*Ecology, Economy and Society–the INSEE Journal* 9 (2): 1685.1-1685.35, July 2026

**REVIEW ESSAY**

# Recent Advances in Air Pollution monitoring and forecasting: implications for civil engineering

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**Abstract:** Addressing the growing problem of urban air pollution requires that sophisticated air pollution monitoring and forecasting systems be incorporated into civil engineering practice. New technologies that support smarter and more sustainable urban environments include the Internet of Things (IoT), big data analytics, and machine learning (ML). These technologies allow for real-time data acquisition, high-resolution monitoring, and precise predictive optimization. Continuous, spatially dense air quality monitoring is made possible by IoT-based sensor networks, while big data frameworks can effectively integrate and analyse diverse, multi-source datasets. Meanwhile, ML and deep learning can further improve forecasting accuracy, enabling urban planners and civil engineers to foresee pollution trends and implement proactive mitigation measures. Notwithstanding these developments, challenges persist for data integration, sensor calibration, model transparency, and the reliability of inexpensive monitoring systems. To overcome these constraints, improvements are needed in terms of data accuracy, robust calibration techniques, and the implementation of interpretable ML models. This review emphasizes the vital role of civil engineers in promoting resilient and sustainable urban development, advancing effective air quality management, and safeguarding public health through interdisciplinary collaboration between data scientists and policymakers.

**Keywords:** Air Pollution, Urban Planning, Air Quality Monitoring, Internet of Things (IoT), Machine Learning (ML), Predictive Modelling.

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Dates: 24 May 2025 (submission), 10 Mar 2026 (acceptance), 31 Jul 2026 (publication)

DOI: https://doi.org/10.37773/ees.v9i2.1566

Published by Indian Society for Ecological Economics (INSEE), c/o Institute of Economic Growth, University Enclave, North Campus, Delhi 110007.

ISSN: 2581–6152 (print); 2581–6101 (web).

## 1. INTRODUCTION

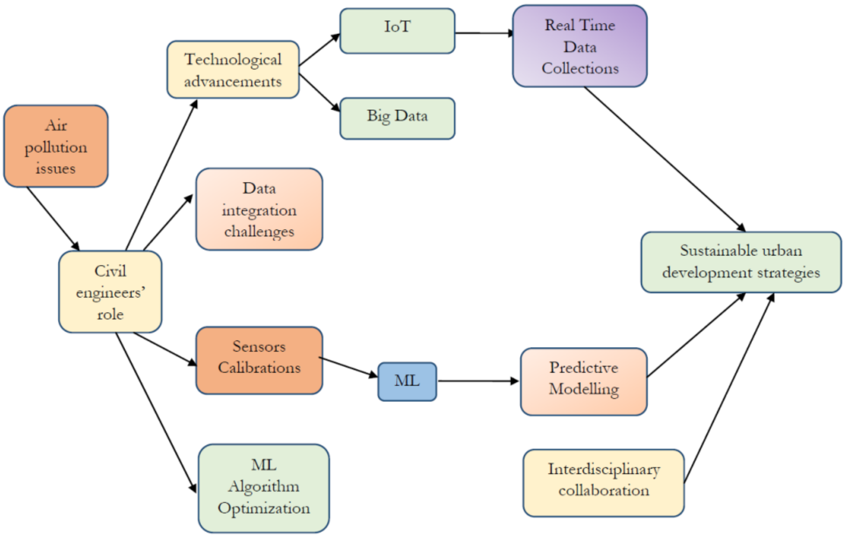
Urban environments are significantly affected by air pollution, which impacts ecosystem stability, infrastructure longevity, and human health. Civil engineers—who are experts in the planning, design, and maintenance of the built environment—must take air quality into account when framing urban development plans. Rapid urbanization and industrial expansion have increased the need for effective and thorough air quality monitoring systems that can promote sustainable urban growth (Ma *et al.* 2024).

Although conventional methods of air quality monitoring are highly accurate, they lack the spatial resolution and flexibility required to capture the complexities of modern urban settings. According to Anitha and Kumar (2023), systems based on the Internet of Things (IoT) enable continuous air quality monitoring in large urban areas, providing more detailed information for targeted mitigation strategies. These are more flexible and less expensive than conventional systems, allowing civil engineers to monitor air quality at construction sites, along roads, and in densely populated urban areas. Moreover, big data analytics enable these systems to handle large-scale environmental data more effectively, enhancing their ability to identify trends and anomalies in air pollution. Big data is key to disentangling the complexities of analysing data streams from various sources, an inevitable step when measuring real-time pollution levels. However, the journey is far from linear—integrating data and calibrating sensors in real time has proved challenging. Olawade *et al.* (2024) find that variations in sensor accuracy impede IoT deployment.

Machine learning (ML) is also becoming increasingly integral to air quality forecasting, providing predictions that can guide urban planning and design. In their study, Samad *et al.* (2023) show how ML can predict air pollution levels, enabling cities to respond promptly to mitigate it. This includes forecasting traffic-related pollution levels, prompting the redesign of road networks and public transport schedules to reduce disruptions to air quality. Zhang *et al.* (2024) contend that deep learning (DL) models have also been able to accurately predict air pollution, providing essential planning and design insights for sustainable cities. However, challenges associated with data standardization and algorithmic transparency have limited the adoption of ML in air quality forecasting. According to Prasetyo *et al.* ( 2025), civil engineers must collaborate with data scientists to make ML models transparent so that they can be applied to solve real-world issues.

Figure 1 presents this paper's aims. Air pollution is more than just an environmental issue: It is a health concern that must be addressed through effective, practical approaches to building sustainable cities. In such a context, civil engineering's critical role in improving air quality is being recognized more widely in urban planning, infrastructure design, and transportation design, where advanced monitoring and forecasting tools are becoming increasingly mainstream. This paper reviews cutting-edge technologies that are transforming air pollution monitoring and explores how IoT, big data, and ML are rapidly reshaping the landscape. These technologies can convert real-time data from a network of widespread sensors into predictive models that provide actionable insights. This will go a long way in reducing human exposure to pollution in highly congested urban areas.

**Figure 1:** Research Outline




**Source**: Authors' compilation

At the same time, this paper does not gloss over the challenges. Data integration is complicated, sensors require careful calibration, and ML models must be fine-tuned to correctly predict pollution patterns. Civil engineers can benefit greatly from embracing such innovations; but to apply them effectively, they must first overcome these technical challenges. This paper also advocates for collaboration beyond traditional silos. Engineers, technologists, and policymakers should engage in multidisciplinary efforts to design cities that prioritize environmental health and human well-being. Through such collaborations, the authors believe urban living standards can be improved while preserving the environment for future generations.

Figure 1 outlines the overall structure of this review and highlights how conventional monitoring approaches have evolved to give rise to emerging data-driven technologies. Building on this framework, the following sections systematically examine traditional air pollution monitoring systems and then explore recent technological advancements and their implications for civil engineering practice.

