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Review

A Systematic Review for Indoor and Outdoor Air Pollution Monitoring Systems Based on Internet of Things

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Abstract: Global population growth and increasing pollution levels are directly related. The effect does not just apply to outdoor spaces. Likewise, the low indoor air quality is also having a negative impact on the health of the building residents. According to the World Health Organization, indoor air pollution is a leading cause of 1.6 million premature deaths annually. Tackling this public health issue, due to the direct relationship between air pollution levels and mortality and morbidity rates as well as overall comfort, is mandatory. Many companies have begun to build inexpensive sensors for use in Internet of Things (IoT)-based applications to pollution monitoring. The research highlights design aspects for sustainable monitoring systems including sensor types, the selected parameters, range of sensors used, cost, microcontrollers, connectivity, communication technologies, and environments. The main contribution of this systematic paper is the synthesis of existing research, knowledge gaps, associated challenges, and future recommendations. Firstly, the IEEE database had the highest contribution to this research (48.51%). The results showed that 87.1%, 66.3%, and 36.8% of studies focused on harmful gas monitoring, thermal comfort parameters, and particulate matter levels pollution, respectively. The most studied harmful gases were CO_2, CO, NO_2, O_3, SO_2, SnO_2, and volatile organic compounds. The cost of the sensors was suitable for people with limited incomes and mostly under USD 5, rising to USD 30 for specific types. Additionally, 40.35% of systems were based on ESP series (ESP8266 and ESP32) microcontrollers, with ESP8266 being preferred in 34 studies. Likewise, IoT cloud and web services were the preferred interfaces (53.28%), while the most frequent communication technology was Wi-Fi (67.37%). Indoor environments (39.60%) were the most studied ones, while the share for outdoor environments reached 20.79% of studies. This is an indication that pollution in closed environments has a direct impact on living quality. As a general conclusion, IoT-based applications may be considered as reliable and cheap alternatives for indoor and outdoor pollution monitoring.

Keywords: air quality; sustainable low-cost sensors; environmental contamination; particulate matter

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1. Introduction

The urban population is increasing rapidly, particularly in developing countries, all over the globe. Moreover, it has quickened in the past few decades. In 2018, around 55.3% of the worldwide population lived in urban zones. This is estimated to grow, reaching 60% by 2030. The fast expansion in urban areas significantly influences the ecological system. A major environmental issue linked to the process of urban development is air pollution. City areas usually have more air contaminants compared to rural areas, which is because of the high number of automobiles and industries, among other pollutant origins. Polluted air may lead to numerous illnesses including respiratory and cardiovascular problems [1].

Pollution is defined as the introduction of substances (solid, liquid, gaseous) or energies (radioactivity, heat, noise, light) into the natural environment that cause detrimental or negative changes in the environment. Pollution elements are either extraneous or naturally available pollutants. Although environmental pollution can be the result of natural accidents, pollution generally refers to anthropogenic activities. Pollution is often categorized as either point-source or nonpoint-source pollution. In 2015, pollution was responsible for causing approximately nine million deaths worldwide [2]. Air, light, littering, noise, plastic, soil, radioactive, thermal, visual, and water are the main pollution types.

In 2019, the exposure to ambient air pollution was found to be the largest factor, responsible for roughly 50% of deaths from all environmental risk factors. More than 50% of these deaths from ambient air pollution exposure occur in China and South Asia, while about 20% of the total global air pollution-related deaths occur in high-income countries in Europe and North America. Given the extensive evidence of health risks at very low concentrations of some pollutants, adequate air quality management, even in countries with relatively low levels of air pollution exposure, is mandatory [3]. The elevated levels of atmospheric pollutants create significant hazards to the health of individuals and the ecological balance [4]. Vehicles, industries, and household practices are critical polluting sources in metropolitan regions. Widespread city air contaminants comprise particulate matter (PM), SO_2, NO_2, ozone, CO, and NO. These tiny airborne particles can deeply penetrate the human physique, compromising the lungs, bloodstream, and heart and increasing the risk of cancer [5].

The baseline data of the UK Biobank study (2006–2010) were used. Mental disorders including symptoms of nerves, anxiety, tension, or depression (NATD) and bipolar disorder were assessed by validated questions. A total of 334,986 participants with measurements of NATD and 90,706 participants with measurements of major depression and bipolar disorder were included in the analysis. After adjusting for covariates, the odds for the risk of NATD symptoms increased by 2.31 (95% CI: 2.15–2.50) times per 10 $\mu g/m^3$ increase in $PM_{2.5}$. The odds for the risk of major depression and bipolar disorder increased by 2.26 and 4.99 times per 10 $\mu g/m^3$ increase in $PM_{2.5}$ [6]. Currently, around 55% of the world's population lives in cities, and it is expected that by 2050, cities will house 75% of the world population. In Spain, 81% of the population lives in cities, so the impact on population health levels is expected to be high [7].

There is a growing worry regarding air pollution and the harmful repercussions on people's physical condition. For this reason, reliable and inexpensive pollutant detection systems are urgently required. Nowadays, pollution is checked by conventional pollution monitoring stations. However, due to partial data access, large size, high cost, and the lack of scalability of air monitoring stations, researchers have recently started paying attention to so-called future pollution monitoring systems. In this sense, the emergence of the Internet of Things (IoT) has provided a prospect for reforming environmental pollution monitoring. It allows for instantaneous data retrieval, interpretation, and sharing [8]. Affordable IoT-based environmental monitoring devices have garnered considerable interest because of their capability to close the divide. Devices for measuring air quality are cost-competitive, allowing for the measurement of various environmental variables and enabling access to a broader user base [9]. The IoT concept is better defined as the ubiquitous presence of cyber-physical systems with advanced sensing, communication, and capabilities [10]. IoT is a web of linked devices with sensors and actuators that enable data gathering, analysis, and sharing through the Internet. Inexpensive pollution surveillance systems use IoT technologies to deal with problems derived from traditional monitoring practices. Issues involve high prices, a narrowed scope, and delayed data retrieval [11]. The affordability and scalability of low-cost pollution monitoring systems have positioned them as attractive alternatives to conventional monitoring systems, particularly in resource-constrained settings. These systems leverage inexpensive sensors, wireless communication technologies, and cloud computing platforms. In this way, it helps establish a network of interconnected devices capable of continuously monitoring various environmental parameters such as air quality, water quality, and PM concentration. An illustration of the layers of the concept of IoT is shown (Figure 1).

