cancer biomarkers (High sensitivity).
CMGS	Detecting subtle changes in heart disease markers (Low detection limits).	Improving resolution for stroke-related gases (High resolution).	Responding to specific pneumonia biomarkers (Selectivity).	Adapting for continuous COPD monitoring (Stability over time).	Capability in early lung cancer detection (Early detection).
AGS	Studying the acoustic signature of heart disease-related gases (Frequency analysis).	Standardized protocols for utilizing AGS in stroke detection (Accurate timing).	Exploring AGS for unique biomarkers in pneumonia (Signature recognition).	Application in continuous COPD monitoring (Real-time monitoring).	Understanding AGS response to early lung cancer markers (Distinct acoustic patterns).

Figure 14. Sensing approach capabilities in non-invasive respiratory disease approximation [49–66].

4.7. Limitations of Gas Sensing Technologies Based on Different Parameters

The limitations of current sensor technologies encompass various factors that can impact their performance and reliability arising from systematic errors or inaccuracies in measurements, which may introduce uncertainties into the data obtained. Additionally, the scope of detection, or the range of gases that sensors can effectively detect, may be limited, affecting their applicability to different environmental conditions or gas mixtures. These technologies were reviewed further based on four parameters given below in Figure 15.

Technology	1. Sensitivity to Env. Conditions	2. Limited Selectivity	3. Calibration Complexity	4. Size & Portability
OGS	Highly sensitive to temperature and humidity variations (ppm/°C, ppm/%RH)	May fail to differentiate between gases with similar spectra (ppm)	Calibration requires controlled environmental conditions	Compact and portable (a few mm to cm)
ECS	Susceptible to temperature fluctuations and humidity (ppm/°C, ppm/%RH)	May exhibit cross-sensitivity to other gases (ppm/ppm)	Calibration necessary to account for drift and bias	Smaller size, portable (a few mm to cm)
CGS	Affected by humidity levels, impacting accuracy (ppm/%RH)	Limited ability to distinguish between gases with similar dielectric properties (ppm)	Requires periodic recalibration due to signal drift (seconds)	Moderate to large size (a few cm to cm+)
CMGS	Vulnerable to changes in ambient temperature (ppm/°C)	May lack sensitivity to certain gases, especially at low concentrations (ppm)	Calibration required to adjust for baseline drift and environmental influences	Variable size, can range from compact to larger (a few cm to inches+)
AGS	Limited in detecting gases beyond a certain range (ppm)	Prone to interference from background noise sources (ppm)	Calibration complex due to environmental noise and signal amplification	Compact and portable (a few mm to cm)

Figure 15. Limitations of sensing technologies and impact on their performance under different conditions [49–66].

Furthermore, environmental interferences such as temperature fluctuations, humidity levels, and the presence of other gases can introduce noise or interference into sensor readings, potentially compromising their accuracy and consistency. Addressing these limitations is crucial for ensuring the effectiveness and utility of gas sensing technologies in critical applications like respiratory health.

5. Indoor Epidemiology-Focused AQ Measurement Configurations and Assemblies

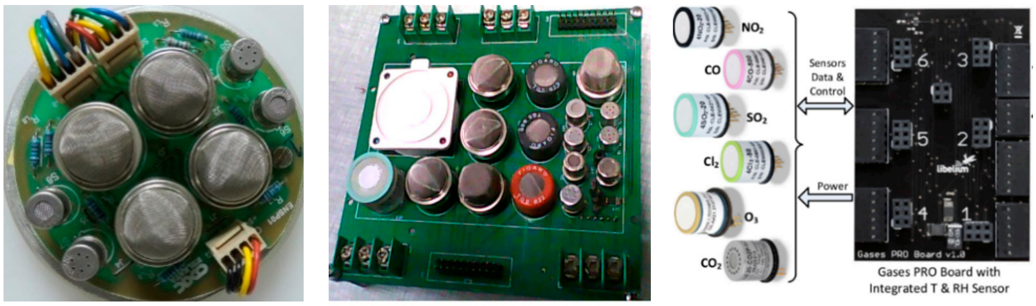
Smart methods like machine learning and data analysis for AQA processes require gas sensors to be in a specific format or topology for accuracy, effectiveness, and trustable measurements [67–71]. There are two core multi-gas sensing or sensor topology (also called electronic nose) arrays and grids, further elaborated as (a) gas sensor arrays and grids based on the System-on-Module (SoM) approach and (b) gas sensor array-on-chip-based SOI.

5.1. Gas Sensor Arrays and Grids Based on System-on-Module (SoM) Approach

The term electronic nose board (ENB) is used by various researchers around the world for a specific multi-sensor heterogeneous instrumentation PCB (Figures 16 and 17) from [67]. The orientation of ENBs for a typical sensing application is called a gas sensing array (GSA) or GS grid (GSG) [68]. The multiple GSAs send data to a central data acquisition collector or gateway, called the GSG [69]. Different GSAs and GSGs from novel works are objectively discussed in [69,70].