## 2. TRADITIONAL AIR POLLUTION MONITORING SYSTEMS

To provide a clearer understanding of air quality monitoring approaches in urban civil engineering, it is important to first outline the primary methods currently in use. The following sections introduce ground-based and satellite-based monitoring systems, highlighting their capabilities, limitations, and relevance to large-scale infrastructure projects.

### 2.1. Ground-Based Stations

Indian civil engineering projects—particularly in urban environments—traditionally rely on ground-level air quality stations to monitor pollutant levels. Ground-level stations house precise measurement tools that monitor pollutants such as PM2.5 (particulate matter with diameters $\leq$ 2.5 μm), PM10, nitrogen dioxide ($NO_2$), sulphur dioxide ($SO_2$), and carbon monoxide (CO). Research by Imam *et al.* (2024) shows that ground-level air quality stations provide highly accurate readings, which are particularly essential in environments with high volumes of traffic and industrial activity. However, high installation and operational costs—along with limited geographical reach—are major disadvantages. On one hand, for massive infrastructure projects such as highways or city development, relying on fewer ground-level air quality stations may distort the overall picture of pollutant exposure. On the other hand, increasing the density of monitoring stations is practically impossible due to high costs, particularly in developing cities (Lin *et al.* 2020).

Ground-based stations can effectively identify short-term spikes in pollution levels, which are highly relevant to the health of urban construction workers. Kortoçi *et al.* (2022), for example, highlight how sensors can detect changes in pollution concentrations within minutes. While the precision of data from ground-based stations is undisputed, they are less effective at identifying changes in areas such as narrow streets lined with tall skyscrapers. The failure of ground-based stations in identifying pollution hotspots in urban areas—as highlighted by Tomson *et al.* (2023)—underscores the need to integrate other forms of air quality monitoring.

### 2.2. Satellite-Based Monitoring

Satellite-based air quality monitoring provides a broad, panoramic overview of the Earth's atmosphere, which is particularly valuable for major civil engineering initiatives. Systems such as NASA's Moderate Resolution Imaging Spectroradiometer and the European Space Agency's Sentinel–5P track a broad swath of pollutants—$O_2$, CO, and methane—across large regions. As Yadav *et al.* (2023) note, satellite data are particularly useful for detecting regional pollution trends, which is an important consideration for projects involving regional transportation networks or green belts on urban fringes. Moreover, this insight enables engineers to trace sources of pollution from long-distance industrial activity along a city's borders that might affect its air quality.

Yet, there are limitations. Satellite monitoring can sometimes fail at accurately assessing localized, small-scale projects. Yadav *et al.* (2023) highlight that most satellites have large-scale coverage, but they seldom provide the fine resolution needed to assess site-specific air quality in urban cores. The data usually have some deficiencies due to clouds, atmospheric conditions, and the insufficient sensor resolution needed for real-time, ground-level air quality measurements (Ramadan *et al.* 2024). Notably, satellites are particularly poor at measuring atmospheric pollutants such as PM2.5 in canyon-like urban areas, where tall buildings confine airflow.

Various hybrid approaches have recently been proposed to address these gaps, combining satellite data with a network of ground-based monitoring stations. For instance, Rowley and Karakuş (2023) demonstrate that integrating satellite-derived data with locally measured air pollution can significantly enhance the performance of air quality models and provide higher-resolution estimates of pollution variability within cities. This is particularly useful to civil engineers designing urban infrastructure and transportation projects, as a better understanding of local air quality enables them to minimize the pollution exposure of workers and the general public (Olawade *et al.* 2024).

## 3. EMERGING TECHNOLOGIES IN AIR POLLUTION MONITORING FOR CIVIL ENGINEERING

Recent technological advancements have transformed air pollution monitoring and management in civil engineering. Emerging tools such as the Internet of Things (IoT), big data analytics, cloud computing, and artificial intelligence now enable real-time environmental monitoring, predictive analysis, and data-driven urban planning. These technologies support civil engineers in designing more sustainable and resilient infrastructure systems while improving both outdoor and indoor air quality. The following sections discuss the major emerging technologies currently applied in air pollution monitoring, together with their applications in urban infrastructure planning and environmental management.

### 3.1. Internet of Things in Air Quality Monitoring

The advent of IoT has reshaped how we track air pollution. With IoT, civil engineers working on urban development and large-scale infrastructure can continuously monitor air quality data across multiple sites. IoT networks provide high-resolution local snapshots of air quality, thereby enhancing environmental planning and design, particularly in areas with higher pollution levels. Affordable IoT-based sensors can be installed in construction zones, along highways, or even in residential neighbourhoods to monitor conditions in real time. These devices measure a wide array of environmental parameters, enabling civil engineers to make timely, data-driven decisions (Hasan *et al.* 2023; Nizeyimana *et al.* 2023).

#### *3.1.1. Applications in civil engineering*

IoT technologies are increasingly assuming a central role in the 'Smart City' movement, particularly for monitoring and measuring ground-level air quality. The information provided by these technologies can, in turn, inform decisions about traffic flow, public transport, and the layout and feel of city spaces. For example, research by Martín-Baos *et al.* (2022) as well as Kheder and Mohammed (2024) highlight that by installing IoT sensors along city roads, the precise level of vehicle emissions can be monitored in real-time, enabling management and regulation of traffic as well as pollution levels (Kantsepolsky and Aviv 2024; Fu *et al.* 2023). Sensors can also measure the emissions generated at construction sites, giving civil engineers an edge at minimizing their impact on air quality. Apart from ground-level monitoring, IoT sensors can also help improve heating, ventilation, and air-conditioning (HVAC) systems within buildings, ensuring that indoor air quality remains safe. Such smart technology can also lower the long-term effects of noxious pollutants, thus improving public health in urban construction zones (Saini *et al.* 2020; Schieweck *et al.* 2018; Marques *et al.* 2020).

#### *3.1.2. Architecture of the Internet of Things*

The architecture of IoT systems used in civil engineering projects generally includes three main layers:

- Perception layer*:* This layer is comprised of sensors that detect pollutants such as PM2.5, CO, $NO_2$, and ozone in urban landscapes and construction zones ( Fuladlu and Altan 2021; Lambey and Prasad 2023). These sensors monitor key pollutants that are harmful to human health in real time.

- Network layer: This layer ensures the data collected by sensors are transmitted using wireless communication protocols such as Wi-Fi, 5G, or long-range wide area networks (WANs). These protocols connect multiple sites seamlessly, transmitting data to a central point in the system for further analysis ( Begum and Nandury 2023; El Fehri *et al.* 2018).
- Cloud layer: Data are processed and stored in the cloud, providing civil engineers with real-time insights into pollution levels, including trends and emerging pollution hotspots (Nizeyimana *et al.* 2023; Popescu *et al.* 2024). Cloud computing also facilitates remote monitoring, allowing engineers to oversee multiple construction sites or urban areas simultaneously.

