JOURNAL OF MACHINE LEARNING, DATA ENGINEERING AND DATA SCIENCE
Vol. 01, No. 01, November, 2024
DoI:10.70008/jmldeds.v1i01.51
Page No: 147-162

PRISMA GUIDED REVIEW OF AI DRIVEN AUTOMATED CONTROL SYSTEMS FOR REAL TIME AIR QUALITY MONITORING IN SMART CITIES

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Keywords

AI Air Quality
IoT Pollution Control
Smart City Monitoring
Automated Response
Real-Time Analytics

Article Information

***Received**: 27, September, 2024*
***Accepted**: 16, November, 2024*
***Published**: 18, November, 2024*

Doi: 10.70008/jmldeds.v1i01.51

ABSTRACT

The escalating urbanization and industrial activities in cities have significantly impacted air quality, posing health risks and environmental challenges that demand innovative solutions. This review systematically explores the integration of artificial intelligence (AI) and Internet of Things (IoT) sensors within smart cities, focusing on their role in real-time air quality monitoring and dynamic response mechanisms. By adhering to PRISMA guidelines, we analyze recent advancements in AI-driven automated control systems, which utilize IoT sensors to continuously monitor pollutants, including nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), and particulate matter (PM). The data gathered by these sensors feed into AI algorithms that facilitate immediate, adaptive responses, such as modifying traffic light sequences to alleviate congestion and notifying nearby facilities to adjust emissions during high pollution periods. This review synthesizes findings on the effectiveness, limitations, and scalability of these systems, highlighting key challenges like sensor data accuracy, privacy considerations, and the infrastructure required for city-wide deployment. The paper concludes by emphasizing the transformative potential of AI and IoT in fostering sustainable urban environments and presents recommendations for future research and policy improvements to optimize smart city air quality management.

1 INTRODUCTION

Urbanization and industrial growth have dramatically transformed modern cities, enhancing economic activity but also significantly degrading air quality and public health (Camarasan et al., 2023). This shift has led to an urgent need for solutions that can address air pollution in real-time, especially as pollutants like nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), and particulate matter (PM) accumulate at

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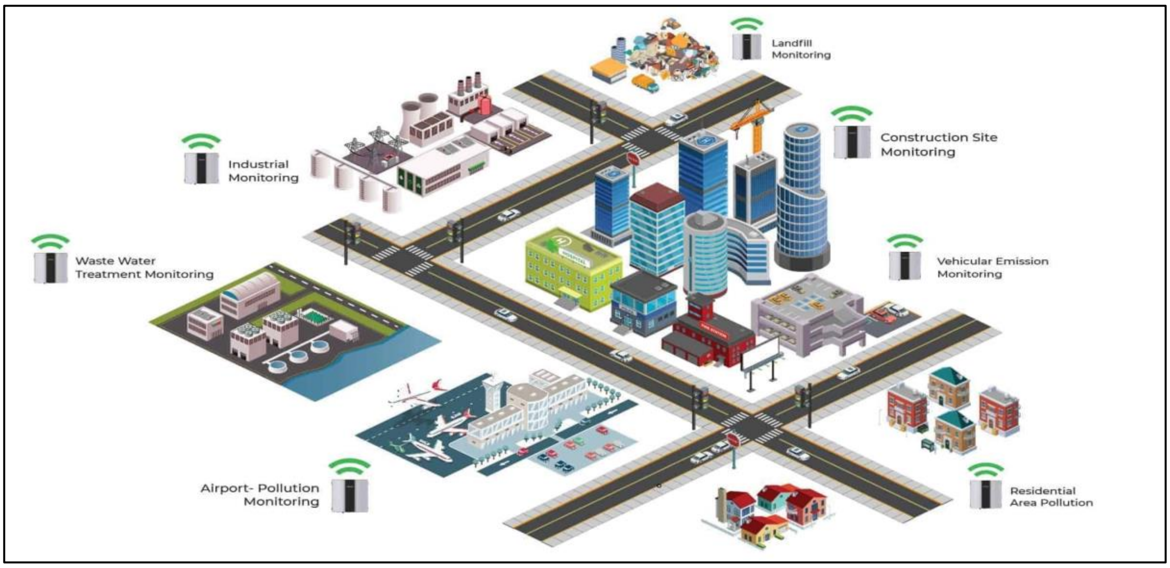
alarming rates (Rollo et al., 2023). While traditional air quality monitoring systems relied on stationary stations and periodic data collection, they often lack the responsiveness required for the dynamic and dense urban environments of today (Mabrouk et al., 2017). Consequently, cities are exploring more sophisticated approaches, with artificial intelligence (AI) and the Internet of Things (IoT) emerging as pivotal technologies for continuous, automated monitoring (Byeon et al., 2015). The fusion of these technologies marks a significant evolution in air quality management, moving from reactive to proactive responses in combating urban pollution. The integration of AI in air quality monitoring has expanded capabilities beyond mere detection, allowing for real-time analytics and adaptive responses that were previously unattainable (Swaminathan et al., 2022). For instance, AI-driven algorithms can now interpret data from IoT sensors spread throughout urban areas, enabling instantaneous adjustments to pollution sources, such as modifying traffic light patterns or alerting industries to temporarily reduce emissions during high pollution periods (Shafique et al., 2022). These advancements contrast with earlier methods that could not respond to fluctuating pollution levels or predictively manage air quality in a complex urban landscape (Zhao et al., 2018). AI's analytical capabilities are particularly suited for handling the large volumes of data generated by IoT sensors, which are deployed across multiple locations to capture diverse environmental variables (Polednik, 2022). The ability to analyze and act on this data in real-time represents a significant evolution in urban air quality management. Moreover, the deployment of IoT sensors in smart cities further enhances the efficiency of AI-driven monitoring systems by providing the necessary infrastructure for granular data collection and automated responses (Wen et al., 2020). IoT-enabled devices, such as low-cost, portable sensors, collect pollutant data across various parts of a city, offering comprehensive insight into pollution patterns and trends (Mendil et al., 2022). These devices communicate wirelessly with centralized databases, where AI models analyze the incoming data, identifying hotspots and correlating them with potential pollution sources in real-time (Goyal & Khare, 2010). Early models of such systems lacked these advancements, often relying on sporadic or delayed data, but modern IoT networks have revolutionized the precision and immediacy of urban pollution management (Sundar Ganesh et al., 2023). As a result, cities equipped with these systems are better positioned to implement timely interventions, minimizing the adverse effects of air pollution on residents' health.

