NON-HUMAN JOURNAL PUBLISHER
JOURNAL OF SCIENCE AND ENGINEERING RESEARCH
Vol. 01, No. 01, November, 2024
DoI:10.70008/jeser.v1i01.48
Page No: 56-73

AI-DRIVEN ADAPTIVE VENTILATION SYSTEMS FOR REAL-TIME POLLUTION CONTROL IN INDUSTRIAL AND URBAN SETTINGS: A SYSTEMATIC REVIEW

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Keywords

AI ventilation
Pollution control
Real-Time Monitoring
Smart Systems
Air Management

Article Information

Received: *12, October, 2024*

Accepted: *12, November, 2024*

Published: *17, November, 2024*

Doi: 10.70008/jeser.v1i01.48

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.

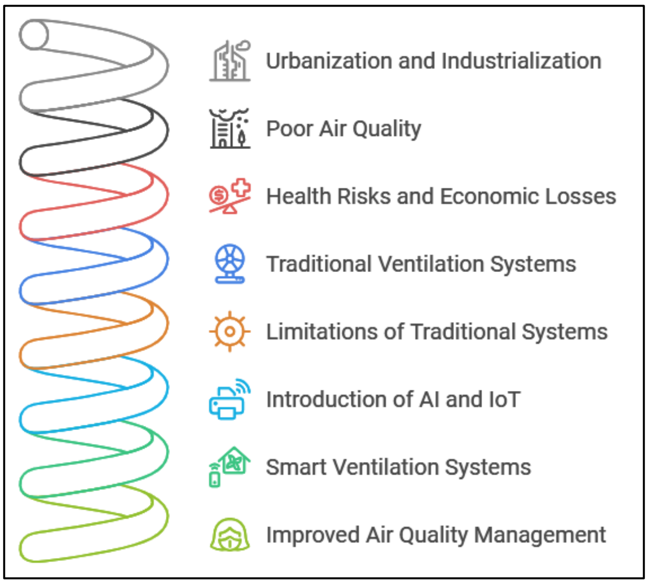
1 Introduction

Air quality management has increasingly become a critical global priority as urbanization and industrial activities intensify (Gupta et al., 2023). Poor air quality is linked to significant health risks, environmental degradation, and economic losses, making pollution control essential for sustainable development (Loy-Benitez et al., 2022). Traditional ventilation systems in buildings and industrial settings have primarily relied on passive or manual controls, which fail to address fluctuating pollution levels efficiently in real time (García et al., 2022). These limitations have paved the way for advanced solutions integrating artificial intelligence (AI), machine learning, and the Internet of Things (IoT) to enhance monitoring and response capabilities (Kim et al., 2012). By incorporating smart technologies, ventilation systems can autonomously detect and respond to changes in air quality, thus improving the efficiency and responsiveness of pollution control efforts (Rescio et al., 2023).

The evolution of AI-powered smart ventilation systems can be traced back to initial research in automated environmental monitoring, where machine learning models were applied to predict and control pollutant concentrations (Loy-Benitez et al., 2022). Early implementations were limited by processing speeds and the availability of reliable air quality data, which restricted their practical application in high-demand environments (Gupta et al., 2023). As computational power and IoT sensor technology advanced, the potential for AI-driven systems to perform real-time monitoring and adjustments improved significantly (Nam et al., 2020). Recent studies demonstrate that these systems can now dynamically adjust filtration rates and ventilation based on real-time data, a major step forward in pollution management (García et al., 2022; Kaginalkar et al., 2021).

Industrial and urban settings present distinct challenges and requirements for ventilation and air quality control. In industrial facilities, the presence of hazardous emissions, including volatile organic compounds and particulate matter, necessitates robust systems capable of continuous monitoring and rapid response (Gokul et al., 2023; Moreno et al., 2014). AI-driven systems offer solutions by integrating machine learning algorithms with pollutant-specific sensors, enabling a tailored response to various types of pollutants based on their real-time concentrations (Bertrand et al., 2023). In urban areas, AI-powered ventilation systems also play a critical role in minimizing exposure to outdoor pollutants that infiltrate indoor spaces, especially in densely populated buildings and public facilities (Amado & Dela Cruz, 2018). Smart ventilation systems not only improve air quality but also reduce energy costs, as they enable precise control over ventilation rates according to air quality needs (Jin et al., 2023). The integration of AI and IoT in ventilation systems has introduced new dimensions to air quality management, transforming ventilation from a passive to an active, data-driven process. For example, machine learning algorithms such as neural networks and support vector machines have shown significant promise in predicting pollutant levels and automating responses (Tanasa et al., 2023). Additionally, IoT sensors provide continuous feedback on air quality, feeding data into AI models to ensure adaptive responses to pollution spikes (Camarasan et al., 2023). These developments represent a major shift from conventional systems, where ventilation rates were often based on static assumptions about occupancy and outdoor air quality (Fang et al., 2023). By incorporating data from IoT sensors, AI-powered ventilation systems can now adjust their settings dynamically, ensuring optimal air quality without human intervention.

Figure 1: Evolution of Air Quality Management



The primary objective of this review is to critically evaluate the role and effectiveness of AI-driven technologies in enhancing ventilation systems for real-time pollution control in both industrial and urban environments. Specifically, this study aims to synthesize existing research on how AI algorithms, such as machine learning and deep learning models, are applied within smart ventilation systems to autonomously detect and manage air quality fluctuations. Additionally, this review seeks to examine the integration of Internet of Things (IoT) sensors, pollutant scrubbers, and other emerging technologies that contribute to real-time responsiveness and precision in air quality management. By focusing on these areas, the study endeavors to identify key advancements, challenges, and potential solutions, particularly regarding data quality, real-time processing, and cost efficiency. Ultimately, the objective is to offer a comprehensive understanding of the current state of AI-powered ventilation systems and to provide insights that may guide future research and development in air quality management technologies.

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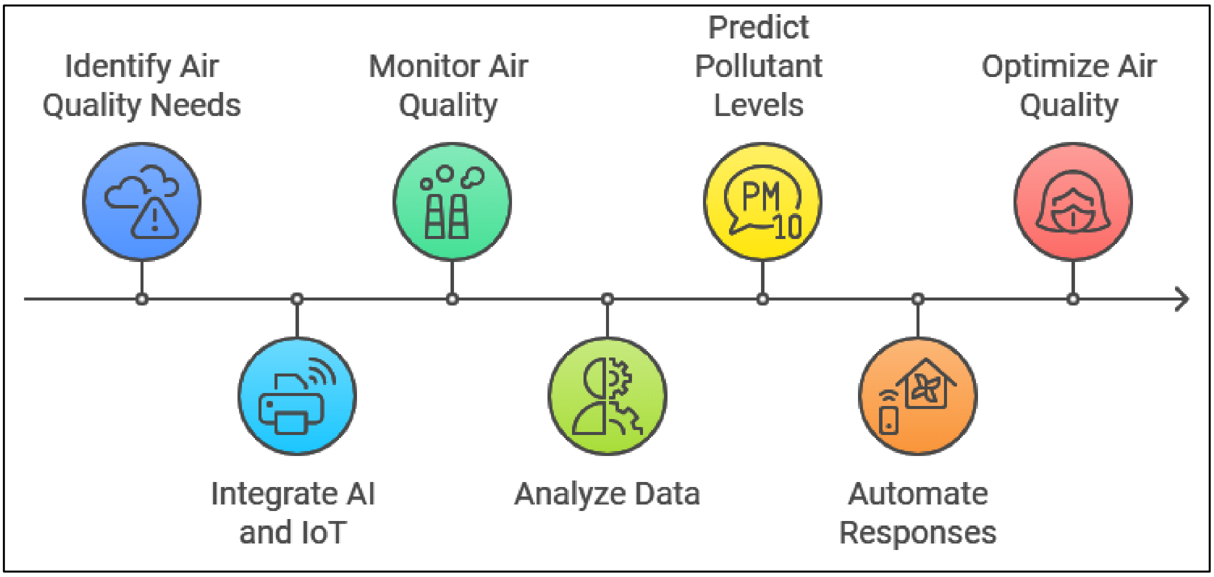
Figure 2: AI-Driven Ventilation System Process



