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Designing an indoor air quality system to ensure occupational health in Mexico

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Abstract. Air pollution in Mexico represents a significant public health concern, particularly in indoor environments where pollutant concentrations may reach critical levels. Urban growth, vehicular activity, and industrial emissions contribute to indoor exposure to carbon dioxide (CO_2), volatile organic compounds (VOCs), and particulate matter (PM2.5 and PM10), which have been associated with adverse health effects. Previous studies have documented outcomes such as fatigue, drowsiness, cardiovascular alterations linked to elevated CO_2 levels, central nervous system impairments from prolonged VOC exposure, and respiratory diseases related to particulate matter. In this context, this paper defines a technical proposal for monitoring indoor environments in Mexico through a systematic literature review and experimentation with data scenarios from Morelos and Puebla. These elements represent initial steps toward the development of an indoor air quality system for the Mexican context. The proposal integrates engineering-based indicators, health impact analysis, and data-driven experimentation to identify environmental risk conditions. It also considers continuous monitoring, data analysis, and risk forecasting as core components for the early detection of hazardous indoor conditions. Designed as a flexible and scalable approach, the proposed system may be adapted to residential, educational, and office settings, as well as future local infrastructure deployments. Overall, this work provides a technical foundation for designing an indoor air quality monitoring system aimed at supporting healthier indoor environments in Mexico.

Resumen La contaminación del aire en México representa un importante problema de salud pública, especialmente en ambientes interiores donde las concentraciones de contaminantes pueden alcanzar niveles críticos. El crecimiento urbano, la actividad vehicular y las emisiones industriales contribuyen a la exposición en interiores al dióxido de carbono (CO_2), los compuestos orgánicos volátiles (COV) y las partículas (PM2.5 y PM10), los cuales se han asociado con efectos adversos para la salud. Estudios previos han documentado consecuencias como fatiga, somnolencia, alteraciones cardiovasculares vinculadas a niveles elevados de CO_2, deterioro del sistema nervioso central por exposición prolongada a COV y enfermedades respiratorias relacionadas con las partículas. En este contexto, este documento define una propuesta técnica para el monitoreo de ambientes interiores en México mediante una revisión sistemática de la literatura y experimentación con escenarios de datos de Morelos y Puebla. Estos elementos representan los primeros pasos hacia el desarrollo de un sistema de calidad del aire interior para el contexto mexicano. La propuesta integra indicadores basados en ingeniería, análisis de impacto en la salud y experimentación basada en datos para identificar condiciones de riesgo ambiental. Asimismo, considera el monitoreo continuo, el análisis de datos y la predicción de riesgos como componentes esenciales para la detección temprana de condiciones peligrosas en interiores. Diseñado como un enfoque flexible y escalable, el sistema propuesto puede adaptarse a entornos residenciales, educativos y de oficina, así como a futuras implementaciones de infraestructura local. En general, este trabajo proporciona una base técnica para el diseño de un sistema de monitoreo de la calidad del aire interior, con el objetivo de promover ambientes interiores más saludables en México.

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Keywords: Air Quality, Air Pollutants, Public Health, Internet of Things, Machine Learning

1 Introduction

Air quality has become a critical problem in Mexico, with both environmental and public health implications. Fast urban growth, the increase in the vehicle fleet, and industrial emissions have intensified the concentration of pollutants, affecting the quality of life of large segments of the population.

As will be discussed in later sections, several related studies have been conducted in other countries; however, their findings vary according to local environmental conditions and patterns of human activity.

Although intelligent HVAC systems, smart air filters, and automated ventilation and air-conditioning solutions have been developed, these technologies often involve high costs and have mainly been validated in the contexts for which they were designed. This leaves a relevant research gap in countries where similar studies remain limited, as the conditions required to ensure indoor air quality may differ significantly.

Studies [1], [2], [3] and [4] evaluated the risks associated with various air pollutants, including carbon dioxide (CO_2), total volatile organic compounds (TVOCs), and particulate matter (PM2.5 and PM10). These pollutants can be found at both acceptable and potentially hazardous levels, making it necessary to monitor these indicators in indoor environments to ensure the physical health of individuals who work and live in them.