(**a**) (**b**) (**c**)

Figure 16. Major contributions in applied GSGs and ENBs. (**a**) Trio GSG for I-AQA [67]. (**b**) Wound infection ENB [68]; (**c**) eight-parameter GSG [69].



(**a**) (**b**) (**c**)

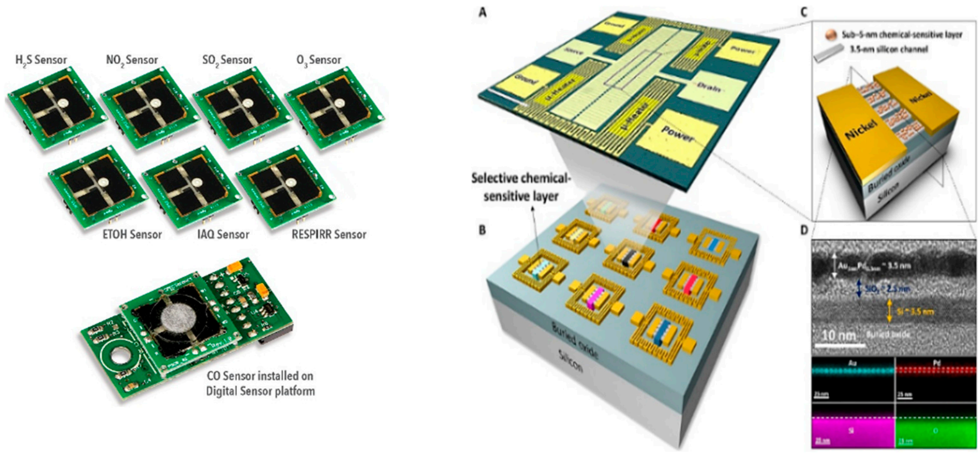
Figure 17. Major contributions in applied GSAs, GSGs, and ENBs. (**a**) Test GSG for I-AQA [70]. (**b**) Eighteen-parameter GSA [71]. (**c**) Smart rig test ENB [72].

The gradient descent method was used to detect food ripening by a GSA interfaced with STM32 in Figure 16a [67]. A later indoor air quality assessment was forecasted by a GSA in Figure 16b. Similarly, a water filtration assessment was performed using particle swarm optimization (PSO) by eight MOX GSA boards forming a GSG interfaced with the MSP430F247 board, as presented in Figure 16c [69,70].

A GSG test was performed in a hospital using least-square estimation for HVAC testing using Trio GSG [70]; i.e., the eight indoor gases were assessed (Figure 17a). In Figure 17b, the SVM was used to assess wound infection by an ENB based on four types of sensors [71]. In April 2020, the most recent ENB was used for the assessment of MFCs in a gas sensor calibration test bench [72], presented in Figure 17c. All of these had a major gap in sensor fusion to mine respiratory health-relevant derivatives.

5.2. Gas Sensor Array-on-Chip-Based SOI

In 2019–2020, a state-of-the-art technology appeared in the market as a GSA on chip, the next step in sensor-on-chip prepositions [73–76]. These arrays delivered accuracy in details of ppb. In 2016, screen-printed electrochemical (SPEC) sensors shrank this gas sensing technology down to a size appropriate for consumer devices that can be made at the volumes and costs suitable to the mass market [73] (Figure 18a). The multi-sensor chip was developed as Digital Sensor Platform on Chip (DSPoC) and the overall ENB was called Open Source DSPoC Kit.



(**a**) (**b**)

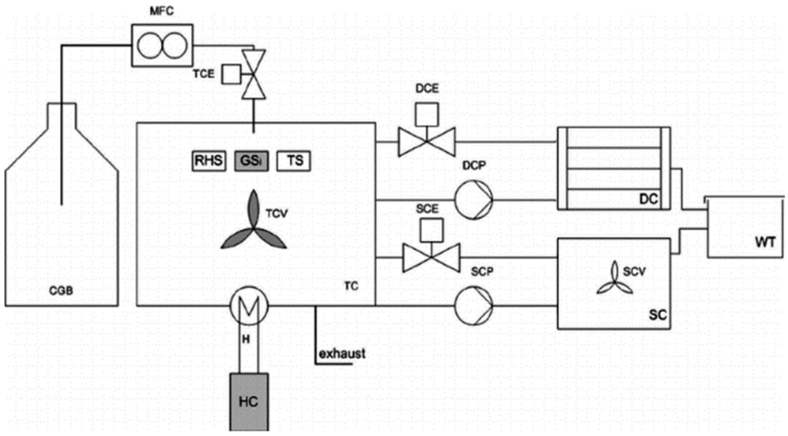
Figure 18. Major contributions in GSAoC-based SOI for applied GSGs and ENBs. (**a**) SPEC DSPoC with GSA on chip [73–76]. (**b**) Monolithic GSA on chip with 3.5 nm wires [77].

