Improving Health Through Indoor Environmental Quality Monitoring: A Review of Data-Driven Models and Smart Sensor Innovations

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Abstract. An important factor affecting building inhabitants' comfort, well-being, and productivity is the quality of the indoor environment. There is a lot of promise in using artificial intelligence to manage environmental quality. AI offers a more effective and proactive method of improving indoor air quality and occupant well-being by predicting, monitoring, and regulating thermal comfort levels and lowering indoor pollution. The present study reviews recent scientific work on monitoring and improving indoor environmental quality (IEQ), focusing on the use of statistical learning models and smart sensor technology. Machine learning has been shown to effectively detect office occupancy using environmental measurements, improving energy efficiency and occupant comfort. Other research has successfully reconstructed indoor temperature profiles, essential for optimizing heating, ventilation and air-conditioning systems. Comprehensive reviews of air quality modeling in urban environments focus on the integration of advanced modeling techniques into urban planning. Studies on smart sensors for real-time monitoring of indoor air quality (IAQ) in various types of buildings demonstrate their potential for improving IAQ and thermal comfort. These studies underline the importance of data-driven approaches and intelligent systems in meeting the challenges of indoor environmental quality management. Future research should focus on integrating these technologies into intelligent building systems to improve energy efficiency, air quality and occupant comfort. Numerous cutting-edge deep learning techniques, including convolutional neural networks (CNNs), long short-term memory networks (LSTMs), decision trees (DTs), support vector machines (SVMs), artificial neural networks (ANNs), and deep neural networks (DNNs), are incorporated into the hybrid framework. Combining these methods improves the framework's capacity to precisely process and examine intricate patterns of data.

1 Introduction

John McCarthy initially used the term artificial intelligence (AI) in 1956 to refer to the ability of computers to perform tasks that ordinarily require human intelligence. Artificial intelligence uses computer programs that mimic human behavior to simulate human cognitive processes. Massive data sets and powerful processing power are necessary, though, for AI to reach its full potential. Large datasets have been essential to AI's recent success, even though technological breakthroughs have played a significant role. Large-scale data organization and evaluation now require AI-driven software solutions, which enable complex decision-making processes that often exceed human capacity. The amount of data generated these days exceeds what humans can quickly and effectively process. Because of this, artificial intelligence (AI) is now important in many different fields, almost all of which stand to benefit from this revolutionary technology [1].

Yang (2024) [2] focused on the application of AI-powered wearable devices in sports health monitoring. These advanced devices, equipped with sophisticated sensors, collect real-time data on key physiological metrics like heart rate, body temperature, and movement patterns. By leveraging AI algorithms, the collected data is processed to provide immediate feedback and insights, aiding in injury prevention, performance optimization, and overall health management for athletes. This research highlights the growing importance of integrating technology with sports science to enhance athletic performance and safeguard athlete health.

Gao, (2024) [3] Investigated how to improve the accuracy and effectiveness of tracking and evaluating human movements in sports and health by using AI-based picture recognition algorithms. These algorithms provide immediate feedback by precisely identifying and assessing physical actions based on the processing of visual input. This approach looks closely at movement patterns and physical conditions in an effort to improve general health management, reduce the risk of injury, and improve athletic performance.

Indoor environmental quality (IEQ) is vital to building occupants' comfort, productivity, and well-being. The importance of optimizing indoor conditions has grown as individuals spend more and more time indoors. The emergence of cutting-edge technology, such as machine learning models and smart sensors, presents new possibilities for tracking and enhancing IEQ in a variety of building types.

Innovative techniques for improving indoor air quality (IAQ), managing thermal comfort, and maximizing energy use in buildings have been the subject of recent studies.. Through the application of data-driven techniques and intelligent systems, scientists hope to develop more accurate and efficient indoor environmental control solutions. This review presents a number

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of important studies that demonstrate the latest developments and possible uses of these technologies in this field.

Bakht et al (2022) [4] presented a hybrid CNN-LSTM-DNN framework, comparing its performance with that of leading deep learning methods, including RNNs (LSTM (Long Short-Term Memory) and Bi-LSTM), CNNs, and DNNs. Metrics like mean absolute error (MAE) and root mean square error (RMSE) were used to gauge performance., and R^2. The study focuses on improving predictive monitoring of PM2.5, aiming to support the creation of early warning systems and enhance ventilation control to maintain sustainable indoor air quality on subway platforms.