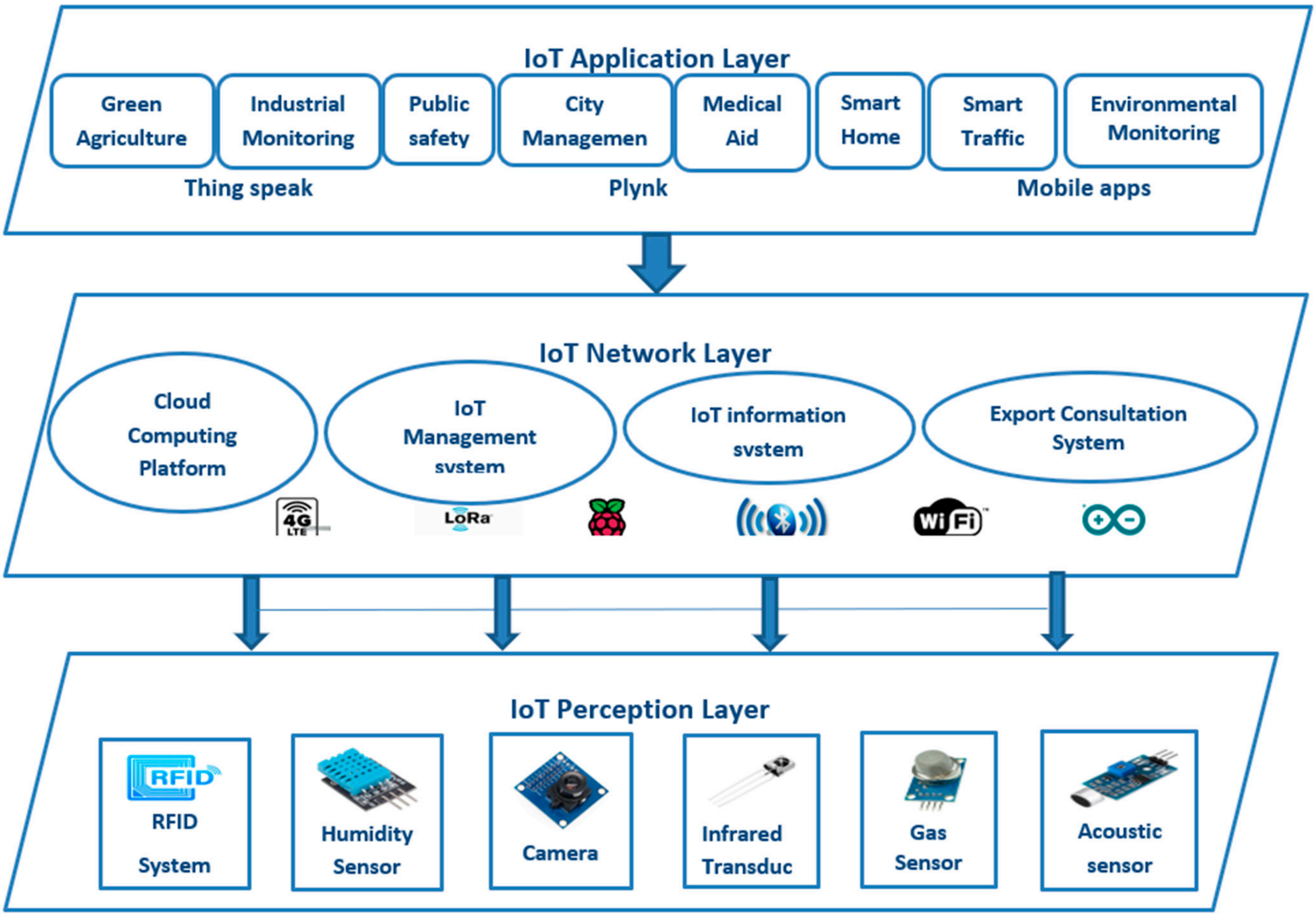

Figure 1. Layers of the Internet of Things.

This systematic review aimed to comprehensively explore and evaluate the state-of-the-art of indoor and outdoor low-cost pollution monitoring systems based on IoT. By synthesizing the existing literature and analyzing the strengths and limitations of these systems, this review sought to provide valuable insights into developing and deploying effective solutions for air pollution monitoring to enhance living environments. The comprehensive systematic review may serve as a guide for students, industry, and researchers, directing their research to meet specific requirements.

2. Methodology

A systematic review is an organized way of extracting, analyzing, and synthesizing information from existing primary databases concerning a specific set of research questions. This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) checklist. It is the most efficient way for researchers to conduct in-depth research. The process was divided into multiple steps to address the challenges associated with air quality (AQ) monitoring systems based on IoT. In the first step, eight specialized questions related to the existing research were selected, together with specific search strings and keywords. During the selection of the most relevant manuscripts from existing databases, inclusion and exclusion criteria were created. After that, data extraction and synthesis were carried out in response to pre-defined research questions. Furthermore, the Section 3 presents a detailed review of the current state-of-the-art of AQ monitoring systems based on IoT as well as the potential difficulties, limitations, and opportunities. The steps for performing this systematic review are detailed in the subsections that follow.

2.1. Research Questions

The authors formulated the following research questions (RQ), which this manuscript sought to answer through a detailed analysis. When defining the study inquiries, thoughtful deliberation to the most vital elements of affordable pollution tracking systems utilizing IoT was followed. The main objective was to determine the essential features that improved performance and the affordability of similar systems. The queries intended to offer a more profound comprehension of the subject while providing valuable data for subsequent studies.

RQ1: What are the different types of sensors utilized in the field of air quality (AQ) monitoring?

RQ2: What parameters can these sensors measure in the context of AQ monitoring?

RQ3: What measurement ranges are specified by sensor manufacturers?

RQ4: What microcontroller units (MCUs) are commonly used to connect these sensors?

RQ5: What interfaces are preferred for AQ monitoring sensing in these systems?

RQ6: What communication technologies are commonly utilized in these systems?

RQ7: What are the more frequent environments for the reviewed cases?

The initial two research inquiries, RQ1 and RQ2, were intended to determine the varied assortment of sensors used by researchers and the most harmful parameters responsible for the impact on air quality. To confirm the measuring capacity of the defined sensors, RQ3 focused on the specified measurement ranges provided by manufacturers. The study helps to comprehend the operational limits of detectors and their appropriateness for measuring pollutants. RQ4 aimed to offer an understanding concerning the widely embraced MCU, which could allow for comprehension of the technical features and application approaches, focusing on the strengths and weaknesses to shorten the research time by choosing the model that meets the requirements. RQ5 provided comprehensive analysis about the preferred interfaces for air pollution parameter presentation. The survey related to communication technologies was the main focus of RQ6. The inquiry sought to determine the preferred means of communication implemented in pollution monitoring systems using IoT technology. Through analyzing the dominant patterns in the field of communication, this analysis aimed to reveal the strategies implemented for exchanging and transmitting data. RQ7 provided information about the environments for reviewed cases, focusing on the most harmful to health. Through addressing these specific inquiries, this analysis offers a complete comprehension of the types of sensors, parameters, measuring ranges, costs, MCUs, connections, communication technologies, and environments for the reviewed cases in pollution monitoring systems relying on IoT. Solutions to these inquiries improve the information repository and aid researchers in making well-informed choices while developing and deploying productive, budget-friendly pollution monitoring systems.

