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AI management platform for privacy-preserving indoor air quality control: Review and future directions

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ABSTRACT

People spend a significant portion of their time in enclosed spaces, making indoor air quality (IAQ) a critical factor for health and productivity. Artificial intelligence (AI)-driven systems that monitor air quality in real-time and utilize historical data for accurate forecasting have emerged as effective solutions to this challenge. However, these systems often raise privacy concerns, as they may inadvertently expose sensitive information about occupants' habits and presence. Addressing these privacy challenges is essential. This research comprehensively reviews the existing literature on traditional and AI-based IAQ management, focusing on privacy-preserving techniques. The analysis reveals that while significant progress has been made in IAQ monitoring, most systems prioritize accuracy at the expense of privacy. Existing approaches often fail to adequately address the risks associated with data collection and the implications for occupant privacy. Emerging AI-driven technologies, such as federated learning and edge computing, offer promising solutions by processing data locally and minimizing privacy risks. This research introduces a novel AI-based IAQ management platform incorporating the SITA (Spatial, Identity, Temporal, and Activity) model. By leveraging customizable privacy settings, the platform enables users to safeguard sensitive information while ensuring effective IAQ management. Integrating Internet of Things (IoT) sensor networks, edge computing, and advanced privacy-preserving technologies, the proposed system delivers a robust and scalable solution that protects both privacy and health.

Abbreviations

AER	Air Exchange Rates
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average
ASHRAE	American Society of Heating, Refrigeration, and Air-Conditioning Engineers
BMS	Building Management Systems

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BPNN	Backpropagation Neural Network
CFD	Computational Fluid Dynamics
CNN	Convolutional Neural Networks
EIA	Energy Information Administration
GRU	Gated Recurrent Unit
HVAC	Heating, Ventilation, and Air Conditioning
IAQ	Indoor Air Quality
IJVS	Impinging Jet Ventilation System
IoT	Internet of Things
LM	Levenberg–Marquardt
LSTM	Long Short-Term Memory
MBA	Mass Balance Approaches
ML	Machine Learning
MLR	Multiple Linear Regression
MV	Mechanical Ventilation
NV	Natural Ventilation
PM	Particulate Matter
RF	Random Forest
RH	Relative Humidity
RNN	Recurrent Neural Network
SD	System dynamics
SITA	Spatial, Identity, Temporal, and Activity
SPM	Suspended Particulate Matter
SVMs	Support Vector Machines
SVR	Support Vector Regression
TVOC	Total Volatile Organic Compounds
VRs	Ventilation Rates
WHO	World Health Organization
xGBoost	Extreme Gradient Boosting

1. Introduction

Indoor air quality (IAQ) significantly influences human health, given that individuals spend approximately 90 % of their lives indoors [1,2]. Poor IAQ is associated with various building-related illnesses [3], such as asthma and respiratory infections. Among the pollutants affecting IAQ, bioaerosols constitute between 5 % and 34 % of indoor particulate matter (PM) concentrations [4–6]. The ongoing COVID-19 pandemic has further amplified the urgency of addressing IAQ.

Regarding occupant health and comfort, IAQ encapsulates air quality within and surrounding buildings. The term's definition differs depending on the individual's perspective and the specific pollutants present [7]. Intriguingly, indoor air pollution accounts for over 90 % of pollutant exposure, as indoor levels are usually hundreds to thousands of times higher than outdoors [8].

Various organizations have established guidelines to mitigate indoor air pollution [9]. For example, the World Health Organization (WHO) recommends a 30-min average concentration of 100 mg/m^3 (or 0.08 ppm) for formaldehyde [9]. In light of airborne transmission risks for infections like SARS-CoV-2 and influenza A (H_1N_1) [10,11], the focus on IAQ is particularly acute in healthcare settings [12]. Maintaining optimal IAQ is imperative for safeguarding public health and well-being. Consequently, there is a critical need for effective methods to monitor and control IAQ.

Artificial Intelligence (AI) has significantly impacted atmospheric and medical sciences, offering innovative solutions for air quality management [13]. When integrated with air quality and meteorological data, AI algorithms enhance our understanding of complex atmospheric phenomena [14–16]. Comparative studies have demonstrated the superiority of AI-driven techniques over traditional approaches in air pollution prediction. For instance, artificial neural networks (ANN) have shown better predictive ability than multiple linear regression (MLR) for PM concentration modeling [17]. Other researchers have explored various AI models, including decision trees [18], backpropagation neural network (BPNN) [19], random forests (RF) [20], and more advanced techniques like support vector regression (SVR) and extreme gradient boosting (xGBoost) [21]. These AI-based approaches have emerged as effective alternatives to conventional IAQ control modeling methods, leveraging real-time sensor data and machine learning (ML) to forecast trends in IAQ parameters [22]. This shift towards AI-driven solutions significantly advances air quality management and pollution prediction.

However, privacy concerns are a growing issue in IAQ surveillance. While AI-based approaches offer advantages for IAQ control by leveraging real-time and historical data for accurate predictions, addressing privacy concerns remains crucial. Naieni et al. [23] found that although many are comfortable with primary data collection, methods are preferred to preserve anonymity. Developing AI management platforms that incorporate privacy-enhancing techniques and secure data handling protocols is essential. Emerging technologies like edge computing, federated learning, and blockchain offer promising solutions for balancing effective IAQ control with privacy protection [24]. Edge computing, in particular, allows for local data processing, reducing the transmission of sensitive information and enabling real-time responses to air quality changes while minimizing personal data exposure. However, the risk of data misuse underscores the ongoing need for advanced privacy measures in AI-based IAQ management systems.

Despite significant advancements in AI-driven IAQ management, there remains a considerable gap in research on privacy-preserving methods for IAQ control. While much of the current literature focuses on AI-based prediction models, there is limited exploration of how these models can be integrated into real-time control systems that safeguard data privacy. Existing research has examined privacy issues in smart homes [25] and addressed occupant privacy concerns in smart cities [26,27]. Still, there is a notable lack of studies focused on privacy in commercial or work-based smart buildings [28]. This leaves a critical gap in understanding how to protect occupant privacy in environments where data is continuously collected and processed for real-time IAQ management.

This study seeks to address this issue by developing AI techniques for IAQ control that prioritize privacy rather than merely focusing on prediction. The specific goals of the study are: (i) to provide a thorough overview of existing research and applications in privacy-preserving IAQ control, differentiating it from prediction-centered approaches; (ii) to present an innovative AI management platform that combines privacy-preserving techniques with IAQ control models, ensuring effective air quality management while safeguarding data; (iii) to explore the practical implementation of this AI platform in real-world scenarios, emphasizing its potential to enhance IAQ management in environments where privacy is a concern.

By tackling the divide between AI prediction and privacy-preserving control, this study adds value to the field of building engineering, offering a framework for sustainable, real-time IAQ management that balances performance with occupant privacy.

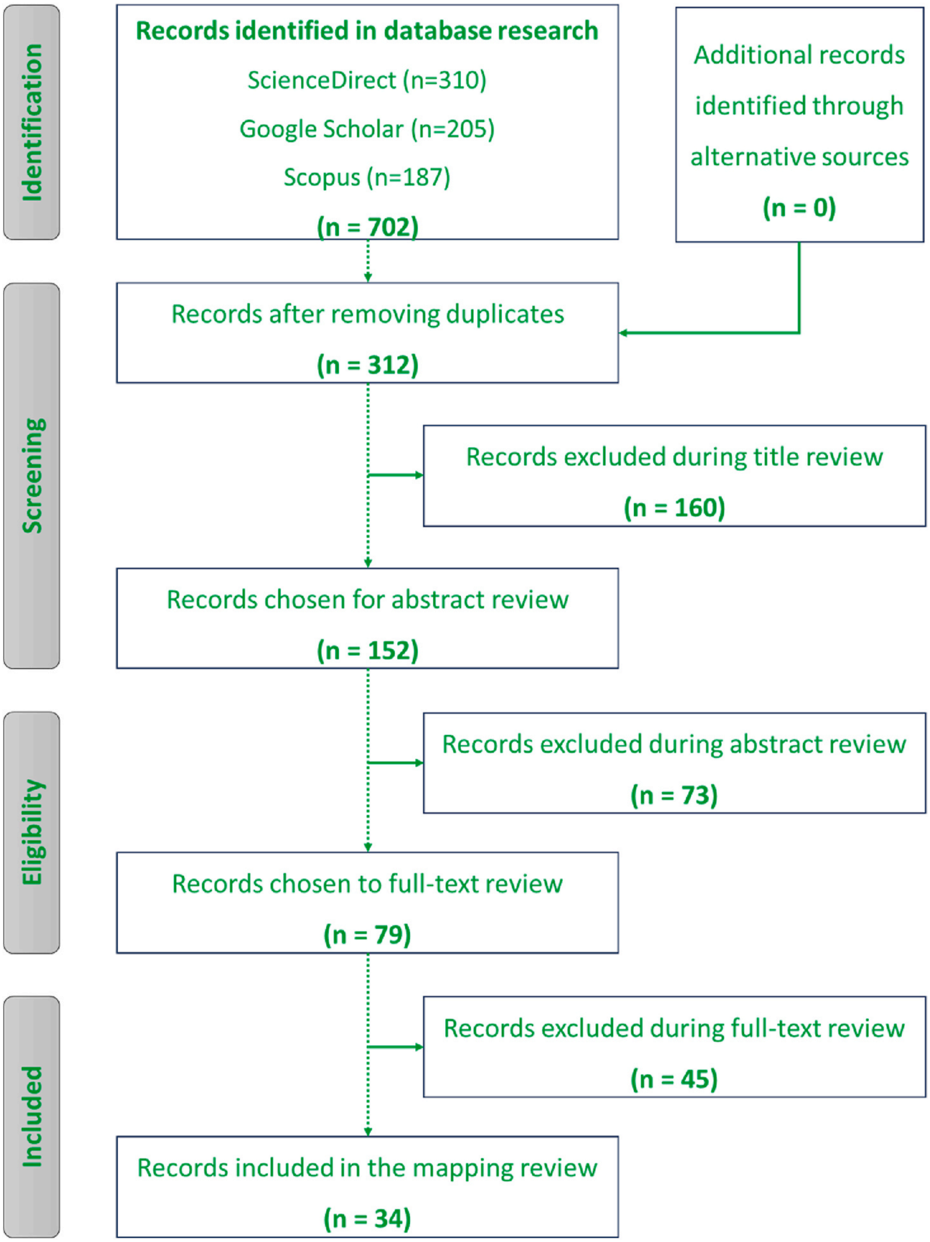

Fig. 1. The PRISMA flow diagram for the systematic review.