In Figure 18, the novel GSoC was developed in 2017 to sense H_2S, H_2, and NO_2 gases with 3.5 nm wires [73–76]. The most recent work was a Single-Chip Gas Sensor Array (SC-GSA) in which a set of four micro-heaters was used to access a single suspended SiO_2 diaphragm [81] using thermal proximity and achieved low power consumption (~10 mW for 300 °C). Plasma-optimized thin films of ZnO, $BaTiO_3$-CuO doped with 1% Ag, WO_3, and V_2O_5 were employed for the selective sensing of CO, CO_2, NO_2, and SO_2. The four sensors were controlled independently and detected CO (~78.3% for 4.75 ppm) at 330 °C, CO_2 (~65% for 900 ppm) at 298 °C, NO_2 (~1948.8% for 0.9 ppm) at 150 °C, and SO_2 (~77% for 3 ppm) at 405 °C operating temperatures. The complete implementation of GSAoC is the current state of the art [77].

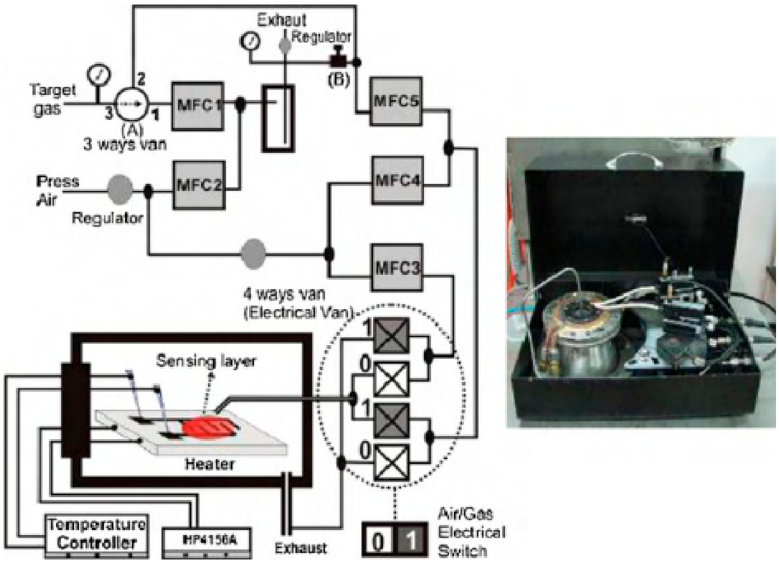
These works needed improvement by exploring a more exhaustive characterization of the respiratory disease-projected IAQ features through ENB, GSA, and GSoC materials and operating conditions, including surface morphology, chemical composition, and environmental stability. This will provide valuable insights into the sensing mechanisms and potential areas of optimization for respiratory disease IAQ proxies.

6. Indoor Epidemiology-Based Calibration and Testing of AQ Gas Sensors

Readings from sensors, especially chemical sensors, shift with temperature and aging, affecting the accuracy of the measured data. Therefore, regular calibration should be conducted. Four major types of automated calibration approaches have been developed and tested to date: (a) Uni-Gas Uni-Sensor Calibration; (b) Uni-Gas Multi-sensor ENB Calibration; (c) IoT-based Networked Multi-Gas ENB Calibration; and (d) Climate Smart Heterogeneous ENB Calibration. Recent work has realized a plethora of efforts made in gas sensor calibration [73–82], presented in Figures 19–21.

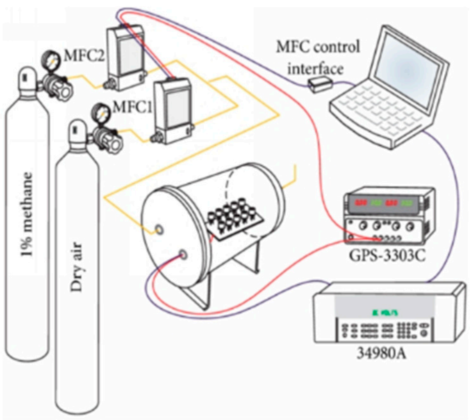


(**a**)