2.2. Search Process

A thorough investigation was implemented to ensure a rigorous and systematic examination of pollution detection systems using IoT-based solutions. To conduct this review, four databases widely recognized in the academic community were used, namely IEEE Explore, Web of Science, Science Direct, and Google Scholar. Databases were selected according to their reliability, based on the publication of high-quality research relevant to this research topic. To ensure the inclusion of relevant documents, a detailed plan was implemented. In this sense, a mix of search queries and keywords related to the theme enabled a productive and targeted search. Searches merging the terms "air quality sensor", "monitoring system", and "internet of things" were mainly implemented. The search approach was uniformly enforced throughout the four chosen databases. The initial review process was implemented by the ChatPDF platform (the brainchild of Mathis Lichtenberger, Berlin, Germany) to acquire insights into manuscript summaries; search results were forwarded to the Sysrev platform (Insilica, LLC, Bethesda, MD, USA), which helped in detecting duplicate articles, then removing them from the selected references. The final analysis and summarization were conducted using the Mendeley Reference Manager v2.115.0 (Mendeley, UK), which has broad features such as managing references as well as the ability to download references from relevant databases. In general, we can use the above-mentioned platforms to evaluate, select, analyze, and finally, summarize the articles reliably. Initially, the search process yielded 183 publications. These publications were identified through IEEE Explore, Web of Science, and Science Direct, with 73, 51, and 32 each, respectively. A smaller number of publications were retrieved from Google Scholar, where only 27 entries were identified. A distribution of studies from the databases shows that the main findings (39.9%) were from IEEE Xplore, followed by Web of Science (27.9%), Science Direct (17.5%), and Google Scholar (14.8%).

2.3. Inclusion and Exclusion Criteria

To ensure the relevance of the literature selected for this systematic review, inclusion and exclusion criteria were established. These criteria helped to identify the most relevant papers among the 183 studies derived from the initial search query (Table 1). Manuscripts that comprehensively addressed indoor and outdoor air quality were prioritized. To focus on the optimal and most common types, clear and detailed sensor information was included. Finally, manuscripts illustrating the system design methodology, which enhances an understanding of the research approach, were emphasized. Additionally, duplicate manuscripts were excluded. Exclusion was extended to manuscripts lacking sensor details or a clear methodology for system design. Finally, to prioritize original empirical contributions, secondary studies that deviated from the primary focus were excluded. These criteria ensured accuracy and appropriateness in the research selection.

Table 1. Inclusion and exclusion criteria for systematic review.

	Inclusion Criteria (IC)		**Exclusion Criteria (EC)**
IC1	Publications beyond 2018	EC1	Duplicates
IC2	Inclusion of pollution parameters related to indoor and outdoor air quality levels	EC2	Missing focus on air quality
IC3	Inclusion of clear details about the used sensors	EC3	Missing details about the used sensors used
IC4	Items based on Internet of Things techniques	EC4	Missing clear design methodology
IC5	Clearly showing the system design methodology	EC5	Secondary studies

2.4. Study Selection

Selected manuscripts were found to comply with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. After this step, eight duplicate articles were removed, leaving 174 publications for additional evaluation. Following the implementation of the inclusion and exclusion criteria, 101 studies were considered eligible to be included in this exhaustive review. To guarantee the significance and quality, all studies were thoroughly examined. To show precise observations regarding the study design, an open and thorough selection procedure conforming to the PRISMA flow diagram (Figure 2) was implemented.

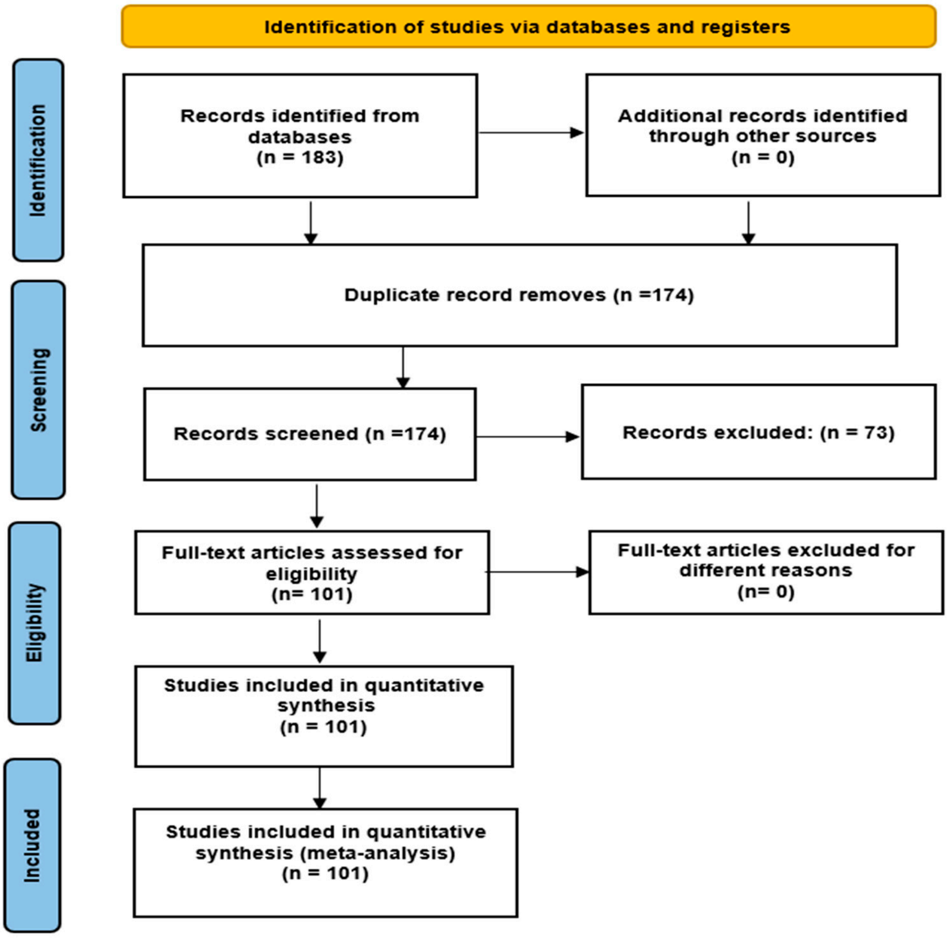

Figure 2. PRISMA flow diagram for systematic review.