2. Methodology

A systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [29] to examine the AI management platform for privacy-preserving IAQ control. The review aimed to map the current research landscape, critically appraise existing methods, and identify future opportunities. The search was performed across three databases – Science Direct, Scopus, and Google Scholar. Combinations of the following keywords were used: "IAQ prediction," "AI platforms," "privacy-preserving techniques," "ML models," "human health," "Internet of Things (IoT)," "edge computing," and "numerical models." Filters were applied to retrieve peer-reviewed English-language journal articles published in the past decade (2014–2024).

The search yielded 312 records after removing duplicates (see Fig. 1). Two independent reviewers screened the titles and abstracts of these records against the inclusion criteria: (1) original research articles, (2) application to IAQ management, and (3) privacy-preserving application in IAQ. Through this screening, 233 records were excluded. The remaining 79 full-text articles were assessed in detail, which resulted in the further exclusion of 45 papers that did not meet all eligibility criteria. Finally, 34 studies were included in the qualitative and quantitative analysis.

3. Background on traditional IAQ management methods

3.1. Conventional IAQ monitoring and prediction methods

3.1.1. Mass balance approaches (MBA)

MBA are indispensable tools in IAQ management for building methods [30]. They encompass the comprehensive evaluation and strategic management of pollutant sources and sinks within indoor environments, aiming to maintain a healthy and comfortable atmosphere. Fundamentally, the MBA operate on the principle that the total quantity of pollutants within a given space remains constant when the pollutant generation or emission rate is in equilibrium with the pollutant removal or loss [31].

Central to MBA are the identification and quantification of pollutant sources within the building [32]. These sources encompass emissions from building materials, furnishings, equipment, and occupant activities, such as cooking and smoking. A nuanced understanding of the scale and characteristics of these sources forms the basis for effective control strategies aimed at mitigating their impact on IAQ. Such systems may include source control measures, such as utilizing low-emission materials, implementing customized ventilation techniques, or establishing designated smoking areas [32,33]. Besides addressing pollutant sources, MBA consider various sinks or removal mechanisms within the indoor environment [34]. These sinks include ventilation systems, filtration units, and natural

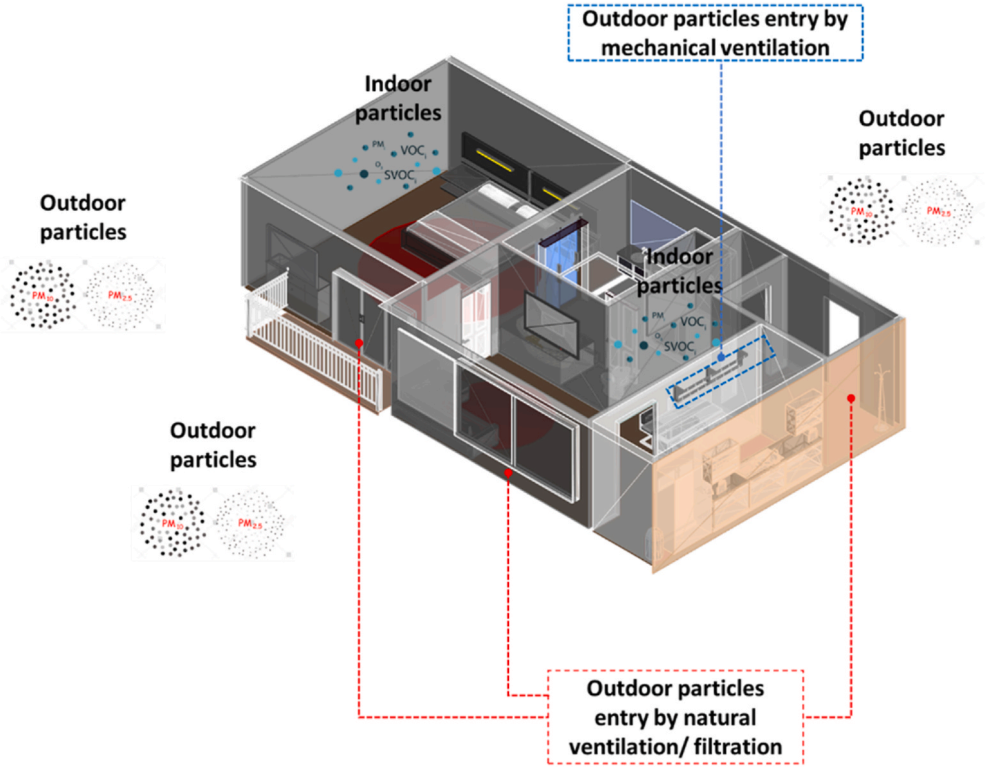

Fig. 2. Routes of outdoor particle infiltration into indoor environments.

processes like deposition and adsorption. Optimizing these removal mechanisms significantly reduces pollutant concentrations, enhancing IAQ [35].

Moreover, MBA extend their purview to assessing pollutant transport and distribution within the building [36]. This encompasses the analysis of airflow patterns, air exchange rates (AER), and the interaction between indoor and outdoor air. Gaining insights into these dynamics allows for developing strategies to optimize ventilation and airflow patterns, thus ensuring the efficient distribution of clean, fresh air throughout the building [37].

MBA provide a systematic framework for assessing and regulating building IAQ. By considering pollutant sources, sinks, and transport mechanisms, these approaches empower the development of effective control strategies tailored to the specific characteristics of the building and the needs of its occupants. Collaboration among building owners, facility managers, and IAQ professionals through the implementation of MBA promises to create healthier and more comfortable indoor environments.

3.1.2. *Indoor-to-outdoor (I/O) ratios approach*

I/O ratios are used to assess IAQ by comparing the concentration of pollutants inside a building to those in the immediate outdoor environment. This approach helps determine the influence of outdoor pollution on IAQ and the effectiveness of building envelope and ventilation systems in filtering outdoor pollutants.

Peak I/O ratios often coincide with high outdoor pollutant concentrations during daylight hours, potentially introducing sampling bias. To address this, researchers have explored alternative methods, such as shorter bulk samples over a few hours or days, providing a single concentration for specific periods of interest [38]. Advanced technologies like laser scattering and electrochemical sensors now enable continuous or real-time measurements, offering higher-resolution assessments of I/O ratios over extended durations [39–41]. Cyrys et al. [42] demonstrated the benefits of well-ventilated spaces over closed-window conditions for PM and black smoke ratios, showing a strong link between indoor and outdoor pollutant levels. Blondeau et al. [43] examined eight educational institutions in France with different ventilation systems, highlighting variations in NO_x and O_3 ratios.

Particle size has been shown to influence I/O ratios. Monn et al. [44] found that PM_{10} ratios varied depending on indoor sources and human activity, with smoking significantly impacting ratios. Jones et al. [41] noted that fine particles exhibited higher ratios than coarse particles. Diapouli et al. [45] reported PM_{10} and $PM_{2.5}$ ratios nearing unity, while ultrafine particles showed ratios below unity. Chen and Zhao [46] concluded that $PM_{2.5}$ ratios around 1.0 indicated limited indoor sources or effective filtration while settings with internal combustion sources displayed higher ratios. The prevailing ventilation methods, mechanical, natural, and infiltration, affect the influx of outdoor particles into indoor environments, see Fig. 2.

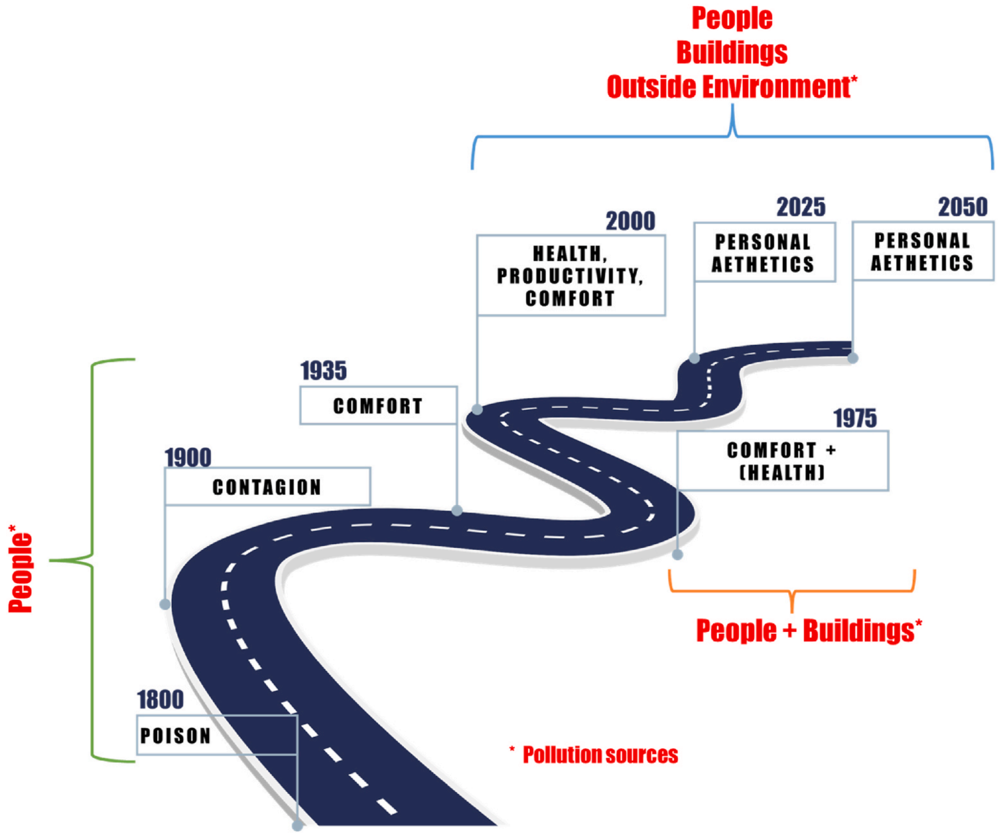

Fig. 3. Evolution of ventilation philosophy from 1800 (adapted from Fanger [59]).