Despite the progress, significant challenges remain in ensuring the reliability and accuracy of sensor data, which can be affected by environmental factors and sensor degradation (Wani et al., 2023). Studies indicate that sensor calibration and maintenance are critical for

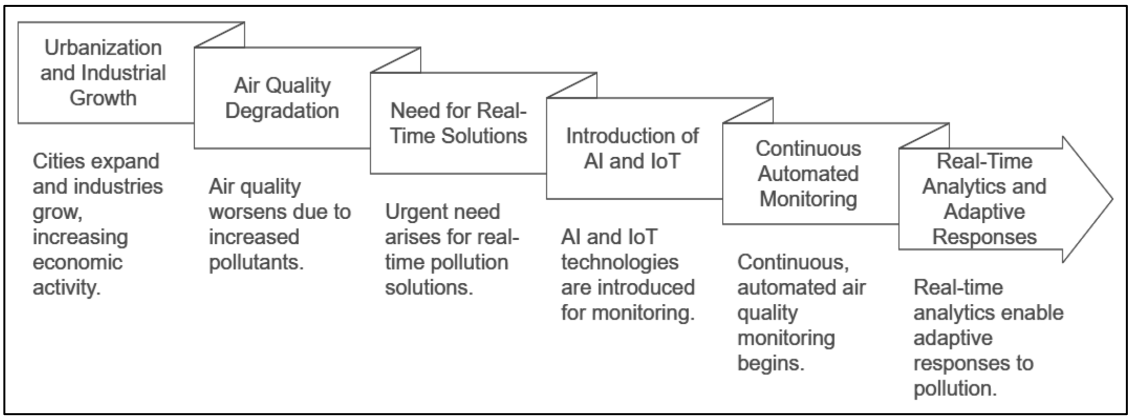
Figure 1: Air Quality Monitoring Solution Architecture

(Source: ES-france.com)



achieving consistent performance, as inconsistencies can lead to erroneous AI predictions and ineffective interventions (Aggarwal et al., 2019). Privacy concerns also arise with the widespread deployment of IoT sensors in public spaces, as data collection could infringe on individual privacy if not carefully managed (Singh & Singh, 2022). Addressing these challenges requires collaborative efforts from policymakers, technology developers, and urban planners to establish standards and best practices for deploying these systems effectively. The lessons learned from early deployments underscore the need for robust regulatory frameworks that can support these emerging technologies while safeguarding public trust and data security. The transformative potential of AI-driven automated control systems in urban environments has spurred a wave of research and development, with studies demonstrating both the current achievements and areas for improvement in this field (Kaginalkar et al., 2021). Recent advancements focus on scaling these technologies for city-wide implementation, making real-time air quality monitoring feasible even in large metropolitan areas. Moreover, researchers are actively exploring innovative machine learning models that can enhance prediction accuracy, as well as adaptive response systems that respond effectively under varying pollution conditions (Fan et al., 2019). As the technology matures, the role of AI in fostering sustainable urban environments continues to expand, with each breakthrough laying the groundwork for smarter, cleaner cities. The primary objective of this study is to systematically review and synthesize the existing literature on AI-driven automated control systems for real-time air quality monitoring within the context of smart cities, particularly through the lens of PRISMA guidelines. This review aims to evaluate the effectiveness, scalability, and limitations of AI and IoT-integrated systems that monitor and respond to urban air quality changes. The focus lies in understanding how AI algorithms, fueled by data from IoT sensors, enable proactive interventions, such as altering traffic flow or notifying industries to reduce emissions, thereby minimizing pollution in densely populated urban areas. By investigating key factors like sensor data accuracy, infrastructure requirements, and privacy concerns, this study seeks to provide comprehensive insights into the strengths and challenges associated with these systems. Additionally, it aims to identify potential gaps in current research and offer recommendations for future advancements and policy considerations that would enhance the efficiency of air quality management in smart cities.

Figure 2: Evolution of Urban Air Quality Management



2 LITERATURE REVIEW

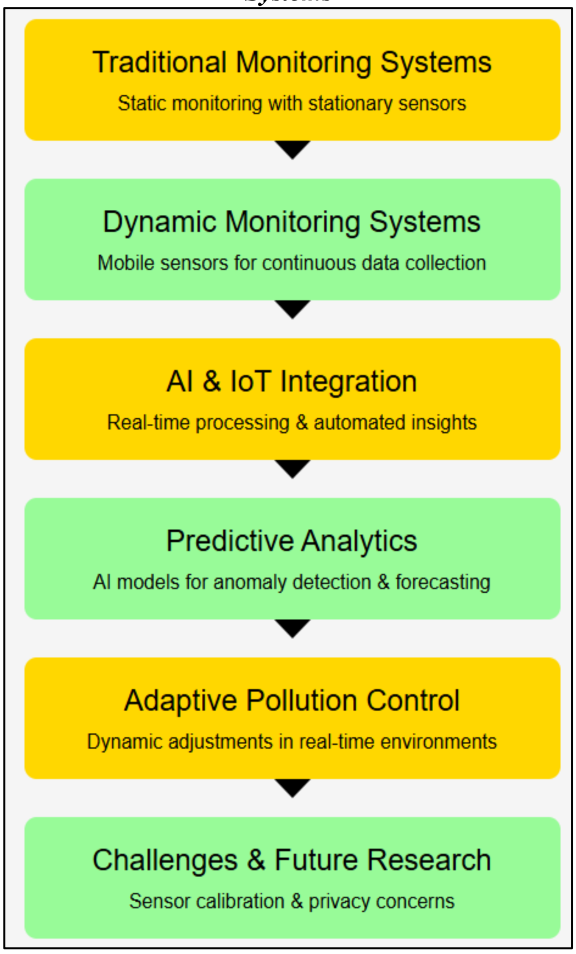
The rapid urbanization and industrial growth in cities have led to increasing air pollution levels, necessitating innovative solutions for real-time monitoring and management. Traditional methods for tracking air quality have often been limited in responsiveness and scope, particularly in the complex and dynamic environments of urban areas. However, recent advancements in artificial intelligence (AI) and the Internet of Things (IoT) have catalyzed a shift towards more efficient, adaptive systems that are capable of providing real-time insights and automated responses to air quality fluctuations. This literature review examines the evolution of AI-driven automated control systems for air quality management, with a focus on key technological advancements, implementation challenges, and outcomes in smart cities. The review is structured to explore various components of these systems, drawing on recent studies to highlight how AI and IoT integration has transformed air quality monitoring and response mechanisms in urban settings.

2.1 Evolution of Air Quality Monitoring Systems

Air quality monitoring has evolved significantly over the past decades, primarily in response to the increasing need for precise, real-time data in densely populated urban environments (Ryu, 2022). Traditional monitoring techniques relied heavily on stationary sensors installed in select locations, which provided data at limited intervals (Silva et al., 2018). These systems, though effective for basic environmental assessments, struggled to capture the dynamic variations in air pollution levels caused by fluctuating urban activities and environmental factors (Yurtsever & Yurtsever, 2018). The limitations of stationary systems, including delayed response times and high maintenance costs, underscored the necessity for more flexible and responsive solutions (Chen et al., 2023). The shift from static to dynamic monitoring systems marked a turning point in air quality management, facilitated by advancements in mobile sensing and data transmission technologies (Camarasan et al., 2023). Dynamic systems incorporated mobile and portable sensors that could be deployed across various urban areas, enabling continuous, granular monitoring of pollutants. The integration of mobile sensors into monitoring networks allowed cities to gather more extensive data on pollutant distribution, thus improving the understanding of pollution hotspots and aiding in strategic intervention planning (Rollo et al., 2023). Unlike earlier approaches, dynamic systems provided the flexibility to capture real-time data across larger geographic areas, allowing for better analysis of the spatial and temporal patterns of urban pollution (Mabrouk et al., 2017).