2.5. Data Extraction and Synthesis

The initial data extraction was applied to all selected publications, leading to the following information: titles and abstracts of the included literature; authors' names; publication year; database; types of used sensors and analyzed parameters (RQ1 and RQ2); measurement ranges (RQ3); utilized MCUs (RQ4); interfaces and communication technologies (RQ5, RQ6); environments for the reviewed cases (RQ7).To tackle the investigation queries described in Section 2.1 (research questions), the information retrieval and integration procedures were carried out. The chosen articles underwent preliminary data evaluation, providing essential information to address the research inquiries thoroughly. Collected information included headings and summaries from the chosen publications, the author name, year of publication, and originating database. Regarding RQ1 and RQ2, the sensor types used in AQ monitoring and ND were recognized, along with specific parameters measured by these sensors. Moreover, measurement ranges specified by manufacturers for these instruments were shown in RQ3. In RQ4, those frequently utilized by MCUs to establish a connection with the sensors were recognized. RQ5 provided a comprehensive analysis of the preferred methods and types of interfaces for the selected pollution parameters. RQ6 was answered by studying the communication technologies widely adopted in pollution monitoring systems. Finally, RQ7 showed the preferred environments in the selected studies.

2.6. Risk of Bias

It is essential to acknowledge that systematic reviews, despite their rigorous methodology, are not immune to biases. In this particular review, several potential sources of bias warrant discussion. The first area of concern pertains to the screening process, where subjectivity may arise due to the interpretation and application of the inclusion and exclusion criteria. For instance, this systematic review focused solely on manuscripts related to air pollution parameters, potentially omitting valuable studies exploring other pollution types. Another significant risk of bias stems from the initial search query performed on the databases. The inclusion criteria limited the scope of the review to the literature published after 2018. Consequently, studies published before this timeframe were not considered, potentially overlooking relevant research that could contribute to a more comprehensive understanding of low-cost pollution monitoring systems based on IoT. Moreover, the search process was limited to a selection of four databases. While these databases are widely recognized and contain reputable indexed journals, excluding other databases such as SpringerLink, Scopus, and PUBMED may have introduced a bias by potentially omitting relevant studies. It is worth noting, however, that the Web of Science provides access to a substantial number of high-quality journals. To minimize bias and enhance the reliability of the findings, future systematic reviews on this topic could consider expanding the search to encompass additional databases, ensuring a more comprehensive coverage of the relevant literature. Additionally, conducting a systematic review that included studies published before 2018 could offer a more holistic perspective on the development and advancements in low-cost pollution monitoring systems based on IoT. However, technological advances have grown exponentially in the last decade, so significant contributions are not expected before 2018.

3. Results

After applying the pre-defined inclusion and exclusion criteria, only 101 studies out of 183 were included in this systematic review. Out of these, IEEE Xplore contributed 49 studies (48.51%), Web of Science provided 23 relevant studies (22.77%), and 18 studies (17.82%) were included from the Google Scholar database. Finally, Science Direct provided 11 relevant studies (10.89%). However, no studies from the SpringerLink, Scopus, or PUBMED databases were found to be relevant, as per the selection criteria of this systematic review. Table 2 shows the year-wise distribution of the included studies from different databases.

Table 2. Publication distribution for each database per year.

Database	2018	2019	2020	2021	2022	2023	No
IEEE Xplore	[12–23]	[5,24–34]	[35–45]	[46–56]	[57,58]	[41,59,60]	49
Web of Science (WoS)	[61–67]	[68–76]	[77,78]	[79]	[80,81]	[82,83]	23
Google scholar	[84–90]	[91–93]	[94–96]	[97,98]	[89,99,100]		18
Science Direct	[101–104]	[105–107]	[26,108,109]	[110]			11

3.1. Answer to RQ1

The studies included in this systematic review provided insights about the 97 different sensor types for AQ detection, thermal comfort, and PM used by previous researchers (Table 3). Considering harmful gas sensors, the MQ series (MQ135, MQ7, MQ136, MQ-131, MQ8, MQ9, MQ6, MQ5, MQ4, MQ2) took the lead by a large margin from the rest of the sensors, reaching 53 out of 88 studies (59%) due to its ease of installation and low cost. However, the calibration and accuracy issues should be carefully addressed. This make was followed by MG 811, MH-Z14, and OX-B431 (four studies each), and the Alpha sensor series (NO_2-B43F, CO-B4) in three studies. The remaining 53 types of sensors were only mentioned in one or two studies each. For measuring the PM levels, of the 12 sensors in 42 studies, the Sharp GP2Y1010AU0F Dust Sensor was the preferred solution in 20 studies (47.6%), followed by the PM series (PMS5003, PMS7003, PMS1003, PMS3003) in 8 studies (19.0%), and DSM501A in 5 studies. Finally, to achieve an ideal thermal comfort, out of the 12 sensors selected in 63 studies, the DHT series (DHT11, DHT22) was the most reliable in 32 studies (49.5%), followed by the BME (280, 680) series in 12 studies, and the SHT series

(SHT21, SHT30, SHT31, SHT25) in 6 studies. In Figure 3, a simplified distribution of the proportions of the sensors above-mentioned is shown.

Table 3. Different sensor types used for air quality monitoring.

Sensor Name	Measured Parameters	Measuring Nominal Range	References
MQ135	NH_3, NO_x, C_2H_5OH, C_6H_6, CO_2, smoke	NH_3: 10–300 ppm; C_6H_6: 10–1000 ppm; C_2H_5OH: 10–300 ppm	[12,15,21–23,25,30–32,34,42,43,47,49–53,55,56,58–61,69,76,80,83–85,87,90,92,94–97,100,105,106,108]
MQ7	CO	20–2000 ppm	[12,14,21,22,30,34,49,50,52,53,55,56,59,69,70,80,81,90,94,98,100,105]
MQ2	SnO_2	300–10,000 ppm	[27,28,34,35,50,56,59,63,70,94]
MQ4	CH_4	200–10,000 ppm	[12,21,32,50,55,63]
MQ5	LPG, NG, town gas	200–10,000 ppm	[42,50,81]
MQ6	LPG, C_4H_{10}, C_3H_8,C_2H_5OH, smoke	200–10,000 ppm	[12,20,50,59,85,90]
MQ9	CO, fuel gas	10–1000 ppm	[12,33,38,41,50,76,83,90]
MQ8	H_2, LPG, CO, O_3	50 ppb O_3 1~200 ppm	[43,50,64,70]
MQ-131	O_3	10–1000 ppm	[26,43,50,70,96]
MQ136	O_3	−200–650 ppm	[43,70]
MH-Z14	CO_2	0–5000 ppm	[39,68,78,98]
OX-B431	O_3, NO_2	20–50 ppm	[5,18,24,77]
MiCS-2714	NO_2, H_2	H_2: 1–1000 ppm, NO_2: 0.05–10 ppm	[64,87]
4-NO_2-20	NO_2	0–20 ppm	[63]
DGS-NO_2 968-043	NO_2	0–5 ppm	[111]
DGS-CO 968-034	CO	1000 ppm	[111]
$NiSb_2O_6$ oxide	CO	0.1–500 ppm	[71]
SEN0219	CO_2	0–5000 ppm	[79]
MG812	CO_2	350–10,000 ppm	[16]
MG 811	CO_2	0–10,000 ppm	[22,55,70,72]
S80053	CO_2	0–20,000 ppm	[29]
MH-Z16	CO_2	400–10,000 ppm	[88,89]
INE20-CO_2P	CO_2	0–5000 ppm	[63]
TDS5008	CO_2	ND	[77]
Telaire T6713	CO_2	0–5000 ppm	[64]
MICS-4514	CO, NO_2	CO: 1–1000 ppm; NO_2: 50–5000 ppb	[68,111]
Alpha sensors (NO_2B43F)	NO_2	NO_2: −200–−650 ppm	[5,18,24,46,77]
Alpha sensors (CO-B4)	CO	CO: 420–650 ppm	[46]
4-CO-500	CO	0–500 ppm	[63]
4co-S Carbon Monoxide Elec Sensor	CO	0–500 ppm	[41]