3.1.3. *Computational fluid dynamics (CFD) approach*

CFD tools have become standard for modeling and evaluating indoor environments. While direct measurements are the most reliable way to characterize IAQ accurately, they are the most expensive, time-consuming, potentially hazardous, and difficult to apply for extensive parametric analyses. Therefore, researchers have advocated using numerical simulations in air quality assessment [47–51]. For instance, Ma and Zhou [52] investigated a sour gas well blowout scenario through CFD analysis. Panagopoulos et al. [53] used CFD technology to model the dispersion of indoor air pollutants such as formaldehyde and VOCs within an apartment. A CFD model was also developed to evaluate potential indoor hazards from an accidental chlorine gas release in an industrial setting [54]. While CFD offers high accuracy and detailed spatial resolution, it has significant computational costs. The simulations are computationally intensive, requiring substantial processing power and time, particularly for large-scale or highly detailed models. Additionally, CFD models necessitate a deep understanding of fluid mechanics and proficiency in numerical methods, making them less accessible to practitioners without specialized training.

A promising approach involves optimizing ventilation rates (VRs) in buildings to balance favorable IAQ and efficient energy use. Existing literature has extensively examined this topic using various methodologies. Notable, CFD is a widely accepted and practiced tool in prior research for engineering ventilation systems [55]. However, successful CFD simulations rely on experimental validation, comprehensive fluid mechanics knowledge, and proficiency in numerical techniques. Consequently, previous studies have adopted alternative methods like ML [22]. While robust for prediction, these approaches can present interpretability challenges and require extensive training datasets for optimal outcomes [56].

3.1.4. *Ventilation and filtration approaches*

The ventilation system is critical in monitoring and controlling IAQ. Inadequate ventilation in buildings can significantly compromise the health of occupants. Extensive research has established that insufficient ventilation substantially contributes to the growing prevalence of health issues. For instance, a study conducted in the isolated settlements of the western Nepalese province of Palpa revealed that the ventilation percentage in buildings was 80 % below the minimum value recommended by the American Society of Heating, Refrigeration, and Air-Conditioning Engineers (ASHRAE) [57]. Furthermore, another investigation demonstrated that poorly ventilated kitchens in Nepal exceeded the standard allowable limit for total suspended solids by 100 times, primarily due to excessive smoke production [58]. Metropolitan areas typically offer better occupational, educational, and living conditions than rural regions, influencing IAQ through fuel choices. Changes in construction, material technology, energy costs, and health awareness are transforming ventilation principles. Buildings are increasingly considered pollution sources, with ventilation standards prioritizing health, economics, and aesthetics beyond comfort. Fig. 3 represents a continued evolution of the concept initially introduced by Fanger in 1996 [59].

Several previous assessments have recommended VRs that exceed the current ventilation regulations and the recorded rates in buildings; for instance, many European residential buildings have VRs below 0.5 h^{-1} [60]. However, it is crucial to evaluate the statistical power and quality of epidemiological data before using it as a basis for regulation. The challenge lies in lacking a reliable and practical method to determine ventilation needs that can effectively eliminate health issues without identifying their underlying causes. Previous reviews employed various methods to analyze the relationship between ventilation and health outcomes. As ventilation is an indirect factor and not the primary cause of the observed association, the wide range of VRs reported in previous studies can be attributed to the complex relationships between ventilation frequencies, pollutant levels, and health outcomes. Therefore, caution must be exercised when utilizing ventilation to address air quality problems, and its effectiveness should only be considered in conjunction with identified elements that can enhance its efficacy [61].

Fig. 4 illustrates the indoor air circulation system in distributing supply and exhaust air while facilitating heat exchange between

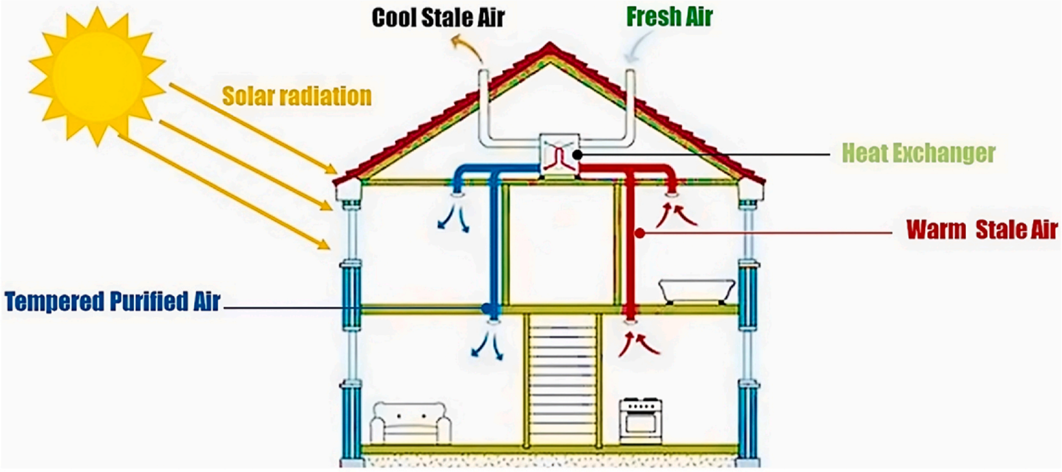

Fig. 4. Indoor air circulation system.

them. The air duct is responsible for moving both supply and exhaust air. The air supply fan brings fresh air into the chamber from below while the exhaust blower expels indoor air downward. To enhance heat exchange, a separator is incorporated into the air duct, shared by both supply and exhaust air paths. When the ventilator operates with low airflow velocity inside the ducts, any particle pollutants from the outdoor air are expected to settle down passively due to gravity [62]. Table 1 summarizes studies that employ physical methods to evaluate IAQ and Table 2 summarizes studies using modeling and conventional statistics for IAQ evaluation.

3.2. Limitations of traditional methods

Traditional IAQ monitoring approaches face several key limitations that restrict their effectiveness in modern building environments. These constraints, such as limited temporal responsiveness, high computational demands, and privacy concerns, highlight the need for alternative solutions to meet contemporary IAQ management's demands better.

One of the primary challenges associated with conventional IAQ monitoring methods is the complexity and cost of the equipment and expertise required to implement them. Many traditional techniques rely on sophisticated instruments that are both expensive and difficult for non-experts to operate, creating a significant barrier to widespread use, especially in settings where vulnerable populations are most impacted by poor air quality [63,64]. Additionally, the dynamic nature of indoor environments further complicates IAQ monitoring. Factors such as outdoor traffic emissions, weather conditions, and indoor activities like cooking or cleaning contribute to fluctuating air quality levels [65]. As a result, static, one-time measurements are rarely sufficient to accurately capture IAQ variations. There is an increasing need for real-time, easily deployable monitoring systems that can provide continuous data and be operated without requiring specialized knowledge.

While providing detailed insights into airflow patterns and contaminant dispersion, CFD and other sophisticated modeling approaches impose substantial computational burdens; these methods typically require significant processing power and time to generate accurate results, making them impractical for continuous, real-time monitoring applications [66]. The computational intensity of these approaches becomes particularly problematic when scaling to large buildings or multiple facilities, as the resources required grow exponentially with the size and complexity of the monitored space [51]. Moreover, the need for specialized expertise to interpret and utilize these complex models adds another layer of operational overhead.

3.3. Role of traditional methods in supporting AI-based system

Traditional IAQ methods are essential in supporting the development and optimization of AI-based systems for IAQ management. These methods provide a foundation of well-established physical principles and models that are benchmarks for AI-driven techniques. For instance, mass balance models offer critical insights into pollutant sources and sinks, which can help AI algorithms understand the dynamics of indoor environments. CFD simulations, while computationally intensive, provide detailed airflow and pollutant distribution data, which can be used to train and validate ML models, enhancing their accuracy and predictive power [67].

Moreover, traditional methods help AI-based systems overcome data limitations [68]. Conventional IAQ models can be integrated into AI systems to supplement the available data in scenarios where sensor data is sparse or unreliable, improving overall system performance. Additionally, traditional methods can serve as fallback mechanisms in cases where AI models encounter uncertainties or insufficient data for decision-making. By combining traditional IAQ methods' strengths with AI's advanced capabilities, such hybrid systems can achieve greater accuracy, efficiency, and scalability. Conventional approaches remain vital in enhancing the robustness and reliability of AI-driven IAQ management systems.

4. AI-based methods for IAQ management

4.1. Overview of AI techniques for IAQ

Implementing AI in IAQ management represents a paradigm shift in environmental monitoring and control systems. AI technologies have demonstrated superior capabilities in managing complex, non-linear relationships between air quality parameters, enhancing prediction accuracy and response times. This advancement has enabled environmental protection agencies and facility managers to implement more effective air quality control strategies and minimize public exposure to airborne pollutants [84,85].

Recent technological developments, particularly in data analytics, computational processing, and ML algorithms, have significantly advanced AI-driven methodologies for IAQ prediction. Integrating big data platforms, parallel processing capabilities, and scalable storage systems has facilitated the development of sophisticated air quality forecasting systems [16,86]. These systems excel in monitoring and predicting concentrations of critical pollutants, including PM, nitrogen dioxide (NO_2), and carbon dioxide (CO_2), which are fundamental indicators of indoor environmental quality.

Comparative analyses have consistently demonstrated the advantages of AI-based approaches over conventional methodologies. Turias et al. (2008) [87] compared BPNN and autoregressive integrated moving average (ARIMA) models for predicting CO, airborne particles, and SO_2 levels in industrial environments. Their research established the superior accuracy and adaptability of BPNN compared to traditional statistical approaches. Similarly, Bozdag et al. (2020) [88] evaluated multiple AI techniques, including ANN, SVR, RF, and xGBoost, in PM_{10} concentration simulation, further validating the robustness of AI-driven methodologies.

The evolution of ML applications in air quality prediction has yielded significant improvements in forecasting accuracy. Delavar et al. (2019) [89] conducted comprehensive research on various ML techniques, including SVR and autoregressive nonlinear neural networks. Their findings revealed remarkable precision in predicting PM_{10} and $PM_{2.5}$ concentrations, with autoregressive nonlinear

Table 1
Studies using physical methods for IAQ evaluation.

