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Review

A Review of Academic and Patent Progress on Internet of Things (IoT) Technologies for Enhanced Environmental Solutions

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Abstract: Environmental pollution is a pressing global issue, and the Internet of Things (IoT) offers transformative potential for its management through its application in advanced real-time monitoring and analytics. However, the heterogeneous and fragmented nature of IoT technologies poses challenges to seamless integration, limiting the efficacy of these solutions in addressing environmental impacts. This paper addresses these challenges by reviewing recent developments in IoT technologies, encompassing sensor networks, computing frameworks, and application layers for enhanced pollution management. A comprehensive analysis of 74,604 academic publications and 35,000 patent documents spanning from 2008 to 2024 is conducted using a textual analysis that combines quantitative bibliometric methods along with a qualitative analysis based on both scholarly research and patent innovations. This approach allows us to identify key challenges in IoT implementation for environmental monitoring—including integration, interoperability, and scalability issues—and to highlight corresponding architectural solutions. Our findings reveal emerging technology trends that aim to overcome a few of these challenges, and we present a scalable IoT architecture as key discussions that enhances system interoperability and efficiency for pollution monitoring. This framework provides targeted solutions for specific tasks in pollution monitoring while guiding decision-makers to adopt solutions effectively.

Keywords: Internet of Things (IoT); pollution management; technology fragmentation; carbon neutrality; patent analysis; environmental analytics; technological convergence; IoT technologies

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1. Introduction

Pollution is an inescapable issue with implications for human health on a global scale. The rising global warming concerns in recent decades and associated climate change have aroused widespread concern worldwide in the past and current decade. Reducing environmental pollution is the most urgent global focus since the effects propagate across national borders [1]. The United Nations Framework Convention (UNFC) on climate change hosted the 21st Conference of the Parties (COP 21), where countries agreed to commit to limiting the global temperature rise to below 2 degrees centigrade. The global response that went into force in 2016 has resulted in multiple successful iterations of national planning. Many global agreements, such as the Paris Agreement, propose that all countries work together to ensure that global average temperature increases are kept below 1.5 °C. Contributing to this global goal, many countries have promised the target of carbon neutrality. Most have committed to achieving carbon neutrality by 2050, including the European Union, the UK, America, Canada, Japan, New Zealand, South Africa, etc. Some countries, such as Uruguay, Finland, Iceland, Austria, and Sweden, plan to reach the targets earlier, and they propose becoming carbon neutral by 2030, 2035, 2040, and 2045. The success of important treaties like the Montreal Treaty has resulted in important environmental, health, and economic benefits, notably including the phase-out of 99% of ozone-depleting chemicals in refrigerators, air conditioners, and other products. The global health and economic benefits are expected to amount to US $2.2 trillion due to averted damages to agriculture, fisheries, and materials.

Furthering the success of such agreements, demands increased the participation of low and medium-income countries, which necessitates affordable, scalable solutions to leapfrog the progress. Technological intervention is expected to play a significant role in reducing pollution; however, the technology transfer rate is low in most sectors [2]. A range of technologies are specifically employed to address the environmental pollution problem, with the most commonly occurring being Internet of Things (IoT) technology [3]. IoT, in the environmental context, is not limited to a network of sensors but represents a broader ecosystem that integrates sensing, communication, computational analysis, and application layers. This enables the transformation of raw environmental data into meaningful insights and actions, addressing delayed responses [4–7]. Therefore, IoT technology finds applications in smart cities, industries, buildings, and vehicles. IoT integrations are increasingly leading toward the implementation of cost-effective anti-pollution technologies [8–10]. It has been extensively applied to low-cost solutions to mitigate environmental issues with its specialized processing, networking, power, and analytics, which have demonstrated promising results [11].

The underlying variety, availability, inclusiveness, and experimentation have made IoT highly divergent in nature, with a high rate of technology fragmentation. One notable application is the deployment of modular IoT technologies equipped with calibrated low-cost sensors, which have been instrumental in enhancing indoor air quality (IAQ) [12]. This research highlights the role of IoT technologies in facilitating environmental monitoring and control systems. Furthermore, ref. [13] emphasizes the important function of IoT technologies within the Industry 4.0 framework, showing its potential to drive advancements in environmental monitoring and control systems. Additionally, another comprehensive research study [14] delves into the intricacies of security and privacy within IoT technologies, providing valuable insights into the development of secure and efficient IoT systems. Also, the research conducted in [15] proposed a four-layered IoT technology as a classification method to better define IoT technology categories, which serve as one of the key enablers of Industry 4.0. However, the availability of multiple innovative IoT solutions poses challenges for management in terms of decision-making. Numerous options to choose from result in decision-maker dilemmas and difficulties in determining which solutions to use and in what use case. The complexity of evaluating and integrating various IoT solutions can lead to delays in decision-making and the translation of innovative solutions into practical implementation. Similar unique challenges have incentivized efforts toward reviews, surveys, and the analysis of bibliometric publication data presenting a general state-of-the-art for IoT specification over time. Neelam and Sood (2020) conducted similar investigations involving a scientometric review-based approach to disaster management [16].

Scientometric and patent analytics can be valuable in examining scientific publications and research trends, and patent analytics, which analyzes intellectual property filings, can help management gain a comprehensive review of available IoT innovation options. IoT has matured as a technology, which is quite evident from the abundant publications, patents, and emerging implementations available. Therefore, the main approach that could help translate this information is an in-depth analysis of the solutions, which can help declutter the emerging solutions. By streamlining the decision-making process, scientometric and patent analytics can help overcome delays and ensure the timely implementation of the most suitable solutions in any domain. For instance, a relatively uncommon tool in engineering processes was prescribed as a solution to information overload on the basis of scientometric and patentometric data analysis [17]. Therefore, employing a systematic approach to literature review and the analysis of patent grants, recent studies have identified the potential of emerging technologies to support creative and innovative problem-solving in engineering, suggesting its incorporation into existing workflows to enhance decision-making and collaboration. As we strive towards Sustainable Development Goal 7 (SDG 7), which calls for universal access to affordable, reliable, and sustainable energy [18], and SDGs 11, 13, 14, and 15, which target air quality, climate, and biodiversity on land and below water [19], IoT not only aids in environmental monitoring but also contributes to the realization of affordable and clean energy solutions, underscoring its importance in shaping a sustainable future. This paper focuses on the following key research aspects:

- A visualization and review of academic manuscripts and global patent portfolios, as well as key technologies (sensors, analytics) in practice towards environmental pollution monitoring using IoT.
- The combined textual analysis of academic scholarly databases and patent data systematically identifies and correlates issues within academic literature with corresponding solutions from patent records.
- Using textual analysis to design a low-cost pollution-detection architecture with IoT.

The research provides knowledge transparency towards accelerated and sustainable pollution management adoption using IoT technology. The contribution of this paper is novel in two ways. First, it involves an attempt to combine bibliometric and patent analysis in the field of IoT technologies in the environmental analytics area, and it enlarges the previous study that mainly focuses on scientific papers [20,21] or the combined approach that has been undertaken in areas such as cell therapy [22]. Second, keyword co-occurrences analysis was conducted to identify the academic and patent portfolio. This approach helps to present the data extracted from academic papers and patents clearly. The paper is organized into six key sections. After a brief introduction, Section 2 presents a background of the essential knowledge required to understand the layering concept involved in IoT technology, review methodology for the pollution management framework, and IoT applicability. Section 3 presents the textual analysis, a systematic methodology for search, filtering, and knowledge extraction, including the consolidation of the publication and patent portfolio that help demonstrate the commonality in the current period of research development and industry practice. Section 4 presents a discussion of key findings from extracted knowledge, and Section 5 presents the implications for policy/management/practitioners that help support decision-makers when it comes to the apt implementation of IoT-based pollution monitoring in their organizations. This is followed by the conclusion and future scope, coupled with the limitations of the study in Section 6. The presented knowledge transparency affords stakeholders (industrial and academic) the ability to acquire awareness for confident IoT incorporation.

2. Background

IoT can be viewed as a network of networks that not only sets up the personal network but also connects all networks with security, analytics, and management [23]. With the help of IoT, humans can solve lots of problems, such as noise mapping in urban areas [24], vehicle traffic analysis [25], smart cities [26], and so on. The research results are obtained through an analysis of academic manuscripts and global patent portfolios. Aiding the analysis, the IoT workings are divided into four layers.

2.1. Four-Layer IoT Structure

Recently, there has been an acceleration in publications and patents that focus on pollution-tracking-related work. There are some famous researchers in IoT-based pollution-detection systems. For instance, Marques and Pitarma mainly focus on indoor air-quality detection with different sensor nodes and deployment formats [27–32]. Salamone et al. mainly focus on indoor environmental quality [33]. To analyze these publications more efficiently, we discuss the four-layer architecture of IoT proposed in this research [15], as presented in Figure 1.

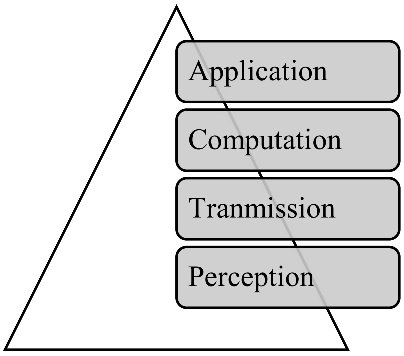

Figure 1. The IoT layer division for an efficient understanding of the literature [15].