These studies confirmed that it is feasible to forecast pollutants using regression machine learning algorithms, with CO_2 being the most complex variable to describe and forecast; a cloud computing implementation is feasible for all variables, in addition to the monitoring system, to predict the increase of pollutants to levels harmful to health, with the challenge being to determine these levels at a global risk level.

In the study [5] quantitative indicators were defined to assess the risk of respiratory diseases using an engineering approach, considering environmental variables and analytical models. This information was analyzed with the support of experts in the fields of medicine, environmental engineering, and civil engineering to evaluate the feasibility of implementing a system to assess indoor air quality in Mexico.

Table 1 shows the risk levels associated with the presence of CO_2 in parts per million described in [6] and [7], those for PM2.5 and PM10 in micrograms per cubic meter described for Mexico in [8], and the values for TVOC which are defined in parts per billion in [9] and [10], and in micrograms per cubic centimeter in [11].

Table 1: Risk level indicators of indoor air quality pollutants

Risk Level	**CO_2 (ppm)**	**PM2.5 (µg/m³)**	**PM10 (µg/m³)**	**TVOC (ppb)**	**TVOC (µg/m³)**
Low	250-800	0-25	0-50	0-65	0-100
Moderate	801-1,000	26-45	51-75	66-220	101-300
High	1,001-2,000	46-80	76-155	221-660	301-1,000
Very High	2,001-5,000	81-147	156-235	661-2,200	1,0001-3,000

These indicators were analyzed to determine the use of fuzzy logic functions in the study [12], and through the conversion of tabular data to images for the application of computer vision algorithms in the study [13], confirming that there is a correlation between these values and the perceived air quality in indoor environments in Mexico.

Due to its ease of deployment and low computational demand, fuzzy logic is the most feasible option for implementing indoor air quality forecasting in Mexico. This is supported by the study's results and its replicability, which will be described below using another test dataset. Graphical representation for deep learning algorithms is an explored option that could be implemented in future work with greater availability of high-power computing resources.

This work gathers and revisits the findings reported in previous studies in order to support the development of a methodological and technical proposal for an indoor air quality monitoring system in Mexico. This proposal is based on a systematic literature review and is also approached from a medical perspective, reviewed with medical experts, to delve deeper into the topic of risk criteria and the feasibility of implementing a solution for assessing indoor air quality risk in Mexican indoor environments. This is achieved through an analysis of the hazards posed by concentrations of CO_2, TVOC, PM2.5, and PM10, thus providing a more detailed view of the health risks these pollutants represent and offering a context for implementing best practices to ensure well-being while in indoor environments in Mexico.

This paper is organized as follows: in “Impact of Analyzed Pollutants on Health”, the previous research on selected indoor air pollutants is described, and what is their impact on the health of the human body of the exposed occupants, giving a context about the consequences of the sick building syndrome; “Literature Review” describes the research on previous data science studies on indoor air quality assessment, summarizing what has already been studied; in “Proposed Solution” the methodology of indoor air quality monitoring and assessment is presented, as the result of studies [3], [5] and [12]; “Discussion” reflects on the results obtained; “Conclusions” list the findings of the research; “Limitations” sates the time constraints and context of the study; finally “Future Works” describes the future directions of the project of implementing a commercial indoor air quality methodology and monitoring system for Mexico.

2 Impact of analyzed pollutants on health

The effects associated with three key pollutants selected for this project with prior research [5] and also corroborated through the literature review described later in this chapter, to determine risk in indoor environments—carbon dioxide (CO_2), total volatile organic compounds (TVOCs), and particulate matter (PM)—will be described below, based on a literature review conducted in collaboration with physicians specializing in cardiology and pulmonology.

This analysis aims to highlight the importance of understanding how these pollutants interact with the human body, affecting critical systems and generating risks that must be mitigated through environmental control and monitoring strategies.

Additionally, this analysis indirectly supports the feasibility of implementing indoor air quality monitoring and control strategies. Beyond improving comfort, ensuring adequate air quality in indoor environments can help prevent health risks that may result in the interruption or cancellation of daily, academic, or work-related activities due to discomfort and associated symptoms.