Ref	Configurations	Climate	Period	Input variables	Source of input data	Main findings	Limitations
[69]	Residential building	USA (New Hampshire; Connecticut	Fall of 2021	Infiltration rates; indoor temp; CO_2; $PM_{2.5}$; TVOC; occupant behaviours and schedules; outdoor conditions; ventilation strategies	Measurement	NV and air leakage generally maintained acceptable IAQ levels for pollutants in residential buildings, but elevated CO_2 concentrations exceeding hazardous limits were observed in specific instances.	A narrow focus on specific regions and timeframe, absence of MV, and limited COVID-19 exploration.
[70]	School building	Denmark (Copenhagen)	Jan 7 to Feb 2, 2015	Location and climate; classroom characteristics; CO_2; temp; window and door opening behavior; energy use	N/A	MV and operable windows reduced CO_2, enhancing IAQ in a temperate climate.	Emphasis on CO_2, potential thermostat/valve influence, and limited CO_2 reduction with feedback display.
[71]	Home building	England	Several periods from the late 1990s to early 2003.	NO_2; CO; CH_2O, VOC; PM_{10}; tem; RH; home airtightness, property characteristics, occupant behavior; household characteristics	Building Research Establishment (BRE)	IAQ in post-1995 English homes occasionally fell below design values, urging improved IAQ strategies to avoid excessive VRs.	Small sample size, potential confounding factors, need for further occupant behavior, and source control investigation.
[72]	School building	England (University of Reading)	N/A	Pollutant concentration; VRs; heat recovery; air quality sensors; equipment efficiency	N/A	Various ventilation strategies show potential for simultaneously improving IAQ and energy efficiency.	Lacks detailed exploration of challenges quantitative data on some strategies, like task ventilation and demand-controlled ventilation.
[73]	Test room	N/A	N/A	Air change rate; temp; contaminant concentration; velocity; thermal comfort	Measurements and CFD simulations	Impinging Jet Ventilation System (IJVS) excels in air distribution and ventilation parameters, surpassing traditional systems, particularly at high heat loads.	Limited scope, lacks exploration of alternative systems, lack in-depth real-world practicality, and energy efficiency analysis.
[74]	School building	Spain (Andalusia, Seville)	Mid-Sep to mid-Jun; from mid-Jun to mid-Sep	Building characteristics; occupancy schedules; climate data; ventilation system parameters; IAQ parameters (CO_2, temp, HR); energy consumption data; heating system characteristics	Experimental tests and simulations	NV systems in warm-climate school buildings reduce energy consumption by 18–33 % while maintaining comfort.	Limited exploration of hybrid solutions for colder or noisy scenarios.
[75]	Primary school	Italy (Cassino)	Pre-retrofit testing in Feb–Mar 2016 and post-retrofit testing in Feb 2018 and Feb 2019	Classroom characteristics; outdoor particle concentrations; indoor and outdoor temp; RH; CO_2 PM_{10}	Measurement	MV systems with heat recovery in classrooms improve IAQ by reducing CO_2 and particle levels and achieving energy savings for heating.	Limited investigation of other pollutants, focusing on one test classroom and potential real-world variations.
[76]	Office buildings	Pakistan (Islamabad)	During summer (Aug 2018, Aug–Sep 2019) and winter (Nov 2019 to Jan 2020)	Indoor/outdoor CO_2; occupancy levels; VRs	Measurement	Evaluated IAQ in naturally and mechanically ventilated office buildings, highlighting CO_2 differences between seasons, identifying the	Limited focus on other pollutants assumes closed windows in naturally ventilated offices.

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Table 1 (*continued*)

Ref	Configurations	Climate	Period	Input variables	Source of input data	Main findings	Limitations
						transient MBA as the most accurate VRs calculation method, and developing an SD-based model for COVID-19-based CO_2 standards.	
[77]	Residential building	China	One year	Ventilation operation status (on/off); bedroom window actions (open/closed); indoor environmental parameters (temp, RH, CO_2, $PM_{2.5}$, and TVOC); outdoor climate parameters: (temp, RH, wind speed and direction, and $PM_{2.5}$)	Measurement	Residents in Chinese residential buildings prioritize thermal comfort over IAQ, with NV durations increasing in warmer climates and MV usage influenced by outdoor air temperature, revealing insights into ventilation behavior.	Limitations include a relatively short measurement duration (one school week), lack of long-term data to confirm findings, and potential variations in filter ages and maintenance strategies for ventilation systems.
[78]	Primary school building	Sweden (Gothenburg)	Over 5 days during the 2019/2020 heating season	Ventilation system; indoor environmental parameters; indoor air pollutants; building characteristics	Measurement	Ventilation strategies significantly influenced IAQ in Swedish primary school classrooms, with balanced MV systems leading to lower concentrations of CO_2, formaldehyde, PM_{10}, and $PM_{2.5}$ compared to natural or exhaust ventilation.	Limitations include a relatively short measurement duration (one school week), lack of long-term data to confirm findings, and potential variations in filter ages and maintenance strategies for ventilation systems.
[79]	Housing building	Denmark	Jan–Feb 2020	Sleep disturbance factors; various personal characteristics and behaviors	Online questionnaire survey	The study explored the link between bedroom ventilation types and subjective sleep quality in Danish homes. MV decreased sleep disruption due to stuffy air and "too cool" conditions. However, lower subjective sleep quality was associated with sleep disturbances caused by stuffy air, noise, and thermal discomfort.	Limitations include reliance on self-reported data, lack of objective measurements, and the need for further validation through field measurements and surveys during different seasons.

neural networks achieving prediction error margins as low as 1.79 g/m^3 over 24-h periods. These results underscore the capacity of AI systems to address complex IAQ management challenges with unprecedented precision. Wang et al. (2020) [90] demonstrated the superior performance of gradient boosting and ANN models compared to traditional land use regression models in both PM and black carbon prediction. This enhanced performance is attributed to AI's capacity to identify and model intricate relationships between environmental parameters and pollutant concentrations that conventional regression models cannot effectively capture.

The integration of meteorological data has further enhanced AI's predictive capabilities. Chaloulakou et al. (2003) [91] documented significant improvements in PM_{10} predictions using ANN models when incorporating weather-related variables. These findings were corroborated by Son and Kim (2020) [92], whose research demonstrated the superior performance of RF in forecasting PM_{10} concentrations when utilizing meteorological data from automated weather systems. Deep learning techniques have remarkably improved indoor gas concentration prediction, particularly CO_2 levels. Hussain et al. (2020) [93] compared conventional models such as k-nearest neighbors with advanced deep learning approaches, precisely long short-term memory (LSTM) networks. Their research revealed that LSTM models achieved 90 % accuracy in real-time forecasting, surpassing the 83 % accuracy of k-NN models. These results highlight the effectiveness of deep learning algorithms in managing dynamic air quality data, which is crucial for maintaining optimal indoor environmental conditions.

The collective evidence from these studies establishes AI as a transformative technology in IAQ prediction and management. AI-based models consistently outperform traditional statistical methods by applying advanced ML algorithms and real-time data analytics. The capacity of AI-based systems to model complex relationships between air quality parameters, with their rapid processing capabilities and robust error tolerance, positions these technologies as essential tools for enhancing indoor environmental quality and

Table 2
Studies using modeling and conventional statistics for IAQ evaluation.

Ref	Configurations	Climate	Period	Input variables	Source of input data	Main finding	Limitations
[80]	School building	Netherlands (Delft University of Technology)	31 Jul; 1 Aug	Building parameters; climatic data; building geometry and layout	CFD simulation	NV strategies can provide comfortable indoor conditions for up to 90 % of occupancy time in high-rise buildings during summer, leading to significant energy savings by reducing the need for traditional MV and air-conditioning systems.	Uncertainties in simulation parameters, lack of consideration for real-world occupant interactions with windows, and a narrow scope focused on a specific building and climate.
[73]	Test room	N/A	N/A	Air change rate; temp; contaminant concentration; velocity; thermal comfort	Measurements and CFD simulations	IJVS (Induction Jet Ventilation System) provides superior air distribution and higher ventilation parameters than traditional systems, especially at higher heat loads	Focus on specific ventilation systems, lack of consideration for a broader range of alternatives, and no in-depth analysis of real-world practicalities and energy efficiency.
[74]	School building	Spain (Andalusia, Seville)	Mid-Sep to mid-Jun; from mid-Jun to mid-Sep	Building characteristics; occupancy schedules; climate data; ventilation system parameters; IAQ parameters (CO_2, temp, HR); energy consumption data; heating system characteristics	Experimental tests and simulations	NV systems in warm-climate school buildings save 18 %–33 % of energy over an academic year while ensuring comfort.	There is no exploration of hybrid solutions for colder or noisy scenarios.
[81]	Residential building	China (Tianjin)	Field tests are on 2–5 weekdays in the fall and winter of 2009.	Indoor temp; RH; CO_2; outdoor parameters; indoor emission sources	Simulation	Novel CO_2 sensor method for real-time AER measurement, accurate in diverse indoor settings, with potential for IAQ and pollutant exposure assessment.	Uncertainties in AER estimation due to inhalation rate variations and using a single-zone measurement technique.
[82]	Housing	Hong Kong	40 years, from 1990 to 2030	Population dynamics; economic factors; housing and transport data; urban land characteristics.	SD simulation	Sustainable land use in Hong Kong requires compact, high-density development based on a comprehensive SD model that considers factors like population, economy, housing, transport, and urban land, with long-term forecasts and policy recommendations.	Simplifying complex parameters and assuming a constant total land area in Hong Kong may not fully capture the region's dynamic urban development.
[83]	N/A	China (Dalian)	50 years and starts from 2000	Population; economic development; vehicle numbers; environmental impact; travel demand; transport supply; traffic congestion.	SD simulation	An SD model analysis recommends restricting the number of vehicles in Dalian to enhance urban transportation sustainability.	In the preliminary nature, there is a need for more accurate variables and parameters, including energy-related aspects, and the development of realistic policy scenarios.

mitigating air pollution impacts.