Table 3. *Cont.*

Sensor Name	Measured Parameters	Measuring Nominal Range	References
(MICS 2614 metal-oxide)	O_3	ND	[91]
DGS-O3 968042	O_3	0–5 ppm	[111]
MiCS2610-11	O_3	<100 ppm	[90]
SP-61	O_3	0–250 ppm	[77]
OX-A431	O_3	0–18 ppm	[63]
ME2-O2	O_2	0~25% *v*/*v*	[22]
CO2Meter K-30	CO_2	0–5000 ppm	[102]
IRC-A1	CO_2	0–5000 ppm	[77]
MH-Z19	CO_2	0–2000 ppm; 0–5000 ppm	[93,99]
CDM7160	CO_2	300–5000 ppm	[101]
GSNT11	NO_2	0–200 ppm	[90]
NE4-NO2	NO_2	0–30 ppm	[41]
SO2-AF	SO_2	0–50 ppm	[90]
4-SO2-20	SO_2	0–20 ppm	[63]
4-CL2-50	Cl_2	0–50 ppm	[63]
KG-HO2	HCHO	0–7 mg/m^3	[75]
KG-TV2	TVOC	0–3 mg/m^3	[75]
KG-C62	C_6H_6	0–320 mg/m^3	[75]
KG-C22	CO_2	0–0.5%	[75]
KG-C12	CO	0–500 ppm	[75]
KG-N22	NO_2	0–20 ppm	[75]
KG-O_3	O_3	0–20 ppm	[75]
CJMCU-30	TVOC/eCO_2	ND	[99]
CJMCU-6814	CO, VOC, NH_3 NO_x	CO: −1000 ppm; NO_2: 0.05–10 ppm	[99]
SCD30CO_2	CO_2, RH and T	400–10,000 ppm	[37,49,81]
SGP30	TVOC, CO	0–1000 ppm	[33,36]
CCS811	TVOC, eCO_2	CO_2: 400–8192 ppm; VOC: 0–1187 ppm	[37,65]
GP2Y1010AU0F Optical Sensor	$PM_{2.5}$, PM_{10}	0–600 μg/m^3	[16,30,31,42,46,50,53,56,57,60, 68,80,86,90,95,97,98,102,106]
PMS 5003	$PM_{2.5}$	0–500 μg/m^3	[29,43,49,66]
DSM501A	$PM_{2.5}$	≤8000 pcs/283 mL	[25,26,38,55,90]
PMS7003 and Plantower	$PM_{2.5}$	0–500 μg/m^3	[5,48]
SPS30 sensor	$PM_{2.5}$	1, 2.5, 4 and 10 μg/m^3	[36,37,111]
SDS021 sensor	$PM_{2.5}$, PM_{10}	0.3–10 μm	[28]
KG-PM2	$PM_{2.5}$, PM_{10}	0–1000 μg/m^3	[75]
SEN0177	$PM_{2.5}$	0~500 μg/m^3	[79,103]
SM-PWM-01C	$PM_{2.5}$	1–999 μg/m^3	[19]

Table 3. *Cont.*

Sensor Name	Measured Parameters	Measuring Nominal Range	References
PMS1003	$PM_{2.5}$, PM_{10}	0~500 g/m^3	[39]
PMS3003	$PM_{2.5}$	0.3~1.0; 1.0~2.5; 2.5~10 (mm)	[35]
PPD42NS	$PM_{2.5}$	0.1 mg/m^3	[62]
DHT22	T, RH	T = −40–80 °C; RH = 0–100%	[14,24,39,41,47,53,64,70,87,95, 99,104,108]
DHT11	T, RH	T = 0–50 °C; RH = 20–90%	[5,15,23,25,28,40,50,55,56,60–62,80,83,90,92,97,105,106]
SHT21	T, RH	T = −40–125 °C; RH = 0–80%	[65,104]
BME280	T, RH, P	T = 0–60 °C; RH = 0–100%; P = 300~1100 hPa	[36,39,49,63,65,101]
SHT30	T, RH	T = −55–125 °C; RH =0–100%	[29]
SHT31	T, RH	T = −40–125 °C; RH = 0–100%	[19]
SHT25	T, RH	T = −40–125 °C; RH = 0–100%	[88]
HMP60	T, RH	T = −40–60 °C; RH = 0–100%	[102]
MCP9802	T	T = −55–125 °C	[101]
KG-TN2	T, RH, illumination, N	T = −40–80 °C; RH = 0–99.0%; I = 0–2000 Lux; N = 0–120 dB	[75]
BMP180	P, T	P = 300–1100 hPa; T = −40–85 °C	[17,38,64,80]
LM35	T	T = −55–150 °C	[16,20,85]
DS18B20	T	T = −55 –125 °C	[17]
BMP280	P, T	P = 300–1100 hPa; T = −40–85 °C	[33,76]
SY-H5220	T, RH	T = 0–60 °C; RH = 30–90%	[85]
HDC1080	T, RH	T = −40–125 °C; RH = 0–100%	[33]
BME680	RH, VOC, T, P	T = −40–85 °C; RH = 0–100%; P = 300–1100 hPa; VOC = 0.5–15 ppm	[37,44,72,73,99,110]
MiCS-5524	CO, CH CH_2OH, VOC	CO: 1–1000 ppm, NH_3:1–500 ppm, CH_2OH: 10–500 ppm	[64]
WSP2110	Air quality, CO, NH_3, NO_2	C_2H_5OH: 10–500 ppm, H_2: 1–1000 ppm, NH_3: 1–500 ppm, CH_4: >1000 ppm, C_3H_8: >1000 ppm, C_4H_{10}: >1000 ppm	[63]
TGS2602	Air quality (VOC, NH_3, H_2S)	CH_2OH: 1~30 ppm	[67]
TGS2603	(C_3H_9N, CH_4)	CH_2OH: 1–10 ppm	[67]
TGS2612	CH_4, LPG, C_3H_8, C_4H_{10}	1–25% LEL of each gas	[67]
TGS2620	CH_3CH_2OH	50–5000 ppm	[67]
TGS-2610	CH_3CH2OH, CH4, C_3H_8, C_4H_{10}	500–10,000 ppm	[62]
MICS-6814	C_6H_5CH, CH_4, C_6H_6, CH_3CH_2OH	1~50 ppm	[74]