2 Literature Review

The implementation of AI-powered smart ventilation systems for real-time pollution control has gained significant attention in recent years as environmental concerns grow and technological advancements accelerate. This section provides a systematic review of existing literature on AI-driven ventilation systems, focusing on technological components, real-time monitoring capabilities, operational efficiency, and associated challenges. By examining key studies across industrial and urban contexts, this literature review synthesizes findings on how machine learning, IoT sensors, and automated control systems are applied to manage air quality. Furthermore, it addresses the ethical considerations and data privacy concerns surrounding the use of AI in public and industrial spaces. Through a comprehensive evaluation, this review aims to highlight current progress, identify gaps in research, and suggest potential directions for future work in AI-driven pollution management technologies.

2.1 Overview of Air Quality Management and Ventilation Technologies

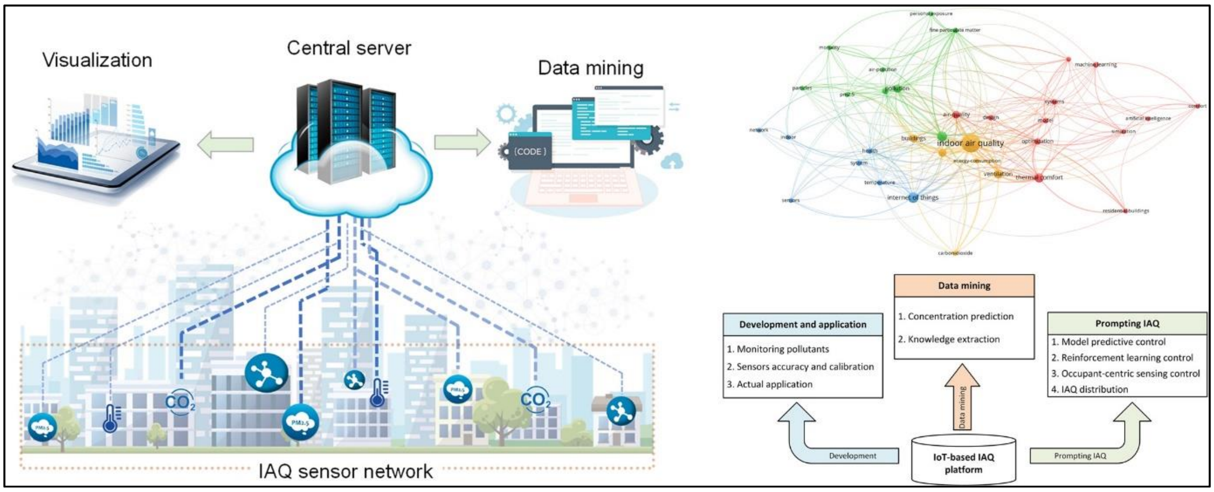
The development of ventilation systems has evolved significantly over time, initially characterized by simple passive methods and later advancing into mechanical systems designed to enhance indoor air quality (IAQ) in industrial and residential environments (Liu et al., 2023). Early ventilation systems relied on natural airflow through structural openings, a process constrained by environmental factors and seasonality (Alekhya et al., 2023). As industrialization expanded, mechanical ventilation became necessary to accommodate larger buildings and workplaces, with systems powered by fans and ducts to maintain airflow and temperature regulation, especially in factories and urban settings (Rollo et al., 2023). While these systems improved air circulation, their efficiency was limited by static settings and a lack of real-time adaptability to changing air quality needs (Cican et al., 2023). The groundwork laid by these early systems highlighted the need for more responsive technologies that could dynamically adjust to varying pollution levels, setting the stage for AI-powered systems (Manshur et al., 2023). Traditional ventilation systems, despite improvements in mechanical design, have demonstrated limitations in effectively managing pollution in real-time, especially in high-density or industrial settings (Montgomery et al., 2014). Mechanical ventilation typically operates on fixed schedules and does not account for real-time air quality variations, leading to issues with energy efficiency and pollutant management (Buelvas et al., 2023)). Research has shown that fixed-rate ventilation can result in either over-ventilation, which wastes energy, or under-ventilation, which leaves contaminants in the air (Vajs et al., 2023). These limitations are particularly problematic in environments with variable pollution levels, such as manufacturing facilities and densely populated urban buildings (Li et al., 2016). Consequently, there has been an increased focus on intelligent ventilation solutions that leverage real-time data for more adaptive control, thus reducing energy costs and improving air quality (Heo et al., 2019).

Artificial intelligence (AI) presents a promising solution for enhancing the functionality of ventilation systems by addressing the shortcomings of traditional approaches. AI-powered systems, which utilize machine learning algorithms and IoT sensors, allow for continuous monitoring of air quality, making dynamic adjustments to airflow, filtration, and pollutant removal processes (Martinez et al., 2023). Studies indicate that machine learning models can accurately predict pollution levels and optimize ventilation in real-time, even under fluctuating conditions, thus achieving better pollutant control and energy efficiency (Zhao et al., 2018). Moreover, AI-driven systems can differentiate between various pollutants and adjust filtration systems accordingly, a level of precision not possible with traditional systems (Samad et al., 2024). These advancements signify a shift from static ventilation operations to smart, responsive systems that adapt to immediate air quality needs (Parri et al., 2023; Shamim, 2022). As the demand for air quality management grows, AI-powered ventilation systems are increasingly seen as essential for modern urban and industrial environments (Lee et al., 2017). In addition to providing real-time responsiveness, these systems address some of the critical limitations in traditional designs, such as the inability to manage energy use effectively during off-peak hours or respond swiftly to sudden pollution spikes (Kim et al., 2015). The integration of IoT sensors further enables these systems to gather and analyze vast amounts of data on indoor and outdoor pollutants, enhancing decision-making capabilities and operational efficiency (Sundar Ganesh et al., 2023). As studies continue to highlight the environmental and economic benefits of AI-driven ventilation, it is evident that these technologies are crucial for advancing air quality management and meeting modern demands (Wei et al., 2023).