4.2. ML for real-time IAQ monitoring

Integrating ML techniques has revolutionized the real-time monitoring and prediction of IAQ parameters, enabling building systems to dynamically adjust ventilation, filtration, and other control strategies. These data-driven approaches have demonstrated superior capabilities in modeling the complex, non-linear relationships between various environmental factors and air quality indicators.

ANNs have emerged as a prominent ML technique for IAQ prediction. ANNs excel at uncovering intricate patterns in data, making them well-suited for tasks such as forecasting occupancy behavior and optimizing multi-zone temperature control for thermal comfort [94,95]. The advantage of ANN-based black-box models lies in their ability to model thermal dynamics without explicitly defining zone-specific characteristics like heat capacity and size [96]. More advanced neural network architectures like recurrent neural networks (RNNs) and convolution neural networks (CNNs) have enhanced real-time IAQ prediction capabilities. LSTM, an advanced RNN algorithm, has gained prominence in time-series forecasting due to its ability to mitigate issues like vanishing gradients [97]. CNNs, on the other hand, excel at analyzing spatially distributed data, such as pollutant concentration maps within a building, by applying convolutional filters that capture local patterns [98].

Beyond black-box models, researchers have explored integrating physical insights and domain knowledge to create grey-box ML models for IAQ prediction. Techniques like support vector machines (SVMs), RFs, XGBoost, and ANNs have been augmented with features reflecting the physical relationships between variables, such as the impact of VRs on CO_2 concentrations [99–103]. This hybrid approach allows the models to provide more meaningful insights into the factors driving IAQ while maintaining the flexibility to capture complex, non-linear relationships. The advancement of grey-box models has yielded further improvements in IAQ prediction accuracy. Zhao et al. (2022) [104] demonstrated that using a time-varying versus constant emission rate model significantly reduced errors in predicting household formaldehyde concentrations, requiring fewer specific building details. Rasmussen and Cornelius (2022) [105] developed a theoretical model to maintain acceptable radon levels indoors, while Matheis et al. (2022) [106] modeled SARS-CoV-2 infection risk among travelers in different public transportation scenarios.

Integrating ML techniques with real-time sensor networks and Internet of Things (IoT) technologies has enabled comprehensive IAQ monitoring and control systems development. These systems can effectively track environmental variables, gaseous pollutants, and PM, providing valuable insights into air quality indicators and allowing for the dynamic adjustment of heating, ventilation, and air conditioning (HVAC) configurations to maintain optimal conditions [107–111]. ML-driven IAQ monitoring and prediction advancements have significant implications for addressing sick building syndrome and enhancing occupant health and comfort. By accurately modeling the complex relationships between environmental factors, such as temperature, humidity, and pollutant concentrations, these systems can inform optimized ventilation strategies and control measures to mitigate the adverse effects of poor IAQ [112–114]. Integrating context-aware systems, which leverage user-specific circumstances and build thermal dynamics to deliver tailored services, further enhances the effectiveness of ML-based IAQ management [115,116]. Developing comprehensive air quality indices, such as the Environment Indoor Air Quality Index, which combines IAQI with Humidex, enables real-time monitoring and timely air quality alerts [117]. Table 3 summarizes the studies using AI models for evaluating IAQ.

4.3. Limitation of AI-based models in IAQ control

In the future, thousands or even millions of networked computing devices will exchange information about IAQ, enabling us to reduce exposure to indoor air pollutants through data-driven learning, prediction, and prevention. However, handling this vast amount of data presents new challenges, requiring experienced programmers to harness IoT technologies to benefit people.

While opportunities and advancements in IoT and AI have greatly improved IAQ management and human well-being without human intervention, they also pose societal challenges. The autonomy of IoT and AI components used for IAQ control raises concerns about potential job displacement. With wireless sensors becoming increasingly independent in operating and maintaining indoor air monitoring equipment and making decisions based on pollutant levels, specific work tasks may no longer be required, leading to potential job losses.

Developing an AI management platform for privacy-preserving IAQ control offers promising opportunities to enhance human health and well-being. However, addressing security, privacy, and societal implications is essential to ensure these technologies' responsible and sustainable implementation in indoor environments.

5. Privacy-preserving techniques in AI-based IAQ management

5.1. Overview of smart building/intelligent sensor and data

Buildings rely on various sensors to evaluate IAQ, including those that measure ambient temperature, carbon dioxide concentration, humidity, volatile organic compounds, and PM. These sensors help establish optimal IAQ ranges [135,136]. The IEA EBC Annex 66 project extensively analyzed occupant sensors and highlighted their importance for assessing indoor environmental conditions [137]. The ASHRAE 2019 HVAC Applications Handbook also recognized the growing role of occupant-centric sensing and controls by dedicating a chapter to the topic [138]. These studies demonstrate increasing recognition and integration of occupant sensors for privacy-preserving IAQ management in buildings.

Occupant well-being and productivity strongly relate to IEQ [136,139,140]. Various sensors are strategically used to evaluate IEQ and comprehensively gauge individual occupant satisfaction. Optimizing energy usage, ensuring thermal comfort, and maintaining IAQ require fully understanding occupancy dynamics within indoor spaces [141–143]. Emerging technologies like smart thermostats, intelligent meters, carbon dioxide sensors, and heart rate monitors examine thermal conditions in occupied areas [144–147]. A nuanced understanding of the indoor setting enhances productivity and overall occupant health. Concurrently, analyzing occupant behavioral trends through occupancy sensors facilitates greater energy efficiency [148,149]. Different sensing technologies interact in

Table 3
Studies using AI models for evaluating IAQ.

Ref	Climate	Configuration	Period	Input variable	Sensor type	AI techniques	Main findings	Limitations
[118]	USA (Indiana)	Commercial building	Aug 29-Sep 29 and Nov 14 - Dec 14	Temp; RH; NH_3	Innova 1412 multi-gas model; T-type thermocouple; infrared motion sensor	Adaptive neuro-fuzzy inference system	The study introduces a model for accurately predicting NH_3 concentrations and emissions in a pig room, enhancing environment control strategies in swine production.	Excludes factors affecting ammonia concentrations, such as the impact of different ventilation system configurations.
[119]	Ireland (Dublin)	Office building	Apr–Dec	NO_2; Temp; RH	EPAM 500 Haz-dust monitor, Teledyne M200 monitor	ANN	Developed an ANN-based approach using the PALM model to predict IAQ from outdoor air quality data, with reasonable predictions for indoor NO_2 but limitations in predicting indoor $PM_{2.5}$, requiring detailed indoor and outdoor data for accuracy.	Applicability is restricted to locations with detailed indoor and outdoor air quality data, limiting generalizability across different building types and sites.
[120]	USA (Iowa)	Commercial building	Jan 2003–Apr 2004	NH_3; SO_2; H_2S; CO_2; PM_{10}	Mobile emission laboratory gas sampling System	Radial basis function neural network	Successful application of statistical methods and neural networks to predict daily source air quality in swine deep-pit finishing buildings, with identified vital input variables and promising accuracy in modeling complex, nonlinear relationships.	Focus on swine deep-pit finishing buildings may limit generalizability to other livestock production facilities, and capturing complex and nonlinear air quality relationships remains challenging.
[121]	N/A	3D space	Feb 2016–Apr 2016	$PM_{2.5}$; CO_2; VOCs; Temp; RH; light quantity	SH-300-DS; PMS3003; SHT11; GL5537; MICS-VZ-89	GRU	Developed a deep learning-based IAQ prediction system considering sensor interactions and optimal time-step size.	Sensitive to sensor data quality, limited coverage, challenges in generalizing to diverse indoor environments, and lack of consideration for external factors and hyperparameter tuning.
[122]	USA (Washington State)	School building	N/A	$PM_{2.5}$	Dylos air quality monitor DC1100 Pro and NOVA PM Sensor SDS011	Multilayer Perceptron	It has developed a deep learning-based IAQ prediction system that considers diverse sensor interactions and optimal time-step size determination.	Focus on CO_2 as the single air quality indicator, limited consideration of seasonal and resident-related factors, and need for exploration of different ML models and parameterizations.
[123]	China (Baoding)	Residential building	Nov 15, 2016–Mar 15, 2017	CO_2; $PM_{2.5}$; PM_{10}; Temp; RH; air velocity	TSI 8520; TSI 7515; TSI 8392A	ANN	Developed a real-time ML model (ANN) for accurately predicting indoor airborne culturable fungi concentrations based on IAQ indicators.	Lack of consideration for external factors influencing indoor airborne fungi concentrations restricted to a specific geographical area dataset.
[124]	South Korea (Seoul)	Waiting rooms and underground platforms	Jan–Dec 2009	$PM_{2.5}$; PM_{10}; CO_2; NO_2; CO; NO; Temp; RH	Telemonitoring system	Standard RNN	Effective prediction of indoor $PM_{2.5}$ concentrations and health risks using a GRU neural network structure, surpassing other RNN models.	Further optimization is required for architecture and dynamic hyperparameter tuning, especially regarding long-term dependencies and computational efficiency.