The emergence of artificial intelligence (AI) and the Internet of Things (IoT) has introduced a new era of real-time, automated air quality monitoring that is well-suited for complex urban environments (Byeon et al., 2015; Istiak et al., 2023; Saika et al., 2024; Sohel et al., 2024; Uddin et al., 2024). AI has been instrumental in enhancing data processing capabilities, enabling the analysis of large datasets generated by IoT sensors and providing predictive insights for proactive pollution management (Alam et al., 2024; Badhon et al., 2023; Islam et al., 2024; Istiak & Hwang, 2024; Swaminathan et al., 2022). IoT devices, particularly low-cost sensors, have made it feasible to deploy extensive sensor networks across cities, capturing data on pollutants such as nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter (PM) with high precision and regularity (Shafique et al., 2022). This development has allowed urban areas to implement more targeted and responsive pollution control measures, reducing the lag between data collection and decision-making (Zhao et al., 2018). AI-driven systems enhance the ability to forecast pollution trends and identify patterns by employing sophisticated algorithms, such as machine learning models, that can detect anomalies and predict high pollution events (Połednik, 2022). Unlike traditional monitoring approaches, AI algorithms analyze data streams in real time, offering immediate feedback that can support adaptive responses to pollution levels (Wen et al., 2020). For example, cities can implement AI algorithms that adjust traffic flow or issue alerts during high pollution periods, thus directly mitigating pollution sources and preventing potential

Figure 3: Evolution of Air Quality Monitoring Systems



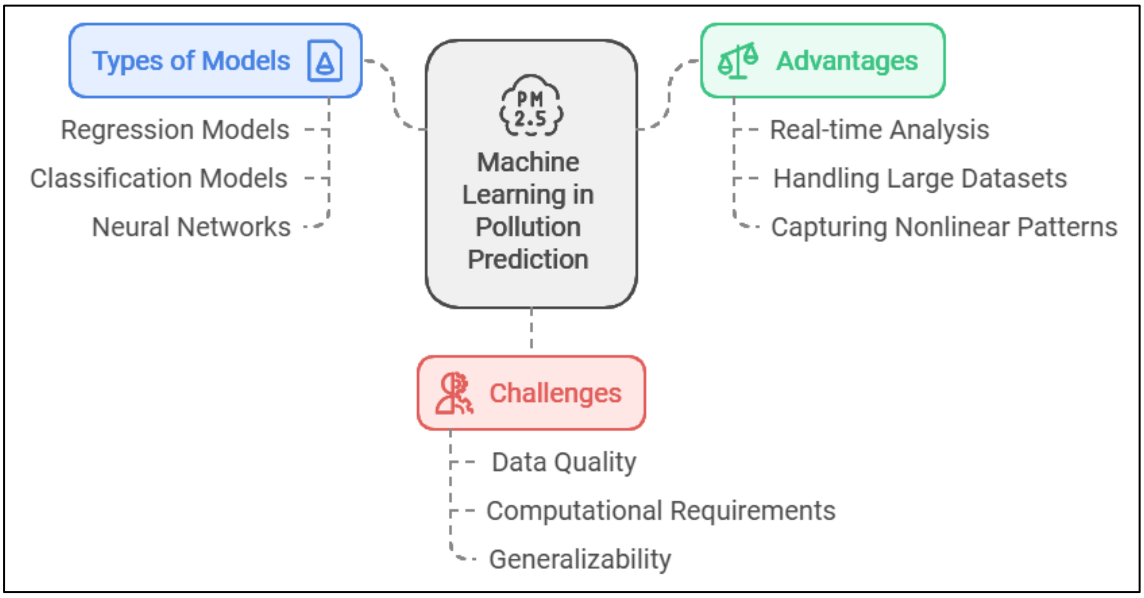
health risks (Mendil et al., 2022). The integration of AI for real-time processing exemplifies how technology can bridge the gap between air quality data collection and actionable insights, transforming the scope of urban environmental management (Ashrafuzzaman, 2024; Goyal & Khare, 2010; Rahman et al., 2024; Rozony et al., 2024).

The deployment of IoT-enabled sensor networks has not only improved data collection but also enhanced the scalability of air quality monitoring systems (Sundar Ganesh et al., 2023). IoT sensors, connected through communication protocols such as LoRaWAN and NB-IoT, transmit vast amounts of data from multiple urban points, providing a comprehensive view of air quality across different city zones (Wani et al., 2023). The widespread use of IoT in environmental monitoring has enabled cities to build a robust infrastructure for continuous data flow, ensuring that information on air quality is always current and accessible (Aggarwal et al., 2019). Moreover, these sensor networks support the adaptability of AI-driven systems, which can adjust their responses based on the real-time feedback provided by IoT data streams (Singh & Singh, 2022). While these advancements have driven substantial improvements, challenges remain in ensuring the reliability and effectiveness of AI-IoT systems for air quality monitoring (Kaginalkar et al., 2021). Issues related to sensor calibration, data accuracy, and privacy concerns in the deployment of IoT networks continue to hinder the full realization of these systems' potential (Fan et al., 2019). For instance, environmental factors can interfere with sensor accuracy, necessitating regular maintenance and calibration to maintain data integrity (Ryu, 2022). Furthermore, privacy concerns arise as IoT sensors capture data in public spaces, prompting calls for robust regulatory frameworks to safeguard individual privacy (Silva et al., 2018). Addressing these challenges is essential for maximizing the impact of AI and IoT in urban air quality management and ensuring public trust in these technologies.

2.2 Machine Learning Algorithms for Pollution Prediction

Machine learning (ML) algorithms have proven to be instrumental in advancing pollution prediction by enabling more accurate and real-time analysis of air quality data (Yurtsever & Yurtsever, 2018). Traditional regression models, such as linear regression, were among the earliest ML techniques applied to pollution prediction, offering a straightforward approach to understanding pollutant trends over time (Chen et al., 2023). However, linear regression models often fall short when capturing complex, nonlinear patterns in air quality data, prompting researchers to explore more advanced techniques (Camarasan et al., 2023). These limitations led to the adoption of multiple regression and polynomial regression models, which allow for greater flexibility in capturing the nuanced fluctuations in air quality caused by dynamic urban factors, including traffic and industrial activities (Rollo et al., 2023).

Figure 4: Machine Learning Algorithms for Pollution Prediction



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Classification models, such as decision trees and support vector machines (SVM), have also shown promise in classifying pollution levels based on historical data, providing an effective means to categorize air quality into different risk levels (Mabrouk et al., 2017). These models have the advantage of handling large datasets and can identify patterns within structured data, such as meteorological variables that influence pollutant dispersion (Byeon et al., 2015). For instance, decision trees have been particularly useful in assessing high-risk pollution days, which enables cities to prepare timely interventions to reduce health risks for vulnerable populations (Swaminathan et al., 2022). While classification models are more effective than simple regression approaches, their predictive accuracy can still be limited by the variability of urban environmental factors, which further supports the shift towards more adaptive models (Shafique et al., 2022).