In the long term, these effects may also lead occupants to significant financial expenses related to medical consultations, treatments, or the management of diseases associated with prolonged exposure to poor indoor air conditions.

2.1 Carbon dioxide

CO_2 is a colorless, odorless, and non-flammable gas composed of one carbon atom bonded to two oxygen atoms by double bonds. According to [14] this compound occurs naturally in the atmosphere and plays essential roles in processes such as photosynthesis and the maintenance of the carbon cycle. However, human activities such as deforestation and the burning of fossil fuels have led to a considerable increase in its atmospheric levels in recent decades. Furthermore, CO_2 has widespread industrial use due to its abundance, chemical stability, and low toxicity, as described in [15].

Table 2 below describes the effects of CO_2 on human health, noting that, in addition to being the most important pollutant, as defined in the study [3], and in addition to directly affecting occupants of indoor environments, its constant generation has medium-term effects on the environment, affecting human health.

Table 2: Effects of CO_2 on human health

Study	Described effects
[16],[17]	High concentrations of CO_2 indoors affect health, comfort and mental performance; symptoms range from drowsiness and fatigue to complex cardiovascular diseases; a persistent challenge in Latin America due to emissions and a lack of binding legislation.
[18],[19],[20]	CO_2 in concentrations of 2% to 10% causes dizziness, nausea, headaches, and mental confusion; risk of asphyxiation at levels of 10%; negative effects in poorly ventilated spaces such as lack of concentration and headaches.
[21]	It is mentioned that despite not being toxic like carbon monoxide, the increase in CO_2 concentrations in the atmosphere related to climate change; potential increase of global temperatures between 2 and 3°C; exacerbation of heat waves; indirectly causing the spread of diseases such as dengue [22] and malaria [23].
[24],[25],[26]	Starting at 1000 ppm of CO_2, there is a decrease in cognitive abilities, fatigue, and a reduction in academic and work performance.
[27]	Reduction of cerebral metabolic rate of oxygen ($CMRO_2$) by 13.4% ± 2.3%

2.2 Volatile organic compounds

Volatile organic compounds (VOCs) are a mixture of chemical substances present in the air, generated by various sources such as cleaning products, industrial processes, and vehicle emissions.

Their concentrations have been linked to aquifer contamination, according to [28], as well as the use of LP gas, solvents, and vehicle emissions, negatively affecting urban air quality, as described in [29].

Globally, as mentioned in study [30], VOCs have been recognized as a crucial indicator for assessing indoor air pollution and its impacts on the health and comfort of occupants.

Table 3 below describes the effects of volatile organic compounds on human health.

Table 3: Effects of volatile organic compounds on human health

Study	Described effects
[31],[32],[33]	Adverse effects of VOCs: irritation of the eyes, nose, and throat; headaches; long-term effects include damage to the liver, kidneys, and central nervous system.
[34]	Occupational exposure to VOCs: neurotoxicity and damage to the reproductive system.
[35], [36]	Environmental impact of VOCs: they contribute to the destruction of the ozone layer; formation of tropospheric ozone and photochemical smog; and exacerbation of respiratory problems in urban areas.

2.3 Particulate Matter

Particulate matter (PM), composed of suspended solid and liquid particles, is classified according to its size as PM10 and PM2.5.

These particles, originating from natural and human sources, can penetrate the respiratory system, causing respiratory and cardiovascular diseases [37], as well as contributing to climate change and altering atmospheric processes [38].

Due to its relationship with vehicle emissions [39], its presence is usually greater in urban areas; moreover, in the specific case of Mexico, it contains high levels of heavy metals [40].

Table 4 below describes the effects of particulate matter on human health, taking into account, in addition to the consequences listed by government organizations such as [41], observations from more recent studies, which include epidemiological and dermatological problems.