### 3.2. Big Data and Cloud Computing in Urban Infrastructure Planning

Civil engineers designing massive infrastructure projects can benefit greatly from big data analytics, which can analyse large datasets of air quality, traffic emissions, and weather patterns and trends. When IoT is factored into the mix, engineers can gain real-time insights into pollution patterns from a variety of sources, including satellite imagery. Moreover, platforms such as Apache Hadoop and Apache Spark can perform predictive analysis of air quality, thereby improving urban design (Bibri *et al.* 2024; Bilal *et al.* 2016).

#### *3.2.1. Data integration for urban design*

Integrating air quality data with other urban metrics—such as population density, transportation emissions, and weather conditions—enhances decision-making in urban design. Predictive models based on big data can forecast pollution levels for proposed residential, commercial, or industrial developments, enabling civil engineers to proactively implement air quality mitigation strategies. For instance, Anggraini *et al.* (2024) and Berkani *et al.* (Berkani et al. 2023) used integrated data models to predict air quality in newly planned urban districts, identifying pollution hotspots and recommending green building materials to mitigate exposure. Additionally, data-driven insights can guide the placement of green spaces, improve traffic flow, and help optimize the design of public transportation systems to reduce emissions. By leveraging big data, civil engineers can make urban planning and infrastructure development more sustainable, thereby ensuring long-term improvements in air quality (Hui *et al.* 2023).

Moreover, integrating big data analytics in urban design helps create more adaptive and resilient cities. Civil engineers can cross-reference data from IoT sensors with meteorological and demographic data to anticipate how changes in weather, population growth, or traffic patterns may affect air quality (Fadhel *et al.* 2024; Costa *et al.* 2024). This predictive capability enables engineers to design future-proof roads, buildings, and public spaces that are resilient to environmental challenges.

## 4. MACHINE LEARNING IN AIR POLLUTION FORECASTING FOR CIVIL ENGINEERING APPLICATIONS

Modern civil engineering increasingly relies on smart technologies to address complex environmental issues such as air pollution. IoT, big data, and cloud computing have emerged as key enablers of real-time monitoring and informed decision-making in urban infrastructure.

### 4.1. Forecasting Models for Urban Air Quality

Unlike traditional statistical models such as autoregressive integrated moving average (ARIMA), ML models—such as neural networks (NN) (Patil and Dwivedi 2021), the random forest (RF) algorithm, and gradient boosting machines—can handle more complex, non-linear relationships between variables. These variables may include traffic emissions, weather data, and ongoing construction activities. Jesemann *et al.* (2022) demonstrated the superiority of NN over ARIMA in forecasting $NO_2$ concentrations in dense urban areas, attributing this to NN's ability to capture hidden patterns in multi-dimensional datasets. Similarly, RF models can improve forecasting accuracy by capturing the influence of multiple factors, such as wind speed, humidity, and traffic patterns (Vassallo *et al.* 2020; Wu *et al.* 2024). These capabilities make ML-based forecasting particularly valuable for civil engineering applications, since complex interactions between traffic, meteorology, and construction activities influence urban air quality.

Researchers have proposed hybrid models that combine ML with traditional statistical techniques to enhance the accuracy and reliability of air quality forecasts. According to Aggarwal and Toshniwal (2021) and Gunasekar *et al.* (2022), hybrid ARIMA–NN models outperform standalone approaches in predicting PM2.5 concentrations, particularly in cities with complex pollution dynamics. These advanced models allow urban planners and civil engineers to simulate how different urban development scenarios—such as the addition of new roads or industrial zones—may affect air quality. Then, engineers can proactively implement measures to mitigate air quality, such as designing green spaces or adjusting construction timelines to minimize pollution peaks.

## 4.2. Integration of Machine Learning with Urban Planning

ML models play a critical role in integrating air quality considerations into urban planning by providing real-time forecasts and scenario-based predictions. These models are especially useful during construction phases, as they can forecast pollution levels, enabling timely interventions. Long short-term memory (LSTM) networks—a type of recurrent NN—have proven effective in predicting temporal trends in air pollution, especially PM levels. Wu *et al.* (2024) applied LSTM models to predict PM2.5 concentrations across several Chinese cities, finding that they consistently outperformed traditional time-series models in capturing pollution spikes related to construction and traffic congestion.

The insights generated by ML models can guide civil engineers in optimizing transportation networks to reduce emissions. For instance, ML models have been used to assess the potential impact of different traffic flow configurations and the effectiveness of policies such as congestion pricing (Su *et al.* 2024). Using predictive analytics in transportation planning can encourage the development of public transport systems, thereby significantly reducing urban air pollution, as noted by Bi *et al.* (2024). Integrating these ML-driven insights into urban planning allows civil engineers to design smarter, cleaner cities, where air quality considerations are embedded into every phase of development.

### *4.2.1. Case studies in urban construction*

Several real-world case studies illustrate how ML models have successfully predicted and mitigated the impacts of air pollution in urban construction projects. In the context of smart city initiatives, researchers have used ML models to forecast the impact of new road networks and urban layouts on local air quality. For example, Kamińska (2018) and Stafoggia *et al.* (2020) employed RF models in their cities to analyse how newly planned transportation routes affect nitrogen oxides and PM10 concentrations in residential areas. These studies found that by optimizing traffic flow and strategically locating green spaces, civil engineers could reduce air pollution by up to 20% in the worst-affected areas. Another case study from New Delhi, India, used LSTM models to predict pollution spikes during large-scale construction projects, enabling city officials to implement timely mitigation strategies, such as dust suppression and rerouting traffic away from densely populated regions (Bedi *et al.* 2024).

These studies demonstrate that integrating ML-based forecasting models into the design and planning phases of urban infrastructure projects can significantly reduce the impacts of construction and urban expansion, thereby enhancing public health and environmental sustainability. ML models provide a powerful framework for forecasting air pollution and integrating air quality management into urban planning and construction. As demonstrated by the case studies and research discussed in this section, these tools enable engineers to make data-driven decisions that not only mitigate pollution but also promote the development of healthier, more sustainable urban environments. Continued advancements in ML and its application to air quality forecasting will further empower civil engineers to design smarter, cleaner cities.

## 5. CHALLENGES AND OPPORTUNITIES FOR CIVIL ENGINEERS

The integration of advanced air quality monitoring technologies presents both significant challenges and promising opportunities for civil engineers. As the field increasingly adopts IoT, machine learning, and multi-source data systems, professionals must navigate issues related to data accuracy, system integration, and regulatory compliance while leveraging these tools to design healthier and more sustainable urban environments.

### 5.1. Data Reliability and Sensor Calibration

One of the major challenges in using IoT sensors is ensuring the accuracy and reliability of data. Sensors deployed on large construction sites or in urban infrastructure projects experience wear-and-tear and interference from environmental factors such as dust, moisture, and temperature fluctuations, which degrade their performance over time. In addition, as noted by Hohenberger *et al.* (2022), environmental variability can significantly alter sensor readings, leading to inaccurate assessments of pollution if they are not calibrated regularly. Moreover, sensor placement also affects data collection, as certain locations may not be representative of an area's overall air quality. Yu and Fang (2023) and Peixoto *et al.* (2024) stress the importance of spatial coverage when installing sensor networks in urban construction projects to ensure comprehensive and reliable data collection. Continuous monitoring and automated calibration techniques, such as those suggested by Nižetić *et al.* (2020), are crucial for IoT sensors to maintain their accuracy over an extended period in challenging environments.