Table 3. *Cont.*

Sensor Name	Measured Parameters	Measuring Nominal Range	References
SAMBA	Air and radiant T, RH, air speed, light levels, sound, P, CO_2, TVOC	102 $\mu g/m^3$	[107]
Waspmote	CO, CO_2, O_2, O_3, NO, NO_2, SO_2, NH_3, CH_4, H_2S, $PM_{0.1}$, $PM_{2.5}$, PM_{10}, T, RH, P	ND	[45,109]

eCO_2: equivalent calculated carbon dioxide, P: atmospheric pressure, LEL: lower explosive limits: liquid petroleum gas, mm: millimeter, NG: natural gas, ND: no data available, PDM: pulse density modulation, PM_{10}: particulate matter (<10 µm), $PM_{2.5}$: particulate matter (<2.5 µm), RH: relative humidity, $PM_{0.1}$: particulate matter (<0.1 µm): temperature, TVOC: total volatile organic compounds, VOC: volatile organic compounds.

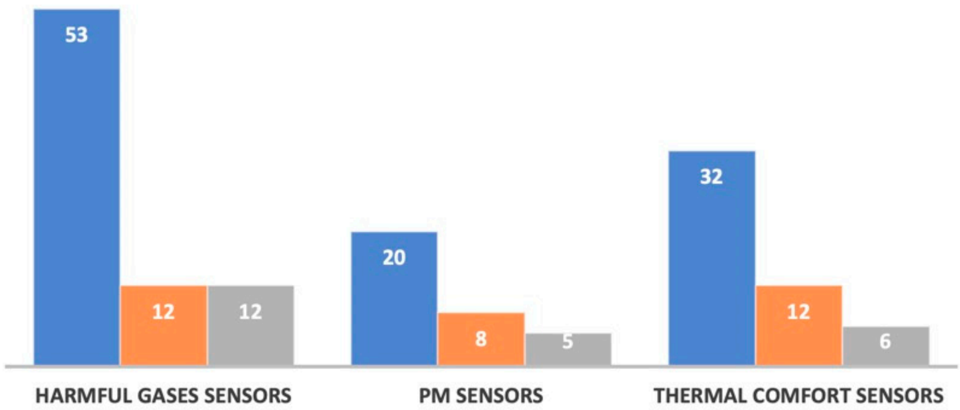

Figure 3. Distribution of air pollutant sensor studies. PM: particulate matter. The colors in the columns above indicate the number of sensors compared to their counterparts with the same parameters. The highest percentage is in blue, followed by orange and gray.

3.2. Answer to RQ2

Table 3 shows the analysis of two parameters of air pollution, namely toxic gases and dust, in addition to comfort parameters (humidity and temperature). Toxic gases are crucial for air pollution. The gases and volatile parts most mentioned in this targeted study were CO, CO_2, NO_2, O_3, SO_2, NH_3, C_3H_8, C_4H_{10}, C_2H_6O, H_2, C_6H_6, CH_4, C_2H_5OH, HCHO, H_2S, H_2S, SnO_2, and TVOC, where they were mentioned in 87.1% of the selected studies on air pollution, with 88 studies out of all studies. These were studied as a unity, instead of separately, as most studies do, because many sensors have the ability to measure several gases together. For this reason, depending on the factory data of the sensors, only the most common gases will be mentioned (CO_2, CO, NO_2, O_3, SO_2, H_2, SnO_2, VOC). Data were followed by the comfort parameters, represented by relative humidity (RH) and temperature (T), which were mentioned in 67 studies, representing 66.3% of the total studies. $PM_{2.5}$ and PM_{10}, two of the most important pollutants, were studied in 42 out of 101 studies selected (41.5%). Results are shown in Figure 4.

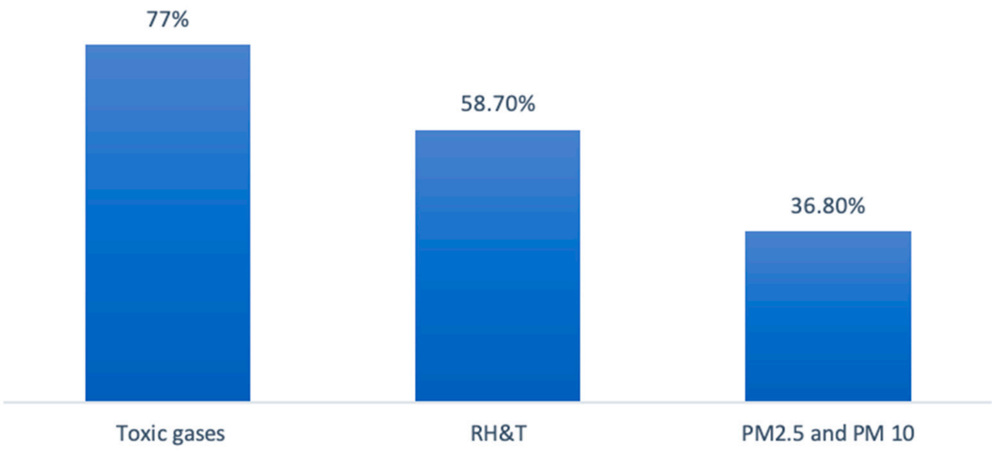

Figure 4. Analysis of different parameters related to pollution in the literature. RH: relative humidity; T: temperature; PM: particulate matter.