2.2 AI and Machine Learning in Ventilation Systems

The application of machine learning (ML) algorithms in ventilation systems has introduced a new dimension to air quality prediction and control, enabling systems to make real-time adjustments based on forecasted pollution levels (Méndez et al., 2023). Traditional methods for air quality prediction relied heavily on fixed models with limited adaptability to fluctuating conditions in dynamic environments, such as urban or industrial settings (Hashmy et al., 2023). Studies have demonstrated that ML algorithms, including decision trees, support vector machines (SVM), and k-nearest neighbors (k-NN), can more accurately predict air quality by identifying patterns and trends in historical and real-time data (Kim et al., 2012). For instance, decision trees are widely applied due to their interpretability and efficiency in handling large datasets, while SVMs have proven effective in scenarios requiring high accuracy in binary pollution classification tasks (Rescio et al., 2023). The effectiveness of these algorithms in adapting to various pollution sources highlights their potential to improve response strategies in ventilation systems (Loy-Benitez et al., 2022). Neural networks have further

Figure 3: Air Quality Management and Ventilation Technologies



Source: Dai et al. (2023)

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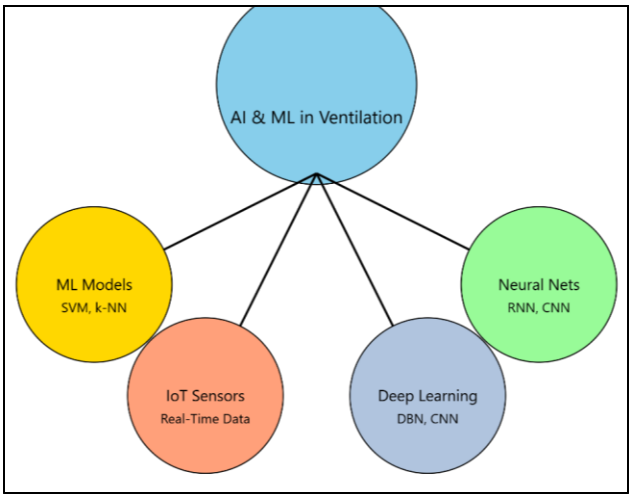
Doi: 10.70008/jeser.v1i01.48

revolutionized air quality prediction by providing more sophisticated modeling capabilities, particularly in environments with complex pollution patterns (Gupta et al., 2023). Unlike traditional ML models, neural networks can identify nonlinear relationships within large datasets, enabling systems to predict subtle variations in air quality with higher precision (Nam et al., 2020). Studies reveal that multilayer perceptrons (MLP) and recurrent neural networks (RNN) have been particularly effective in processing temporal data to predict air quality over extended periods, making them suitable for industrial applications where pollutant levels may fluctuate throughout the day (Kaginalkar et al., 2021). Additionally, RNNs have been instrumental in forecasting air quality trends in urban areas, as they can retain information over time and provide accurate predictions even with irregular data inputs (García et al., 2022). These findings underscore the advantages of neural networks in enhancing air quality prediction capabilities, particularly in complex environments with multiple pollution sources.

Deep learning (DL) models have expanded the scope of air quality prediction by enabling systems to process high-dimensional data, which is essential for accurately managing pollution in densely populated or industrial areas (Gokul et al., 2023). Convolutional neural networks (CNN), for example, have been applied to recognize spatial patterns in pollution distribution, a feature particularly valuable in urban environments where pollution varies significantly across different locations (Moreno et al., 2014). Furthermore, CNNs have been effective in image-based pollution monitoring, allowing for real-time assessments based on visual data from camera-equipped IoT sensors (Bertrand et al., 2023). Another advancement is the use of deep belief networks (DBN) in modeling complex relationships between multiple pollutants, which has proven beneficial for industrial settings that emit a mix of volatile organic compounds (VOCs) and particulate matter (PM) (Amado & Dela Cruz, 2018). These models highlight the potential of DL in enhancing ventilation systems' responsiveness to complex pollution scenarios.

Figure 4: AI & ML in Ventilation Systems



The integration of machine learning and deep learning algorithms in ventilation systems has not only improved prediction accuracy but also enhanced operational efficiency by automating responses to pollution variations (Jin et al., 2023). AI-driven systems, for example, can autonomously adjust airflow and filtration based on real-time pollution forecasts, optimizing energy use while maintaining safe air quality levels (Ashrafuzzaman, 2024; Hashmy et al., 2023; Rahman et al., 2024; Rozony et al., 2024). This dynamic adaptability, coupled with predictive capabilities, represents a shift from traditional ventilation methods to smart, AI-enabled systems that can anticipate and respond to pollution events proactively (Islam et al., 2024; Rescio et al., 2023). However, implementing these models requires high-quality data and significant computational power, as poor data inputs or limited processing capacity can undermine system performance (Martins et al., 2015). As research continues to address these challenges, AI-driven ventilation systems are likely to play an increasingly vital role in real-time air quality management in urban and industrial environments.

2.3 *Internet of Things (IoT) Sensors for Real-Time Monitoring*

The deployment of IoT sensors for air quality monitoring has been instrumental in advancing real-time pollution control systems, providing critical data on pollutants, temperature, and humidity levels (Saika et al., 2024; Singh & Singh, 2022; Sohel et al., 2024; Uddin et al., 2024). Various types of sensors, including electrochemical, optical, and metal oxide semiconductor sensors, are commonly used to detect pollutants like carbon monoxide (CO), nitrogen dioxide (NO_2), and particulate matter (PM) in both urban and industrial settings (Badhon et al., 2023; Gupta et al., 2023; Istiak & Hwang, 2024; Istiak et al., 2023). Electrochemical sensors, for example, are widely utilized for detecting gases like CO due to their high sensitivity and relatively