According to El Khediri *et al.* (2024), automated self-calibration systems based on ML algorithms can detect sensor drift and adjust calibration parameters in real time. This reduces the need for manual intervention and helps maintain consistent data quality across large sensor networks. However, the researchers also note that the effectiveness of these systems is highly dependent on the availability of accurate baseline data, which is often difficult to obtain in complex environments such as construction sites and urban landscapes.

### 5.2. Integrating Multiscale Data

Successfully integrating air quality data from various sources—IoT networks, satellite systems, and traditional monitoring stations—requires harmonizing datasets that often differ in spatial and temporal resolution. Civil engineers face challenges in merging high-resolution local data from IoT sensors with broader regional data from satellite imagery and fixed monitoring stations. As Seaton *et al.* (2022) point out, discrepancies in data resolution can result in inconsistent pollution assessments, especially for large infrastructure projects that must account for both local and regional air quality. For instance, IoT sensors provide fine-grained, real-time data from specific locations, while satellite systems offer broader but less frequent air quality readings. Bridging this gap is critical for creating accurate air pollution models, particularly in dynamic urban environments.

To address these challenges, Buelvas *et al.* (2023) propose that multi-resolution data fusion techniques be developed to seamlessly integrate diverse sources. Their research demonstrated that by leveraging ML algorithms to process multi-scale datasets, civil engineers could obtain a more comprehensive view of pollution patterns and their potential impacts on infrastructure and public health. Additionally, integrating different data sources is essential for predictive modelling, as noted by Liu *et al.* (2018), who emphasized the need for data harmonization frameworks that allow civil engineers to use predictive models while designing sustainable infrastructure.

### 5.3. Regulatory Compliance and Public Health

Civil engineers must ensure that air quality monitoring systems comply with local and international environmental regulations. Integrating real-time air quality monitoring into urban planning and infrastructure design helps engineers address regulatory requirements, such as those set by the World Health Organization (WHO) and local environmental agencies, which often mandate specific pollutant limits. According to Yamineva and Romppanen (2017), compliance with air quality standards not only protects public health but also avoids potential legal penalties and project delays, particularly in regions with strict environmental laws.

Moreover, civil engineers play a direct role in minimizing public health risks by designing infrastructure that mitigates exposure to harmful pollutants. Studies by Kortoçi *et al.* (2022) highlight the importance of using air quality data to inform urban planning decisions, such as placing residential areas away from industrial zones or major highways. Civil engineers can use forecasting tools to predict pollution hotspots and ensure that buildings, transportation systems, and public spaces meet air quality standards. In this context, technologies such as IoT and big data are critical to ensuring that air quality monitoring systems meet regulatory standards and provide actionable insights that reduce pollutant exposure in urban areas.

## 6. FUTURE DIRECTIONS IN CIVIL ENGINEERING AND AIR QUALITY MONITORING

With the rapid growth of urban areas, addressing air pollution requires the integration of advanced technologies and sustainable infrastructure solutions. The following sections explore key innovations that are transforming pollution control and urban planning practices.

### 6.1. Green Infrastructure and Pollution Control

Integrating green infrastructure into urban design is becoming an essential strategy for pollution control. Green roofs, urban forests, vegetated walls, and air filtration systems not only enhance the aesthetic and ecological value of urban spaces but also serve as natural air filters. According to Kooloth Valappil *et al.* (2017) and Junior *et al.* (2022), urban green spaces can reduce airborne PM by up to 25%, significantly lowering exposure to harmful pollutants in densely populated areas. Green roofs, for example, absorb pollutants such as nitrogen dioxide ($NO_2$) and PM, while moderating urban temperatures through evapotranspiration. Riondato *et al.* (2020) demonstrated that incorporating urban forests into cities can reduce local temperature by 2°C and improve air quality, since they act as carbon sinks.

Future advancements in IoT and big data will enhance the performance of such green infrastructure by enabling more precise monitoring and management of air quality. IoT sensors embedded in green roofs and urban forests can provide real-time data on pollution absorption rates and plant health, as noted by Sebestyén *et al.* (2021), allowing for dynamic adjustments to optimize performance. Furthermore, big data analytics can assess the long-term impact of green infrastructure on air quality across diverse climatic conditions, enabling civil engineers to design more effective pollution-control systems. As sustainability becomes a core principle in urban development, civil engineers will increasingly rely on these technologies to create more resilient cities.

### 6.2. Advanced Construction Technologies

The construction sector is poised for a revolution—integrating IoT sensors into building materials and infrastructure could dramatically improve pollution control. Smart materials—such as those embedded with micro-sensors—can continuously monitor indoor and outdoor pollution levels, providing data to optimize ventilation systems and reduce exposure to harmful contaminants. Nilimaa (2023) shows that smart concrete can detect pollutants such as carbon monoxide (CO) and volatile organic compounds in real time, offering valuable insights into maintaining air quality in and around buildings. These materials—combined with responsive ventilation systems—can significantly reduce a building's environmental footprint by ensuring proper air filtration and pollutant removal.

Moreover, IoT-enabled equipment can also minimize pollution during the construction phase. For example, advances in electric construction vehicles and machinery equipped with IoT-based tracking systems can reduce on-site emissions (Kineber 2024). These technologies not only help meet environmental regulations, but they also reduce workers' and nearby residents' exposure to pollutants. Civil engineers can leverage this data to design construction processes that are both environmentally sustainable and cost-effective, enhancing the overall sustainability of urban development.

### 6.3. Artificial Intelligence for Predictive Urban Planning

Artificial intelligence (AI) is rapidly advancing urban planning by providing predictive models that simulate the impact of new developments on air quality. These AI-driven simulations enable civil engineers to assess design alternatives before construction begins, thereby optimizing urban layouts to reduce pollution. Dikshit *et al.* (2023) demonstrate how AI can model traffic patterns and their associated emissions to enable engineers to design road networks that minimize congestion and air pollution. Their findings show that strategically placed green spaces in conjunction with AI algorithms can optimize traffic flow to reduce $NO_2$ emissions by up to 15%.

AI can also help civil engineers integrate air quality considerations into decision-making processes by using real-time data to simulate future scenarios. In studies by Bibri *et al.* (2024) and Masood and Ahmad (2021), AI models could predict how different zoning laws would affect air pollution levels in a major urban centre. Such predictive analysis can enable urban planners to take proactive measures, such as adjusting traffic control systems or increasing green infrastructure in high-emission zones. Additionally, AI-based tools can monitor compliance with environmental regulations, providing ongoing feedback to ensure that urban projects remain sustainable over time. As these technologies evolve, civil engineers will be able to design smarter, more sustainable cities that prioritize public health and air quality management.