Candanedo and Feldheim (2016) [5] used light, temperature, humidity, and CO_2 data to study the use of statistical learning models for occupancy detection in office settings. Their findings show how energy efficiency and building automation systems can be enhanced by machine learning. The study looked at the application of models developed in the open-source R program, including Random Forest (RF), Gradient Boosting Machines (GBM), Linear Discriminant Analysis (LDA), and Classification and Regression Trees (CART). To our knowledge, there has never yet been any documentation in the scientific literature regarding the utilization and efficacy of RF, GBM, and LDA models for occupancy detection.

Next, using data-driven models, Candanedo et al. (2018) [6] focused on reconstructing indoor temperature measurements. Reconstructing temperatures accurately is essential for improving heating, ventilation, and air conditioning (HVAC) systems and evaluating building performance.

A thorough analysis of São Paulo, Brazil's air quality modeling, was carried out by Gavidia-Calderón et al. (2024) [7]. Their research emphasizes how modern modeling methods must be integrated with urban planning in order to successfully manage air pollution challenges.

Qabbal and colleagues have conducted extensive research on smart sensor technology for indoor air quality (IAQ) monitoring. Their studies cover various aspects of IAQ management and provide valuable insights into the potential of smart sensors for improving indoor environments**:**

1. Smart Sensor Applications in Tertiary Buildings: Qabbal et al., (2012) [8] examined the use of smart sensors connected to a Raspberry Pi for real-time IAQ measurements in a tertiary building. Their study demonstrated the feasibility of using low-cost, smart sensor technology to continuously monitor IAQ parameters, enabling more effective control of the indoor environment.

2. Retrofitted University Buildings: The most recent work by Qabbal et al., (2022) [9] involved assessing IAQ and thermal comfort in a retrofitted university building. Utilizing low-cost smart sensors, they conducted a comprehensive evaluation of the building's indoor environment. This study emphasized the practicality and benefits of deploying smart sensors in existing buildings to enhance IAQ and occupant comfort.

These studies illustrate significant advancements in smart sensor technology for IAQ monitoring. The research underscores the importance of real-time data collection and analysis in effectively managing indoor environments.

2 Background information

Advancements in indoor environmental quality (IEQ) monitoring have been significantly influ-enced by data-driven models and smart sensor technologies. This review synthesizes recent lit-erature, highlighting the integration of IoT systems, machine learning, and innovative sensor technologies to enhance IEQ management.

2.1 Smart Sensor Technologies

• Passive Infrared Sensors (PIR): These sensors are pivotal for occupancy monitoring, offering cost-effective and privacy-conscious solutions. They facilitate energy efficiency and user com-fort in smart buildings by accurately detecting occupancy patterns by Shokrollahi et al. (2024) [10].
• Indoor Air Quality (IAQ) Sensors: IoT-based IAQ platforms have emerged, providing reliable monitoring capabilities. However, only 9.1% of these platforms currently utilize data-driven models for effective IAQ management by Dai et al. (2023) [11].

2.2 Data-Driven Models

Machine Learning Applications: The application of machine learning techniques in smart buildings has shown promise in optimizing ventilation and enhancing occupant comfort. These models can predict IAQ and inform control strategies for ventilation systems by Aldakheel et al. (2023) [12].

2.3 Related Works

The literature indicates a growing trend towards integrating smart technologies in building man-agement systems, emphasizing the need for real-time monitoring and occupant-centric ap-proaches to improve IEQ by Wiryasaputra et al. (2023) [13] and Aldakheel et al. (2023) [12].
While advancements in sensor technologies and data-driven models are promising, challenges remain in their widespread implementation and integration into existing systems. Future research should focus on enhancing these technologies to create more effective and user-friendly IEQ monitoring solutions.

3 Occupancy modeling previous work

To differentiate between weekday and weekend trends and give time series data for energy models, a stochastic occupancy model was developed using survey data [14]. Through the use of Bayesian statistics, a later model that integrated CO_2 sensors, passive infrared sensors, and video cameras was able to reduce inaccuracy from 70% to 11% [15].

Two models for occupancy prediction were presented [16]. One used camera data and applied a multivariate Gaussian distribution, while the other model simulated movement using an agent-based model (ABM). Additionally, a graphical model for multi-zone buildings was developed, and the impacts of data noise on room occupancy were assessed using an agent-based model [17, 18].

A dynamic occupancy model based on temperature, ventilation, and CO_2 levels outperformed previous techniques such as support vector machines and neural networks, achieving 88% accuracy [19]. Online access is provided for the experimental data.

Energy Plus was able to incorporate occupancy models with wireless sensor networks and cameras, which showed promise for large yearly energy savings.

Table 1. Models, parameters and reported accuracies for occupancy detection.