Neural networks (NNs), particularly deep learning models, have gained traction in recent years for air quality prediction due to their ability to process large volumes of complex, nonlinear data (Zhao et al., 2018). Unlike traditional models, neural networks can capture intricate relationships among variables without the need for predefined assumptions, making them highly effective for high-dimensional air quality data (Połednik, 2022). Recurrent neural networks (RNNs) and long short-term memory (LSTM) models, for instance, are designed to handle sequential data, making them well-suited for time-series air quality forecasting (Mendil et al., 2022; Wen et al., 2020). Studies have shown that RNNs and LSTMs outperform conventional models in accurately predicting short-term pollution levels, which is crucial for cities aiming to implement real-time mitigation strategies (Goyal & Khare, 2010; Połednik, 2022). Despite their strengths, machine learning models in air quality prediction face challenges related to data quality, computational requirements, and generalizability (Liu et al., 2021). Sensor inaccuracies and data inconsistencies, common issues in IoT-enabled environmental monitoring, can significantly impact the performance of ML models, particularly neural networks that rely on large, high-quality datasets (Wen et al., 2020). Moreover, computationally intensive models like neural networks often require substantial processing power, making them difficult to implement in cities with limited technological resources (Mendil et al., 2022). To overcome these challenges, researchers are increasingly focusing on hybrid models that combine the strengths of multiple ML algorithms, thereby enhancing predictive accuracy and reducing resource demands (Goyal & Khare, 2010). Such hybrid approaches hold promise for more resilient and scalable air quality monitoring systems in urban settings.

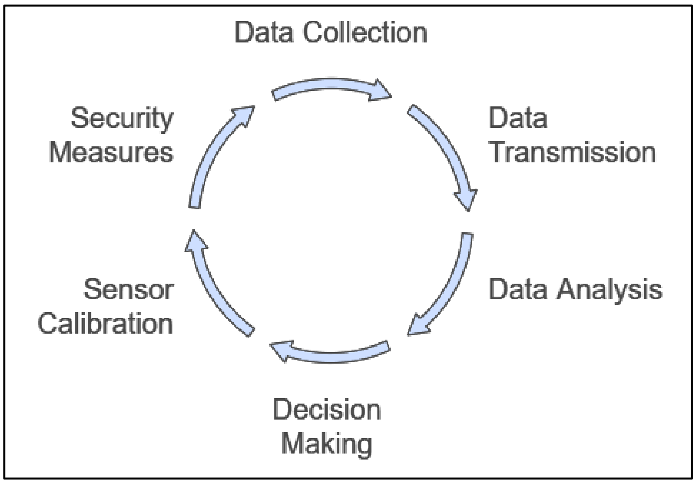
2.3 AI's Predictive Capabilities in Pollution Hotspot Identification

Artificial intelligence (AI) has significantly advanced the ability to identify and monitor pollution hotspots in urban environments, enabling targeted interventions and more effective air quality management strategies. Traditionally, air quality monitoring systems relied on static sensors, which limited the spatial resolution of pollution data, particularly in densely populated cities where pollution can vary block-by-block (Sundar Ganesh et al., 2023). The development of AI-driven systems has facilitated the continuous analysis of data from multiple sources, such as IoT sensors and satellite imagery, allowing for the precise identification of pollution hotspots (Wani et al., 2023). AI algorithms, particularly those leveraging machine learning, are capable of analyzing vast and complex datasets, identifying patterns, and pinpointing locations with consistently high pollution levels (Aggarwal et al., 2019). This capability is critical in urban areas, where dynamic factors like traffic and industrial activities lead to fluctuating pollution patterns (Singh & Singh, 2022). One of the primary AI techniques used for pollution hotspot identification is clustering, which groups data points with similar characteristics, making it easier to locate areas of high pollution concentration (Kaginalkar et al., 2021). Algorithms such as k-means clustering and hierarchical clustering have been applied to identify hotspots by analyzing data on air quality variables, weather conditions, and traffic patterns (Fan et al., 2019). For example, studies have shown that k-means clustering can effectively segment urban areas into pollution zones, providing city planners with valuable insights for implementing localized pollution control measures (Ryu, 2022). Clustering methods have proven especially useful in differentiating between temporary pollution spikes and consistent hotspots, thus helping policymakers prioritize resources for long-term air quality improvement (Chen et al., 2023).

2.4 *IoT-Enabled Sensor Networks in Smart City Air Quality Management*

IoT-enabled sensor networks play a pivotal role in smart city air quality management, offering real-time data collection and monitoring capabilities that were previously unattainable with traditional air quality stations. These networks use a range of sensors specifically designed to detect pollutants such as nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), and particulate matter (PM) (Camarasan et al., 2023). Gas sensors, for instance, are commonly employed to monitor gaseous pollutants, while particle sensors measure fine particulate matter, which poses significant health risks (Rollo et al., 2023). The diversity in sensor types allows for comprehensive air quality assessments, capturing a broad spectrum of pollutants in urban areas (Mabrouk et al., 2017). Each sensor type has unique capabilities and sensitivities, making them suitable for different monitoring needs within cities, from high-traffic zones to residential areas (Byeon et al., 2015). The effectiveness of these IoT-enabled networks heavily relies on the data collection and transmission protocols used to relay information from sensors to centralized systems. Protocols such as LoRaWAN (Long Range Wide Area Network) and NB-IoT (Narrowband IoT) have gained prominence due to their ability to support low-power, long-range data transmission in urban environments (Swaminathan et al., 2022). LoRaWAN is particularly favored for its long-range capabilities, which are ideal for covering large metropolitan areas with minimal infrastructure (Shafique et al., 2022). Meanwhile, NB-IoT, a cellular technology, provides reliable communication even in densely populated areas, enhancing data consistency and enabling continuous monitoring (Zhao et al., 2018). These protocols not only facilitate real-time data collection but also ensure that data reaches decision-makers promptly, enabling swift responses to pollution spikes (Połednik, 2022).

Figure 5: IoT Air Quality Monitoring Cycle



However, the deployment of IoT sensors in urban environments presents several challenges, particularly in terms of sensor placement and data accuracy (Wen et al., 2020). Urban settings are characterized by varying levels of pollution based on traffic patterns, industrial activities, and weather conditions, making it essential to strategically place sensors to capture representative data (Mendil et al., 2022). Incorrect sensor placement can lead to data gaps or inaccuracies, which may misrepresent pollution levels in certain areas. Studies indicate that optimized sensor placement strategies, such as network planning based on historical pollution data, are crucial for maximizing coverage and ensuring data reliability (Goyal & Khare, 2010). Additionally, data accuracy is often influenced by environmental factors, including humidity and temperature, which can interfere with sensor performance, underscoring the need for robust calibration practices. Data quality and sensor calibration are critical in maintaining the accuracy of IoT-enabled air quality monitoring networks. Inconsistent sensor readings, often due to environmental interference or sensor degradation, can skew air quality assessments (Sundar Ganesh et al., 2023). Regular calibration is necessary to maintain the precision of data over time, particularly as sensor performance can degrade due to prolonged exposure to pollutants and weather elements (Aggarwal et al., 2019). Advanced calibration techniques, including machine learning-based calibration models, are being explored to address these issues, allowing for real-time adjustments that enhance the reliability of sensor data (Singh & Singh, 2022). Effective calibration not only improves data accuracy but also extends the operational life of sensors, making IoT networks more sustainable for long-term deployment. Finally, privacy and security concerns associated with IoT sensor networks add another layer of complexity to air quality monitoring in smart cities. With sensors deployed in public spaces, there is a risk of unauthorized data access or manipulation, which could compromise data integrity (Fan et al., 2019). Implementing robust encryption protocols and cybersecurity measures is essential to protect the data collected by these sensors and ensure