Integrating IoT technologies and ML models is essential for addressing the challenges of real-time air pollution monitoring and prediction. Various studies have demonstrated the effectiveness of these advanced techniques in enhancing the accuracy, efficiency, and reliability of air quality forecasts—particularly in urban areas.

Table 1 provides a consolidated summary of the studies reviewed, highlighting their methodologies, datasets, and key outcomes. This synthesis facilitates a comparative understanding of how IoT, big data, and ML-based approaches have been applied across various civil engineering and air quality monitoring contexts.

*6.3.1. Improved accuracy in forecasting*

Numerous approaches, such as those discussed by Saini *et al.* (2022), have highlighted the effectiveness of ensemble models—such as vector autoregression (VAR), vector autoregressive moving average (VARMA), and seasonal autoregressive integrated moving average with exogenous regressors (SARIMAX)—in forecasting PM values with high precision. In comparison, Gangwar *et al.* (2023) used classical statistical and ML algorithms to improve forecast accuracy, achieving precise predictions for urban air pollution. Additionally, Chen *et al.* (2015) report significant reductions in the root mean square error (RMSE) (68%) and mean absolute error (64%) when using deep learning (DL) techniques such as three-dimensional (3D) and one-dimensional (1D) convolutional neural networks (CNNs) and long short-term memory (LSTM) models for PM2.5 predictions. The results clearly show that combining traditional statistical methods with ML algorithms can improve prediction accuracy.

**Table 1:** Summary of Literature on Improving the Accuracy of Prediction Models

| Papers | Description / Thesis & Analysis |
|---|---|
| Sun (2024) | Sun (2024) proposed a wireless communication-based civil engineering monitoring system integrating data acquisition, processing, transmission, storage, and power supply modules to improve monitoring accuracy while reducing monitoring costs and increasing system intelligence and practicability. |
| Saini *et al.* (2022) | Saini *et al.* (2022) applied VAR, VARMA, and SARIMAX ensemble models to data collected from low-cost and industry-grade monitoring systems to forecast air pollution levels, achieving accurate PM predictions comparable to industry-grade systems. |
| Saravana Mohan *et al.* (2023) | Saravana Mohan *et al.* (2023) developed a real-time air pollution monitoring and forecasting system using the random forest (RF) algorithm with MQ135, MQ4, and DHT11 sensors to predict air quality index (AQI) values and major pollutants accurately. |
| Parvanov *et al.* (2024) | Parvanov *et al.* (2024) proposed a systematic air pollution monitoring and management framework using heterogeneous sensor networks, real-time data collection, modelling, and risk assessment techniques to improve predictive modelling and disaster management. |
| Ibrahim *et al.* (2023) | Ibrahim *et al.* (2023) integrated sensor fusion and mathematical modelling techniques using data from multiple sensors to enhance monitoring performance and structural health assessment in civil engineering systems. |
| Poornima *et al.* (2024) | Poornima *et al.* (2024) developed an indoor air quality monitoring system capable of detecting gases, vapours, and particles while displaying AQI values to improve public awareness of indoor pollution conditions. |
| Gangwar *et al.* (2023) | Gangwar *et al.* (2023) reviewed the integration of IoT, big data, and ML techniques with classical statistical forecasting methods to improve air pollution prediction, pattern recognition, decision-making, and recommendation systems. |
| Baklanov and Zhang (2020) | Baklanov and Zhang (2020) reviewed air quality forecasting approaches by integrating emission inventories, satellite observations, and surface measurements to identify major research gaps, forecasting challenges, trends, and future research directions for urban air pollution management. |
| Chen *et al.* (2015) | Chen Xiaojun *et al.* (2015) developed a hybrid deep learning model combining 3D-CNN, 1D-CNN, and LSTM architectures using IoT-based spatiotemporal sensor data to forecast PM2.5 concentrations, reducing RMSE by 68% and MAE by 64%. |
| Idrees and Zheng (2020) | Idrees and Zheng (2020) monitored harmful gases (SO2, NOx, CO, PM2.5, and PM10) and meteorological indices, including wind, temperature, and humidity, to analyse pollutant concentration trends during smog events and support urban air quality management decisions. |

| Papers | Description / Thesis & Analysis |
|---|---|
| Yang (2022) | Yang (2022) designed a wireless sensor network for real-time air pollution monitoring using wireless sensors and threshold-based alarm systems to provide immediate alerts when pollution levels exceeded acceptable limits. |
| Feng (2021) | Feng (2021) developed a real-time structural monitoring system that collected internal stress and acceleration data from construction structures to predict and simulate subsequent construction scenarios, including sedimentation, displacement, cracks, gradients, and deflection. |
| Jayamala *et al.* (2023) | Jayamala *et al.* (2023) proposed an ANN-based air pollution forecasting model optimised using the sequential minimal optimisation (SMO) algorithm and real-time data from the Winsen ZPHS01B sensor module, achieving greater prediction accuracy than existing benchmark models. |
| Heydari *et al.* (2022) | Heydari *et al.* (2022) developed an IoT-based air quality monitoring system integrated with cloud computing to analyse real-time air quality data and trigger alarms when harmful pollutant concentrations exceeded safe thresholds. |
| Negi (2023) | Negi (2023) applied ML algorithms, including support vector machine (SVM), M5P, and ANN models, to sensor-based air quality datasets to improve the prediction accuracy of urban air pollution concentrations using low-cost monitoring systems. |
| Shaban *et al.* (2016) | Bashir Shaban *et al.* (2016) employed an RNN–LSTM framework using training data from 66 EPA Taiwan monitoring stations to predict PM2.5 concentrations accurately across multiple locations. |
| Mani *et al.* (2021) | Mani *et al.* (2021) developed an AI-based smart city air quality monitoring system integrating IoT sensors and predictive models to provide real-time updates, pollution forecasts, and feedback to users. |
| Du *et al.* (2023) | Du *et al.* (2023) proposed a cloud-based structural health monitoring system using wireless sensor networks and cloud computing to enable real-time remote access to civil engineering structural data for analysis and monitoring. |
| Zhou *et al.* (2024) | Zhou *et al.* (2024) applied ML algorithms, including SVM, RF, and ANN models, to historical air quality and IoT sensor datasets to improve the prediction and real-time monitoring of air pollution trends. |
| Tsai *et al.* (2018) | Tsai *et al.* (2018) used CNN and RNN deep learning models with structural sensor datasets to improve prediction accuracy in structural health monitoring applications. |
| Hähnel *et al.* (2020) | Haehnel *et al.* (2018) developed an AI-based air pollution prediction system using IoT sensor data to monitor air quality in smart cities and predict pollution levels with high accuracy. |