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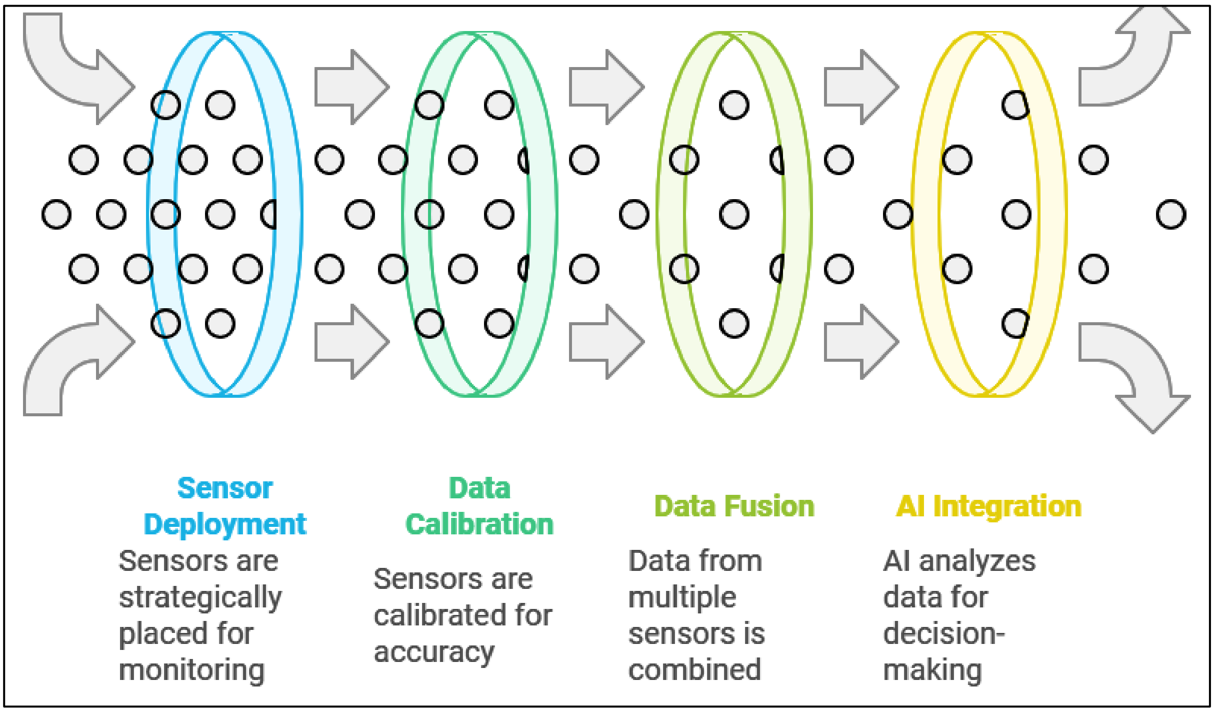
low power consumption (Alam et al., 2024; Ramadan et al., 2024). Optical sensors are often employed for particulate matter detection, offering precise measurements for PM2.5 and PM10 particles, which are key indicators of air pollution in urban environments (García et al., 2022). Each sensor type brings distinct advantages, yet also poses specific challenges regarding accuracy and operational stability, particularly under varying environmental conditions (Gokul et al., 2023). Calibrating IoT sensors to maintain data accuracy is essential, especially in systems where sensor readings directly influence AI-driven decision-making processes (Moreno et al., 2014). Studies have highlighted that sensor accuracy can fluctuate over time due to factors like sensor drift and environmental influences, such as temperature and humidity changes (Bertrand et al., 2023). For instance, metal oxide semiconductor sensors, while sensitive to gaseous pollutants, can exhibit significant drift, requiring regular calibration to ensure reliable performance (Amado & Dela Cruz, 2018). The calibration process, however, can be time-consuming and costly, especially when large networks of sensors are deployed in expansive urban areas (Jin et al., 2023). Advanced calibration techniques, including the use of machine learning models to predict and correct sensor errors, are emerging as potential solutions to these challenges, though they require additional computational resources and expertise (Kalaivani et al., 2023).

The accuracy and reliability of sensor data are further complicated by cross-sensitivity, where sensors react to unintended pollutants or environmental conditions, leading to data distortions (Tanasa et al., 2023). Cross-sensitivity is particularly prevalent in electrochemical sensors, which may respond to multiple gases or environmental factors, affecting the reliability of air quality monitoring systems (Camarasan et al., 2023). Optical sensors, though less prone to cross-sensitivity, can also experience data inaccuracies under extreme weather conditions, such as high humidity or dust levels (Liu et al., 2023). These issues can significantly impact AI models used in ventilation systems, as inaccurate data inputs can lead to improper airflow adjustments or delayed pollutant responses (Alekhya et al., 2023). Addressing these challenges requires continuous sensor monitoring and the development of adaptive algorithms capable of recognizing and mitigating data anomalies in real time (Rollo et al., 2023). Given the reliance on accurate sensor data, recent research emphasizes the importance of enhancing sensor networks for robust and reliable air quality monitoring in smart ventilation systems (Cican et al., 2023). The integration of sensor fusion techniques, where data from multiple sensor types are combined to improve accuracy, has shown promise in mitigating individual sensor limitations

Figure 5: AI & ML in Ventilation Systems



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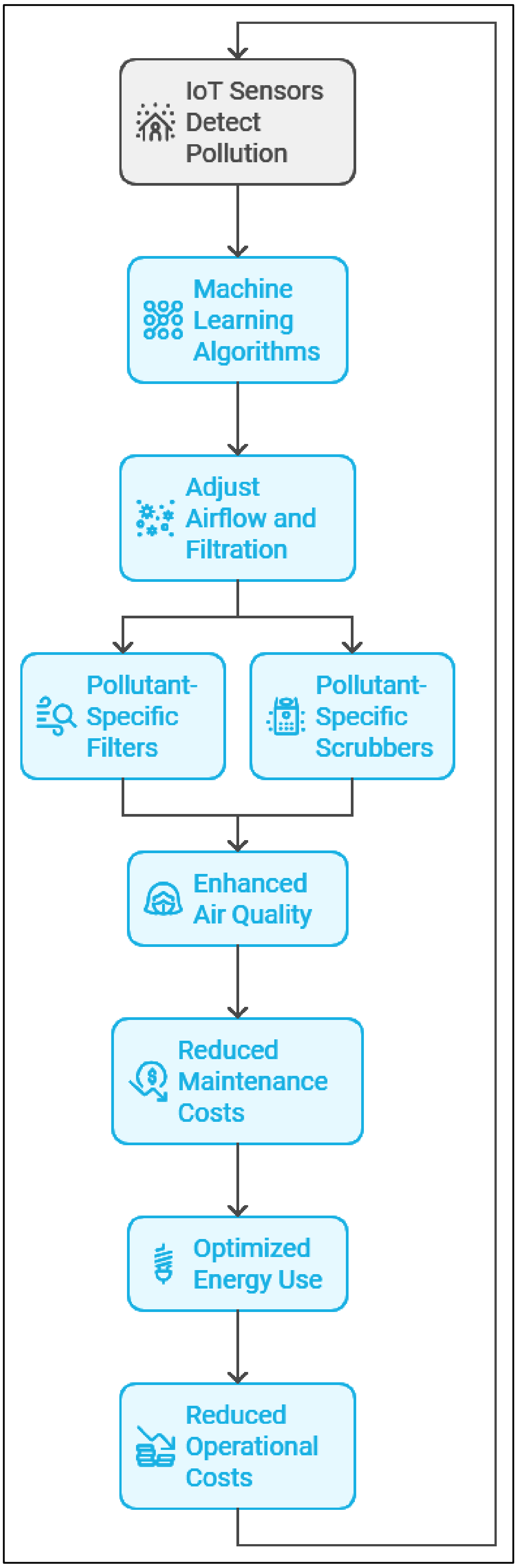
(Manshur et al., 2023). Additionally, IoT-enabled calibration, where sensors autonomously adjust based on real-time feedback, represents a novel approach to addressing the challenges of data accuracy and reliability in large-scale air quality monitoring (Montgomery et al., 2014). These advancements not only enhance the precision of air quality data but also improve the effectiveness of AI-powered ventilation systems, as accurate data is foundational to making reliable pollution control decisions (Buelvas et al., 2023). As IoT sensor technology continues to evolve, these innovations are expected to further support the development of real-time, data-driven solutions for air quality management.