The IoT architecture operates as a comprehensive ecosystem, where the perception layer collects data, the transmission layer enables communication, and the computation and application layers transform raw data into actionable insights for end users. The perception layer aims to sense the environment. The 'Things' in the IoT means the endpoint devices that generate and send data captured from the environment to the transmission layer. The different sensors on a campus, city, plant, office, or any place, as well as the endpoint devices and so-called objects, can obtain the sense of touch, vision, hearing, thinking, and so on. Due to low computing power and storage capacity, the objects will send back captured data intermittently through the transmission layer using communication protocols. Some standard communication protocols and wireless networks for IoT are summarized in Table 1.

Table 1. Standard protocols and wireless networks for IoT.

Type	Name	Feature
Protocol	MQTT	Machine-to-machine, lightweight
	Modbus	Serial communication protocol for industrial devices to fulfill the industrial IoT (IIoT) is TCP/IP. Precious version like RTU do not align with the needs of IoT infrastructure
	IPv4, IPv6	The rules to control the communication between computers over a network
Wireless network	LoRaWan	Suitable for battery-operated wireless devices with high flexibility of localization and mobility
	Zigbee	Low-power mesh network based on IEEE 802.15.4 standards [15]
	Bluetooth	Wireless personal area networks are mainly used in mobile-computing platforms and gadgets

Due to the limited commutating ability of IoT devices, the computing layer is essential in data processing. The primary purpose of the computing layer is to combine data management, cloud computing, pattern recognition, and smart recommender system functionality. This layer involves hardware, algorithms, and computing works, turning the captured data into information. Meanwhile, the application layer serves as a line between the processed data and end users. By providing front-end interfaces that allow for interaction and automated control, the application layer displays the output by interpretating the available information. The result may be an application in customer or business fields that meets market and industrial requirements. The perception and transmission layers are central to IoT, but the computation and application layers are equally critical as they turn collected data into meaningful insights and automated responses.

The demonstration of the use of IoT technology to monitor and manage pollution is presented in Table 2, which adapts the four-layer architecture [15]. It re-arranges the information extracted from publications showcasing what these researchers do and how they deploy the pollution-tracking IoT system. The table succinctly summarizes the most popular methodology and technology used in different IoT layers and also takes a glimpse at the potential of pollution-monitoring systems. However, creating such a tabulation is time-consuming and requires a lot of human effort. In the perception layer, sensors are used to collect the original environment data; the data collected include the temperature, humidity, light, sound, levels of gas in the environment, and so on. In the transmission layer, protocols and wireless networks like Wi-Fi and Zigbee are applied. The computation layer includes hardware (such as WEMOS D1 mini, Arduino, esp8266), data storage and algorithms (such as My SQL, MS SQL, data center), and computing works (such as IoT hub); these components play a vital role in environmental data collection, data storage, and data processing. The application layer contains the elements of transferring processed data into availabel usage in customer and business fields. Systems with interfaces and automation and control (such as smart lamps to detect indoor environment quality warning alarm systems) form the main elements of the application layer in IoT. Systems with front-end interfaces enable real-time monitoring by presenting customers with the current status, automation, and control leverage of the processed data in the computation layer to control the devices automatically and effectively.

Table 2. Pollution-detection studies in the format of four IoT layers.

Ref.	Perception Layer	Transmission Layer	Computation Layer	Application Layer
[27]	Particulate matter sensor (PMS5003)	Wi-Fi, SQL server	WEMOS D1 mini(microcontroller)	iDust system (web application, ASP.NET), warning alarm system
[32]	Air temperature and humidity sensor (SHT10), CO_2 sensor (T6615), CO sensor (MQ7), glow sensor (LDR5mm)	Zigbee, Wi-Fi	Arduino, esp8266, Xigbee module, Wemos mini D1, MySQL, php, android	Indoor air quality(iAQ) web, iAQ mobile
[31]	Humidity sensor (DHT22), CO_2 sensor (K30), photoresistor	Zigbee	XBee S2 module	Smart lamp to detect indoor environment quality
[34]	Water meter, gas meter, quality meter, electricity meter	WLAN, Wi-Fi, RS-485/232, Ethernet etc.	Data center (model layer: energy consumption analysis, energy data mining; objective layer: operation research)	Emission reduction
[35]	CO_2 sensor (MH-Z16), PM sensor (Grove dust), light sensor (SI1145), Air temperature and humidity sensor (DHT11), ultrasonic sensor	Wi-Fi	Arduino Uno, MS SQL, IoT hub, Azure web application	Indoor air-quality Web application

2.2. Related Works

Recently, there has been an acceleration in publications and patents that focus on pollution-tracking-related work where academic publication data and patent data have emerged as valuable tools for addressing environmental pollution monitoring challenges. Patents offer valuable insights into real-world applications, showcasing how theoretical research is translated into tangible inventions and innovations impacting various industries. Similar investigations have already aided stakeholders in the past in landscaping emerging technologies related to Industry 4.0 [15] and in investigating adoption frameworks of emerging solutions in the engineering context [36]. However, prior studies have explored the intersection of these datasets to identify key technologies and trends in environmental monitoring, but they have yet to systematically link academic research with patented solutions. This gap is significant because patented solutions often represent the culmination of years of research and development, and they may offer significant advantages over existing technologies. By systematically linking academic research with patented solutions, we can gain a more comprehensive understanding of the available technologies and identify promising new directions for research and development. The investigation proposed in this study aims to bridge the gap between academic publication data and patent data for environmental monitoring applications by conducting an analysis of both datasets. This analysis will focus on identifying and correlating emerging environmental monitoring technologies with corresponding patent-protected innovations. The results of this analysis will be used to design a low-cost pollution-detection architecture utilizing IoT and to develop an adoption framework tailored to small and medium-sized enterprises.

In contrast to prior research that explored vascular health and risk management literature primarily through academic publications [37], our study expands the scope by incorporating a significantly larger volume of patent data, enabling a more comprehensive analysis. Specifically, we analyze bibliographic data, allowing for a deeper examination of technological trends and innovations in pollution management. By integrating insights from both academic and patent literature, our research offers a more robust and holistic understanding of the evolving IoT landscape. Our dual-source approach facilitates the identification of synergies between theoretical challenges and practical solutions, providing a more detailed view of the state-of-the-art in IoT technologies for environmental monitoring.

2.3. Methodology

Figure 2 provides a detailed overview of the methodology, which starts with the compilation of a dataset designed to capture efforts to mitigate environmental pollution. This involves collecting relevant patent data and academic papers to ensure a comprehensive dataset for analysis. The data are downloaded based on a frequency review, focusing on the period from 2008 to 2024 to track the continuous development of technology. We divided this period into two phases: 2008 to 2015 as the development phase, and 2016 to 2024 as the maturity phase. After the data collection, a preliminary review is conducted. VOSviewer 1.6.17 is used to filter key patents and publications based on their popularity. This tool helped us to identify the most influential items within the dataset and generate a matrix of patents and publications relevant to our research questions. We analyzed this matrix using correlation methods to build a framework addressing our specific research inquiries. This framework provides a structured approach to understanding the relationships and intersections between patents and academic publications in the context of pollution monitoring and IoT layers. Section 4 presents the results of this analysis, highlighting the identified intersections and correlations between patent filings and academic research. Finally, the conclusions summarized in Section 6 the overall findings, offering insights into the current state of innovation in pollution monitoring, potential areas for future research, and implications for technological advancements in addressing environmental concerns.

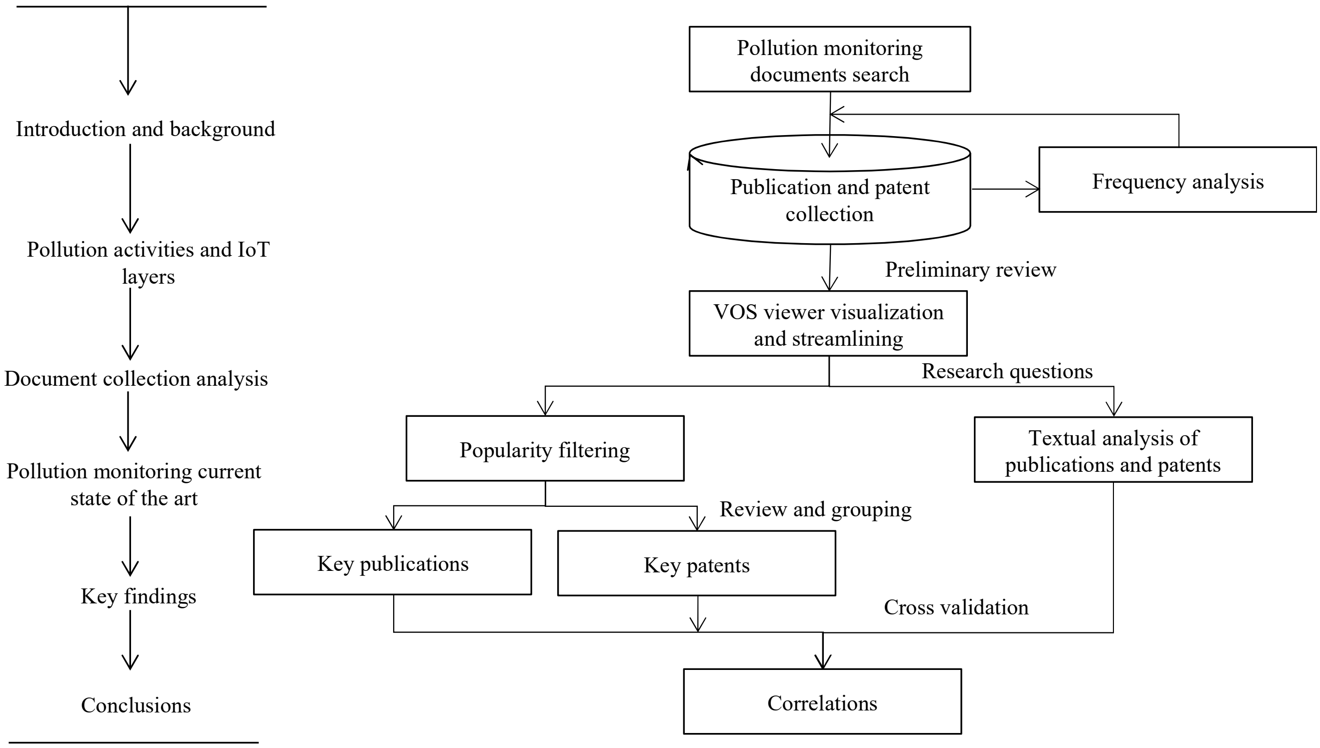

Figure 2. Methodology overview comprising data collection analysis and framework construction.