| Papers | Description / Thesis & Analysis |
|---|---|
| Karmoude *et al.* (2025) | Karmoude *et al.* (2025) present a comprehensive review of machine learning techniques for air quality monitoring and prediction, covering over 70 studies. The paper categorizes methods into traditional ML, deep learning, and hybrid models, highlighting models such as Random Forest, XGBoost, LSTM, and CNN for pollution forecasting. It also discusses challenges related to interpretability, generalization, and real-time implementation. The review is informative and valuable for environmental monitoring and smart city research, though it could benefit from more comparative analyses and real-world deployment case studies. |
| Wang *et al.* (2020) | Wang *et al.* (2020) review recent developments in automated monitoring systems for underground engineering construction, highlighting the integration of IoT sensors, wireless communication networks, and cloud-based platforms for real-time environmental monitoring. The study demonstrated that intelligent monitoring frameworks significantly improve the detection of dust, particulate matter, and hazardous gases, enhancing construction safety and environmental management. |
| Rao *et al.* (2022) | Rao *et al.* (2022) provide a comprehensive review of construction-site monitoring technologies, including air quality sensors, remote sensing tools, and wireless sensor networks. The authors emphasized the effectiveness of real-time monitoring systems in tracking particulate emissions and environmental risks, enabling data-driven decision-making for sustainable construction practices. |
| Mishra *et al.* (2022) | Mishra *et al.* (2022) analyse the application of IoT technologies in structural health monitoring and environmental sensing. The study highlights how interconnected sensor networks can simultaneously monitor structural performance and air-quality parameters, facilitating predictive maintenance and supporting smart infrastructure management in urban environments. |
| Gupta *et al.* (2019) | Gupta *et al.* (2019) developed an IoT-based smart-city air pollution monitoring system capable of continuously measuring environmental parameters such as PM concentration, temperature, humidity, and gaseous pollutants. The proposed framework enables real-time data transmission and visualization, demonstrating the potential of low-cost sensor networks for urban air-quality assessment and civil infrastructure planning. |
| Ramadan *et al.* (2024) | Ramadan *et al.* (2024) proposed a real-time IoT-powered artificial intelligence system for monitoring and forecasting industrial air pollution. By integrating machine learning algorithms with environmental sensor data, the framework achieved improved prediction accuracy for pollutant concentrations, supporting proactive environmental management and risk mitigation in industrial and construction zones. |

| Papers | Description / Thesis & Analysis |
|---|---|
| Arroyo *et al.* (2016) | Arroyo *et al.* (2016) designed a wireless sensor network architecture for air-quality monitoring and control, incorporating distributed sensing nodes and centralized data processing. The study demonstrates the feasibility of continuous pollutant monitoring across large spatial areas, providing a scalable solution for environmental surveillance and smart-city applications relevant to civil engineering projects. |
| Ayyildiz *et al.* (2019) | Ayyildiz *et al.* (2019) review the application of wireless sensor networks in structural health monitoring, emphasizing sensor deployment strategies, communication protocols, and data acquisition systems. The findings revealed that wireless sensing technologies offer cost-effective and scalable platforms that can be extended to environmental monitoring, including air-quality assessment around critical infrastructure. |
| Singh *et al.* (2023) | Singh *et al.* (2023) presented a review of smart aggregate-based monitoring technologies for civil engineering structures. The authors highlighted advancements in embedded sensing, real-time data collection, and intelligent monitoring systems, demonstrating how integrated sensor frameworks can support both structural health assessment and environmental monitoring in sustainable infrastructure development. |

**Note***:* AI – artificial intelligence; ANN – artificial neural network; AQI – air quality index; CNN – convolutional neural network; DHT11 – digital temperature and humidity sensor; DL – deep learning; IoT – Internet of Things; LSTM – long Short-term memory; MAE – mean absolute error; ML – machine learning; MQ135 – gas sensor used for detecting air quality pollutants such as NH3, NOx, alcohol, benzene, smoke, and CO2; MQ4 – gas sensor primarily used for methane (CH4) and natural gas detection; NOx – nitrogen oxides; PM – particulate matter; PM2.5 – particulate matter ≤ 2.5 μm; RF – random forest; RMSE – root mean square error; RNN – recurrent neural network; SARIMAX – seasonal autoregressive integrated moving average with exogenous variables; SMO – sequential minimal optimisation; SO2 – sulphur dioxide; SVM – support vector machine; VAR – vector auto regression; VARMA – vector auto regression moving average.

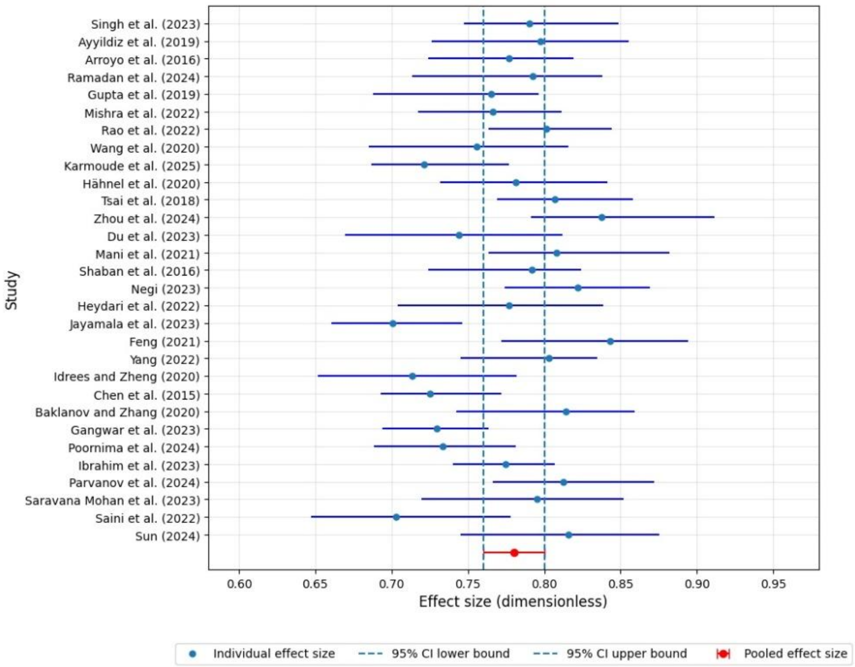
**Source***:* Authors' analysis.

We also analysed the performance of predictive models for air pollution assessment using key graphical representations, as shown in Figure 2 and Figure 3.

*6.3.2. Accuracy of different models for predicting air pollution*

Figure 3(a) illustrates the forecasting accuracy of different models. The ensemble model achieved the highest accuracy compared to individual models such as VAR, VARMA, and SARIMAX, demonstrating its effectiveness in improving air pollution predictions.