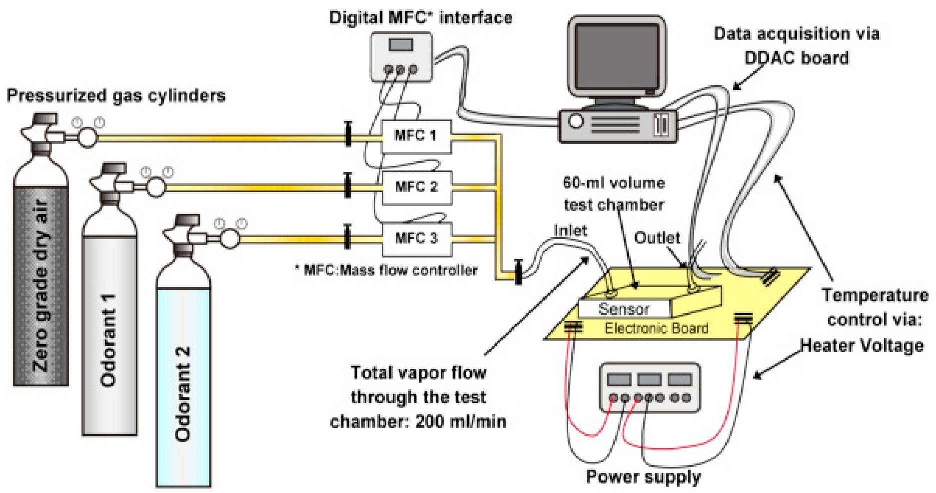
(**b**)

Figure 19. The AQ gas sensor calibration chamber-based system [74]. (**a**) P&ID of a unit AQGS testing and calibration system. (**b**) System assembly and architecture.



(**a**)

Figure 20. *Cont.*



(**b**)

Figure 20. The computer-supervised AQGS testing systems [80,81]. (**a**) AQGS array testing and calibration system [80]. (**b**) The ENB testing and calibration system [81].

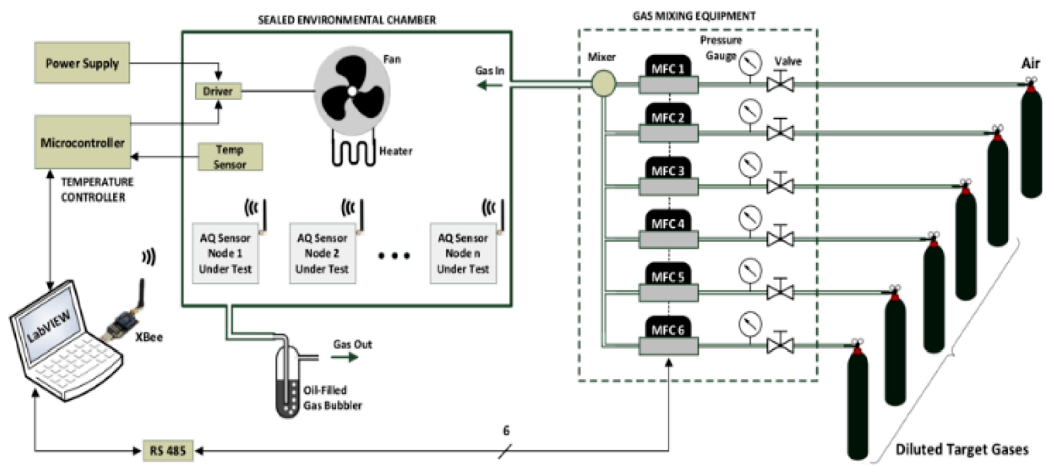


Figure 21. IoT-based Smart AQ GSA testing and calibration system [84].

6.1. Uni-Gas Uni-Sensor Calibration

In 2009, the first structured gas sensor calibration system was designed and implemented by a measurement calibration system that was developed by Casey, J.G. et al. [74], presented in Figure 19a.

A standard AQS calibration follows a [75] schematic as follows: (a) an air-sealed chamber with inflow and outflow valves; (b) mass flow controllers (MFCs) for the desired concentration of gas from a cylinder or a PID controller gas flow loop; (c) gas cylinders with different concentrations; (d) a temperature actuator (heater); (e) a humidity actuator (steam regulator); (f) gas collectors for the environmental model; and (g) measurement instruments other than gas sensors for comparison interfaced with a computer. In Figure 19a, an industry-standard instrumentation topology, i.e., a piping and instrumentation diagram (P&ID), is presented for an AQGS. It consists of 14 components: (1) CGB: calibration gas bottle; (2) MFC: mass flow control; (3) TCE: testing chamber electro-valve; (4) DCE: drying chamber electro-valve; (5) SC: saturation chamber electro-valve; (6) DCP: drying chamber pump; (7) SCP: saturation chamber pump; (8) DC: drying chamber; (9) SC: saturation chamber; (10) HC: heater control; (11) H: heater; (12) WT: water tank; (13) TCV: testing chamber ventilator; and (14) SCV: saturation chamber ventilator. The chamber ventilator's internal architecture varies with the sensing technology detailed in a survey on gas sensing (Xiao Liu et al. [76]), and these studies needed improve in terms of the process alignment aspects of sensing and breathing conditions to cover respiratory features like inhaling and exhaling flowrates and concentrations. Two studies on testing the performance of field gas sensor calibration techniques were proposed by Joanna et al. [77] for Colorado.