3. Analysis

The data analysis started with the graphical descriptive analysis of both papers and patents. VOSviewer was used to cluster and design the graphical layout of the information extarcted from the academic papers and patents. The aim of this step is to clearly present the keywords from the data for a better understanding of the portfotlio of papers and patents. VOSviewer, a software tool for creating maps based on network data like co-authorship, co-occurrence, citation, bibliographic coupling, or co-citation links [38], is applied to our research to extract the pattern behind the corpora efficiently. VOSviewer constructs a map with three steps. The first step, called similarity matrix construction, is to build up a similarity matrix as the input of the second step. The similarity matrix construction is based on a co-occurrence between patent and publication documents. There are two kinds of counting methods to build up the similarity matrix. One is complete counting, and the other is fractional counting. The third step is to transform the solution, such as translation, rotation, and reflection, and reach the optimal global solution. In translation, VOSviewer translates the solution so that it is centered on the origin. In rotation, VOSviewer applied the principal component analysis to maximize the variance on the solution's horizontal dimension. In reflection, VOSviewer uses the median of two dimensions to decide the reflection on the vertical or horizontal axis.

3.1. Search Query

The academic databases we used to identify relevant studies are Scopus, Web of Science, and Incopat, and the search was focused on the combination of IoT architecture with a pollution-monitoring system, which included pollution and IoT. The search queries are presented in Table 3. Scopus index, along with Web of Science, covering the Science Citation Index Expanded (SCI-EXPANDED), Social Sciences Citation Index (SSCI), Conference Proceedings Citation Index—Science (CPCI-S), and Conference Proceedings Citation Index—Social Science & Humanities (CPCI-SSH), was used for the publication search. This dual indexation selection helps leverage the highly selective and strict criteria across data search platforms. The search query has two parts. The first part of the search index includes pollution and its synonym, and the second part contains IoT. The Scopus and Web of Science results are merged and removed for any duplicity in the data, resulting in a total dataset consisting of 74,604 publications.

Table 3. Searching query.

Source	Keywords	Year Limit	Result
Scopus	TITLE-ABS-KEY (environment AND "internet of things")	PUBYEAR > 1 January 2008 < 1 January 2024	28,721
Web of Science	ALL FIELDS: environment AND ALL FIELDS: (internet of things)	Timespan: 1 January 2008–1 January 2024	46,333
Incopat	CTB = (environment) AND CTB = ("internet of things")	(PY $\geq$ (1 January 2008) AND PY $\leq$ (1 January 2024));	35,000

3.2. Academic and Patent Portfolio

The collected publication dataset is analyzed using VOSviewer to extract the pattern of author keywords from academic and patent documents. After data pre-processing, such as word lemmatization, stop word removal, and noise removal, visualization of the correlation between words is obtained. First, using the full counting method, the keywords of the corpus are analyzed to produce the network chart of keywords for the publications published from 2008 to 2015, as shown in Figures 3 and 4, and for the documents published from 2016 to 2024, as shown in Figures 5 and 6, respectively. Figure 3 only has 145 publications from 2008 to 2015, with 479 author keywords in total with a fixed threshold (minimum number of occurrences of keywords) of 2 to avoid that the selected words are not so uncommon. In the end, 58 words met the requirement, and we used another parameter setting as the default. In Figure 3, the major nodes are IoT, wireless sensor networks, environmental monitoring, gas sensors, and so on. The publications published from 2008 to 2015 mainly focus on air pollution rather than water pollution, soil pollution, etc. Therefore, we zoom in on Figure 6 and leave some air pollution-related words as the center shown in Figure 4. Although the search query is general, it is observed that most of the work is about sensor technologies and how to network the sensors that contrast with the computation layer in the dataset collected.

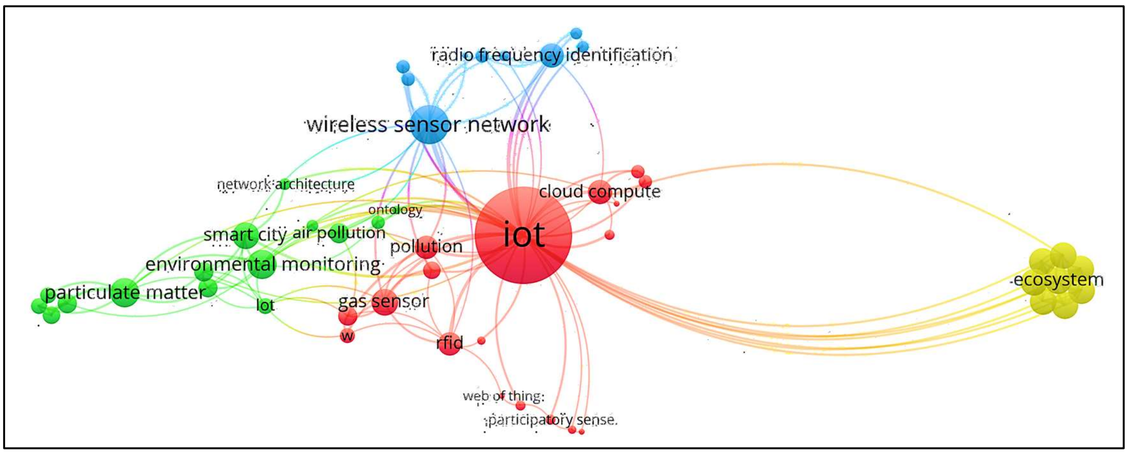

Figure 3. Network chart of keywords for publication from 2008 to 2015, resulting in four clusters.

Figure 4a delves closer into looking at nodes that focus on the environment. Researchers applied IoT technology to environmental monitoring as early as 2008, during which environmental monitoring mainly focused on pollution, especially air pollution. In Figure 6a,c, we can realize the node of air pollution and that of pollution related to other nodes like sensors, Arduino, wireless sensor networks, RFID, etc., which implies the researchers apply this technology to carry out environmental monitoring.

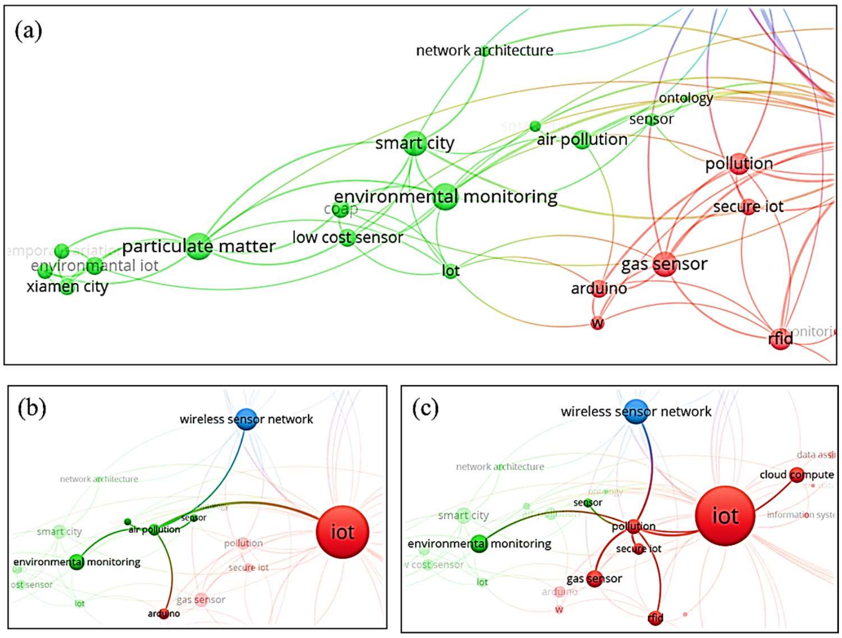

Figure 4. (**a**) Zoom of the result of Figure 3 (**b**) Network chart of keywords for publication from 2008 to 2015 with 'air pollution' in the center. (**c**) Network chart of keywords for publication from 2008 to 2015 with 'pollution' in the center.