Source	Classification Models Employed	Sensors/Parameters	Accuracy For Occupancy
[20]	Hidden markov models, Neural networks, Support Vector Machines (SVM)	CO_2 inside room CO_2 outside room	NA
[21]	Latent dirichlet allocation	PIR	NA
[22]	Decision Trees (DT)	CO_2, computer current, light, PIR, sound	Ranging from 81% to 98.441% (only PIR) Only light: 81.01% Only sound: 90.78% Only CO_2: 94.68%
[23]	Radial basis function neural network	Lighting, sound, Reed sensor, CO_2, temperature, RH, PIR	Note: Accuracy for number of occupants 63.23–66.43%
[24]	Artificial Neural Networks (MATLAB and WEKA [25])	CO_2, sound, relative humidity, air temperature, computer temperature, PIR	Note: Accuracy for number of occupants 70.4–72.37%
[26]	Artificial Neural Networks (WEKA)	Temperature, humidity, light, Volatile Organic Compounds (VOCs), CO_2	Note: Accuracy for number of occupants 67–69%
[27]	K-nearest neighbors, Linear regression, and artificial neural networks	PIR, Thermal array sensor	NA
[28]	Support Vector machine (SVM), K-nearest neighbor (KNN), Thresholding	Electric power consumption (W)	59–90%
[29]	Support Vector machine (SVM), k-nearest neighbor (KNN), Artificial Neural Network (ANN), naïve Bayesian (NB), tree augmented naïve Bayes network (TAN), decision tree (DT). Used WEKA.	CO_2, Reed sensor (for door), relative humidity, temperature, light, sound, PIR	88.9–98.2%For DT algorithms in two rooms: CO_2: 66.36–89.86% Light: 58.88–69.52% T: 55.26–65.32% CO_2 and T: 69.15–89.12%

4 Hybrid CNN-LSTM framework for predicting indoor air quality in subways

Two types of data were used in this study's Yeongtong station measurements: indoor partic-ulate detection utilizing a GRIMM aerosol spectrometer and ambient data from the Air-Korea website. Using 31 channels to measure aerosol particles from 0.25 µm to 32 µm, the Model 11-A spectrometer was used to track the real-time PM concentration.

5 Innovations in smart sensor technology for IAQ management

5.1 Applications of Smart Sensors development in Various Building Types

The purpose of this study is to assess the demonstration building's indoor air quality (IAQ) and comfort. It looks at how well the ventilation system handles high CO_2 levels in classrooms. To assess a variety of pollutants and comfort parameters, including formaldehyde, benzene, CO_2, VOCs, CO, $PM_{2.5}$, humidity, temperature, noise, and brightness, a smart sensor was designed. Building managers can be informed in real time about any problems with the heating, cooling, or ventilation systems via this sensor. Mapping IAQ and comfort levels, locating pollution hotspots, maximizing ventilation for improved air quality, and increasing energy efficiency to boost occupant productivity are some of the goals of the study.

6 Optimizing HVAC systems: reconstruction of indoor temperature

The Random Forest model's ability to predict interior temperature depends critically on wind speed, pressure, and total electrical energy. Depending on other models (like neural networks and support vector machines), the relative importance of these factors may vary. Complete datasets provide less skewed statistics when compared to datasets with missing values, which primarily affect the summer months and slightly raise median room temperatures. The study finds that internal gains significantly affect the temperature of the well-insulated passive house; the laundry room, with its large electrical equipment, has the highest median temperature. Higher solar gain management is required since living room temperatures have been observed to climb as high as 30.8°C and expected to reach as high as 32.8°C. In the workplace, the lowest temperature ever recorded was 14.9°C.

7 Emissions used in air quality

7.1 Ozone

We used the formula 1 ppb = 1.96 µg m−3 to convert units to ppb in order to assess the effectiveness of the model. Emery et al. (2017) [30] reported that every study surpassed the R > 0.75 threshold for the Pearson correlation coefficient, meaning that all research satisfied the standard. Out of all the simulations, seven accomplished the criterion for normalized mean bias (NMB) at less than 15%, but only two reached the benchmark for normalized mean error (NME) at less than 25%. With R values between 0.62 and 0.93, MB values between −18 ppb and 12 ppb, and RMSE between 7.7 and 27.1 ppb, the median mean bias (MB) was almost zero (see Fig. 1a to e). Seasonal variations did not affect performance. For the O_3 modeling, cut-offs of 40 ppb and 60 ppb were utilized by Peralta et al. (2023) [31] and Martins and Andrade (2008b) [32] for the spring and summer, respectively.