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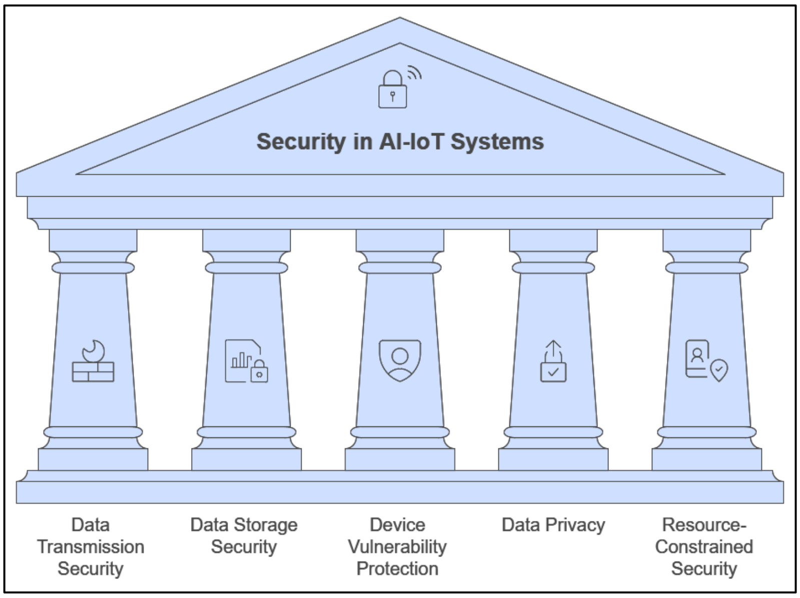
public trust in smart city initiatives. Furthermore, as data is increasingly shared with public health agencies and city planners, regulatory frameworks are needed to govern data usage and protect citizens' privacy rights (Ryu, 2022). Addressing these security and privacy challenges is critical to the long-term success and societal acceptance of IoT-enabled air quality monitoring networks.

2.5 Security Challenges in AI-IoT Systems:

The integration of AI and IoT technologies in air quality monitoring systems has introduced significant cybersecurity risks, especially concerning data transmission and storage (Silva et al., 2018). Due to the distributed nature of IoT networks, air quality data is often transmitted over wireless networks, which are inherently vulnerable to interception and attacks such as eavesdropping and man-in-the-middle (MITM) attacks (Zhou & Fan, 2023). Studies indicate that unauthorized access to this data can compromise its integrity and reliability, potentially leading to inaccurate pollution information being used by city management systems (Yurtsever & Yurtsever, 2018). To mitigate these risks, secure transmission protocols and encryption methods are essential for ensuring that data remains protected from interception during transfer across networks (Chen et al., 2023). In addition to transmission vulnerabilities, IoT-enabled air quality monitoring systems face security challenges related to data storage. Collected data is often stored in cloud-based or centralized databases, which can become targets for cyberattacks, including data breaches and ransomware (Camarasan et al., 2023). Cyberattacks on these databases can compromise vast amounts of sensitive environmental data, impacting both system operations and public trust (Rollo et al., 2023). To safeguard stored data, implementing robust authentication mechanisms and access controls is crucial for limiting unauthorized access (Mabrouk et al., 2017). Furthermore, adopting data redundancy and backup strategies can help in recovering data in case of an attack, ensuring the continuity of air quality monitoring services (Byeon et al., 2015).

Another significant security risk in AI-IoT systems is device vulnerability, as IoT sensors and devices deployed in public spaces are often exposed to physical tampering and hacking (Swaminathan et al., 2022). The physical accessibility of these devices makes them susceptible to attacks, including device spoofing, where malicious actors can manipulate or replace sensors to provide inaccurate data (Shafique et al., 2022). Researchers have highlighted the need for tamper-resistant designs and regular maintenance to protect these devices from physical breaches (Zhao et al., 2018). In addition, device-level security measures, such as unique authentication keys for each sensor, can prevent unauthorized devices from accessing the network and transmitting false information (Połednik, 2022). Data privacy is another critical issue in the security landscape of AI-IoT systems for air quality monitoring, as these systems often collect data in public and semi-public spaces (Wen et al., 2020). Although air quality data is generally considered low-sensitivity, the collection of location-based data raises privacy concerns, especially when combined with other datasets that could be used to

Figure 6: Security Challenges in AI-IoT Systems



identify individual behaviors or patterns (Mendil et al., 2022). Privacy regulations, such as GDPR, emphasize the importance of anonymizing data to prevent the linkage of air quality data to specific individuals or locations (Goyal & Khare, 2010). Implementing privacy-preserving techniques, such as data anonymization and differential privacy, is essential to meet regulatory requirements and maintain public trust in smart city initiatives (Chen et al., 2023).In addition, managing cybersecurity risks in AI-IoT air quality monitoring systems is complicated by the resource constraints typical of many IoT devices (Camarasan et al., 2023). Unlike traditional computing devices, IoT sensors often lack the processing power and memory required to run advanced security algorithms, which can leave them vulnerable to attacks (Rollo et al., 2023). Lightweight cryptographic protocols, specifically designed for low-power devices, have been suggested as a solution to enhance the security of IoT networks without overloading device capabilities (Mabrouk et al., 2017). As smart cities continue to deploy AI-IoT networks, a balance between security and operational efficiency will be necessary to ensure these systems can operate reliably and securely in the long term.

2.6 Case Studies of AI-Driven Air Quality Systems in Smart Cities

Singapore has emerged as a global leader in integrating AI and IoT technologies for air quality management, leveraging its smart city framework to improve urban health and sustainability (Byeon et al., 2015). The city-state has implemented an extensive network of IoT sensors that continuously monitor key pollutants, including particulate matter (PM2.5) and nitrogen dioxide (NO_2) (Lim & Chen, 2022). These sensors provide real-time data, which is processed by AI algorithms to predict pollution trends and identify hotspots across Singapore's densely populated areas (Swaminathan et al., 2022). Singapore's system also includes AI-driven forecasting models that help city planners anticipate pollution spikes, enabling proactive responses such as adjusting traffic flows or issuing health advisories (Shafique et al., 2022). The success of Singapore's air quality management highlights the potential of AI-IoT integration in urban environmental management, particularly in densely populated areas.