In Figure 5, we only have 692 publications from 2016 to 2024, with 1714 most significant author keywords. If we set the threshold as 2, then 323 words meet the requirement, which is sufficient for us to analyze. However, the nodes in the network chart are very crowded, and the chart needs to be easier to look at clearly. Therefore, we set the threshold as 3 with a total of 140 words and used the frame label to show the words clearly. In Figure 5, we can see that the research from 2016 to 2024 does not mainly focus on air pollution but on different kinds of environmental fields, such as water quality, indoor air quality, waste management, noise pollution, sustainability, and so on. Therefore, we show more detail in Figure 6. In Figure 6a, we can see that air pollution connects lots of nodes in different clusters, which implies that the IoT technology applied in the air pollution field is well-developed. Figure 6b–d shows that the issues of water quality, waste management, and air have been emphasized in recent years.

Since the network graphs can produce an irregular pattern in the corpus, the information extracted from the figure could be better organized. Therefore, we take advantage of the four IoT layers shown to simplify the complicated network chart and make sure we can obtain precise results and correlations. Based on the clustering result of VOSviewer, we choose keywords related to the four IoT layers and the pollution management framework, identifying the pattern behind the network chart in detail. We show the keywords chosen and the clustering result. The application layer is used to solve problems in the real world. Based on the pollution management framework, the main effect is pollution, and the application layer can manage the pollution. For the management-related words, we list quality, energy, monitoring, application, prediction, sustain, reduction, manage, and system. For effect-related words, we have pollution, which implies the general pollution types. The computation layer, used to turn the captured data into valuable information, is relevant to the management and effect of the pollution management framework. To understand how the pollutants affect the environment, we rely on computing power to pre-process and fix the data math calculation.

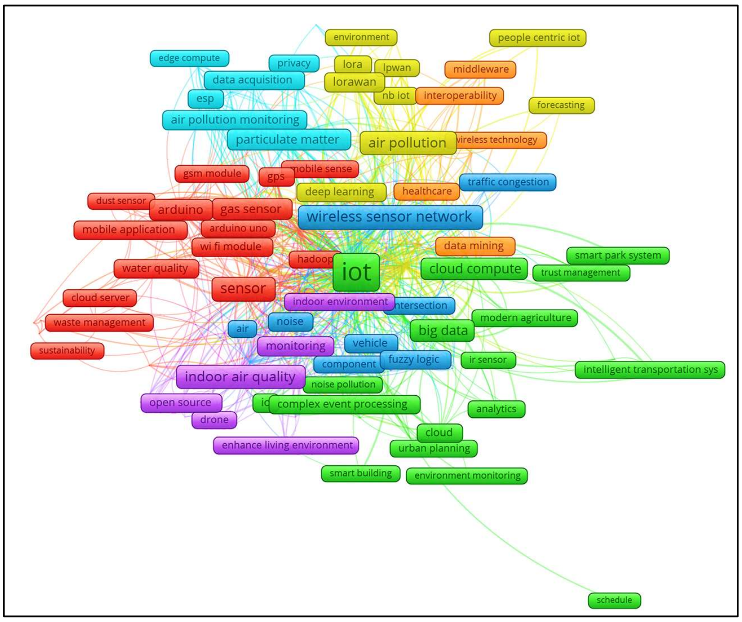

Figure 5. Network chart of keywords for publication from 2016 to 2024, with seven clusters.

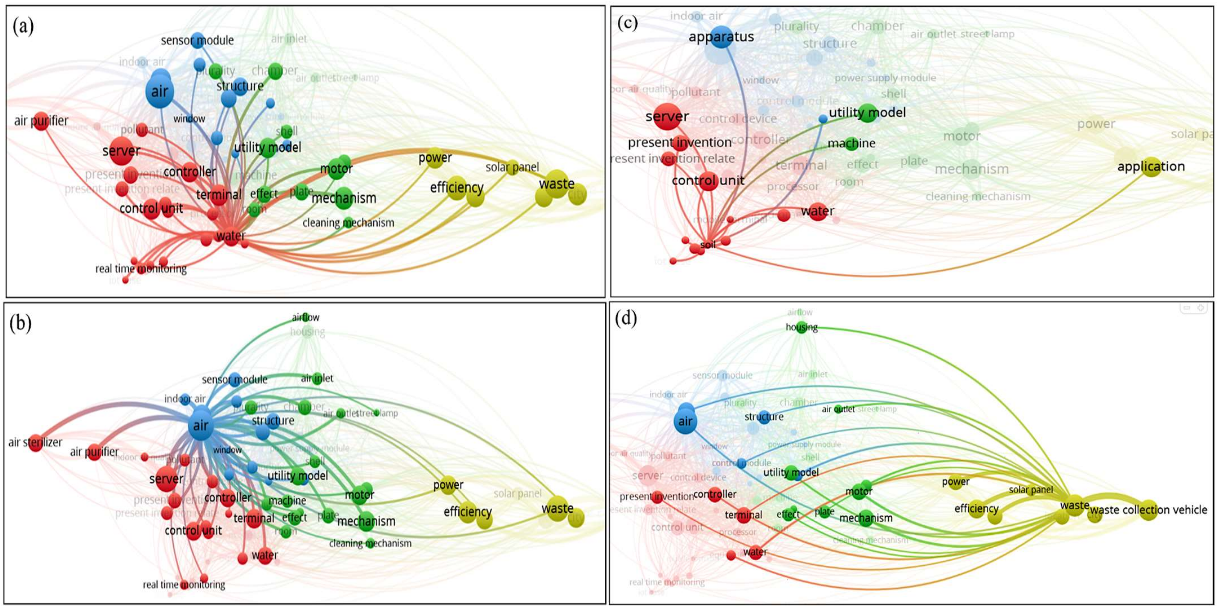

Figure 6. Network chart of keywords for publication from 2016 to 2024 (**a**) 'water' (**b**) 'soil' (**c**) 'air' (**d**) 'waste'.

Moreover, we need the computation layer to analyze the data and obtain some valuable results to fulfill pollution management. Under the computation layer, we apply analysis and analytics, process, and compute for the management and effect-related words. The transmission layer used for data transferring is not highly connected with the pollution management framework. However, with this layer, we can build up the IoT-based pollution-monitoring system. As a result, we still find some communication protocol words under the transmission layer and set them as management-related words. The perception layer, used to sense the environment, is highly relevant to the pollution management framework's propagation, outcome, and action. Under the perception layer, we list gas, dust, ozone, particulate matter, etc., as the propagation/outcome-related words. Moreover, for action-related words, we choose emission, traffic, vehicle, and congestion. There are too many words extracted from the VOSviewer result. To reduce the size of input words of the similarity matrix, we cluster the words in a different segment of the IoT layer in a tabulated form, as shown in Table 4.

Table 4. The VOS clustering result is based on four IoT layers and pollution management frameworks.

Layer	Pollution Framework	Relevant Keywords	VOS Clustering Result	Ref./Patent No.
Application	Management	Quality	Indoor air quality	[28,32,33]
			Indoor environmental quality	[39,40]
			Air quality	[31,41–47]
			Water quality	[48,49]
		Monitor	Real-time monitoring	[28,31,33,35,48,50,51]
			Environmental monitoring	[52]
			Pollution monitoring	[41,49,53]
		Reduction & Prediction	Pollution reduction	[35,50,54–56]
			Energy consumption reduction	[54,57,58]
			Prediction	[46,47,53]
		Sustain	Sustainable city	[53,55,59]
			Sustainability	[45,59]
		Management	Waste management	[45,55]
Computation	Effect	Pollution	Air pollution	[31,41,42,44,50,57]
			Environmental pollution	[31,52,55]
			Urban pollution	[42,53,57]
			Water pollution	[48,49]
			Noise pollution	[31,41,55,57]
	-	Analytics	Data analytics	[35,50,55,59]
			Neural network	[35,48]
		Compute	Fog compute	[53,56]
			Green compute	[54]
Transmission	-	Network	Wireless sensor network	[28,33,41,42,49,54,57–59]
		Communication protocol	Lora	[42,47]
			Zigbee	[33,39,41,49]
			Wi-Fi	[28,31,33,35,42,59]
		Positioning system	GPS	[40,41,44,47,49,52,56,59,60]
Perception	Propagation/Outcome /Action [a]	Air	Ozone	[43,44]
			Carbon emission	[31,33,35,39,44,59]
			Particulate matter	[28,41,42,44,46,50,52]
			Temperature	[31,33,40,41,44,47,52,60]
		Sensor	Dust sensor	[31,44,53]
			Low-cost sensor	[28,31,40–42,44,46]
			Gas sensor	[28,31,33,41,42,44,53,59], (CN203241793U, 2013)
			IR sensor	[48,60]
			Ultrasonic sensor	(CN203241793U, 2013)
		Emission	Carbon emission	[31,33,35,39,44,55,59]

[a] Actions that relate to pollution are covered in the abstract or background and are not the key focus in the publication set.

A similar investigation is applied to patent documents since they inculcate the concepts of "novelty", "obviousness", and "inventive content" as central parameters in patenting. The exploration based on patent data has provided crucial insights, including locations of organizations in the technological network based on patent citations [61]. However, the meaning of the intellectual property framework is quite different from how academic research commonly interprets it; instead, these terms are applied in a strictly defined legalistic fashion. For example, combining a particular antihypertonic drug and a particular diuretic can have "novelty", even though members of the antihypertonic and diuretic drug classes have been combined for decades to treat hypertonia synergistically. Patent documents are very different from scientific journal papers in terms of intent, semantics, pre-publication critique, and publishing policy. The primary purpose of submitting a manuscript to an academic journal is to concisely communicate new scientific data and information to a specialized audience of peers. At least two of these peers will anonymously review the manuscript and decide its fate according to the commonly accepted criteria of the scientific community. In contrast, a patent is filed with the perspective of securing exclusivity of use for future commercial applications and strategically preserving the inventors' and assignees' competitive edge. The requirement for legally explicit statements frequently leads to the use of language that is considered repetitive, redundant, or outright trivial by the average scientist working in the respective field. The review is conducted by a single, personally identified examiner who is not necessarily an expert in the field and who conducts the review according to legally defined criteria without attempting to undertake an assessment of feasibility. Regardless of the result of this examination, every patent document is published within about 18 months of its filing date unless the submission is retracted.