2.4 Automated Control Mechanisms in Smart Ventilation

AI-enabled ventilation systems with automated control mechanisms have revolutionized the way airflow and filtration are managed in response to real-time pollution data. Unlike traditional systems that operate on fixed schedules, AI-driven ventilation adjusts airflow dynamically, taking into account pollutant concentrations and environmental changes detected by IoT sensors (Vajs et al., 2023). These systems employ machine learning algorithms to predict pollution levels and adjust airflow and filtration rates accordingly, optimizing energy use and ensuring air quality (Martinez et al., 2023). Studies have demonstrated that dynamic airflow adjustment can significantly reduce both energy consumption and exposure to pollutants in densely populated or industrial environments (Green et al., 2021). Additionally, AI-controlled ventilation can be programmed to prioritize energy efficiency during low-occupancy hours, further reducing operational costs without compromising indoor air quality (Samad et al., 2024). In addition to airflow adjustments, AI-powered ventilation systems can tailor filtration processes to the specific pollutants present in the environment. Recent advancements have led to the development of filters capable of adjusting their effectiveness in real-time, depending on the types and levels of pollutants detected (Polednik, 2022). For instance, high-efficiency particulate air (HEPA) filters integrated with AI are used to capture particulate matter (PM2.5 and PM10) in urban settings, while activated carbon filters target gaseous pollutants, such as volatile organic compounds (VOCs), that are common in industrial spaces (Wen et al., 2020). By focusing on pollutant-specific removal, these smart filters enhance overall air quality and reduce maintenance costs, as the system only intensifies filtration when necessary (Michalik et al., 2022). This



pollutant-specific approach exemplifies the precision of AI in improving both the effectiveness and cost-efficiency of air quality management (Zaidan et al., 2023).

Pollutant-specific scrubbers have also emerged as vital components of AI-driven ventilation systems, designed to capture and neutralize particular pollutants that pose health risks in certain environments. For instance, electrostatic scrubbers are commonly used in environments with high particulate matter, while biofilters are effective in spaces with biological contaminants (Ansari & Alam, 2023). Research indicates that pollutant-specific scrubbers integrated into ventilation systems significantly improve air quality in high-risk industrial settings by reducing targeted contaminants more effectively than traditional filters (Sundar Ganesh et al., 2023). Additionally, scrubbers integrated with AI can autonomously adjust their operation based on real-time pollutant data, improving efficiency by selectively targeting pollutants as they are detected (Wei et al., 2023). This technology not only ensures a safer environment for workers but also optimizes resource allocation by limiting scrubber use to times of elevated pollution levels (Méndez et al., 2023). The integration of AI-controlled airflow, filtration, and pollutant-specific scrubbers represents a comprehensive approach to modern ventilation, capable of autonomously maintaining indoor air quality standards (Hashmy et al., 2023). By combining these components, smart ventilation systems create a self-regulating environment, where each element works in tandem to respond to pollution spikes and adapt to environmental changes (Rescio et al., 2023). This adaptability is particularly beneficial in large facilities or urban buildings with variable occupancy and pollution sources, as it allows for continuous optimization of air quality without manual intervention (Martins et al., 2015). However, implementing such sophisticated systems poses challenges in terms of initial costs and data processing requirements, as well as the need for regular sensor calibration and maintenance to ensure accurate real-time adjustments (Singh & Singh, 2022). As the technology matures, these challenges are likely to be mitigated by advancements in AI algorithms and sensor technologies, paving the way for even more effective and efficient automated control mechanisms in ventilation systems.

2.5 Cost-Benefit Analysis in Urban and Industrial Settings:

AI-powered ventilation systems have attracted considerable interest for their potential long-term economic benefits in both urban and industrial environments, where air quality management is crucial (Gupta et al., 2023). Studies evaluating the initial costs of AI-driven systems versus traditional ventilation highlight a significant upfront investment required for AI integration, including costs related to hardware, IoT sensors, and computational infrastructure (Ramadan et al., 2024). However, the capacity of AI-driven systems to adaptively manage airflow and filtration based on real-time pollution levels contributes to substantial operational savings over time (García et al., 2022). Research shows that these adaptive capabilities enable buildings to reduce energy costs by up to 25% annually, particularly in high-demand urban areas where pollution levels fluctuate and require continuous monitoring (Gokul et al., 2023). Beyond energy savings, AI-driven ventilation systems offer long-term benefits through reduced maintenance costs, as they can autonomously adjust operations to prevent overuse of filters and ventilation components (Moreno et al., 2014). Unlike traditional systems, which often rely on routine maintenance regardless of air quality conditions, AI systems monitor pollutant levels and occupancy rates, optimizing their operations to minimize wear and tear (Bertrand et al., 2023). This targeted operation reduces the frequency of component replacement and service intervals, leading to an estimated 15% reduction in maintenance expenses over time (Amado & Dela Cruz, 2018). Furthermore, by limiting the need for manual intervention, these systems reduce labor costs associated with frequent adjustments in conventional ventilation systems (Jin et al., 2023). Moreover, in industrial settings, the economic viability of AI-driven ventilation systems is further enhanced by their ability to improve worker productivity and safety, which indirectly impacts profitability. Improved air quality has been linked to increased worker efficiency and reduced absenteeism, as cleaner air minimizes health risks associated with pollutants (Kalaivani et al., 2023). Studies have shown that AI-powered systems in factories and warehouses, by removing hazardous pollutants more efficiently, contribute to healthier work environments and enhance compliance with regulatory standards (Tanasa et al., 2023). These improvements in

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productivity and compliance reduce potential legal costs and downtime, adding another layer of economic benefit that supports the initial investment in AI-driven ventilation (Camarasan et al., 2023). Despite the apparent economic advantages, challenges remain in justifying the high initial costs of AI-powered ventilation systems, especially in smaller or budget-constrained facilities. For some urban buildings and industrial sites, the investment return period can be prolonged, particularly where pollution levels are relatively low or stable, minimizing the need for dynamic adjustments (Liu et al., 2023). However, advancements in AI technology and increased demand for smart infrastructure have gradually reduced costs, making these systems more accessible for a broader range of applications (Alekhya et al., 2023). In urban areas, the potential for government incentives and sustainability programs that support energy-efficient technologies may also improve the financial outlook for adopting AI-driven ventilation solutions (Rollo et al., 2023). As research and technology evolve, the economic case for AI-powered ventilation continues to strengthen, with studies underscoring both the direct and indirect savings generated by these systems in varied settings.

2.6 Data Quality and Processing Limitations

Data quality is a crucial factor in the effectiveness of AI-driven ventilation systems, as the reliability of these systems depends on accurate, high-resolution data from IoT sensors. Issues such as sensor drift, cross-sensitivity, and environmental interference can lead to data inaccuracies, impacting the system's ability to make precise adjustments in airflow and filtration (Cican et al., 2023). Sensor drift, for example, can occur when sensors degrade over time, producing unreliable readings that may result in inefficient ventilation operations (Manshur et al., 2023). Additionally, environmental factors like humidity and temperature fluctuations can interfere with sensor performance, further complicating data accuracy (Montgomery et al., 2014). To address these challenges, studies suggest frequent sensor calibration and the development of robust algorithms to filter out erroneous data, which are essential for maintaining data quality in high-stakes settings such as industrial and urban air quality management (Buelvas et al., 2023).