(*continued on next page*)

Table 3 (*continued*)

Ref	Climate	Configuration	Period	Input variable	Sensor type	AI techniques	Main findings	Limitations
[125]	Czech Republic (Ostrava)	Residential building	Winter and Summer, Feb 1, 2013–Sep 21, 2014	CO_2; Temp; RH	Siemens QPA2062 and QAC22 sensors	Decision tree regression method	Introduces a novel decision tree regression method to predict CO_2 levels in a smart home based on temperature and RH measurements with a precision of 46.25 ppm, facilitating monitoring of residents' activities and service optimization.	Lack of thorough consideration of potential challenges and limitations, including the influence of additional factors on CO_2 levels beyond temperature and humidity.
[126]	South Korea (Seoul)	School building	Aug 2020–Jul 2021	Temp; RH; $PM_{1.0}$; $PM_{2.5}$; PM_{10}; and CO_2	DHT-22; plantower's PMS7003; T6713 sensor	ANN	Developed an integrated ANN model for indoor environmental quality in a school, accurately predicting CO_2, PM_{10}, and $PM_{2.5}$ variables and proposing an optimal control algorithm.	Reliance on simulation data without field validation, potential PM spatial variability issues, limited thermal comfort representation, real-world applicability uncertainty, ongoing control algorithm development, and need for error compensation algorithm validation.
[127]	South Korea	Child Daycare Centers	May 2021	CO_2, $PM_{2.5}$, and VOCs	N/A	ANN; LM; Bayesian regularization; Broyden–Fletcher–Goldfarb–Shanno quasi-Newton	ANN models with various training algorithms accurately predict indoor air pollutant concentrations (CO_2, $PM_{2.5}$, VOCs) in child daycare centers, with the LM model performing the best.	Focusing on daycare centers may limit generalization to other indoor environments; investigations of pollutants like CO and PM_{10} were not conducted.
[128]	China	Residential building	Mar 14 -Apr 29, 2020	Temp; RH; CO_2; PM	IoT sensor	N/A	Introduces an intelligent built environment monitor system, allowing accurate continuous monitoring, interactive occupant feedback, and simultaneous collection of subjective and objective IEQ data across multiple buildings.	There is limited discussion of potential biases in occupant voting behavior, and there is a lack of in-depth analysis of long-term operational reliability beyond third-party high-frequency tests under extreme conditions.
[129]	South Korea (Suwon)	Residential building	Aug 2020–Jul 2021	Temp; RH; $PM_{1.0}$; $PM_{2.5}$; PM_{10}; CO_2	DHT-22; PMS7003; T6713		Developed a real-time IoT-based indoor environment monitoring system using Raspberry Pi, facilitating easy IAQ and energy consumption monitoring with the potential for efficient environment control and optimization.	There is a lack of detailed accuracy and reliability analysis of sensor data and no comprehensive evaluation of energy optimization capabilities.
[130]	N/A	Office	Dec 31, 2021–Jan 4, 2022	CO_2; VOC; HCHO; $PM_{2.5}$; PM_{10}	N/A	Fuzzy air quality index	Presents an IoT technology-based IAQ monitoring and control system with various sensors, a novel fuzzy air quality index model, and an adaptive control mechanism, effectively assessing and improving IAQ.	It lacks a comprehensive discussion of the potential challenges and drawbacks of implementing the proposed IoT-based air quality monitoring and control system in real-world scenarios.

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Table 3 (*continued*)

Ref	Climate	Configuration	Period	Input variable	Sensor type	AI techniques	Main findings	Limitations
[131]	N/A	IoT lab	Dec 2019–Mar 2020	NH_3; CO; NO_2; CH_4; CO_2; $PM_{2.5}$; Temp; RH	IoT sensor (GSM/ Wi-Fi)	NN; LSTM	Presents an IoT-based IAQ monitoring and prediction system using ML algorithms, achieving high accuracy in pollutant classification and air quality prediction, emphasizing its relevance in the context of the COVID-19 pandemic.	There are challenges in ubiquitous IAQ assessment with distributed IoT nodes, potential sensor lifespan, calibration issues, and the need for long-term monitoring to capture dynamic indoor air conditions accurately.
[132]	China (Xi'an)	Residential building	Oct 1, 2017–Sep 30, 2018	$PM_{2.5}$; CO_2	IoT sensor (Wi-Fi)		MV is more effective than NV, mainly during winter's severe outdoor pollution, but requires more extended operation for significant improvements. Indoor CO_2 levels correlate with temperature differences. MV can lead to higher CO_2 levels, highlighting the need to manage both pollutants.	Lack of detailed characterization of residents' behaviors, potential influences of building envelope conditions on IAQ, and absence of real-time outdoor pollutant source data.
[133]	UK (Newcastle upon Tyne)	Office building	Nov 1–30, 2020.	CO_2; PM; VOC	IoT sensor (Wi-Fi)	N/A	Successfully developed and validated a low-cost IoT-enabled multimodal device for IEQ monitoring with good inter-sensor reliability, suitable for continuous tracking despite accuracy limitations.	Specific sensor focus, potential variability among units, and lack of general calibration offsets for similar sensors.
[134]	Italy (Apulia Region)	School building	Jan 18 - Feb 8, 2021	CO_2	N/A	N/A	Real-time CO_2 monitoring in classrooms showed that tailored ventilation protocols based on CO_2 levels effectively improved IAQ and reduced SARS-CoV-2 transmission risk, except in cases with structural limitations.	Absence of MV systems, reliance on teachers for window and door openings, and inability to address structural constraints in some classrooms.

buildings to decipher indoor climate characteristics and complex occupancy behaviors.

In the field of building development, there is a significant motivation to enhance the value of buildings. Researchers have highlighted this desire to increase the matter as a driving factor in building development [150]. However, stricter regulations and climate change awareness have shifted focus toward reducing energy usage, a core design requirement in modern buildings [151].

5.2. Introduction to state-of-the-art privacy models

According to the U.S. Energy Information Administration (EIA), significant smart meter deployment occurred in electric utilities by 2015, with 64.7 million units installed and approximately 88 % in residential homes [152]. These intelligent meters provide real-time readings at higher sampling rates, monitoring and recording energy usage at least hourly with daily data collection by utilities. Smart meters range from simple hourly interval recording to advanced bidirectional models transmitting instantaneous data. Similar water and natural gas utility meter trends are expected, though specific EIA statistics are unavailable. However, the widespread adoption of smart meters raises serious privacy concerns. These devices inadvertently reveal detailed household activity information, risking breaches and behavioral profiling. Additionally, advanced analytics could deduce home presence and infer health conditions, posing risks.

Molina-Markham et al. [153] addressed smart meter privacy concerns. They demonstrated complex consumption patterns that are easily extractable from meter data using commercial tools, even without knowledge of household activity. Monitoring three dormitories' energy use every second for two months revealed occupancy and sleep/eating patterns. The proposed system includes a remote utility server, neighborhood gateways, and intelligent home meters for enhanced privacy. Zero-knowledge protocols enable the server to prove possession of concealed customer data factors to gateways/servers while withholding sensitive details [154]. This strategy empowers utilities to achieve goals without compromising customer confidentiality. Apthorpe et al. [155] similarly examined issues. While encryption is robust, they note internet service providers and network observers' ability to deduce household insights from smart home internet traffic studied remedies, including traffic obstruction, tunneling, and shaping. However, outbound communication restriction presents impracticality as it renders devices inoperable. Virtual private networks provide security but not complete privacy.

In the growing digital era, data collection, sharing, and use awareness drive increasing demand for privacy methods [156,157]. This heightened concern has led to the establishment of various privacy laws, such as the European Union's General Data Protection Regulation [158] and India's Digital Personal Protection [159]. These regulations seek to standardize how data is managed and protected, emphasizing the need for privacy in today's digital landscape.

5.3. Edge computing for real-time privacy-preserving IAQ control

The integration of edge computing in IAQ monitoring systems represents a significant advancement in addressing privacy concerns while maintaining operational efficiency. This section explores the multifaceted role of edge computing in enhancing privacy preservation, its technical implementation, and its broader implications for IAQ management.

5.3.1. Paradigm shift: from cloud-centric to edge-centric processing

Traditional cloud-based IAQ monitoring systems have relied heavily on centralized data processing, necessitating the transmission of vast quantities of potentially sensitive information to remote servers. While computationally efficient, this approach raises significant privacy concerns [160]. Edge computing offers a paradigm shift by enabling data processing at or near the source of data generation, thereby minimizing the need for extensive data transmission [161].

The transition to edge-centric processing in IAQ monitoring is particularly crucial given the sensitive nature of the data collected. IAQ sensors often capture information that can inadvertently reveal occupancy patterns, personal habits, and even health-related data of building occupants [162]. By processing this data locally, edge computing significantly reduces the attack surface for potential privacy breaches, aligning with the principles of data minimization outlined in modern privacy regulations such as the General Data Protection Regulation (GDPR) [163].

5.3.2. Technical implementation and challenges

Implementing edge computing in IAQ systems involves deploying computational resources closer to the data sources, typically edge servers or advanced IoT devices. These edge nodes are responsible for data aggregation, preliminary analysis, and decision-making processes traditionally handled by cloud servers [164].

While beneficial for privacy-preserving IAQ management, the transition to edge computing is challenging. One significant limitation is the resource constraints of edge devices, which restrict the complexity of algorithms that can be executed locally. To overcome this, researchers have introduced several optimization techniques. Lightweight ML models have been developed, offering compressed versions of algorithms that can run efficiently on edge devices while maintaining acceptable levels of accuracy [165]. Additionally, adaptive offloading strategies have been proposed, wherein dynamic decision-making algorithms determine whether to process data locally or offload it to the cloud based on data sensitivity, computational demands, and network conditions [166]. Furthermore, distributed learning approaches, such as federated learning, allow for collaborative model training across multiple edge devices without centralizing raw data, thereby enhancing privacy and computational efficiency [167]. These approaches are critical for ensuring the feasibility and effectiveness of edge-based IAQ management systems in real-world applications.

5.3.3. Privacy-preserving techniques in edge-based IAQ systems

Edge computing serves as an enabler for implementing advanced privacy-preserving techniques in IAQ monitoring. Differential privacy, a technique that introduces controlled noise into datasets or query results, prevents the identification of individuals while maintaining the overall statistical utility of the data [168]. In edge-based IAQ systems, differential privacy can be applied at the data collection point, ensuring that individual privacy is protected even if data is transmitted beyond the edge. The application of local differential privacy in edge-based environmental monitoring systems, achieving a balance between data utility and privacy protection [169].

Homomorphic encryption allows computations on encrypted data without decryption, enabling privacy-preserving data analysis [170]. While fully homomorphic encryption remains computationally intensive for edge devices, partial homomorphic encryption schemes have shown promise in IoT environments [171]. In IAQ monitoring, this technique can be used to securely aggregate data from multiple sensors without exposing individual readings.

Secure Multi-Party Computation (SMC) protocols enable multiple parties to jointly compute a function over their inputs while keeping those inputs private. In the context of IAQ monitoring, SMC can facilitate collaborative analysis of air quality data across multiple buildings or zones without sharing raw sensor data [172]. Edge devices can serve as secure computation nodes in these protocols, further enhancing privacy.

5.3.4. Implications for IAQ management and user trust

Adopting edge computing in IAQ monitoring systems has far-reaching implications for performance and user trust. By processing data locally, edge-based systems can provide near-instantaneous responses to changes in air quality, enabling more effective and timely interventions [173]. Local processing also reduces reliance on network connectivity, ensuring continuous monitoring and decision-making even during network disruptions [160].