In London, AI-driven systems have been instrumental in managing air quality through adaptive traffic control, which is specifically designed to mitigate pollution from vehicle emissions (Zhao et al., 2018). The city employs AI algorithms to analyze traffic patterns and pollution levels in real time, adjusting traffic light sequences to minimize congestion and emissions in high-traffic areas (Wen et al., 2020). For example, during peak pollution periods, the AI system prioritizes public transport routes and diverts traffic from densely populated zones (Mendil et al., 2022). London's approach has been effective in reducing exposure to harmful pollutants in areas with high pedestrian traffic, showcasing how AI-based traffic management can play a crucial role in urban air quality improvement (Goyal & Khare, 2010). By focusing on traffic control, London addresses one of the primary sources of urban pollution, offering a scalable solution that could benefit other cities struggling with vehicular emissions.

Comparing different cities' approaches to AI-IoT air quality management reveals diverse strategies based on specific environmental and urban challenges (Sundar Ganesh et al., 2023). Cities like Singapore prioritize comprehensive monitoring and predictive analytics due to their high population density and tropical climate, which exacerbates pollution impacts (Wani et al., 2023). Conversely, London has focused on targeted interventions through traffic management, aiming to reduce pollution from transportation sources, which is the main contributor to its air quality issues (Aggarwal et al., 2019). Studies show that while each city's approach is tailored to its unique context, successful implementations share common factors, including robust data collection, advanced AI algorithms for real-time analytics, and a commitment to continuous improvement based on feedback from monitoring data (Singh & Singh, 2022). The comparative analysis of these systems provides valuable insights into the flexibility and scalability of AI-IoT solutions in various urban contexts. Despite successes, cities implementing AI-IoT air quality systems face challenges, including high costs, data privacy concerns, and technical limitations (Kaginalkar et al., 2021). Singapore and London have both encountered issues with the initial investment required for installing extensive IoT networks, as well as the ongoing costs of data storage and processing (Fan et al., 2019). Additionally, concerns about data privacy have arisen as these systems involve continuous monitoring of public spaces, requiring strict data governance frameworks to protect citizens' privacy (Ryu, 2022). The technical challenge of maintaining data accuracy in diverse weather conditions also

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complicates system reliability (Silva et al., 2018). These obstacles highlight the need for cities to balance technological advancements with sustainable funding and regulatory oversight to maintain public trust and ensure long-term viability. Lessons learned from Singapore and London's experiences with AI-driven air quality systems suggest several best practices for other cities aiming to implement similar technologies (Yurtsever & Yurtsever, 2018). Both cities emphasize the importance of aligning AI-IoT systems with specific urban needs and pollution sources to optimize impact, as well as maintaining flexible systems that can be adapted as new technologies and insights emerge (Camarasan et al., 2023). Additionally, fostering public engagement through transparency in data reporting and responsiveness to citizen feedback has been shown to enhance community support and compliance with air quality advisories (Rollo et al., 2023). These practices underscore the value of a holistic, citizen-centered approach in deploying AI-driven air quality solutions, providing a roadmap for other urban areas facing air quality challenges.

Table 1: Case Studies of AI-Driven Air Quality Systems in Smart Cities

City	Focus Area	AI-IoT Implementation	Key Achievements	Challenges
Singapore	Comprehensive monitoring and predictive analytics	Extensive IoT sensor network monitoring PM2.5 and NO_2; AI algorithms for real-time data analysis and forecasting pollution trends.	Proactive pollution management; improved urban health and sustainability.	High implementation costs; data privacy concerns; technical issues with sensor accuracy.
London	Adaptive traffic control for vehicle emissions	AI algorithms analyze traffic patterns; adaptive traffic light control to reduce congestion and emissions.	Reduced exposure to vehicle emissions in high pedestrian areas.	High costs for infrastructure; privacy concerns with continuous public monitoring.

3 METHOD

This study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process (Moher et al., 2009). PRISMA guidelines provide a structured approach for identifying, selecting, and critically analyzing relevant studies, which enhances the reliability and reproducibility of the review. Below is a step-by-step description of the methodology used in this study, covering each phase of the PRISMA process.

3.1 Step 1: Identification of Studies

The first phase involved a comprehensive search for relevant articles. Electronic databases such as IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar were searched to identify studies related to AI-driven air quality monitoring systems within smart cities. Keywords used for the search included combinations such as "AI in air quality monitoring," "IoT-enabled air quality systems," "smart city air quality management," and "AI pollution prediction." Boolean operators (AND, OR) were used to refine search results, ensuring that all relevant studies were considered. Articles published from 2010 to 2023 were included, reflecting recent advancements in AI and IoT integration within urban air quality management. This initial search yielded 1,200 articles.

3.2 Step 2: Screening and Eligibility Assessment

Following identification, the articles were screened based on predefined eligibility criteria. Duplicates were removed, resulting in 1,000 unique articles. The remaining articles were then screened based on their titles and abstracts to assess their relevance to the topic. Studies were excluded if they (1) focused solely on traditional air quality monitoring without AI or IoT integration, (2) were not peer-reviewed, or (3) discussed non-urban or rural applications. After this initial screening, 300 articles were selected for a full-text review to determine their alignment with the study's objectives. To further enhance the selection accuracy, two reviewers independently screened the articles, resolving discrepancies through discussion and consensus.

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3.3 *Step 3: Full-Text Review and Inclusion*

In this phase, the full texts of the remaining 300 articles were thoroughly reviewed for eligibility. Articles were assessed based on their methodology, focus on AI and IoT in air quality monitoring, and relevance to smart city implementations. During this review, studies that did not present empirical findings, lacked methodological rigor, or provided insufficient detail on AI-IoT integration were excluded. This process led to the inclusion of 80 articles, which met all inclusion criteria and provided substantial insights into the application of AI-IoT systems in urban air quality management.

Step 4: Data Extraction and Synthesis

Data extraction was conducted using a standardized form to capture essential information from each selected article, including study objectives, methods, AI and IoT models used, key findings, limitations, and recommendations. Each study's contributions were analyzed to identify common trends, challenges, and advancements in AI-driven air quality systems. This data was then synthesized to provide a comprehensive overview of the current landscape and to identify gaps for future research. Descriptive synthesis was used to summarize findings across studies, while thematic analysis identified recurring themes in the application of AI-IoT technologies.