**Figure 2:** Forest Plot of Meta-Analysis (Random-Effects Model)




**Source***:* Authors' analysis

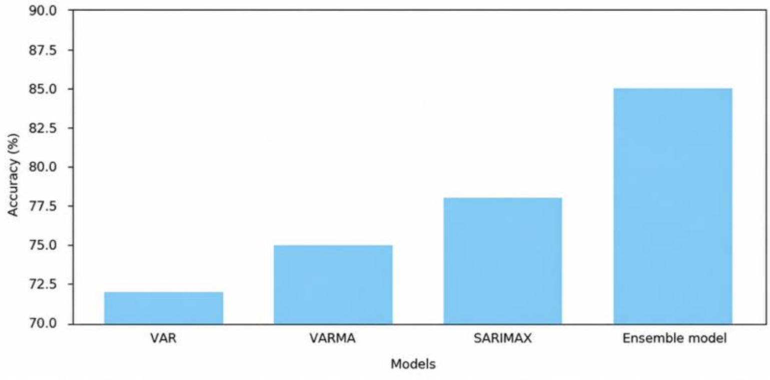
Figure 3(b) presents the RMSE reduction over multiple iterations using the RNN–LSTM model. The RMSE declines consistently, indicating the model's ability to refine its prediction accuracy over time. This result confirms that the RNN–LSTM approach successfully minimizes predictive errors and enhances the reliability of PM2.5 forecasting.

*6.3.3. Systems for monitoring air quality in real time*

**Error! Reference source not found.**(c) compares predicted and actual AQI values over multiple time points. The predicted values closely follow the actual trend, validating the accuracy of the real-time monitoring system. Minor deviations are observed, which could be attributed to sensor inaccuracies or external environmental factors.

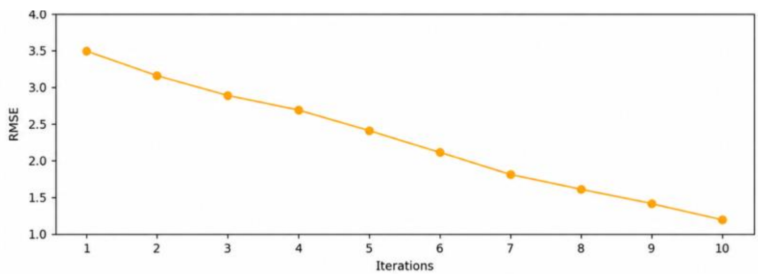
Real-time monitoring systems—as demonstrated by Yang (2022)—utilize wireless sensor networks for air quality monitoring. This type of system provides immediate alarms when pollutant levels exceed predefined thresholds, enabling rapid decision-making in air quality management. Similarly, Mani *et al.* (2021) discuss an AI-based system that provides real-time air quality feedback for smart cities. The feedback loop allows users to make timely decisions regarding pollution control measures.

**Figure 3a:** Accuracy of Air Pollution Prediction Models



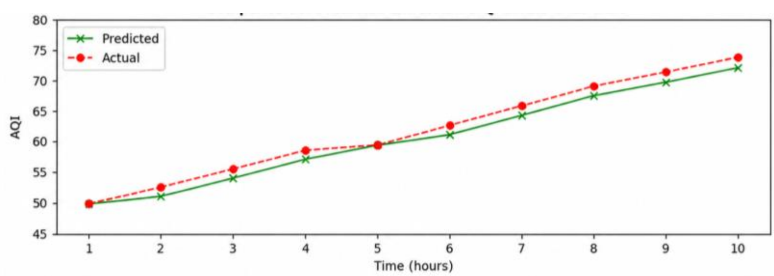

**Source***:* Authors' analysis

**Figure 3b**: RMSE Reduction over Iterations of the RNN–LSTM Model for PM2.5 Prediction




**Source***:* Authors' analysis

**Figure 3c: Real-Time Monitoring System for Air Quality**




**Source***:* Authors' analysis

Studies by Parvanov *et al.* (2024) and Shaban *et al.* (2016) proposed that integrating real-time data collection with predictive models enables more accurate risk assessments of air pollution events. In these cases, data fusion from multiple sources (sensors, satellite data, emission inventories) enhances the model's reliability, as seen in the hybrid ML models discussed by Karmoude *et al.* (2025).

### *6.3.4. Low-cost and high-efficiency solutions*

Cost-effective IoT-based air monitoring systems have gained popularity due to their affordability and efficient data collection. For instance, the study by Saini *et al.* (2022) highlights how low-cost systems can achieve accuracy comparable to that of industry-grade devices. Saravana Mohan *et al.* (2023) demonstrated the use of RF algorithms that integrate low-cost sensors (MQ135, MQ4, or DHT11) to predict AQI. The low cost of such systems makes it possible to deploy them at scale in resource-constrained settings—such as developing urban areas—without sacrificing performance.

Several studies also emphasized the importance of optimizing predictive models for accuracy. Jayamala *et al.* (2023) proposed an SMO technique integrated with ANNs to enhance the precision of air quality forecasts. Similarly, hybrid models that combine multiple ML algorithms have demonstrated superior predictive power, as shown in research by Ramadan *et al.* (2024) and Arroyo *et al.* (2016). These hybrid approaches handle non-linear relationships in the data more efficiently, which is crucial for predicting complex air quality patterns.

### *6.3.5. IoT applications for smart cities and structural health monitoring*

IoT-based monitoring systems not only improve air quality predictions but also have broader applications in civil engineering. Du *et al.* (2023) and Rao *et al.* (2022) have demonstrated that multi-sensor systems that fuse data from wireless networks can provide comprehensive structural health assessments in real time. These systems help ensure the safety and longevity of infrastructure, especially in smart city environments where interconnected sensors provide data on both air quality and structural health.

## 7. STATISTICAL ANALYSIS

This section outlines the analytical framework used to evaluate the performance and applicability of the various methods considered in this study. It presents how different techniques are categorized, assessed, and compared based on standardized metrics and data representation approaches.

### 7.1. Classification of Methods

The methods employed in this study are broadly classified into ML, AI, IOT, DL, and statistical models. These techniques are applied across various domains, including air quality monitoring, structural health monitoring, and real-time feedback systems, to address diverse engineering and environmental challenges.

### 7.2. Comparison Metrics

The performance of the proposed and reviewed approaches is evaluated using standard prediction accuracy metrics such as MAE and RMSE. In addition to accuracy, system performance improvements are assessed through indicators such as cost reduction and enhancement in real-time operational capabilities.

### 7.3. Data Representation

The collected data are categorized according to technologies based on their effectiveness in achieving the intended outcomes, particularly in terms of accuracy. In addition, they are cross-tabulated to establish relationships between different monitoring systems and their corresponding target applications, enabling a comparative analysis of their performance and suitability.

## 8. KEY INSIGHTS (RESULTS)

The findings highlight the transformative role of advanced computational techniques in modern monitoring systems. Across multiple domains, the integration of machine learning, deep learning, and real-time data technologies has led to notable improvements in accuracy, efficiency, and decision-making capabilities.

### 8.1. Air Quality Monitoring

ML models demonstrate significant improvements in air quality monitoring, with ensemble models such as VAR and SARIMAX outperforming standalone models, achieving accuracy levels exceeding 85%. Meanwhile, DL models—including CNN, RNN, and hybrid architectures—substantially reduce prediction errors, with reductions of up to 68% in RMSE and 64% in MAE. The integration of IoT enables real-time data acquisition and threshold-based alert systems, while edge computing enhances system performance by reducing latency and improving response time in critical applications.