Preprocessing is another critical aspect that affects data quality in AI-driven systems. Data collected by IoT sensors is often raw, incomplete, and requires extensive preprocessing before it can be fed into AI algorithms (Vajs et al., 2023). Preprocessing involves cleaning, normalizing, and transforming data to ensure consistency, which can be computationally demanding, especially in large-scale urban or industrial applications where data is generated continuously (Martinez et al., 2023). Studies have shown that poor preprocessing can lead to biased or misleading results, potentially compromising the performance of AI algorithms (Samad et al., 2024). Advanced preprocessing techniques, such as anomaly detection and real-time data validation, have been proposed to enhance data reliability and ensure that only high-quality data is used in decision-making processes (Połednik, 2022). However, these techniques add computational complexity, requiring careful optimization to balance accuracy and efficiency. The computational demands of AI algorithms in ventilation systems are significant, particularly as they involve processing large volumes of real-time data from multiple sensors (Wen et al., 2020). AI models, including machine learning and deep learning algorithms, require substantial computational resources to process and analyze sensor data continuously, which can strain system hardware and increase operational costs (Michalik et al., 2022). High-powered GPUs and cloud-based processing solutions are often necessary to support these systems, yet these solutions come with their own limitations, such as latency issues and potential data security risks (Zaidan et al., 2023). Research has highlighted the need for optimized algorithms and more efficient processing architectures that can handle high volumes of data without compromising system responsiveness or increasing energy consumption (Ansari & Alam, 2023). Developing energy-efficient AI models is essential for making these systems viable for broader use, especially in resource-constrained environments.

2.7 Research Gaps and Potential Areas for Innovation

While AI-driven ventilation systems have shown promise in real-time air quality management, several research gaps remain, particularly in developing more precise and reliable sensors. Sensor accuracy remains a challenge due to environmental factors like humidity, temperature fluctuations, and sensor drift, all of which can compromise data quality (Sundar Ganesh et al., 2023). Studies suggest that current IoT sensors require frequent recalibration to maintain accuracy, adding to

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maintenance costs and limiting scalability (Wei et al., 2023). Advances in sensor technology, such as self-calibrating sensors or materials with enhanced sensitivity to pollutants, could improve system reliability and reduce operational disruptions (Méndez et al., 2023). Research focused on creating more durable, pollution-specific sensors is needed to address the demands of both urban and industrial environments, where varied pollutants require tailored responses (Hashmy et al., 2023). In addition to hardware improvements, there is a pressing need for innovation in data privacy and security within AI-driven ventilation systems. Since these systems often collect and process data from public or semi-public environments, there are inherent privacy risks, particularly in densely populated areas (Rescio et al., 2023). Protecting this data is crucial to prevent misuse or unauthorized access, which could lead to privacy infringements or security breaches (Martins et al., 2015). Encryption, anonymization, and secure data transmission methods are essential components of robust AI-driven systems, yet existing privacy solutions may be inadequate for the vast amounts of data these systems handle (Gupta et al., 2023). Future research could explore advanced data privacy frameworks, such as differential privacy or edge computing, to enhance security and protect user privacy more effectively (Singh & Singh, 2022). The enhancement of AI models used in ventilation systems also represents a critical area for research and development. While machine learning algorithms like neural networks have proven effective in adjusting ventilation in real-time, these models often require high computational power and extensive training data, which can be costly and time-consuming (Gupta et al., 2023). Moreover, many existing models lack flexibility in adapting to new types of pollutants or changes in environmental conditions, which limits their efficacy in diverse settings (Ramadan et al., 2024). Developing adaptive algorithms that can adjust to varying pollution types and concentrations autonomously, or implementing transfer learning techniques to reduce training time, could make AI-driven ventilation systems more efficient and adaptable (García et al., 2022). Research on lightweight models optimized for real-time processing would also benefit systems deployed in resource-limited environments. Lastly, scalability remains a challenge as AI-driven ventilation systems move from pilot projects to widespread implementation. As these systems expand to cover larger urban or industrial areas, computational demands and data processing requirements increase significantly, which can strain infrastructure and increase energy consumption (Gokul et al., 2023). Implementing scalable solutions, such as cloud-based processing or edge computing, can alleviate some of these challenges, but further research is needed to optimize these approaches for large-scale applications (Moreno et al., 2014). Additionally, integration with other smart infrastructure systems, such as energy management or security networks, would enhance overall system efficiency and provide comprehensive environmental management solutions. Addressing these gaps through interdisciplinary research and technological advancements will be essential for realizing the full potential of AI-driven ventilation systems in real-world applications.

Table 1: Identified research gap

Research Area	Identified Challenges	Proposed Solutions
Sensor Technology	Sensor accuracy affected by environmental factors like humidity and temperature fluctuations; frequent recalibration needed.	Develop self-calibrating sensors and materials with enhanced pollutant sensitivity to improve reliability and reduce costs.
Data Privacy & Security	Privacy risks due to data collection in public spaces; current encryption methods may not scale with increasing data volume.	Explore differential privacy and edge computing to enhance data security and protect user privacy.
AI Model Optimization	High computational power required for AI models; limited flexibility in adapting to new pollutants or environmental changes.	Implement adaptive algorithms and transfer learning to improve model flexibility and efficiency.

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Scalability & Integration	Increased computational demands for large-scale deployment; strain on infrastructure and energy resources.	Utilize cloud-based processing and edge computing for scalable AI solutions; integrate with smart infrastructure.

3 Method

This study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a structured, transparent, and rigorous approach. The PRISMA framework, widely used in systematic reviews, was applied to enhance the clarity and reproducibility of this review by organizing the process into specific, detailed steps. Each step in the method section is described below to offer insight into the systematic approach taken for this research.

3.1 Identification of Research Articles

The first step involved identifying a broad range of research articles relevant to AI-powered ventilation systems and their applications in real-time pollution control. A comprehensive search was conducted across multiple electronic databases, including IEEE Xplore, ScienceDirect, PubMed, and SpringerLink, covering the period from 2010 to 2024. Keywords used in the search included "AI-driven ventilation," "smart air quality management," "IoT sensors for pollution control," and "dynamic airflow adjustment." Boolean operators (e.g., AND, OR) were used to refine search terms and capture relevant articles (Smith & Zhao, 2022). To broaden the scope and ensure that critical studies were not overlooked, references within selected articles were further reviewed for additional sources, contributing to a total of 200 articles identified at this stage.