Furthermore, edge computing empowers users with greater control over their data, aligning with the growing demand for data sovereignty in smart environments [174]. The data minimization approach inherent in edge computing aligns closely with the requirements of privacy regulations such as EU General Data Protection Regulation (GDPR) and California's Consumer Privacy Act (CCPA), simplifying compliance efforts for IAQ system operators.

5.4. Differential privacy in privacy-preserving IAQ management

Differential privacy is a method that protects individual data by ensuring that no single data point significantly influences the results of statistical analysis [175,176]. This approach involves adding controlled noise to datasets, making it difficult to trace information back to individuals while preserving essential characteristics for analysis [177]. Common mechanisms like the Laplace, exponential, and gaussian mechanisms introduce varying noise levels to achieve this [176,178,179]. However, adding noise can diminish the data's accuracy, creating a trade-off between privacy and the quality of analysis [180].

In the context of IAQ, this trade-off becomes particularly challenging. IAQ systems rely on precise data to maintain air quality standards in real-time, and excessive noise could compromise the system's effectiveness. The privacy budget (ϵ), which controls the balance between privacy and utility, needs careful adjustment to avoid degrading IAQ monitoring performance. While differential privacy has proven effective in general applications, its challenges in IAQ management include data usability. In settings where real-time decision-making is critical, such as managing indoor pollutant levels, the randomization introduced by differential privacy can undermine model performance. This issue is exacerbated in federated learning, where many devices contribute data. By adjusting noise distributions, data utility can be preserved while maintaining privacy [181,182]. This approach is crucial for AI-based IAQ systems, which need robust privacy and reliable performance.

In IAQ management, where sensitive data such as occupant behavior and environmental preferences are processed, differential privacy must balance privacy and data accuracy. Overcoming the limitations of data randomization while ensuring accurate IAQ predictions remains a crucial challenge, significantly as privacy concerns grow alongside the adoption of AI-based building management systems.

5.5. Federated learning in privacy-preserving IAQ management

Federated learning has emerged as a prominent area of interest within ML, particularly in rapidly evolving mobile network technologies such as 5G and beyond. Low latency, high data rates, and extensive, intensive connectivity capacity characterize these advanced networks. They are ideally suited to support various devices, including the IoT, wearable technologies, smartphones, and intelligent machines in industrial settings. With the proliferation of these interconnected devices, federated learning has gained significant attention as an extension of distributed ML, facilitating the training of ML and deep learning algorithms directly on the data generated by edge devices such as laptops, smartphones, and IoT systems [183].

The principal advantage of federated learning lies in its ability to move computation closer to the data source, thereby preserving data privacy and reducing the need to transfer data to centralized servers or cloud-based systems. This approach mitigates privacy concerns by keeping sensitive data on local devices and addressing the stringent latency requirements for real-time applications. Federated learning enables decentralized learning, where edge devices perform computations locally and contribute to the training of ML models by updating parameters in a distributed manner without consolidating all data in a single location [183].

As the deployment of smart devices, machines, and IoT systems becomes increasingly widespread, federated learning is expected to enhance the efficiency and privacy of data-driven applications in future mobile network systems. This technology will continue to evolve alongside advancements in 5G and beyond infrastructure, contributing to the broader adoption of privacy-preserving AI solutions, particularly in managing IEQ systems. The ability to perform real-time, distributed learning on edge devices while maintaining data privacy and reducing latency positions federated learning as a critical component of next-generation AI-driven smart environments. However, federated learning enhances privacy in IAQ management, but it faces challenges. Communication overhead from frequent model updates strains networks in large-scale systems. Device and data heterogeneity complicates consistent performance, as varying device capabilities and diverse IAQ data reduce model generalization. Additionally, the privacy-utility trade-off—where added noise for privacy degrades accuracy—poses a challenge, especially for precise IAQ control. Finally, resource limitations on edge devices, such as limited power and processing capacity, hinder scalability and real-time responsiveness. Fig. 5 shows architecture enables federal learning across multiple clients without sharing their raw data, ensuring data privacy while improving the overall model performance.

6. Proposed AI management platform for privacy-preserving IAQ control

6.1. *Design of the AI management platform*

The proposed AI Management Platform for IAQ control implements a comprehensive privacy-preserving framework built upon the SITA (Spatial, Identity, Temporal, and Activity) model. This model gives users granular control over their privacy settings while maintaining system functionality [184]. The platform's architecture integrates IoT sensor networks, edge computing capabilities, and advanced privacy preservation techniques to create a robust IAQ monitoring and control system.

The SITA model addresses the limitations of traditional binary privacy settings by introducing multiple privacy levels for each data dimension. This approach enables users to fine-tune their data-sharing preferences according to specific needs and concerns [185]. The platform classifies all collected data into four primary dimensions: spatial data (location information), identity data (personal details), temporal data (timing of activities), and activity data (behavioral patterns and preferences). Each dimension can be assigned a privacy level ranging from zero (complete privacy) to four (unrestricted access), allowing for precise control over data sharing while maintaining essential system functionality.

As Fig. 6 illustrates, we employed the SITA model to add privacy levels to the original data. Data will first be collected from multiple sensors and aggregated in the original dataset. This data undergoes SITA transformation based on a consistent SITA configuration. The exact configuration applies across all user data and entries to isolate and analyze each SITA dimension's impact on IAQ predictive performance. The SITA transformation produces a private dataset with enhanced security against privacy attacks suitable for ML-based prediction model creation. This method highlights IoT automation potential, where the SITA model seamlessly transforms incoming data during assimilation into a dataset. The data manager accesses only the resultant private dataset. Implications of this privacy model on intelligent building data, especially IAQ forecasting, are discussed within the context of data ownership and enhanced privacy. However, this advancement reduces data utility, potentially affecting predictive model precision from the modified dataset.

6.2. *Operating principles of the platform*

The platform follows a structured workflow that begins with data acquisition through distributed IoT sensors measuring various IAQ parameters, including temperature, humidity, CO_2 levels, and PM concentrations [186]. The collected data undergoes initial processing at the edge devices, where the SITA transformation is applied based on predetermined privacy configurations. This edge-first approach significantly reduces privacy risks by implementing privacy preservation measures before data transmission.

The system employs a sophisticated data processing pipeline that aggregates sensor data into a comprehensive dataset while

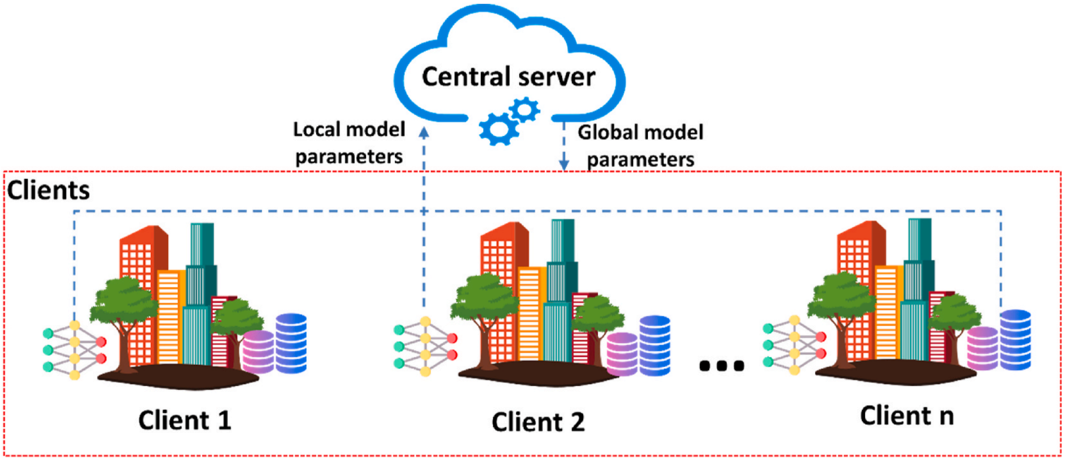

Fig. 5. The architecture of horizontal federal learning.

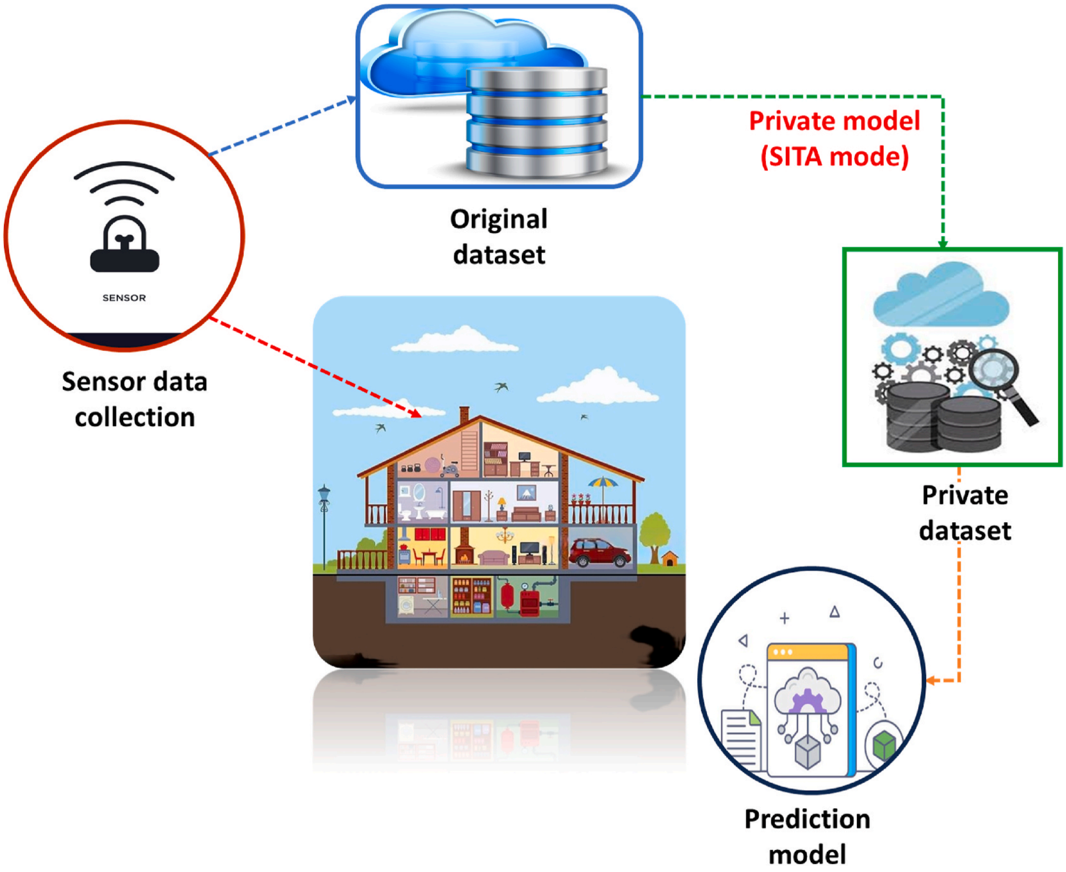

Fig. 6. Proposed privacy model use for AIQ prediction.

maintaining consistency with user-defined privacy preferences machines [185]. The SITA-driven transformation process applies uniform privacy settings across all datasets, ensuring standardized privacy protection while preserving the data's utility for analysis. This transformed dataset is the foundation for developing predictive models using ML techniques, including neural networks and SVMs [185].