The characterization study conducted by Leidinger et al. led to a new horizon in test gas generation systems [78]. In Figure 18b, an experimental gas sensor test and calibration system for SnO2 nanowire-based gas sensors are presented (Le Viet Thong et al. [79]). The test was performed by measuring all sensors with liquid petroleum gas (LPG, 500–2000 ppm) and NH3 (300–1000 ppm) at different temperatures (50–450 °C) using a setup with high-speed switching gas flow (from/to air to/from balance gas). Balance gases (0.1% in air) were purchased from Air Liquid Group, Singapore. The system employed a flow-through with a constant rate of 200 sccm.

6.2. Uni-Gas Multi-Sensor ENB Calibration

The miniaturized environmental control chambers presented in Figure 20 were introduced by Yi Chen et al. [80] and Jordi Follonosa et al. [81].

As seen in Figure 20a, the sensor array was placed in a test chamber with a volume of 20 L, composed of ten metal oxide semiconductor gas sensors (TGS 2620) by Joanna et al. [81]. The sensor array resistances were acquired by a half-bridge configuration and collected by a multifunction switch/measuring unit of 34,980 A via an electrical interface on the chamber. The gas mixture, based on a PID experiment by Jordi et al. [82] and using the dynamic response of each sensor, was recorded at a sample rate of 100 Hz. In this chamber, the RH (0~10%) was varied and captured using a 16-channel ADC. The time-series sequence for the entire dataset from the 16-channel acquisition system from sensors in the given order is as follows: (CH0-CH15): TGS2602; TGS2602; TGS2600; TGS2600; TGS2610; TGS2610; TGS2620; TGS2620; TGS2602; TGS2602; TGS2600; TGS2600; TGS2610; TGS2610; TGS2620; TGS2620 [83]. This discussion will follow sub-type capacitive sensors (the first type of gas sensor), further trimmed down to included gas sensors based on contactless capacitive electrodes to cover respiratory diseases and diagnosis.

6.3. IoT-Based Networked Multi-Gas ENB Calibration

In 2020, the most recent smart gas sensor calibration test rig appeared in the literature from Mohieddine A. Benammar et al. [84], presented in Figure 21. In Figure 21, Smart TestRig took account of all major improvements recommended in studies by Maag, B. et al. [85] for gas sensor calibration in air monitoring deployments.

The Smart AQ GSA test rig by Mohieddine A. Benammar et al. [84] in Figure 20 was developed considering the gaps in the study by Spinelle, L. et al. [86] to present a field calibration of a cluster of low-cost available sensors for air quality monitoring using O_3 and NO_2. Mijling, B. et al. [87] worked on the field calibration of electrochemical NO_2 sensors in a citizen science context. Hagan et al. [88] presented the calibration and assessment of electrochemical gas sensors by co-location with regulatory-grade instruments; Hasenfratz. D. et al. [89] presented the on-the-fly calibration of low-cost gas sensors; Yang, F. et al.'s work [90] introduced the dynamic calibration of electrochemical gas sensors for accelerated analytic quantification; and Tian, B. et al. [91] proposed an environment-adaptive calibration system for indoor low-cost electrochemical gas sensors.

6.4. Climate Smart Heterogeneous ENB Calibration

As shown in Figure 22, Sayahi et al. [92] performed the entire testing and calibration of several gas sensors using a custom sensing chamber (volume ~300 cm^3), a PID controller electric heater.

The gases were individually mixed with dry synthetic air and introduced inside the test chamber at a controlled flow rate of 50 cm^3/min. One of the core innovations in this work was an evacuation pump scheme with 8×10^{-1} Torr using a rotary vacuum pump. In the next generation, testing calibration system curve fitting was performed and error proportionalities were calculated for porous silicon-filled Pd/SiC nano-cauliflower thin films for high-performance H_2 gas sensors, for example, by Asghar et al. [93].