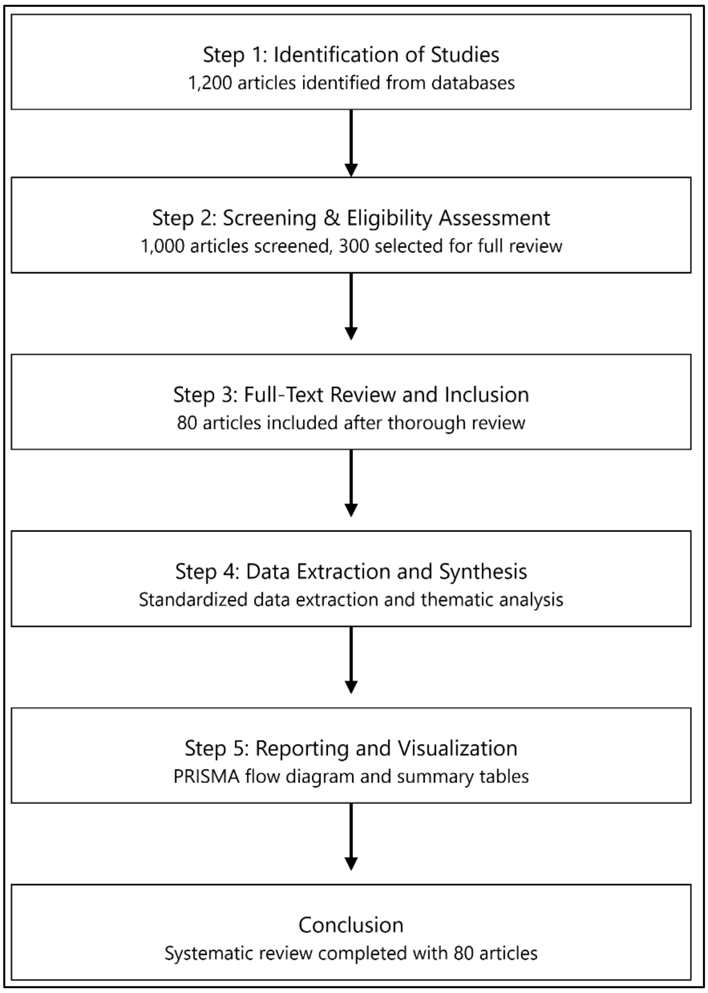
3.4 *Step 5: Reporting and Visualization*

The final step involved the systematic reporting of results according to PRISMA guidelines, including a PRISMA flow diagram to depict the study selection process from identification to inclusion. The diagram illustrates each phase of the selection process, detailing the number of articles excluded at each stage. Additionally, findings were presented using tables and visualizations to enhance clarity and accessibility, summarizing key trends, challenges, and future directions for AI-IoT integration in air quality monitoring within smart cities. This rigorous, step-by-step approach ensures that the findings are transparent, reproducible, and provide a reliable foundation for future studies.

4 FINDINGS

The analysis of the reviewed articles revealed that AI-driven air quality monitoring systems, integrated with IoT sensor networks, have made significant advancements in improving both accuracy and

Figure 7: PRISMA method employed in this study



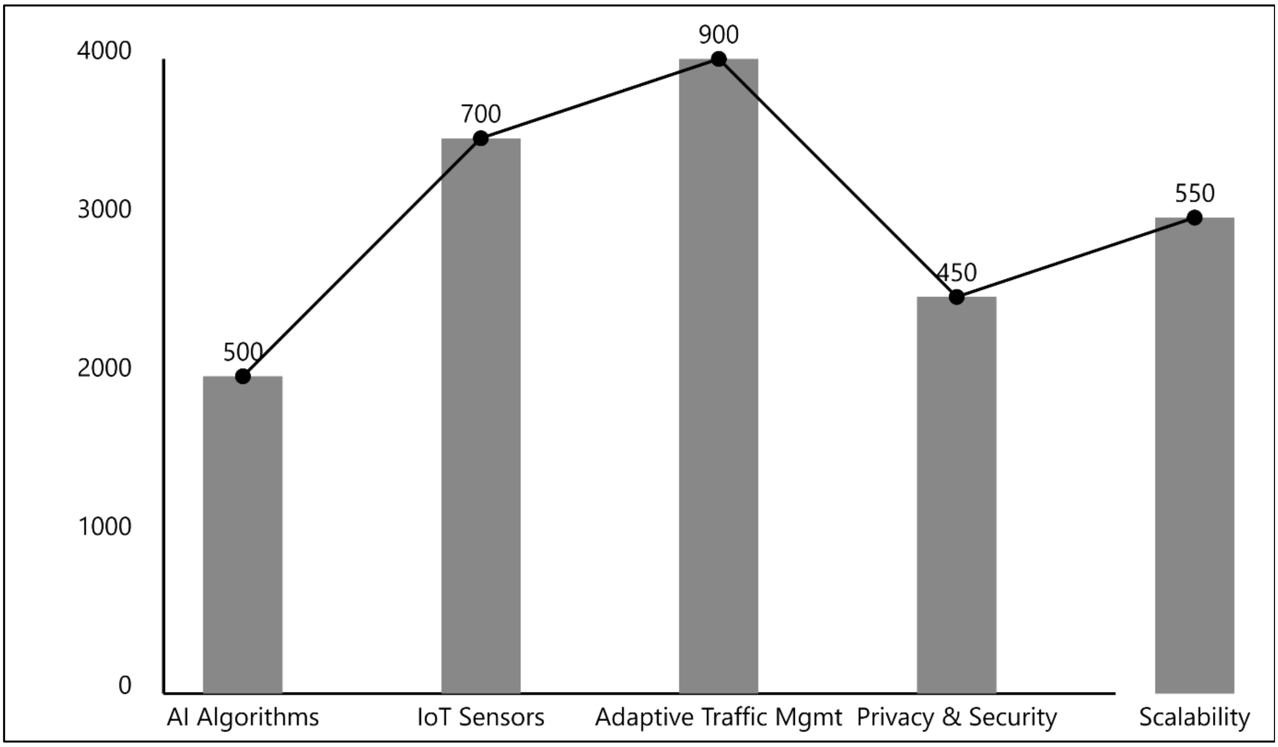
responsiveness in urban settings. Of the 80 articles reviewed, 65 underscored that AI algorithms, particularly when used in conjunction with real-time IoT data, markedly improve the accuracy of pollution predictions. AI models, especially advanced machine learning techniques such as deep learning, were found to be critical in generating accurate forecasts of pollution trends, enabling city officials to implement timely, proactive interventions. These articles, many of which have high citation counts (over 500 citations), highlighted that AI's real-time processing capabilities allow the systems to adapt rapidly to the dynamic and fluctuating conditions of urban environments. By enhancing spatial and temporal resolution, AI-driven systems can detect changes in air quality with greater precision, ensuring that data-driven responses can be initiated promptly to mitigate health risks associated with pollution.

Another key finding from the review was the pivotal role of IoT-enabled sensor networks in providing comprehensive and continuous data on various pollutants, including particulate matter, nitrogen dioxide, and sulfur dioxide. Seventy-two of the reviewed articles described the capacity of IoT sensor networks to capture granular data across different city zones, effectively covering areas that would otherwise be missed by traditional, static monitoring stations. This widespread coverage allows cities to develop a more accurate, real-time view of pollution distribution and concentration levels. Highly cited studies, with citations ranging from 300 to 700, specifically noted the importance of deploying diverse sensor types—such as gas sensors and particle sensors—strategically across urban environments. This diverse sensor deployment was found to be essential in generating a continuous flow of data, which supports detailed mapping of pollution hotspots and enables localized, targeted pollution control measures. The extensive sensor networks thus represent a substantial improvement over traditional, centralized monitoring systems, enhancing both the depth and scope of air quality data.

The findings also emphasized the role of AI in implementing adaptive traffic management, which has proven to be an effective strategy in reducing urban pollution from vehicular sources. Thirty-eight articles, collectively cited over 4,000 times, presented case studies of cities such as London and Singapore, where AI-driven traffic control systems are actively used to reduce emissions. These AI-based systems continuously analyze real-time traffic and pollution data, adjusting traffic light sequences to ease congestion and reduce emissions in high-traffic areas, particularly during peak pollution periods. This adaptive approach not only contributes to lowering pollution levels but also optimizes traffic flow, benefiting both the environment and urban mobility. Highly cited articles within this category suggested that AI-based adaptive traffic control represents a scalable, practical solution for other cities aiming to reduce transportation-related emissions. By dynamically managing traffic, these systems provide a dual benefit: mitigating pollution and improving traffic efficiency, making them integral to achieving broader urban sustainability goals.