The popular patent filter is a filter to screen out the unimportant patents with low citing count (A) and low cited count (B) in the patent dataset P with m pieces of patents. To avoid the old patent having a higher probability of containing more A and B, we divide A_j the A of the j-th patent, by the existing years of the publication y_i, where $y_i = 2020$¯the year in which the patent was created, and we repeat the same process for $\mathrm{B_j}$ as well. The annual $\mathrm{A_j}$ and annual $\mathrm{B_j}$ can be expressed as Equations (1) and (2):

$$\overline{A}_j = \frac{A_j}{y_i},\ j = 1, \ldots, m \tag{1}$$

$$\overline{B}_j = \frac{B_j}{y_i},\ j = 1, \ldots, m \tag{2}$$

After that, we set the 90th percentile of $\overline{A}_j$ and $\overline{B}_j$, $\mathrm{j} = 1, \ldots, \mathrm{m}$, denoted as $P_{90}^{(\overline{A}_j)}$ and $P_{90}^{(\overline{B}_j)}$, as the threshold to screen out the unimportant publication. The filtered dataset D' is given as follows:

$$\mathrm{P}' = \{p|\ \overline{A}_j > P_{90}^{(\overline{A}_j)} \text{ or } \overline{B}_j > P_{90}^{(\overline{B}_j)}, \mathrm{j} = 1, \ldots, \mathrm{m}\} \tag{3}$$

To identify the technology trend in a different country, we separate P into k parts based on the k countries in P, denoted as $P^t,\ t = 1, \ldots, k$. Consequently, with the help of Equation (1) to Equation (3), we can find the popular patent in every country and realize the technology trend in the field of sustainable pollution management via IoT. In Figure 7, we can see that the patents from 2008 to 2015 mainly focused on storage, signal, transmission, water-quality sensors, and solar cell modules. The focus more on water quality is quite different from the publications mainly focusing on air pollution. In Figure 8, we show the network chart of titles and abstracts for patents from 2016 to 2024.

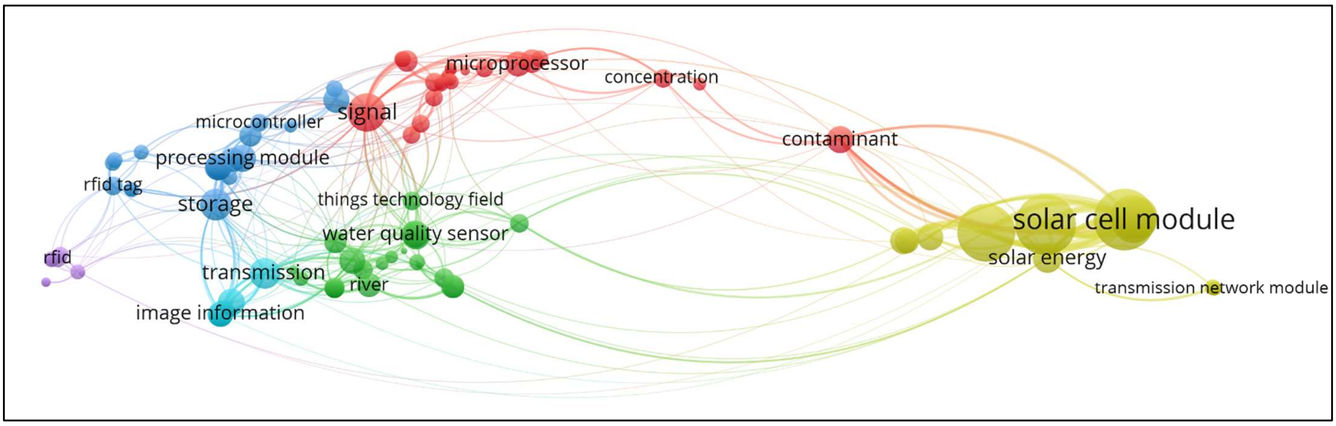

Figure 7. Network chart of titles and abstracts for patents from 2008 to 2015, with a total of 177 patents.

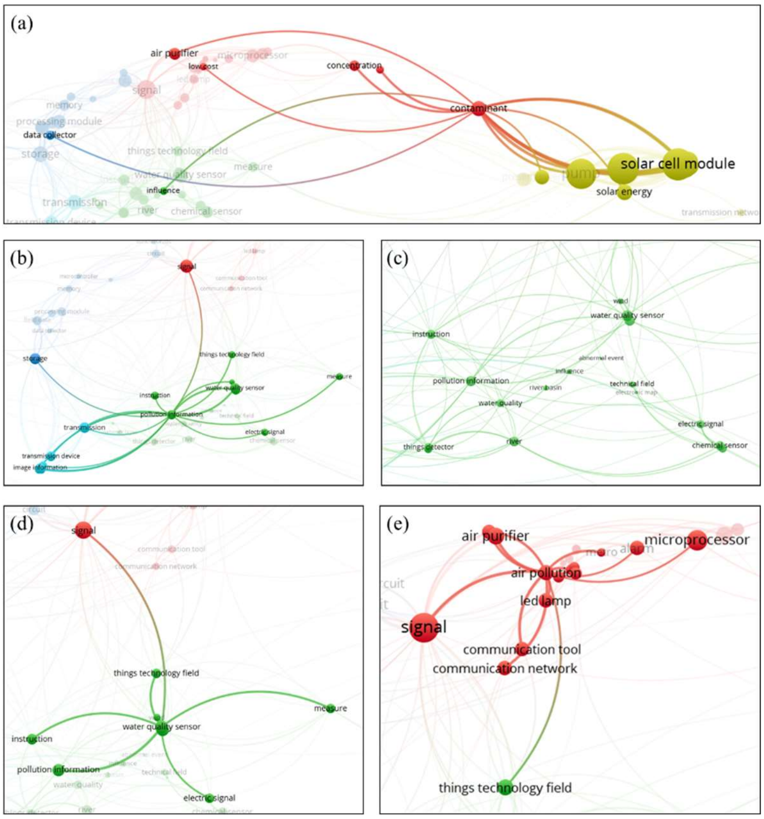

Figure 8. Network chart of titles and abstracts for patents from 2008 to 2015 (**a**) 'contaminant' (**b**) 'water quality' (**a**,**c**) zoom of the result of Figure 7. (**d**) 'water-quality sensor' (**e**) 'air pollution' in the center.

The interesting thing is that more and more patents concern air pollution in this time scope. There are three significant nodes of interest to us, i.e., air, water, and waste. We can classify the nodes linked with air and water into the four IoT layers, that is, the sensor module and mechanism go to the perception layer; server and power go to the transmission layer; controller and structure go to the computation layer; and real-time monitoring goes to the application layer. This shows that the IoT applied in pollution-monitoring technology will work. In Figure 9, there are five main clustering results: water, utility module, controller air, server, apparatus mechanism, motor waste, waste collection vehicle, application and communication module, sensor module, and control module.

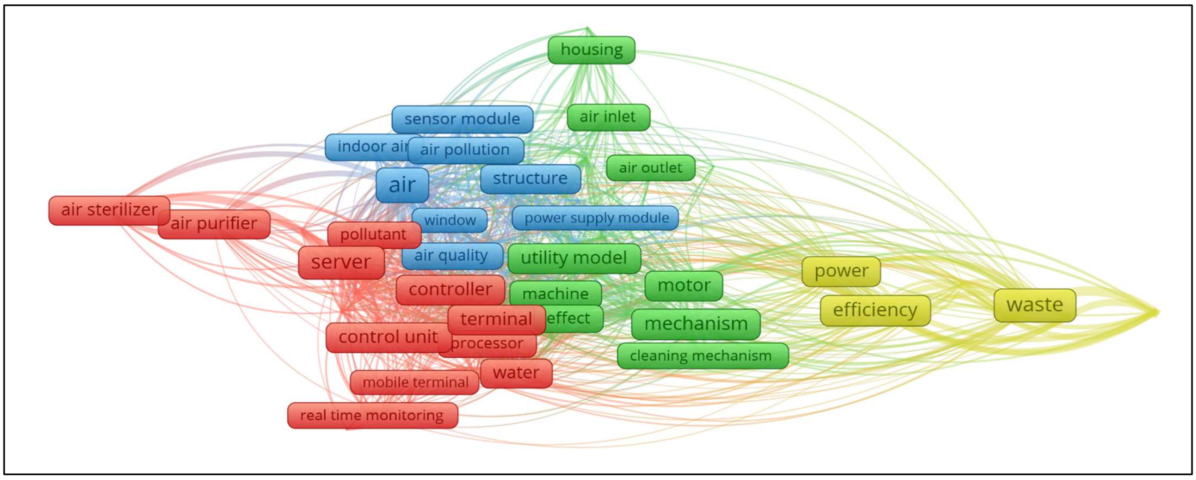

Figure 9. Network chart of title and abstract for patents from 2016 to 2024, with a total of 902 patents.