3.3. Answer to RQ3

The analysis of the sensor measurement range is included in Table 3. Manufacturer specifications play an essential role in sensor selection, since contaminant concentration may vary depending on the installation environment. A total of 59% of the harmful gas studies used MQ series sensors, which have ranges between 10 and 1000 ppm (CO_2), 10–300 ppm (NH_3), 10–1000 ppm (C_6H_6), 10–300 ppm (C_2H_5OH), 20–2000 ppm (CO), 300–10,000 ppm (SnO_2), 200–10,000 ppm (CH_4), 10 1000 ppm, 50 ppb (O_3), 1200 ppm (H_2), 225–650 Na/ppm (SO_2), and −225 to 650 ppm (NO_2).The effective range for a widely used dust sensor (Sharp GP2Y1010AU0F) used in 47.6% of the selected studies was 0–600 $\mu g/m^3$. Following this, in the case of the PMS series, the range was lower (0–500 $\mu g/m^3$). Temperature and humidity sensors are capable of measuring values on both the negative scale and within a wide positive range. The most commonly used sensors were DHT11 (T = 0–50 °C; RH = 20–90%), followed by DHT22 (T = −40 to +80 °C; RH = 0–100%), and then the BME series (280, 680) (T = 0–60 °C; RH = 0–100%, T = −40 to +85 °C, RH = 0–100%). The selection of gas sensors depends on their sensor range. Multi-gas sensors typically have a higher parts per million range compared to single gas sensor units. Additionally, there are significant challenges associated with ensuring accuracy and calibration when it comes to gas sensors. Therefore, it is essential to establish a careful and interdependent relationship between these factors when choosing the appropriate sensors. Results are shown in Figure 5.

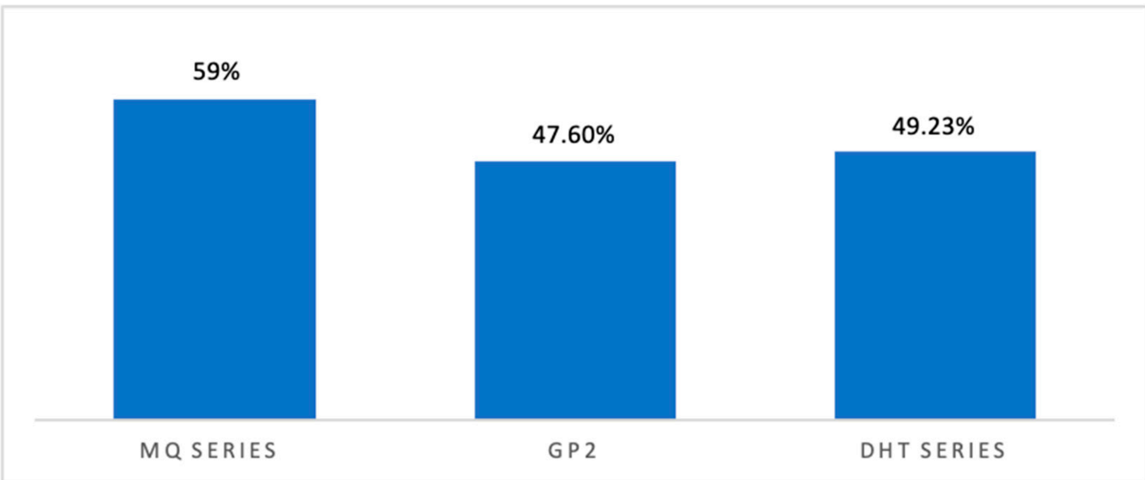

Figure 5. Most commonly used sensor models compared to their counterparts.

On the one hand, most thermal comfort sensors (12 out of 17) are available for an estimated price under USD 10. Most dust sensors cost under USD 21 (7 out of 11 sensor types). Finally, anomaly gas sensors, which were the most important in this systematic study, showed an average cost from USD 5 to USD 30 (34 out of 46). However, because several products are not available online, we could not provide an accurate pricing analysis for a number of sensors. Considering the total monitoring system, cost of field calibration, and setup, additional hardware requirements and installation fees should also be included.

3.4. Answer to RQ4

Table 4 provides an analysis of the MCUs used for the development of AQ monitoring systems. Based on the results of the 23 MCU models used, ESP (ESP8266 and ESP32) modules with Wi-Fi built-in were the most preferred ones in 46 studies (40.35% studies). Gateway MCUs were used instead of slave MCU. In 32 studies, ESP8266 was the most commonly used one. However, the Arduino series (Uno, Nano, Mega 2560, Yun, and Mega) was analyzed in 38 studies (33.33%). This was followed by the Raspberry Pi series (2, 3, and 4) with 26 studies (22.18%) as the most preferred slave and gateway MCU. All of these MCUs are available as open-source platforms for real-time monitoring applications. For each MCU model (ATmega328P (Microchip Technology, Chandler, AZ, USA), Waspmote (Libelium, Zaragoza, Spain), Wemos D1Mini (Wemos, Amsterdam, The Netherlands) and Pycom Gpy (Guildford, UK)), only two studies were found. However, for the MCUs mentioned here (M0 microcontroller (STMicroelectronics, Geneva, Switzerland), AVR MCU (Microchip technology, Chandler, AZ, USA), ARM7 (ARM Holdings, Cambridge, UK), STM32F103C8T6 MCU (ARM Holdings, Cambridge, UK), Atmel's AVR MCU (Microchip technology, Chandler, AZ, USA), ATSAMD21G18 MCU (ARM Holdings, Cambridge, UK), and PIC16F877A (Microchip technology, Chandler, AZ, USA)), only one study was selected. The cost is the main concern regarding its implementation. Finally, four studies [82,89,96,108] did not provide clear details about the used gateway operations or slaves.

Table 4. Microcontrollers used to connect sensors.

Microcontrollers	References
Arduino Uno	[12,20,22,23,31,34,35,38,42,43,47,51,52,55,61,69,72,79,81,84,85,91,92,98,102,103,105,107,108]
Arduino Nano	[12,56,81,106]
Arduino mega$_{2560}$	[45,86,111]
Arduino Yun	[18]
Arduino mega	[39]
ESP8266	[12,14,21–23,25,27,34,35,46,49,50,52–55,59–62,66,71,73,74,76,82,85,90,93,95,96,104]
ESP32	[26,30,32,37,39,40,50,68,71,77,78,80,88,89,97,99,100,110,111]
Raspberry Pi	[5,12,31,38,55,65,83,101]
Raspberry Pi2	[63,87]
Raspberry Pi3	[15,24,28,32,33,39,44,48,70,72,75,76,106]
Raspberry Pi4	[57,82]
ATmega328P	[40,59,69,90]
M0	[48]
AVR	[13,41]
Wemos D1Mini	[53,66]

Table 4. *Cont.*

Microcontrollers	References
ARM7	[94]
STM32F103C8T6	[29]
Atmel AVR	[13]
ATSAMD21G18	[36]
Waspmote, meshlium	[45,109]
ATmega328	[16,62]
Pycom Gpy	[88,111]
PIC16F877A	[21]