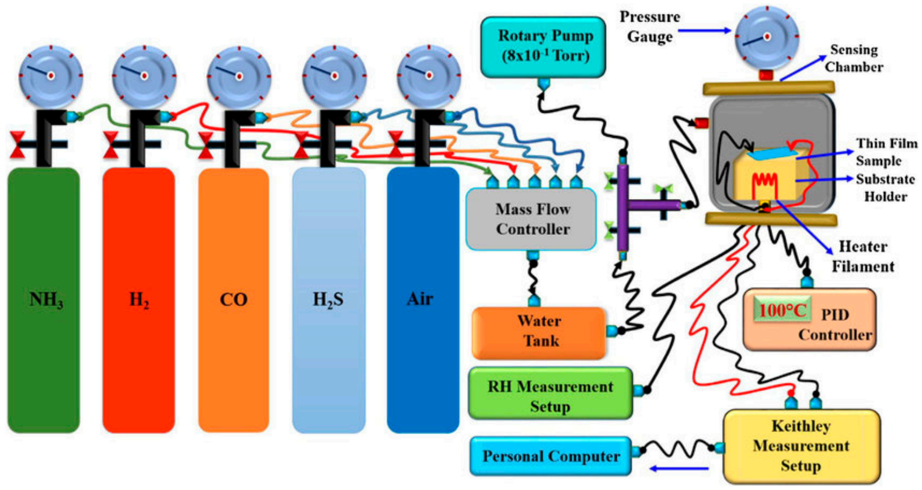


Figure 22. Air quality mesh network testing and calibration system [92].

6.5. Epidemiological Scalability through Calibration Approaches in Non-Invasive Diagnosis

The population overshoots demanded a huge number of patients to be monitored and diagnosed in a short time, which mandated the scalability of calibration methods for multiple human subjects presented in Table 5.

Table 5. Indoor epidemiological scalability of and calibration approaches at institutional level.

Institutional-Level Indoor Epidemiological Merits	Uni-Gas Uni-Sensor Calibration	Uni-Gas Multi-Sensor ENB Calibration	IoT-Based Networked Multi-Gas ENB Calibration	Climate Smart Heterogeneous ENB Calibration
Calibration Scale (per 24 h)	1–24	10–120	10–1840	10–144
System Setup Cost (per 10 sensors)	USD 2~5.1 M	USD 0.4~2 M	USD 1~1.8 M	USD 4~7 M
Types of Sensors Supported	4	4	5	5
IoT Support and Remote Calibration	No	No	Yes	No
Calibration Cost (per 10 sensors)	USD 3–10	USD 12–19	USD 2–8	USD 35–120
Real-time AQI-based Climate-Focused Calibration	No	No	No	Yes
ML/DL Model-in-Loop Support	No	No	Yes	No

In Table 5, the selected epidemiological merits play a pivotal role in the scalable diagnosis of respiratory health conditions (asthma, COPD, ischemic heart disease, stroke, pneumonia, LRIs, lung cancer, and sick building syndrome) as part of a bigger picture at institutional levels like the WHO, NIH, CDC, and US-EPA in the following manner:

1. A precise calibration Scale, such as a 24 h interval, ensures consistent accuracy, while the system setup cost for deploying 10 sensors directly influences the feasibility of widespread implementation;
2. Supporting multiple sensor types allows for a comprehensive assessment, facilitating a detailed understanding of specific respiratory health concerns related to diverse indoor air contaminants;
3. The combination of IoT support and remote calibration enables real-time adjustments, ensuring continuous accuracy;
4. The cost-effectiveness of calibration activities directly impacts operational expenses;
5. Real-time AQI-based climate-focused calibration tailors adjustments to specific climate conditions, enhancing the precision of health-related data;

6. ML/DL model-in-loop support integrates advanced learning models, contributing to the adaptability and diagnostic capabilities of the system.

Together, these calibration parameters collectively enhance the accuracy, efficiency, and applicability of sensor systems, crucial in the diagnosis and management of respiratory diseases.

7. Indoor Epidemiology and Respiratory Diseases

Acute respiratory infections, TB, asthma, chronic obstructive pulmonary disease, pneumoconiosis, head and neck malignancies, and lung cancer have all been linked to indoor pollution exposure [94]. The direct relationship presented in the relevant works is compiled in Table 6, given below.

Table 6. Epidemiological relationship between IAQ and respiratory health issues [94–108].

#	Indoor Pollutants	Indoor Diseases and Health Problems
1	PM2.5 and PM10 [94–105]	Heart or lung illness, nonfatal heart attacks, irregular heartbeats, worsened asthma, impaired lung function, and a rise in respiratory symptoms including coughing or trouble breathing.
2	NO_2 [97–100]	At high quantities, it shortens breath and irritates the mucous membranes of the nose, throat, and eyes. Long-term inhalation of nitrogen dioxide can cause lung damage. It could result in persistent bronchitis. Those who have asthma and chronic obstructive lung disease may experience worsening symptoms from exposure to low levels (COPD). Also, it could make other respiratory illnesses worse.
3	CO [98–102]	Chronic headaches, nausea, stomach pain, vomiting, weakness, dizziness, fainting, confused mental neural response, exhaustion, loss of consciousness, seizure, and irreversible brain damage are some of the symptoms. In the worst scenarios, death is also conceivable.
4	CO_2 [103–106]	Respiratory tract infections, chronic obstructive pulmonary disease (COPD), asthma, and rhinosinusitis.
5	VoCs [105–108]	Some VOCs are known or suspected carcinogens. Inflammation, including irritation of the eyes, nose, and throat; headaches and lack of coordination; nausea; liver, renal, or central nervous system damage.