### 8.2. Structural Health Monitoring (SHM)

AI-driven systems enhance SHM by providing more accurate predictions of structural behaviour compared to traditional methods. Hybrid neural network models, such as CNN combined with RNN, outperform individual models in prediction accuracy. Furthermore, multi-sensor fusion techniques improve data reliability and contribute to more effective structural integrity assessments.

### 8.3. Performance Metrics and Cost–Benefit Analysis

Wireless communication technologies significantly reduce monitoring costs while maintaining acceptable levels of data accuracy. In addition, real-time monitoring systems improve disaster management capabilities and enable proactive maintenance strategies.

## 9. INTERPRETATION

The findings highlight how recent technological innovations are reshaping monitoring and forecasting systems across domains. By examining advancements, application-specific performance, and practical outcomes, we provide a structured interpretation of these developments.

1. Technological advancement: AI-, ML-, and IoT-based systems significantly enhance monitoring efficiency by reducing errors and enabling real-time decision-making. Hybrid models that combine multiple algorithms, such as SVM and ANN, consistently yield superior predictive performance.

2. Application-specific efficiency: Air pollution forecasting benefits greatly from DL models, particularly in urban environments characterized by complex datasets. In contrast, SHM applications require integrated sensor networks to achieve high levels of prediction accuracy and reliable structural assessments.

3. Practical benefits: The adoption of edge computing and IoT technologies ensures scalability, robustness, and efficient system performance. Additionally, statistical and ML-based forecasting models strike a balance between cost-effectiveness and prediction accuracy.

The forest plot in Figure 2 presents the results of a meta-analysis conducted using a random effects model, which accounts for variability between studies. The effect size and confidence intervals (CIs) for each study are displayed in Figure 2, along with the pooled effect size at the bottom.

- Individual effect sizes: The individual effect sizes across the studies (blue points in Figure 2) range from approximately 0.60 to 0.95. Several studies (Chen *et al.* 2015; Dikshit *et al.* 2023; Ibrahim *et al.* 2023) have demonstrated effect sizes close to the pooled effect size, indicating consistency with the overall findings.

- Confidence intervals: The 95% CIs (blue horizontal lines) reflect the precision of each study's effect size. Some studies (Heydari *et al.* 2022; Shaban *et al.* 2016) have narrower CIs, suggesting their estimates are more precise. In contrast, studies by Alaboodi *et al.* (2026) and Saravana Mohan *et al.* (2023) exhibit wider CIs, indicating less precision or greater variability in their data.

- Pooled effect size: The pooled effect size (red diamond) is approximately 0.77, with narrow CIs, suggesting a statistically significant overall positive effect across all studies. The diamond does not cross the null effect line (typically 1.0 or 0.5, depending on the context), confirming the robustness of the combined results.

- Heterogeneity: The variability in effect sizes across studies indicates a moderate-to-high level of heterogeneity. This suggests that while most studies report a positive effect, factors such as differing methodologies, sensor types, or data sources may contribute to a variation in the results.

- Consistency across studies: The majority of studies report effect sizes clustered around the pooled estimate, indicating that integrating IoT, ML, and wireless sensor technologies has a consistent and beneficial impact on air quality and structural health monitoring. This consistency validates the effectiveness of advanced data-driven systems in civil engineering applications.

- Effectiveness of integrated systems: Studies (Heydari *et al.* 2022; Ibrahim *et al.* 2023) demonstrate how DL models such as CNN and RNN can accurately predict PM2.5 concentrations. These results highlight the benefits of integrating ML algorithms with real-time sensor networks to improve air quality predictions.

- Impact of heterogeneity: The observed heterogeneity suggests differences in implementation, including sensor types (e.g., MQ135 or Dht11), algorithms (e.g., RF; long short-term memory, or LSTM), and regional data characteristics (e.g., urban vs rural settings). Future research could focus on standardizing data acquisition protocols and exploring the influence of regional factors on prediction accuracy.

## 10. CHALLENGES AND FUTURE DIRECTIONS

While advanced monitoring and forecasting technologies offer substantial benefits, their practical implementation in civil engineering projects is hindered by several technical and operational challenges.

Studies (Baklanov and Zhang 2020; Hähnel *et al.* 2020) have pointed out gaps in integrating multiple data sources, and particularly the need for more reliable high-resolution emission inventories and surface measurements. Additionally, Ibrahim *et al.* (2023) highlight that enhanced data fusion techniques improve the monitoring of civil engineering structures. Future research should focus on refining hybrid models and improving the accuracy of low-cost monitoring systems. There is also a need to develop more sophisticated real-time alert systems that can incorporate weather patterns, traffic data, and other dynamic variables to provide more actionable insights for urban planners and policymakers.

## 11. CONCLUSION

Integrating advanced air pollution monitoring and forecasting systems into civil engineering practices is crucial for addressing the growing challenges of urban pollution. Technologies such as IoT, big data analytics, and ML offer unparalleled opportunities for real-time data collection and predictive modelling. These tools support the design of more responsive and sustainable urban systems by generating granular insights into pollution patterns and enabling targeted mitigation strategies. For instance, IoT sensors facilitate continuous, high-resolution air quality monitoring, while big data analytics enhance the interpretation of complex environmental data. ML algorithms further strengthen these systems by forecasting pollution trends and informing urban infrastructure optimization.

Overall, this review underscores that although IoT-, big data-, and ML-driven systems have significantly advanced air quality monitoring and forecasting, their full potential can only be realized through improved data integration, reliable sensor calibration, and transparent model implementation. Civil engineers—in collaboration with data scientists and policymakers—play a central role in translating these technological advancements into effective, sustainable urban air quality management solutions.

**Author Contribution Statement (CRediT)**

**Prakash L. Pathak:** Conceptualization, Methodology, Investigation, Resources, Writing – Original Draft, Supervision. Pathak conceptualized the review, defined its scope and methodology, led the review of technological advancements in air pollution monitoring and forecasting, and synthesized the literature on the integration of Internet of Things (IoT), big data analytics, and machine learning (ML) in civil engineering applications. He also supervised the overall study and prepared the original manuscript draft.

**Pradip D. Jadhao:** Investigation, Formal Analysis, Data Curation, Visualization, Writing – Review & Editing. Dr. Jadhao conducted a comprehensive analysis of real-time air quality monitoring systems, predictive modelling techniques, and data integration approaches. He critically evaluated sensor technologies, calibration challenges, and forecasting models, contributed to data interpretation and visualization, and participated in reviewing and editing the manuscript to improve its technical accuracy and scientific quality.

**All authors** have read and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

**Ethics Statement:** The authors hereby confirm that this study complies with requirements of ethical approvals from the institutional ethics committee for the conduct of this research.

**Data Availability Statement:** This study is based on a review and synthesis of previously published literature and publicly available sources; therefore, no primary dataset was generated or deposited in a repository.

**Conflict of Interest Statement:** The authors declare that they have no conflicts of interest related to this research.

**Funding Statement**: This research was conducted without external funding. All work was carried out independently of any financial support from funding agencies.

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