Table 4: Effects of particulate matter on human health

Study	Described effects
[41]	Irritation of the eyes, nose, and throat; headaches, loss of coordination, and nausea; damage to the liver, kidneys, and central nervous system. It is suspected of being a cause of cancer. Exposure causes the following symptoms: conjunctival irritation, discomfort in the nose and throat, headache, allergic skin reaction, dyspnea, decreased serum cholinesterase levels, nausea, vomiting, epistaxis, fatigue, and dizziness.
[42]	Increased viral infections in children: influenza, respiratory syncytial virus (RSV), and colds.
[43], [44]	Skin effects: tanning and premature aging; inflammatory diseases such as atopic dermatitis, acne, and various allergic reactions.
[45]	Multiplicative pulmonary inflammation, vascular remodeling, and fibrosis.

3 Literature Review

This section describes the systematic literature review conducted using various sources, with the objective of identifying the current state of research related to indoor air quality and the technological solutions applied for its assessment and control.

The main purpose was to generate the knowledge from the methodologies applied from the Internet of Things (IoT) and big data perspective on indoor air quality assessment in other countries, focusing on answering the following research questions.

Q01. How can a comprehensive process for collecting, processing, and analyzing data be designed and implemented to evaluate the risk of contagion of respiratory diseases in different areas?

Q02. What are the key characteristics and hidden patterns in the datasets that could indicate a higher risk of respiratory disease transmission, in an area, and how can a predictive model be developed based on these findings?

Q03. How can the optimal population sample size be determined and appropriate sampling techniques selected to ensure the validity and reliability of data analyses on the risk of contagion of respiratory diseases such as COVID-19 in enclosed spaces?

Q04. How can an efficient and secure data storage infrastructure be designed and implemented that is capable of handling large volumes of data related to the risk analysis of respiratory diseases?

Q05. What are the most effective interventions for mitigating the risk of transmission of respiratory diseases once it has been identified, and how can their effectiveness be evaluated through data analysis?

Q06. How can data collection mechanisms be designed and optimized to maximize the quality and usefulness of the data collected for analyzing the risks of transmission of respiratory diseases?

Q07. What advanced analytical methods and data analysis tools can be applied to improve the ability to predict and manage the risks of transmission of respiratory diseases?

The review included the environmental parameters considered, paradigms or technologies applied, main challenges identified for monitoring, characteristics of hazardous environments in terms of air quality, and storage technologies used in the systems studied. This organization allowed for a comprehensive understanding of existing approaches, as well as methodological trends in both measurement and data analysis.

The Systematic Literature Review methodology, described in [46], was used to develop the state of the art. This methodology aims to identify, evaluate, and combine evidence from primary studies according to acceptance criteria for inclusion within the theoretical framework.

The online tool Parsifal, available in [47], was used to analyze articles from various sources.

The different stages of the systematic literature review will be presented below.

3.1 Planning

Prior to the systematic literature review, the objective was to gather information for the implementation of a model for acquiring and storing environmental data to analyze conditions that increase the risk of respiratory disease transmission.

This stage was carried out by defining research questions and objectives, thereby generating a search strategy to locate the documents to be reviewed.

The planning phase defined the objective as determining the risk level of cardiovascular, neurological, and pulmonary diseases, as well as the transmission of respiratory diseases in enclosed university environments.

3.2 Keywords

The keywords selected for the study are the following: “Machine Learning”, “Data Analysis”, “Monitoring Variables”, “Respiratory Disease Prevention”, “Data Cleansing”, “Information Technologies”, “Indoor Air Quality”, “Sick Building Syndrome”.

3.3 Search String

The search string is a fundamental tool in a systematic literature review, as it allows for the precise and comprehensive identification of studies relevant to the research topic.

The search string is constructed from the research questions and objectives set forth in the review and consists of a series of terms and keywords that help identify relevant studies. These terms and keywords are carefully selected to include all possible variations that may be used in the literature and are grouped into different thematic categories to facilitate the search.

The search string used is as follows:

(“COVID” OR “Covid transmission” OR “Sick Building” OR “Respiratory Disease”) AND (“Big Data” OR “Data Analysis” OR “Machine Learning”) AND (“Data cleansing” OR “Monitoring”) AND (“Information Technologies” OR “IoT”)

3.4 Importing Studies

Using the previously described search string, the following sites were searched and studies were imported.