7.2 PM2.5

Nine research out of eleven on $PM_{2.5}$ provided performance measures. Out of these, only two met the R criteria (R > 0.7). Two of the NMB values (±30%) met the criteria set by Emery et al. (2017) [30]. The values varied from 4.30% to 50.60%. A single study met the criteria (<50%), with NME values ranging from 40.44% to 68.94%. The MB values varied from -32.2 to 76.4 µg m−3, the R values from 0.19 to 0.73, and the RMSE values from 3.8 to 35 µg m−3 (see Fig. 1f to h). Seasons did not affect performance. Incomplete emission data, ambiguities surrounding the generation of secondary organic aerosol (SOA), old CETESB data, and the absence of SOA precursors all contribute to the underestimation of $PM_{2.5}$ (Vara-Vela et al., 2018) [33].

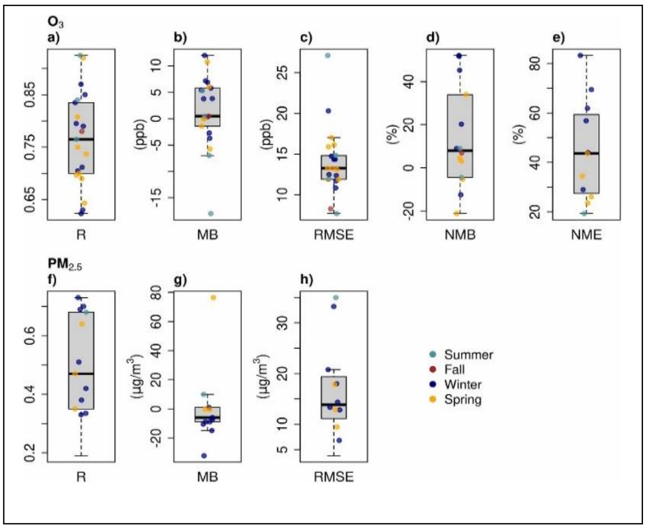

Fig. 1. Distribution of air quality model performance statistics. Pearson correlation (R), Mean bias (MB), Root mean square error (RMSE), Normalized mean bias (NMB), and Normalized Mean Error (NME).

8 Application of human health embedded intelligent monitoring system based on artificial intelligence and sports analysis

The WHMSHAR platform evaluates AI-based wearable sensors in sports health monitoring. It features a portable terminal for collecting real-time data, a smartphone for data analysis and personalized feedback, and a background server for data storage and aggregation. This setup demonstrates the platform's potential to enhance health monitoring and personalized recommendations in sports [2].

8.1 Simulation of Algorithms

To identify running and walking activities, a simple classification algorithm was employed. Two algorithms, JuhaParkka and D.M. Karantonis, were tested on a mobile device for comparative analysis.

9 Simulation and analysis of motion trajectory recognition in multimedia visual images

In order to assess athletes' postures, motions, and general physical state, deep learning algorithms and pattern recognition technologies are used. Health advice and guidance tailored to each individual are made possible by this analysis. The findings show that these techniques are accurate in identifying and evaluating the physical conditions of athletes, providing customized guidance that increases training efficiency, protects against injuries, and raises the caliber and quantity of athletic performance [3].

9.1 Design of Simulation Models

Joint simulation analysis is essential in multi-body dynamics and control systems, with ADAMS and MATLAB being key tools. ADAMS provides detailed mechanical dynamics analysis, including performance prediction and load calculations. This paper suggests using ADAMS in conjunction with MATLAB to validate predictive models and enhance future experimental platform design.

10 Conclusion

This study highlights recent advancements in improving Indoor Environmental Quality (IEQ) through artificial intelligence models and smart sensors. By focusing on transdisciplinary approaches, method classification, and performance evaluation, this review identifies research gaps and opportunities. We hope these perspectives will guide the future integration of these technologies into smart building systems for more effective and sustainable solutions.

The AirQo sensor kit represents a major step forward in affordable air quality monitoring. These sensors provide real-time data, allowing for immediate responses to pollution and targeted health interventions. Their accessibility supports community involvement and advocacy for cleaner air. The successful deployment of the AirQo sensor kit in various environments demonstrates its potential to enhance global air quality management, highlighting the need for ongoing innovation in monitoring technologies to improve public health and environmental sustainability.

The integration of artificial intelligence (AI) in industrial robotics and wearable health monitoring systems is driving significant advancements. In industry, AI optimizes robotic motion control and object detection through sophisticated algorithms, enhancing manufacturing efficiency. Meanwhile, AI-powered wearable devices in sports and health monitoring use sensor technology to provide real-time insights into movement and physiological data, improving athletic performance and health management. These developments highlight AI's growing role in both industrial automation and personalized health, promising continued innovation and expanded capabilities in the future.

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