The parameter setting is: type of data: text data, data source: read from bibliographic database files, fields from which terms will be extracted: title and abstract fields, counting method: full counting, threshold: 15, number of terms: 161. The parameter setting for the graph visualization is as follows. Weight: total link strength. Label: frame. Minimum cluster size: 10 (the result has 5 clusters in total). This is the rough pattern of the corpus, but the network is too complicated, and the information extracted from the figure needs to be well-organized. Simplified results are presented in Table 5.

Table 5. Patent clustering results based on the four IoT layers and a pollution management framework.

Layer	Pollution Framework	Relevant Keywords	VOS Clustering Result	Reference Patents
Application	Management	Quality	Water quality	[(CN103175513A, 2013), (CN105824280A, 2016), (CN108120815B, 2019)
			Indoor air quality	(CN103792944A, 2014), (KR2017094877A, 2017), (KR2016076782A, 2016), (KR1798394B1, 2017)
			Air quality	(CN104820072A, 2015), (CN104410706A, 2015), (EP3513184A1, 2019), (KR2017052743A, 2017)
		Monitor	Real-time monitoring	(CN103175513A, 2013), (CN103489053A, 2014), (CN103792944A, 2014), (CN104820072A, 2015), (CN104760490B, 2017), (CN202057645U, 2011), (WO2018098721A1, 2018), (KR2017094877A, 2017), (CN105890657A, 2016), (CN203011912U, 2013) to (CN108120815B, 2019),
			Water-quality monitoring	(CN103175513A, 2013), (CN103489053A, 2014), (CN105824280A, 2016), (CN103543706A, 2014), (CN202057645U, 2011), (CN103236020A, 2013), (CN203011912U, 2013), (CN108120815B, 2019)
			Personal air-quality monitoring	(CN104760490B, 2017), (EP3513184A1, 2019)
			Environmental monitoring	(CN105824280A, 2016), (CN204776976U, 2015), (WO2018098721A1, 2018), (US20150026044A1, 2015)
		Layer	Application layer	(CN103543706A, 2014), (CN102625485B, 2015)
			Network layer	(CN104820072A, 2015), (CN103543706A, 2014), (CN203011912U, 2013), (CN102625485B, 2015)
			Sensor layer	(CN103543706A, 2014), (CN203011912U, 2013), (CN102625485B, 2015)

Table 5. *Cont.*

Layer	Pollution Framework	Relevant Keywords	VOS Clustering Result	Reference Patents
Computation	Effect	Pollution	Pollutant	(CN105824280A, 2016), (CN202057645U, 2011), (CN103236020A, 2013), (WO2018098721A1, 2018), (CN203011912U, 2013), (CN108489553A, 2018)
			Air pollution	(CN101799977A, 2010), (CN104760490B, 2017), (CN104410706A, 2015), (KR2017094877A, 2017), (CN105890657A, 2016), (KR2017052743A, 2017)
			Noise pollution	(CN105824280A, 2016), (US12151612B2, 2024)
		Waste	Waste	(CN105824280A, 2016), (CN204776976U, 2015)
	-	Module	Communication module	(CN203241793U, 2013), (US20150026044A1, 2015), (KR2017094877A, 2017), (KR2016076782A, 2016), (KR2017052743A, 2017)
			Wireless communication module	(CN203241793U, 2013), (CN103792944A, 2014), (CN101799977A, 2010), (CN104820072A, 2015), (CN103543706A, 2014), (CN204776976U, 2015), (CN105890657A, 2016)
			Control module	(CN103489053A, 2014), (CN101799977A, 2010), (CN204776976U, 2015), (KR2017052743A, 2017)
			Display module	(CN204776976U, 2015), (US20150026044A1, 2015)
			Power supply module	(CN102960197A, 2013), (CN105890657A, 2016)
		Computer	Server	(CN103792944A, 2014), (WO2018098721A1, 2018), (CN105890657A, 2016), (KR1798394B1, 2017)
			Central processer	(CN103792944A, 2014), (CN103543706A, 2014), (CN204776976U, 2015)
			Cloud	(CN103489053A, 2014), (CN104820072A, 2015), (CN104410706A, 2015), (CN203011912U, 2013)
			Neural network	(CN103175513A, 2013), (CN108120815B, 2019)
Transmission	-	Wireless	RFID	(CN203241793U, 2013), (CN116616952A, 2023)
			Wireless communication	(CN104760490B, 2017), (CN103236020A, 2013), (KR1798394B1, 2017)
Perception	Propagation /Outcome	Water	Water environment	(CN103175513A, 2013), (CN202057645U, 2011), (CN203011912U, 2013), (CN108120815B, 2019)
			Sewage	(CN203011912U, 2013), (CN108120815B, 2019)
			Drainage	(CN103543706A, 2014), (CN108120815B, 2019)
		Air	Air purifier	(CN103792944A, 2014), (CN104760490B, 2017), (KR2016076782A, 2016), (EP3513184A1 2019), (KR2017052743A, 2017), (KR1798394B1, 2017)
			Air sterilizer	(KR2017052743A, 2017), (KR1798394B1, 2017)
			Airflow	(EP3513184A1, 2019), (KR2017052743A, 2017), (KR1798394B1, 2017)
		Sensor	Sensor module	(CN103175513A, 2013), (CN102960197A, 2013), (CN204776976U, 2015), (US20150026044A1, 2015), (KR2017094877A, 2017), (CN105890657A, 2016), (CN108120815B, 2019), (CN102625485B, 2015)
			Gas sensor	(CN104760490B, 2017), (CN104410706A, 2015)
			Water-quality sensor	(CN103175513A, 2013), (CN103543706A, 2014), (CN203011912U, 2013), (CN108120815B, 2019)

The key references from the tabulated entries in Tables 4 and 5 are summarized in this section. Some researchers focusing on patent data alone have used CPC analysis as a validation of the theme of clustered results; this approach has not been followed in this study due to multiple data sources. Researchers have proposed various mechanisms to monitor environmental pollution and reduce its impact on the environment.

1. Advancements in Environmental Monitoring Technologies: In alignment with SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), SDG 14 (Life Below Water), and SDG 15 (Life on Land), advancements in environmental monitoring technologies have become pivotal in addressing global environmental challenges. Researchers worldwide have made significant strides in proposing innovative mechanisms to monitor and mitigate environmental pollution. Sharafat et al. (2020) introduced a real-time air-pollution measurement system utilizing an arrayed sensor network, incorporating solar-recharged batteries and long-range communication technologies [59]. Liu et al. (2018) proposed a remote monitoring and control system to the plant walls, which utilizes cloud technology to automate the management procedure and improve the scalability [35]. Mohammed et al. (2022) explored the use of a low-cost drone swarm for air-pollution monitoring, employing UAVs and sensors [41]. Steven et al. (2019) successfully deployed a LoRaWAN-enabled AQ sensor network across Southampton, UK, based on initial air-quality testing [42]. Hafeez et al. (2018) focused on marine pollution, emphasizing sensor technologies and remote sensing for monitoring marine areas [48]. Sun et al. (2020) presented a smart algorithm detecting and tracking pollution stains, particularly oil spills, using wireless nodes [49]. Woo-García et al. (2024) proposed an autonomous energy wireless sensor network for monitoring environmental variables with a tree topology configuration [62].
2. Energy-Efficient IoT Strategies and Low-Cost Monitoring Systems: In line with SGD 7, which aims to ensure universal access to affordable and reliable energy, Arshad et al. (2017) delved into strategies for minimizing energy consumption in IoT, addressing energy-efficient data centers, sensor data transmission, and energy-efficient policies [54]. Alam et al. (2017) provided a low-cost environmental pollution-monitoring system encompassing toxic gas measurements, sound pollution, and temperature monitoring [63]. Feenstra et al. (2019) designed a low-cost method for measuring ozone pollution using mobile sensors [43]. Oralhan et al. (2017) optimized waste collection through sensor-equipped garbage containers, resulting in significant cost savings [55]. Lin et al. (2017) outlined a people-centric and cognitive IoT environmental sensing platform, incorporating closed loops of interactions among nodes, devices, and servers [50].
3. Innovative Approaches for Intelligent Transportation and Crowd Sensing: Lee et al. (2016) proposed an Internet of Vehicles approach for distributed transport decision-making [56]. Marjanović et al. (2016) introduced a framework for Green Mobile Crowd Sensing, employing quality-driven sensor management for optimal sensor selection [57]. Benammar et al. (2018) developed a real-time environmental monitoring system measuring various environmental parameters [52]. Thongchai et al. (2019) analyzed data from low-cost PM2.5 sensors for air-quality monitoring in a vulnerable Thailand city, focusing on high PM2.5 pollution [46].
4. Patented Solutions in Environmental Monitoring and Resource Management: Several patented inventions highlight diverse applications of IoT in environmental monitoring. The CN203241793U patent features a ZigBee/GPRS or 3G-based gateway with an IP camera and RFID device applicable in agriculture, management, and decision-making. CN103175513A claims a hydrology and water-quality monitoring method based on IoT technology. CN105824280A presents an IoT environment monitoring system with various monitoring ends for central monitoring, water environment, noise, and solid waste. Other patents include intelligent traffic systems (CN101799977A), cloud computing-based air-quality monitoring (CN104820072A),

three-dimensional intelligent seedling management (CN102960197A), and water pollution emergency treatment (CN103236020A). These patents showcase a wide array of innovative solutions in environmental monitoring and resource management.