Table 5 shows the number of studies imported.

Table 5: Imported studies for each source

Source	Imported Studies
ACM	142
Bibliotecas UPAEP	16
EBSCO host Research Database	10
Google	57
IEEEXplorer	39
Springer	73
Scopus	81

3.5 Inclusion Criteria

The inclusion criteria are the conditions a study must meet to be considered for inclusion in the systematic review. Their purpose is to define what type of information is relevant to the research objective, ensuring that the selected works are aligned with the topic and contribute useful elements to the analysis.

The selected criteria are as follows:

I. Articles on data analysis of respiratory disease transmission risks.

II. Articles on environmental monitoring to determine biosafety risks.

Studies meeting at least one of the acceptance criteria and not meeting any of the exclusion criteria were considered accepted.

3.6 Exclusion Criteria

Exclusion criteria are the conditions that allow us to discard studies that will not be part of the systematic review.

Their function is to eliminate information that does not fit the purpose of the study, whether due to lack of relevance to the topic, unavailability, low methodological quality, or because it does not contribute significant evidence to the final analysis.

I. Articles with unavailable text

II. Articles outside the scope of the study

III. Medical articles

IV. Articles published before 2018

V. Duplicate studies

VI. Secondary or tertiary studies

VII. Articles in languages other than English or Spanish

Using these criteria, it was possible to select the articles focused on the objective of obtaining the theoretical framework for the development of data storage and processing implementations for defining risk environments.

3.7 Data Collection

For data collection, articles were read, and the content, consistency, and relevance were ensured using polytomous questions.

I. Is the article related to the topic?

II. Does the article mention data scenarios that represent a risk of contagion from respiratory diseases?

III. Does the article present IoT integration in the analysis of respiratory disease risk in enclosed environments?

IV. Does the article present tests performed to determine the risk of contagion and the expected and obtained results?

V. Is the article relevant to the topic?

VI. Does the article mention the data structures for storing and querying information about the tests performed?

VII. Does the article mention data analysis tools?

The questions were answered for each article with the possible responses of Yes (score 1), Partially (score 0.5), and No (score 0).

A minimum score of 4.5 was established for an article to be considered.

3.8 Data Extraction

For those articles that met the criteria, the following information was extracted:

I. Authors

II. Year of publication

III. Country of publication

IV. Environmental parameters considered

V. Devices used

VI. Paradigms/technologies used

VII. Main challenges for monitoring

VIII. Proposed solution

IX. Characteristics of the environment conducive to contagion

X. Definition of risk level

XI. Storage technologies used

3.9 Results of the Systematic Literature Review

As shown in Figure 1 below, fifty-six articles directly related to the research topic were filtered out: the application of machine learning and the Internet of Things to define the risk of contagion of respiratory diseases in enclosed environments. This confirms that there is an area of research that has not yet been explored.