The experimental protocol encompasses several phases, which we will elucidate in subsequent sections in Fig. 7. AI Platform Design and Development: The AI platform is meticulously designed and developed in this initial phase. It comprises hardware and software components carefully engineered to work harmoniously. The hardware includes IoT sensor devices strategically placed to collect vital data, while the software is tailored to process this data efficiently. Data Collection and Analysis: The next step is data collection and analysis once the AI platform is in place. IoT sensor devices are installed throughout the indoor environment to monitor various parameters related to air quality, such as pollutant levels, temperature, and humidity. External weather datasets are also incorporated into the analysis to provide a comprehensive view of the indoor environment. The collected data is then analyzed using advanced algorithms and ML techniques to derive meaningful insights into IAQ trends and potential issues. User Interface Development: A user-friendly interface is a crucial component of the AI management platform. A user interface is developed during this step to provide building occupants access to real-time IAQ information. This interface lets users view air quality metrics, receive alerts, and make informed environmental decisions. It is designed with simplicity and ease of use to ensure occupants can interact with the system effortlessly. Evaluation: The final step involves evaluating the entire system. This assessment aims to determine the effectiveness of the AI management platform in maintaining IAQ while respecting user privacy. Key performance indicators are monitored, and the system's ability to provide accurate and timely information to users is assessed. Any adjustments or improvements are identified during this phase to ensure the platform operates optimally.

6.3. *Practical implementation and application*

The implementation protocol for the proposed AI-driven IAQ management platform encompasses several key phases, including platform design, development, and integration with existing building management systems (BMS). The hardware infrastructure consists of strategically placed IoT sensor devices for continuous data collection, while the software components handle data processing, real-time analytics, and privacy preservation through advanced AI techniques. Building occupants can access IAQ information

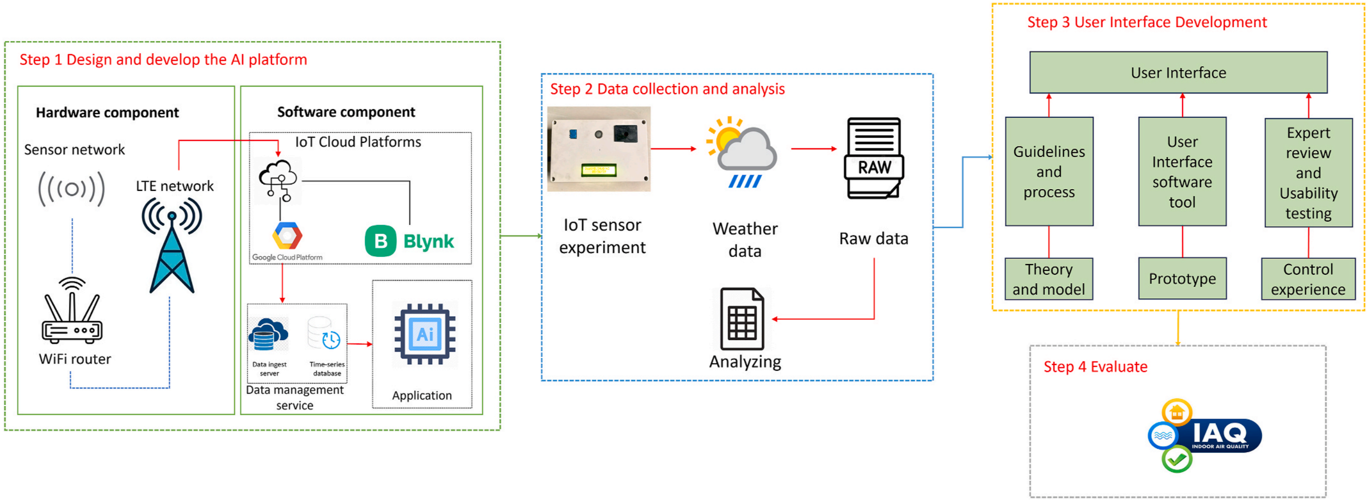

Fig. 7. Ai management platform for privacy-preserving IAQ control.

in real-time via a user-friendly interface that respects their privacy preferences, leveraging the SITA model's customizable controls.

Users customize their privacy settings by assigning a SITA level to each dimension and determining how data is shared with the application. For example, users might configure their settings as Spatial: 1, Identity: 4, Temporal: 2, and Activity: 3. The application would receive limited spatial data, full access to identity data, partially shared temporal data, and aggregated activity data [185]. Four numbers represent this configuration method, each corresponding to a specific dimension's privacy level. For instance, configuration "1423″ indicates spatial data, identity, temporal, and activity. The SITA model offers a user-focused and customizable approach to privacy management, meeting the contemporary demand for greater control over personal data in digital environments. By balancing simplicity with flexibility, the model addresses user needs and complies with regulatory requirements, fostering trust in data-driven applications.

The integration of edge computing capabilities enhances the platform's functionality by processing sensitive data locally, reducing the need for data transmission to external servers and thereby mitigating privacy risks. This localized data processing improves privacy protection and allows for more responsive IAQ monitoring and control, as the system can analyze incoming sensor data and make adjustments in real-time.

The practical implementation of the platform in real-world buildings involves integration with existing BMS and IoT networks, enabling real-time data collection and control of indoor environmental quality. The system's scalability makes it applicable to various building types, including residential, commercial, and healthcare environments, each with unique privacy and air quality demands. For instance, the system allows occupants to optimize IAQ without exposing sensitive personal data in residential buildings. The platform ensures comfort and privacy in commercial settings, such as offices, enhancing productivity while maintaining regulatory compliance. The system provides continuous IAQ monitoring and control in healthcare facilities, improving air quality while safeguarding patient confidentiality.

Although the platform offers significant advantages, several challenges must be addressed to ensure smooth deployment. The cost of IoT sensor installation and BMS upgrades may pose initial barriers, though these are expected to decrease as technology becomes more widespread. Additionally, AI models' scalability and ability to maintain energy efficiency while optimizing IAQ across large and complex buildings remains a crucial consideration. Training building operators to manage and maintain the platform is also essential for ensuring its long-term success.

The platform's effectiveness is evaluated by monitoring key performance indicators (KPIs) such as IAQ levels, system responsiveness, and user satisfaction regarding privacy settings. The platform's success is measured by its ability to provide accurate, timely information while adhering to users' privacy preferences. By balancing the demands of privacy, performance, and scalability, the system demonstrates the viability of privacy-preserving AI approaches in practical IAQ management applications.

7. Conclusion

This review has explored the critical role of AI-based solutions in advancing privacy-preserving IAQ management, offering a comprehensive evaluation of emerging technologies that enhance air quality control and data privacy. The essential contribution of this article lies in its holistic approach to integrating AI with privacy-preserving techniques, addressing a significant gap in current IAQ management practices. While traditional IAQ methods have provided foundational insights, they often fail to address the privacy concerns and computational inefficiencies inherent in real-time data processing systems.

This article contributes to the identification and comparative analysis of promising AI-based techniques, such as federated learning and edge computing, for IAQ management. This article demonstrates the potential of these technologies to improve real-time air quality monitoring and outlines their practical implications for balancing performance, scalability, and privacy. By processing data locally and reducing the reliance on centralized data collection, these methods offer new pathways for secure, scalable, and efficient IAQ management in diverse building environments. Another contribution is the study's emphasis on the trade-offs between privacy and performance. This issue is particularly relevant in the growing adoption of AI in building management systems. This article offers a framework for navigating these trade-offs, providing a clear roadmap for implementing AI-driven solutions that do not compromise data privacy while achieving accurate and timely IAQ control.

To advance AI-based, privacy-preserving IAQ management, it is important to develop lightweight AI models that address edge devices' computational limitations while optimizing prediction accuracy and privacy protection. Future research should focus on improving the scalability and efficiency of federated learning systems to ensure they can handle non-uniform data from diverse building environments. Moreover, there is a need to refine advanced privacy-preserving algorithms, such as differential privacy and homomorphic encryption, specifically for IAQ applications. These algorithms must effectively balance privacy concerns with the need for accurate and reliable IAQ predictions, particularly in sensitive environments like healthcare and commercial buildings.

In addition to these technological advancements, establishing comprehensive regulatory frameworks and best practices is essential. Ensuring AI-driven IAQ systems comply with privacy regulations such as the European Union General Data Protection Regulation and California's Consumer Privacy Act will foster trust and encourage broader adoption. Collaborative efforts between researchers, developers, and policymakers will be critical to defining guidelines that address performance and privacy in real-world applications.

CRediT authorship contribution statement

Tran Van Quang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dat Tien Doan:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Jack Ngarambe:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Ali Ghaffarianhoseini:** Writing – review & editing, Writing – original draft, Validation, Investigation. **Amirhosein Ghaffarianhoseini:** Writing – review & editing, Writing – original draft, Validation, Investigation. **Tongrui Zhang:** Writing – review & editing, Writing – original draft, Validation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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