The death statistics presented in different global studies and state agencies like the WHO and NIH associated with indoor pollutants, in order of intensity, are summarized in Table 7.

Table 7. Annual fatality statistics for indoor pollutants' induced diseases [107–121].

%	Respiratory Diseases	Fatalities Details
32%	Ischemic heart disease [108–111]	Affects 32% of people. Exposure to home air pollution is responsible for 12% of all fatalities from ischemic heart disease, or more than a million premature deaths yearly.
23%	Stroke [112–115]	Accounts for 23% of deaths, with the usage of solid fuels and kerosene in the home contributing to household air pollution regularly, accounting for around 12% of all stroke deaths.
21%	Pneumonia and Lower Respiratory Infections (LRIs) [116–121]	LRIs account for 21% of fatalities, and exposure to indoor air pollution nearly doubles the risk of childhood LRI and accounts for 44% of all pneumonia-related deaths in children under the age of five. Adults who have acute LRIs are in danger from household air pollution, which also causes 22% of all adult fatalities from pneumonia.
19%	Chronic obstructive pulmonary disease (COPD) [122–125]	Accounts for 19% of cases. In low- and middle-income nations, exposure to home air pollution is the reason for 23% of all fatalities from COPD in adults.
6%	Lung Cancer [126–131]	A total of 6% of lung cancer-related fatalities in adults are linked to exposure to carcinogens from home air pollution brought on by the use of kerosene or solid fuels like wood, charcoal, or coal. This exposure accounts for around 11% of lung cancer deaths in adults.

8. Practical Considerations in Real-World Deployment of Low-Cost AQ Sensors for Indoor Respiratory Conditions and Disease Diagnosis

Respiratory diseases are a scalable and long-term chronological health concern for both respiratory patients and healthy people. The existing studies need to be improved and reviewed based on practical considerations, such as decision-making challenges for public institutions. At the public health level, the major decisions to be made for regional institutions are (a) the cost of entire low-cost AQ sensor infrastructure; (b) the size of area being covered; (c) manufacturing setup, such as importing all sensors in quantities of millions, which can be a big shock to national revenue reserves that is practically not feasible; (d) their compatibility with existing low-cost sensor systems, and integration with publicly deployed reference grade instruments (GC-MS, PTR-ToF-MS, ICP-MS, and gas analyzers); (e) targeted sampling rates for the acquisition of maximum signatures; (f) operational lifecycles for entire public health campaigns (may lapse over years); (g) their calibration costs for such a huge setup; (h) sets of target variables, such as different configurations of ENBs, GSAs, and GSGs; (i) embedding this all into a single public respiratory health network to be monitored live by atmospheric health and respiratory condition medical specialists; and (j), for regional bodies, the mapping is the key requirement to have a holistic view of entire respiratory conditions. In addition to these decision-making challenges, the practicing ecosystem that involves respiratory and atmospheric health researchers, manufacturers, and EPA stakeholders in respiratory diagnosis centers' adaptation is also relevant. To address all of these key decision-making parameters, seven factors are presented in Table 8.

Table 8. Real-time operational capabilities and lifecycle cost evaluation [132–152].

USD ($)	Rooms Monitored (>100)				GSA/GSG Assemblies (>10X)			
Cost Elements	**OGS**	**ECS**	**CGS**	**MOS**	**OGS ENB**	**ECS ENB**	**CGS ENB**	**MOS ENB**
Lifeline Cost (K) [132–135]	10	1.5	17.1	3.7	3.5	0.7	1.3	0.4
Manufacturing Setup Cost (M) [69–95,136]	23~40	18~29	7~13	33~80	13~17	8~11	9~10	3~5
Calibration Cost (K) [137–140]	17	12	19	4	29	15	9.5	1.4
Adaptation Cost (K) [19,141–144]	30	7	5	2	12	3	1.1	0.3
Sampling Rate Upgrade Cost (K) [45–58,145–147]	3	11	9	1.2	0.2	0.9	0.3	0.12
Networked Sensing Cost (K) [148,150]	1	1	1	1	1.7	0.1	0.1	0.1
Real-time AQI Mapping Cost (K) [144,151,152]	0.7	2.3	3.7	1.3	0.5	1.6	9.5	0.09