4. Key Findings

To efficiently address problems, it is necessary to properly utilize existing information technology structures and to use the techniques to build up an ecosystem for pollution sensors. The analysis of publications and corresponding theoretical advancements reveals the maturation of IoT technology, which has recently overcome several previously identified adoption barriers. Additionally, the examination of patent grant data illustrates the emergence of increasingly sophisticated and capable solutions. Through a thorough textual review, we can clearly delineate the transition from the initial fragmented phase of IoT development, when the technology was first introduced, to the present, where it demonstrates comprehensive ecosystem-based solutions that are fully developed.

Among various communication protocols, most researchers chose Zigbee and IEEE 802.15.4, a new protocol for sensor communication, to fulfil the data transmission works. The main advantages of using Zigbee are low power consumption and high deployment flexibility. Moreover, as soon as sensors detected some data, the sensor module would not immediately send the information back to the center but would pre-process the firsthand information. Compared with the traditional sensor network architecture, as in Figure 10, this step can eliminate the noise in the data and enhance the reliability of the whole system.

Wireless communication technology, such as Wi-Fi, Bluetooth, Radio Frequency Identification, 4G, etc., is widely used in modern life. Furthermore, wireless connectivity can be used to ensure environmental protection. For instance, Mohammed et al. (2022), Rachana et al. (2017), Khedo et al. (2017), Ni et al. (2018), and Sharafat et al. (2020) have used the pollution sensor with a wireless sensor network (WSN) to realize the gas pollution detection [41,59,64–66]. Hafeez et al. (2018) [48], Sun et al. (2020) [49], and Zielinski et al. (2009) [67] have used WSN technology to track marine pollutants. Arzate-Rivas et al. (2024) presented an IoT Energy Management System (EMS) based on a Wireless Sensor and Actuator Network (WSAN) using Wi-Fi for environmental monitoring and remote control [58]. Furthermore, Gholizadeh et al. (2018) have taken advantage of remote sensing techniques to detect soil contaminants. In three different pollution-monitoring categories, gas, liquid, and soil detection, the gas quality monitor is the most common pollution-detection system [68]. The patent (CN103543706A) uses a wireless network for bidirectional transmission between the application layer and the perception layer to improve the intelligent and digital management level of the drainage systems. CN204776976U claims a garbage bin intelligent management system utilizing a wireless receiving terminal to promptly deal with the full garbage bin. CN103792944A presents a multimedia purification and dust collection robot, and a wireless communication module is used to help with cloud service and real-time monitoring. CN105890657A discloses a photovoltaic energy air-pollution monitoring system with a wireless transmission module that is used to send the air-pollution data collected in real time to the server.

For the sake of carbon emissions from vehicle and industrial activities, most of the research focuses on air pollutants tracking in the urban region. As evident in the bibliometric network analysis, the IoT node relates to air/water pollution; the node of air/water pollution can reach lots of other nodes and bring more opportunities for application. Figure 10 shows the typical block diagram for pollution-detection systems with IoT architecture. The system provides larger spatial coverage and reliable, real-time information with the four layers. To fulfill an economical, consistent, and wide-range pollution detection and data transmission, a few detection systems have been implemented, such as Wi-Fi, Bluetooth, and other well-known wireless communication technologies, such as Zigbee technology. Compared with other technology, Zigbee has the properties of low power consumption, low cost, a large network capacity, and security protection. With the limited budget, commercial single-board microcontrollers like Arduino, Raspberry Pi, and Libelium Waspmote, etc., are mainly used to deploy the monitoring systems. If the targeted pollution area is in cities, then some researchers will use public Wi-Fi and data centers to build up the whole pollution-tracking system. In the study by Rao et al. (2021), the authors created a real-time air-pollution monitoring system based on Zigbee [64]. Their pollution-detection network architecture comprises four stages. Stage one is gas sensor calibration with characteristic equations; stage two is configuring wireless sensor nodes for pollution monitoring; stage three is middleware development; and the last stage is ground deployment. The pollutant monitoring experiment was carried out at the industrial belt in India, and the result shows that the system created by the authors was able to collect air pollutants consistently under various conditions and timings.

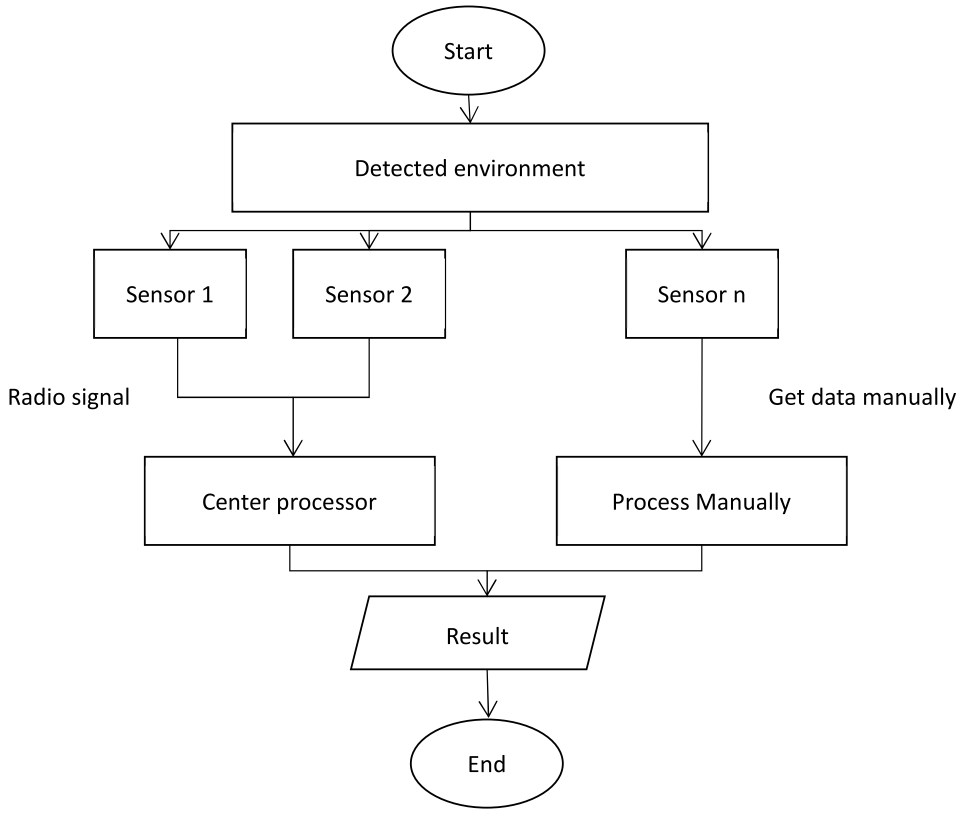

Figure 10. Legacy Pollution-Monitoring Architecture (2008–2015).

Mohammed et al. (2022) chose to use unmanned aerial vehicles (UAVs) to realize air-pollutant monitoring [41]. The project aims to build up 3D environmental air-pollutant monitor systems via UAVs. There are some problems with fulfilling the goal. First, the extra sensor attached to the UAV will affect the balance of the multi-copter. Therefore, the workgroup in this study used the external handler to carry the sensor to keep the UAV balanced. Second, multiple UAVs are used to monitor the live air data at different altitudes to detect the air-pollution data at different heights. However, there is no reasonable communication protocol between each drone and data transmission. It takes effort to retrieve all the UAVs to the base and manually save the data from each UAV. With the concern of developing cost-effective, low-power, and portable features, Rachana et al. (2017) combined Arduino mega2560/Uno, Raspberry Pi 3, a pressure sensor (BMP80), CO_2 sensor (CDM7160), and temperature sensor (SHT21) [64]. Eventually, the authors developed a real-time urban air-quality system called Environbat 2.1. With a user-friendly interface and open data access for global usage, people can easily take advantage of the environmental data.

Sometimes, air pollution is caused by the leakage of a pipeline used to transport toxic gas, especially in the petrochemical industry. As a result, the timely, reliable detection of gas leakage accidents can provide the information to handle air-pollution problems and minimize the casualties and economic loss. Ni et al. (2018) put an effort into toxic gas leak monitoring [66].

Based on the Zigbee technology, the signal of contaminants would be sent back to the coordinator module. The coordinator module would cover the data processing work and visualize the result on the monitoring platform. If the signal of contaminants exceeded the normal threshold, the monitoring system would send users an alarm through the Global System for a Mobile module (GSM) to reduce the damage. Hafeez et al. (2018) created a smart system to track pollution in the marine environment [48]. The authors took advantage of the polar properties of hydrocarbon, i.e., hydrocarbon can be avoided when mixed with water. Therefore, hydrocarbon pollutants can be easily removed. However, hydrocarbon spills usually spread fast. The authors used boat-type gadgets with a self-tracking algorithm to locate the polluted area. This innovation makes sure that pollutants in the ocean can be removed as soon as possible. Figure 11 shows advanced architectures that incorporate emerging solutions for a pollution-detection system with IoT architecture in four layers; the system provides a larger spatial coverage and reliable, real-time information.

One of the most significant trends in IoT for environmental monitoring is the adoption of advanced communication protocols like Zigbee and IEEE 802.15.4. These protocols are favored for their low power consumption and high flexibility in deployment, which are crucial for sustainable, long-term environmental monitoring. Zigbee, in particular, has become prominent due to its ability to pre-process data at the sensor level, reducing noise and enhancing the reliability of the entire monitoring system.