3.5. Answer to RQ5

The preferred data consulting methods are presented in Table 5. It shows that 65 studies (53.28%) focused on the development of a web page or server, an IoT cloud, and an application programming interface (API) for displaying AQ level characteristics. Moreover, 38 studies (31.15%) used a mobile app to display the real-time status of the measured AQ parameters. LCD, LED, and OLED displays were preferred in 15 studies (12.30%), and only three studies used the Serial Monitor IDE. In 26 studies, more than one way of presenting data was found [21,22,24,25,30,33,40–43,46,56,58,66,67,72,76,82,83,87,96,104,105,111]. However, several authors did not provide clear details about the preferred data consulting methods [30,36,39]. Mobile apps provide a reliable solution for real-time measurements since they allow users to stay up-to-date ubiquitously regarding AQ conditions. An LCD display also provides on-site updates and off-site tracking solutions. Solutions were mainly based on the web or in addition to other solutions; the web is considered as the ideal solution for monitoring from everywhere in the world and any device. The more popular platforms were ThinkSpeak (https://thingspeak.com/, accessed on 1 August 2023), followed by Blayank (https://blynk.io/, accessed on 1 August 2023), which contains a cloud, displays in real-time, and is open source.

Table 5. Preferred interfaces for air quality monitoring.

Interfaces	References
Web services, webpage, IoT cloud, and API	[5,12–14,16,18,20,22,24–31,35,36,38,39,41,43,45,46,48–54,56,57,59,61–64,66–70,72–74,76,77,79–82,84,85,87–91,93,95–98,101–105,107,110]
Mobile app	[12–14,16,18,21,23–25,27,29,30,32,34,39,40,42,44,47,53,60,62,64,68,72–74,78,82,83,93,95,96,99,103]
LCD, LED, OLED displays	[20,21,35,41,44,50,51,55,59,60,84,86,104,108]
Serial monitor IDE	[47,49,92]

API: application programming interface, IDE: integrated development environment, LED: light emitting diode, LCD: liquid crystal display, app: mobile application, OLED: organic light-emitting diode.

3.6. Answer to RQ6

According to Table 6, it may be found that wireless fidelity (Wi-Fi) is the most preferred communication technology, followed by the Global System for Mobile Communications (GSM), in addition to a small wireless networking protocol designed for IEEE 802.15.4 radios and 8-bit microcontrollers (ZigBee) as well as modules, which are embedded solutions providing wireless end-point connectivity to devices (Xbee), long range (LoRa), and Bluetooth low energy (BLE) technologies, respectively. In total, 64 studies (67.37%) used Wi-Fi for AQ monitoring systems. However, 11 studies preferred 3/4G and GSM techniques, followed by RF techniques (ZigBee and Xbee) with 9 studies, while LoRa and serial port were present in 5 studies each. Eight out of a hundred and one studies did not include clear details about the communication method, while only one study relied on an LCD screen to display data. The ESP series (ESP8266, ESP32 and ESP01) ranked first among used the Wi-Fi technologies, scoring more than 80% in 52 out of 64 studies. The most preferred protocols for Wi-Fi communication were MQTT and IEEE 802.11 b/n/g, whereas IEEE 802.15.4 was used for ZigBee communication. Wi-Fi and 3G/4G communication technologies have gained significant attention. In contrast, other technologies have not received as much recognition, despite their low power consumption. This is primarily because they remain constrained by limited coverage, typically not exceeding 2 km at best, and fail to meet the requirements of the environmental monitoring of sites or cities remotely and continuously from anywhere in the world.

Table 6. Preferred communication technologies.

Communication Technologies	References
Wi-Fi model, shield, or ESP series	[12,14,19,21–24,27,29–35,37,38,40,43–46,49–56,59–62,64–66,68–70,72–74,76–78,80,82,84,85,90,91,93–98,100,103–105,109,110]
LoRa WAN	[29,36,46,48,62]
ZigBee and Xbee RF	[5,13,18,23,24,63,90,102,107]
(BLE)	[65]
3/4G modem and GPS/GPRS/GSM	[15,20,24,39,41,45,79,81,91,106,109]
Ethernet and USB or serial port	[16,45,47,57,92]

BLE: Bluetooth low energy, ESP: Espressif modules, GPS: global positioning system, GPRS: general packet radio service, GSM: global system for mobile communication, LoRa: long range, USB: universal serial bus, Wi-Fi: wireless fidelity.

3.7. Answer to RQ7

After analyzing Table 7, indoor environments were found in 40 studies (39.60%), while outdoor environments were present in 21 studies (20.79%). Finally, 40 studies (39.60%) either specialized in both indoor and outdoor environments or did not mention it. Interests seem to be broader in indoor environments, because the risks of pollutants in closed places are higher and have a direct impact in the short-term. Although the impact of pollution in outdoor environments is no less dangerous, the risk is considered indirect and in the long-term.

Table 7. Environments for the reviewed cases.

Environment	References
Indoor	[17,19,22,23,25,29–34,37,40,42,45,47,53,57,63,64,66–69,73–75,80,82,87–89,93,95,98,101,102,104,107,110]
Outdoor	[5,14,16,18,21,24,28,38,46,48,50,54,55,71,76,79,81,84,86,91,109,111]
Indoor and outdoor or the environment is not mentioned	[12,13,15,16,18,20,26,27,35,36,41,43,44,49–52,56,58–62,65,70,72,77,78,83,85,90,92,94,96,97,99,100,103,105,106,108]

4. Conclusions

This is the first systematic review paper to highlight air pollution in indoor and outdoor environments. The highest number of studies was found in the IEEE database because it specializes in research in electrical and electronic engineering technology. The MQ series sensor took the lead from the rest of the sensors in the number of selected studies regarding harmful gas sensors. For measuring the particulate matter (PM) levels, the Sharp

GP2Y1010AU0F Dust Sensor was the preferred solution. However, the DHT series was selected regarding the comfort parameters. The majority of the manuscripts focused on harmful gases (CO_2, CO, NO_2, O_3, SO_2, SnO_2, and volatile organic compounds), thermal comfort parameters, and PM levels. Many systems are based on Esp and Arduino series microcontrollers, with ESP8266 being the preferred. Furthermore, preferred interfaces focused on the development of a webpage, server, or an Internet of Things cloud for displaying air quality characteristics. In total, the majority of studies used Wi-Fi for air-quality-level monitoring systems. The indoor environments achieved the highest attention. Nevertheless, the current study also has its limitations as the pre-defined inclusion and exclusion criteria were limited. In a future work, the inclusion of more types of pollutants (i.e., water and soil ones) is recommended. Furthermore, the studies were provided from four databases; the inclusion of more databases would strengthen the study.

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