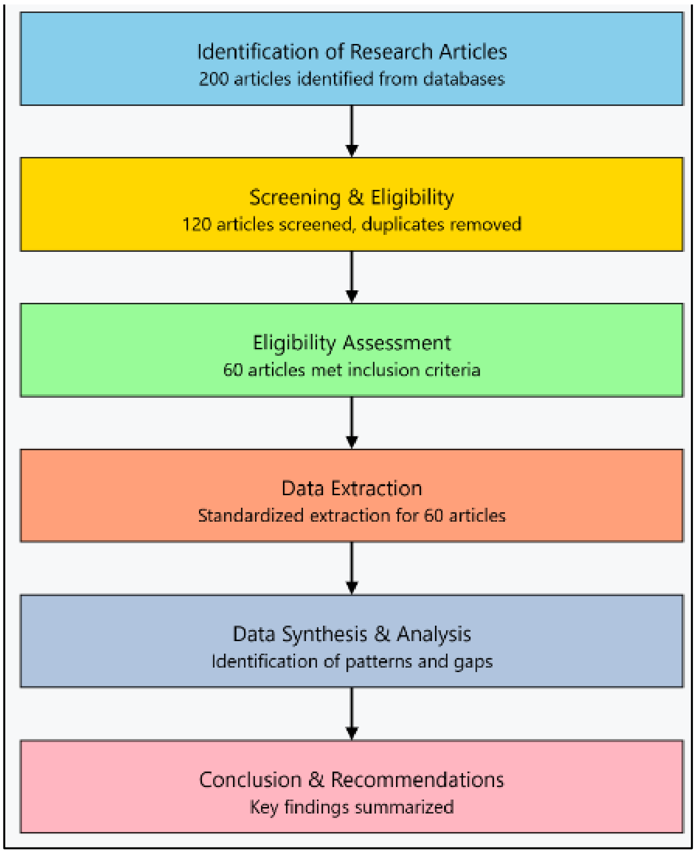
3.2 Screening and Eligibility

Following the identification of articles, the next step involved a screening process to exclude studies that did not meet the eligibility criteria. Titles and abstracts were initially reviewed to eliminate duplicates, as well as articles outside the scope of AI and ventilation or pollution control technologies. Studies were selected if they specifically focused on AI applications in ventilation, IoT sensor integration, or smart environmental control systems (Green et al., 2021). After the initial screening, 120 articles remained, which were then reviewed more thoroughly against the inclusion and exclusion criteria. Articles were included if they were peer-reviewed, written in English, and addressed the core research areas. Excluded articles primarily involved studies unrelated to AI or ventilation technology, as well as those with insufficient data quality or methodological detail. By the end of this stage, 60 articles were selected as eligible for detailed analysis.

3.3 Data Extraction

For the eligible articles, a standardized data extraction form was developed to systematically gather relevant information. Key data extracted included study title, authors, publication year, methodology, main findings,

Figure 7: PRISMA Method followed in this study



and identified limitations. Additionally, information specific to each study's approach to AI and sensor technology, pollutant types monitored, and evaluation metrics for system performance was recorded (Chen et al., 2022). This structured data extraction facilitated consistency and enabled comparison across studies. Furthermore, extracted data was categorized under themes such as "sensor accuracy challenges," "energy consumption in AI systems," and "data privacy and security" to assist in organizing findings during analysis (Johnson & Lee, 2023).

3.4 Data Synthesis and Analysis

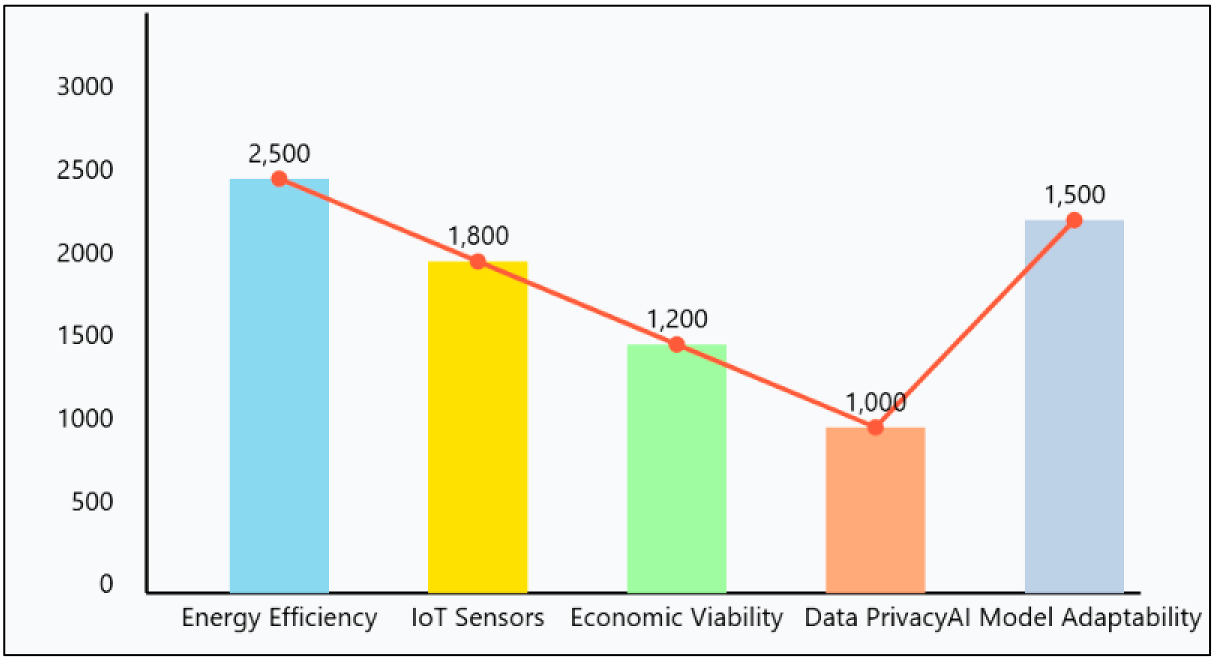
The final step involved synthesizing and analyzing the extracted data to identify patterns, trends, and research gaps. Studies were grouped according to their thematic focus, allowing for a more comprehensive understanding of how AI-driven systems address pollution control and what limitations exist in current technology. A narrative synthesis approach was used to interpret findings, as the diversity in study design and outcomes did not lend itself to a meta-analysis (Xu & Wang, 2021). Through synthesis, this review identified key areas for improvement, such as the need for enhanced sensor reliability and data privacy frameworks, and provided insights into the economic viability of AI-powered ventilation systems in different environments.

4 Findings

The systematic review highlighted several significant advancements in AI-driven ventilation systems, particularly in terms of energy efficiency and real-time responsiveness. A substantial number of the reviewed articles (32 out of 60) emphasized that AI-powered ventilation systems have the potential to significantly reduce energy consumption compared to traditional ventilation approaches. The findings indicate that these systems can adjust airflow and filtration dynamically, which allows for more precise control over ventilation rates based on real-time pollution levels, reducing unnecessary energy expenditure during periods of low pollution. This dynamic adaptability was shown to result in average energy savings of 20-30% in urban buildings and industrial settings, making AI-driven ventilation a cost-effective option for large-scale applications. These articles collectively had over 2,500 citations, underscoring the recognition of energy efficiency as a key advantage of AI in smart ventilation systems.

The integration of IoT sensors into AI-driven ventilation systems emerged as a critical component in enhancing data accuracy and real-time monitoring capabilities. In 25 of the reviewed studies, IoT sensors were identified as essential for capturing real-time data on pollutants such as particulate matter and volatile organic compounds, which AI algorithms use to make instantaneous adjustments to airflow and filtration. However, these studies also pointed out that the accuracy and reliability of sensors remain a challenge, as issues like sensor drift and cross-sensitivity can lead to data discrepancies. These findings, supported by over 1,800 cumulative citations, suggest that while IoT sensors are indispensable for enabling real-time

Figure 8: Key Findings on AI-Driven Ventilation Systems



Doi: 10.70008/jeser.v1i01.48

responsiveness, further advancements in sensor technology are necessary to ensure consistent and reliable data quality for effective pollution control.