Parallel to the evolution of communication protocols, wireless communication technologies such as Wi-Fi, Bluetooth, RFID, and 4G are increasingly integrated into IoT systems. These technologies facilitate the seamless transmission of data from sensors to central processing units, enabling real-time monitoring and rapid response to environmental changes. WSN have become a cornerstone in IoT-based environmental monitoring. They allow for the deployment of distributed sensing systems that can cover large areas and provide comprehensive data on pollution levels. WSNs are not only used for gas pollution detection but also for tracking marine pollutants and soil contaminants, showcasing their versatility and importance in environmental protection.

Lastly, the development of sophisticated monitoring systems that leverage these technologies is a clear trend. These systems are designed to provide larger spatial coverage and offer reliable, real-time information, which is pivotal for effective environmental management. The integration of IoT with these advanced monitoring systems is a testament to the progress in IoT technology, moving from initial fragmented solutions to comprehensive ecosystem-based approaches that address environmental challenges holistically.

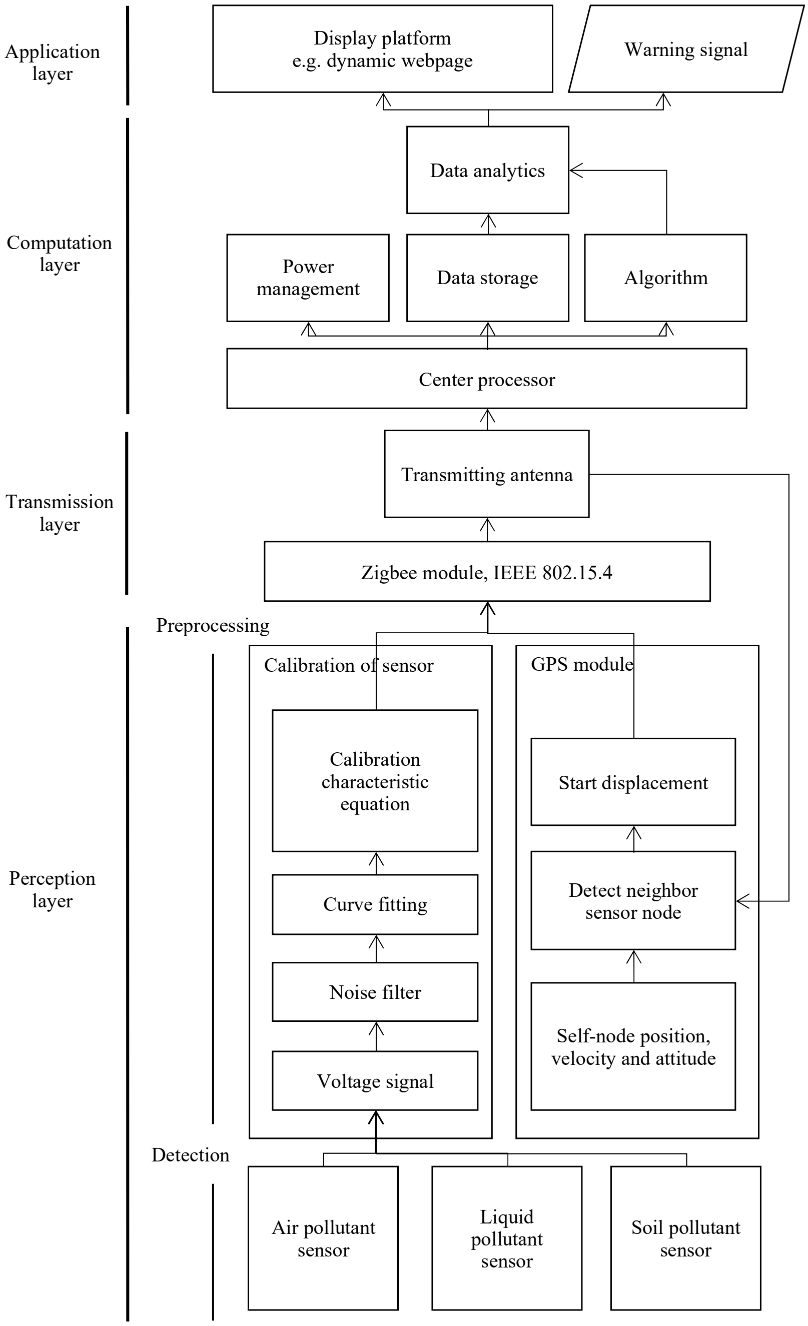

Figure 11. Recent Trends in Pollution-Monitoring Architecture (2016–2024).

5. Implications for Policy/Management/Practitioners

IoT-based devices have a lot of potential for cost reduction and reliability using low-cost sensors, and there is a need for further research on sensing elements. The analysis carried out in this study provides the latest insights into the developments and progress in technology, allowing policymakers and practitioners to stay up-to-date with the latest trends and advances. Furthermore, it helps to identify potential areas for investment and development, enabling management to make informed decisions regarding the integration of IoT-based pollution management technologies into their organizational framework. The proposed IoT architecture ensures low cost and takes into consideration the latest technological developments from many emerging architectures, thereby overcoming technology fragmentation. An important observation from the reviewed works is the utilization of open-source components, such as Arduino boards and compatible sensors, which offer significant advantages in addressing economic constraints. The open-source philosophy not only facilitates cost-effective implementation but also encourages knowledge sharing by providing reusable and adaptable hardware and software designs. Highlighting converging technology patterns from both scientific and implementation perspectives leads to more coherent and effective IoT-based pollution management solutions. The use of IoT environmental sensors and low-power, wide-area network (LPWAN) technology can provide policy managers with accurate and real-time data on various environmental factors. This can help them make informed decisions and develop effective policies for environmental conservation and management.

6. Conclusions and Limitations

This study presents an extensive review to explain the nexus between pollution and sustainability, leveraging 16 years of bibliometric and patent data. The structured search, optimized with keyword frequency counts, has culminated in a curated dataset that highlights the critical role of IoT sensors and architectures in pollution-monitoring systems. The traditional challenge of pollution-tracking technology—the absence of a universal protocol for sensor communication—has been addressed through the proposed key discussions of the work. This proposed architecture, designed with sensor communication at its core, harnesses the power of WSN to provide real-time, actionable insights. This capability not only expedites response times but also extends the reach of monitoring efforts, ensuring comprehensive area coverage. The adoption of new, emerging technologies is imperative for mitigating environmental impacts. This paper advocates for the integration of key SDGs, notably SDG 7, SDG 11, SDG 13, SDG 14, and SDG 15, into the fabric of IoT solutions. These goals are centered on ensuring access to affordable, reliable, and clean energy, as well as maintaining air quality, combating climate change, and preserving biodiversity both on land and underwater. We align these objectives with global and national initiatives aimed at reducing carbon emissions, highlighting the pivotal role that technological innovations play in attaining these environmental milestones. Though the key discussions offer opportunities, the inability to identify stakeholders and the corresponding use cases are the limitations of the study. To address these limitations, ongoing research direction incorporates machine-learning models to provide a robust solution for extracting and analyzing use cases from large datasets for context-aware analytics. This includes identifying patterns linked to specific stages of the technology hype cycle and aligning them with organizational objectives. Future research should expand on this by incorporating ML-based textual analysis, further enhanced by additional data sources such as open-source code repositories. By leveraging machine-learning models, this research could automate the identification of actionable insights, reduce human dependency, and enable the integration of diverse datasets across technologies and domains. This is particularly critical for advancing IoT as a pillar of emerging concepts, such as digital twin, requiring the alignment of data dimensions across multidisciplinary frameworks to enhance scalability and address adoption barriers.

7. Patent

An agricultural production monitoring and management system based on Internet of Things. (2013). CN203241793U.

System and method for monitoring hydrology and water quality of river basin under influence of water projects based on Internet of Things. (2013). CN103175513A.

A method based on cloud calculation and expert system of intelligent water resource management platform. (2014). CN103489053A.

Internet of Things multimedia purifying dust intelligent robot. (2014). CN103792944A.

An Internet of Things environment monitoring system. (2016). CN105824280A.

Intelligent traffic system. (2010). CN101799977A.

An air-quality monitoring system based on electronic nose cloud computing and method thereof. (2015). CN104820072A.

A three-dimensional intelligent seedling robot platform for the production of plant factory. (2013). CN102960197A.

A drainage Internet of Things system. (2014). CN103543706A.

A garbage intelligent management system based on technology of Internet of Things. (2015). CN204776976U.

In-car air quality intelligent regulating system and using method thereof. (2017). CN104760490B.

A water-quality automatic monitoring system based on Internet of Things. (2011). CN202057645U.

System and method for large water body sudden water pollution emergency disposal based on Internet of Things. (2013). CN103236020A.

Urban anti-haze treatment system. (2015). CN104410706A.

Environmental data monitoring method and system. (2018). WO2018098721A1.

Method, protocol, and system for universal sensor communication. (2015). US20150026044A1.

Indoor ventilation control system based on Internet of Things and method for the same. (2017). KR2017094877A.

Terminal device for the improvement of the indoor environment based on the Internet of Things. (2016). KR2016076782A.

A photovoltaic energy-saving air pollution monitoring system based on Internet of Things. (2016). CN105890657A.

Apparatus, system, and method for a portable personal air quality monitor. (2019). EP3513184A1.

Air purifier. (2017). KR2017052743A.

The IoT base center control type apparatus for the smart sterilizer. (2017). KR1798394B1.

A water environment Internet of Things device. (2013). CN203011912U.

A sewage emission enterprise network management system. (2019). CN108120815B.

System and method for monitoring hydrology and water quality of river basin under the influence of water projects based on Internet of Things. (2013). CN103175513B.

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