From Table 8, it can assessed that the financial considerations associated with implementing gas sensor technologies play a crucial role in enhancing the diagnosis of respiratory diseases and addressing indoor air quality challenges. Firstly, the lifeline cost, representing the long-term financial commitment, influences the sustainability of sensor deployment across different health conditions, such as asthma, COPD, ischemic heart disease, strokes, pneumonia, lung cancer, and sick building syndrome (SBS). The works with co-respiratory-cardiological association hold a key life-saving capacity [149–152]. Secondly, the manufacturing setup cost, involving the initial investment and scalability for mass production, significantly impacts the feasibility of widespread sensor deployment for health monitoring. Calibration cost, an essential factor in maintaining sensor accuracy, contributes to effective diagnosis. Adaptation cost considers modifications needed to accommodate changing environmental conditions, while the sampling rate upgrade cost influences the precision of data collection, measured in ppm. Networked sensing cost, associated with collaborative monitoring and real-time data sharing, plays a vital role in comprehensive health analysis. Finally, real-time air quality index (AQI) mapping cost contributes to the mapping and visualization of air quality data, aiding in disease trigger prediction. Each of these factors plays a nuanced role in ensuring the effective utilization of gas sensor technologies for respiratory disease diagnosis.

9. Future Recommendations and Research Directions

After reviewing existing works and future vision for the current challenges in this body of knowledge, the following can be looked at discretely for each technology:

- In OGSs, the exploration of advanced materials such as chalcogenide glasses, perovskite nanocrystals, and quantum dots to enhance sensing performance is needed along with the investigation of novel photonic crystal architectures and fiber optic configurations for improved sensitivity and selectivity. Likewise, innovation in standardized testing methodologies such as EPA Method TO-15 and ASTM D6348 to ensure consistent sensor performance across diverse environments can be a future promise while ensuring focus on miniaturization techniques and biocompatible materials, like graphene derivatives, for healthcare applications.
- For ECSs, novel investigation in nanomaterial-enabled ECS platforms with tailored electrode configurations for enhanced selectivity through the development of advanced signal processing techniques, such as cyclic voltammetry (CV) and impedance spectroscopy (EIS) for improved analytical capabilities, can be new horizons to explore. Additionally, the standardization of calibration methodologies using EPA Method 325 and ASTM D6245 to address complex gas matrices should be looked at from the perspective of the integration of metal–organic frameworks (MOFs) and zeolitic imidazolate frameworks (ZIFs) to enhance long-term stability.
- The future challenges in potential research on CGSs can be overcome by researching dielectric materials such as metal oxides, perovskites, and two-dimensional materials like graphene and transition metal dichalcogenides (TMDs). This can be matured using gas-specific calibration methods based on EPA Method 25A and ASTM D7419, alongside humidity compensation strategies, while investigating flexible substrate materials such as polydimethylsiloxane (PDMS) derivatives for wearable applications. Furthermore, novel standardization testing protocols using ASTM D7419 and ISO 10156 to ensure accuracy and reliability can be improved.
- The potential for scientific investigation into CMGSs can be explored using sensitive calorimetric materials such as noble metal nanostructures and metal–organic frameworks (MOFs) for enhanced detection capabilities to develop dynamic response kinetics through advanced signal processing algorithms and thermodynamic modeling frameworks. From the standardization aspect, analytical techniques like isothermal titration calorimetry (ITC) and differential scanning calorimetry (DSC) for quantitative analysis along with energy-efficient designs and materials to improve overall sensor performance and efficiency can be very promising.
- In the niche of AGSs, much potential in investigating piezoelectric materials like lead zirconate titanate (PZT) and aluminum nitride (AlN) for enhanced acoustic wave propagation exists to develop gas discrimination methodologies using advanced algorithms such as principal component analysis (PCA) and neural networks. This can further be harnessed by employing standardized testing protocols like ASTM E2079 and ISO 11095 to ensure robust sensor performance in various environments. In addition, interdisciplinary approaches integrating complex materials, like carbon nanotube (CNT) composites and graphene-based heterostructures for improved sensitivity and selectivity, should be explored.

10. Conclusions

This comprehensive study delved into the crucial intersection of indoor air quality and respiratory health and aimed to address the challenge of diagnosing diseases associated with indoor respiration by establishing robust correlations between indoor air quality sensors and pertinent health outcomes. For quality investigation, six bibliometric analysis techniques were employed, thereby augmenting the precision, caliber, and thematic focus of the research. Through bibliometric evaluation, this review distilled salient insights from 152 scholarly articles, discerningly identifying relevant publications from authoritative sources such as the WHO, NIH, CDC, and US-EPA; this research methodology helped in the inclusion of articles that focused the scholarly investigation of this study. The impact of this work is evident in shedding light on the significant role of low-cost sensors, calibrated through advanced calibration systems, in tackling major respiratory diseases. These discerned findings not only enrich the scholarly discourse but also furnish invaluable insights for stakeholders spanning atmospheric science, public health, and environmental policy-making arenas. From end-users to governmental entities, this corpus of work facilitates informed decision making in sensing technologies; their capabilities, limitations, and calibration; and their relevance to respiratory concerns along with practical considerations in field practices in indoor air quality monitoring and management, along with future recommendations.

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