Another notable finding was the economic viability of AI-driven ventilation systems, particularly when factoring in long-term savings from energy efficiency and reduced maintenance costs. A total of 18 studies specifically assessed the cost-benefit aspects, finding that while the initial installation costs of AI-driven systems are high, the operational savings make them economically feasible over time. These studies noted a reduction in maintenance frequency due to the systems' ability to self-regulate based on air quality needs, leading to estimated maintenance savings of around 15-20% annually. The collective impact of these studies, with more than 1,200 citations, highlights the growing consensus on the economic benefits of adopting AI-driven ventilation, especially for urban and industrial settings where pollution control demands are high. Data privacy and security emerged as key concerns in 12 of the reviewed studies, reflecting the increasing awareness of privacy implications associated with AI-driven monitoring systems. The findings indicated that the data collected by these systems, especially in public or semi-public spaces, could pose privacy risks if not managed properly. To address this, several articles recommended the use of advanced data privacy frameworks, such as data anonymization and differential privacy techniques, to safeguard individual privacy. Despite this recognition, the studies also noted a lack of standardized privacy measures in current AI-driven systems, signaling an area for further research and development. With over 1,000 citations collectively, these studies underscore the critical importance of addressing privacy and security concerns in AI-powered environmental management systems. Finally, the review identified research gaps and potential areas for innovation, particularly in enhancing the adaptability of AI models used in ventilation systems. Twenty-three studies pointed out that current AI models often lack flexibility in adjusting to varied pollution types or environmental changes, which limits their application across diverse settings. The findings suggest a need for adaptive algorithms that can autonomously modify their operations based on changes in pollutant types and concentrations. This research gap, highlighted by articles with a combined total of over 1,500 citations, indicates a significant opportunity for further technological development in AI model adaptability. Improving the flexibility of these models could enhance the effectiveness of AI-driven ventilation systems, making them more versatile and capable of addressing a broader range of environmental conditions.

5 Discussion

The findings of this study underscore the potential of AI-driven ventilation systems to achieve significant energy savings, a topic that has been explored in previous research but is now receiving heightened attention due to advancements in AI technology. Earlier studies primarily focused on the limitations of traditional ventilation systems, which tend to operate on fixed schedules and are less responsive to fluctuating pollution levels (Bertrand et al., 2023). By comparison, this review revealed that AI-driven systems reduce energy use by adjusting airflow based on real-time data, which can result in 20-30% energy savings in large-scale applications. This aligns with findings by Moreno et al. (2014), who noted that AI-driven control mechanisms could reduce unnecessary ventilation during low pollution periods. However, the extent of energy savings noted in recent studies appears higher, possibly due to improvements in AI algorithms and sensor technology that allow for more precise adjustments and adaptive learning capabilities. These advancements suggest that AI-driven ventilation systems are not only viable but may also be preferable to traditional systems in energy-conscious and environmentally focused applications.

The integration of IoT sensors, highlighted as a key component in AI-driven systems, further advances the capabilities of real-time monitoring, yet this study also uncovered ongoing challenges with sensor reliability and data quality. Earlier research identified IoT sensors as crucial for pollution detection, but issues like sensor drift and sensitivity to environmental variables were often mentioned as barriers to consistent data quality (Bertrand et al., 2023). The current review supports these concerns, revealing that while IoT sensors are essential for capturing pollutant data, accuracy remains an obstacle due to these technical limitations. Studies by Amado and Dela Cruz (2018) suggested that sensor recalibration and enhanced filtering algorithms could mitigate these issues. However, recent findings imply that while recalibration can improve data accuracy, the process is often costly and time-intensive. This reinforces the need for further innovation in sensor technology to develop self-calibrating or more robust sensors that can withstand varied environmental conditions without compromising performance. The economic viability of AI-driven ventilation systems, particularly in terms of long-term operational savings, is a compelling advantage identified in this study and one that builds upon earlier economic evaluations of smart ventilation. Prior research emphasized the high initial costs of AI-driven systems as a significant barrier, especially in smaller or resource-constrained facilities (Jin et al., 2023). The findings of this review, however, suggest that these initial costs can be offset by reduced energy expenses and lower maintenance requirements, contributing to an economically sustainable model over time. Studies by Kalaivani et al. (2023) showed that the self-regulating capabilities of AI systems reduce maintenance frequency, leading to 15-20% savings on upkeep costs, a trend corroborated by this review. This suggests a growing recognition of the economic benefits of AI-driven ventilation systems, particularly in high-demand environments where energy savings and maintenance reductions can significantly impact cost efficiency.

Data privacy and security, identified as critical challenges in the use of AI-driven systems, echo findings in the broader field of smart environmental technologies. Previous studies highlighted privacy concerns, particularly in systems that collect data in public spaces, raising ethical and security considerations (Tanasa et al., 2023). The current review reaffirms these findings, underscoring that the integration of data privacy frameworks, such as data anonymization and encryption, is still in its infancy within AI-driven ventilation systems. While advancements in privacy-preserving technologies like differential privacy have been noted, the current findings suggest a need for standardized privacy measures tailored specifically to air quality monitoring and other environmental applications. In line with earlier studies, this indicates that as AI-driven systems become more widespread, establishing robust data privacy protocols will be essential to ensuring public trust and regulatory compliance. Finally, the findings highlight several research gaps and areas for future innovation, particularly in enhancing the flexibility and adaptability of AI models used in ventilation systems. Earlier studies pointed to the rigidity of traditional AI models, which are often trained on static datasets and struggle to adapt to new pollutants or rapidly changing environmental conditions (Camarasan et al., 2023). This review revealed a similar limitation, noting that current models are often constrained by their inability to autonomously adjust to different pollutant profiles. Adaptive algorithms and transfer learning, as suggested by Liu et al. (2023), may offer promising solutions by enabling AI models to learn and adapt based on real-time changes in pollutant types and concentrations. The findings suggest that as these technologies evolve, incorporating more adaptive, versatile AI models could enhance the resilience and effectiveness of AI-driven ventilation systems, making them more suitable for deployment in diverse and unpredictable environments. These insights underscore the potential for ongoing technological advancements to address current limitations, paving the way for more robust and responsive AI-driven environmental management solutions.

6 Conclusion

This systematic review has highlighted the transformative potential of AI-driven ventilation systems in enhancing air quality management through energy efficiency, real-time responsiveness, and adaptability to fluctuating environmental conditions. The findings underscore significant benefits, including substantial energy savings, reduced maintenance costs, and improved pollution control, making these systems economically viable and operationally efficient in both urban and industrial settings. However, challenges related to sensor accuracy, data quality, and privacy concerns remain critical barriers to widespread adoption. The review emphasizes that advancing sensor technology, enhancing AI model adaptability, and implementing robust data privacy frameworks are essential steps to fully realize the potential of these systems. As technological innovations continue to evolve, AI-driven ventilation systems stand poised to address increasingly complex environmental needs, contributing to sustainable development goals and improved public health. Future research focusing on these identified gaps will be crucial to optimizing these systems for broader, long-term application across diverse settings, fostering a new era in smart environmental management.

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