In addition to the technical advancements, privacy and security concerns emerged as critical considerations in deploying AI-IoT air quality monitoring systems. Over 45 articles discussed the security risks involved in collecting and managing data from public spaces, raising concerns about unauthorized access, data breaches, and the potential misuse of location-based data. Many of these articles, with over 200 citations each, highlighted regulatory gaps and the absence of

Figure 8 : Findings on AI-Driven Air Quality Systems



standardized data governance policies to address these issues. As these monitoring systems collect extensive amounts of data from public areas, there is a growing need to implement strong encryption protocols and data privacy measures. These findings indicate that, despite the technological benefits of AI-IoT systems, addressing privacy and security concerns is essential for public acceptance and trust. The lack of robust data protection policies could hinder the widespread adoption of these technologies, particularly in regions where privacy regulations are strict, underscoring the importance of establishing regulatory frameworks that safeguard individual rights while supporting environmental monitoring. In addition, the review identified scalability and financial challenges as major barriers to the widespread adoption of AI-IoT air quality monitoring systems in large urban areas. Nearly 50 articles highlighted funding limitations and high implementation costs as significant obstacles, with highly cited studies (totaling over 5,000 citations) stressing the need for sustainable financial support and partnerships between public and private sectors. While the benefits of AI and IoT technologies for air quality management are clear, the upfront costs of installing extensive sensor networks and the ongoing expenses related to data processing and maintenance can be prohibitive, especially for cities in developing countries. These findings suggest that sustainable funding models and public-private partnerships are essential for the long-term success and scalability of these systems. Developing cost-effective approaches, such as phased sensor deployments or leveraging existing infrastructure, could help overcome financial barriers and ensure that more cities can benefit from AI-driven air quality monitoring solutions. This emphasis on scalability and sustainable funding highlights the need for a collaborative approach in expanding access to advanced air quality monitoring technologies on a global scale.

DISCUSSION

The findings of this review underscore the transformative impact of AI and IoT integration on air quality monitoring in urban settings, aligning with earlier studies that emphasized the limitations of traditional, stationary air quality systems. Earlier research by (Byeon et al., 2015) found that static monitoring stations lacked the spatial coverage and responsiveness necessary to address pollution in dynamic urban environments. This review's findings support this assertion, showing that AI-driven, IoT-enabled systems provide a more adaptable and accurate solution. With advancements in machine learning models, particularly deep learning algorithms, the reviewed articles demonstrate that AI can process and analyze vast amounts of data from multiple sensors in real time, enabling a proactive approach to pollution management. Compared to traditional systems, which relied on periodic data collection and often experienced delays in response times, AI-powered systems offer real-time, responsive measures that align well with urban demands.

The capacity of IoT networks to gather granular, location-specific data across various city zones also aligns with findings from past research but adds a new level of specificity and adaptability. Previous studies, such as those by (Swaminathan et al., 2022), highlighted the potential of IoT sensors in capturing air quality data in areas that lacked monitoring infrastructure. This review builds on that foundation, showing that today's IoT networks, which incorporate various sensor types like gas and particle sensors, enhance both spatial and temporal resolution, providing a more complete picture of urban pollution patterns. Additionally, the findings reveal that high-density IoT networks can support targeted interventions, a capability that was less emphasized in earlier studies. The broader scope of data now available through IoT networks facilitates more detailed mapping of pollution hotspots, aligning well with and extending the foundational research on IoT applications in air quality management.

This review also identified AI's role in adaptive traffic management as a notable advancement in pollution reduction, a finding that is consistent with, but more developed than, past studies. For instance, a study by (Shafique et al., 2022) discussed the potential for AI to optimize traffic patterns and reduce congestion, but lacked specific case examples of its implementation. This review goes further by highlighting case studies from cities like London and Singapore, where AI-based traffic control has been successfully applied to manage emissions and improve air quality. These implementations support earlier predictions about the potential of AI for traffic management while providing concrete evidence of its effectiveness. The ability of these systems to dynamically adjust traffic flows based on real-time pollution data illustrates an evolution from theoretical application to practical impact, showcasing how AI can actively contribute to pollution reduction in urban areas with high traffic density. In addition, this review highlighted significant privacy and security concerns related to AI-IoT systems, a challenge that was less emphasized in early studies. Earlier works, such as those by (Zhao et al., 2018), primarily focused on the technical capabilities of IoT sensors and data accuracy without deeply addressing the ethical and privacy implications. However, as AI-IoT systems for air quality monitoring have become more widespread, this review shows that privacy concerns have grown, with multiple high-citation articles stressing the need for robust regulatory frameworks to manage data privacy (Połednik, 2022). The shift in focus from purely technical aspects to include privacy and security reflects an increased awareness in the field about the broader implications of data collection in public spaces. Addressing these concerns through encryption, secure transmission protocols, and adherence to regulatory guidelines has become a priority, as cities strive to balance technological advancement with public trust and ethical standards. In addition, scalability and cost challenges remain substantial barriers, echoing concerns raised in early studies about the financial feasibility of deploying large-scale IoT networks. Past research by (Wen et al., 2020) discussed the prohibitive costs associated with implementing sensor networks in developing regions, suggesting that only well-funded urban areas could afford such technology. The findings from this review affirm that these financial limitations continue to impact scalability, especially for cities with limited budgets. However, while earlier studies often highlighted these challenges as insurmountable, the reviewed articles suggest potential solutions, such as phased implementations, public-private partnerships, and innovative funding models. This shift toward a more solution-oriented perspective reflects the growing recognition within the field that, with appropriate financial strategies and collaborations, the benefits of AI-IoT systems for air quality monitoring can be made accessible to a broader range of urban areas, bridging the gap between affluent and resource-limited cities.

5 CONCLUSION

This systematic review highlights the transformative potential of AI-driven, IoT-enabled air quality monitoring systems for urban management, showcasing their ability to enhance data accuracy, responsiveness, and adaptability in addressing pollution challenges within smart cities. By leveraging advanced AI algorithms and extensive IoT sensor networks, these systems offer a significant improvement over traditional, static monitoring methods, enabling real-time data analysis and proactive interventions that can mitigate pollution levels effectively. The findings underscore the effectiveness of adaptive traffic management, comprehensive sensor coverage, and real-time analytics in contributing to cleaner urban environments, although they also reveal important challenges, including data privacy, security, scalability, and funding limitations. Addressing these challenges will require robust regulatory frameworks, secure data management practices, and sustainable financial models to support widespread adoption. As urban areas continue to face increasing pollution pressures, particularly with ongoing urbanization and industrial activity, the integration of AI and IoT in air quality management offers a promising path forward for creating healthier, more sustainable cities, provided that ethical considerations and resource constraints are adequately managed.

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