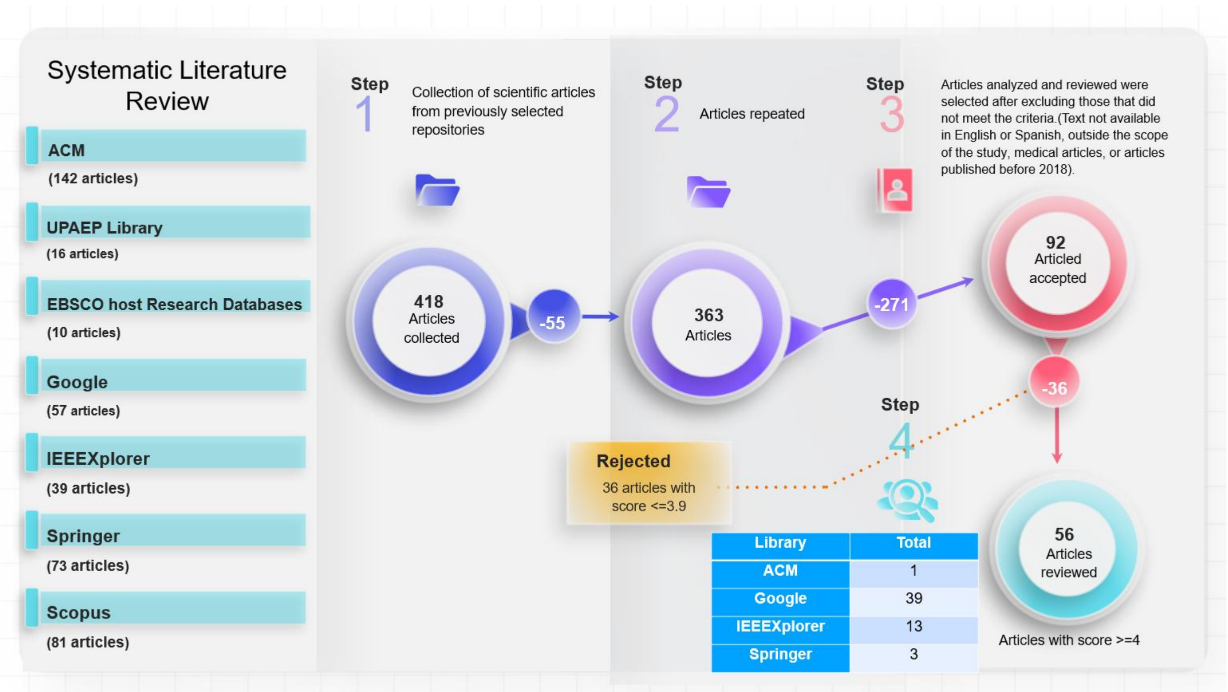

Figure 1. Systematic Literature Review Results

Using the methodology, 56 articles were selected from four main sources (ACM, Google, IEEEXplorer, and Springer), which are listed separately by source in Table 6.

Table 6: Selected studies for each source

Source	Selected Studies	Total of Selected Studies
ACM	[48]	1
Google	[49][50][51][52][53][54][55][56][57][58][59][60][61][62][63][64][65][66][67][68][69][70][71][72][73][74][75][76][77][78][79][80][81][82][83][84][85][86][87]	39
IEEEXplorer	[88][89][90][91][92][93][94][95][96][97][98][99][100]	13
Springer	[101][102][103]	3

3.10 Research Questions

Using the consulted information, preliminary answers were analyzed for the research questions described in the objectives. These answers are not definitive; however, they provide a guide for the development of the experiments during the execution of the research.

The answers, according to the literature review, are as follows:

Q01. How can a comprehensive process for collecting, processing, and analyzing data be designed and implemented to evaluate the risk of contagion of respiratory diseases in different areas?

In all sources, an IoT system was used to collect data directly from sensors.

The use of surveys or web-based data acquisition was not found in the literature; the analysis was performed solely considering the data obtained from measurements.

We found different answers in the literature regarding the variables used. Table 7 lists the variables used below.

Table 7: Environmental variables described in literature

Source	Selected Studies
Carbon dioxide (CO_2)	[48][50][54][59][64][65][67][68][69][70][72][77][78][80][81][90][93][94][96][99]
Nitrogen dioxide (NO2)	[50][61][69][74][93]
Carbon monoxide (CO)	[50][69][70][78][81][89][93][94][97]
Particulate matter (PM)	[48][50][51][57][62][68][69][70][73][78][81][86][88][91][93][94][96][97][99][102]
Ozone (O3)	[50][78][81]
Total volatile organic compounds (TVOCs)	[48][53][70][71][81][96][99]
Air quality index (determined by measuring instrument)	[49][52][55][56][58][60][66][75][76][79][82][83][87][92][98][100][101][103]
Temperature	[68][70][81][82][89][97][99]
Relative humidity	[63][70][81][82][89][97][99]

Q02. What are the key characteristics and hidden patterns in the datasets that could indicate a higher risk of respiratory disease transmission, in an area, and how can a predictive model be developed based on these findings?

All the articles mention using air quality indices for the presence of pollutants as part of the solution. Six main approaches were found: linear regression, use of time series, recurrent neural networks, use of neural network technologies, nearest neighbor analysis, statistical analysis, and continuous monitoring without forecasting; these are found in the consulted sources, as can be seen in Table 8.

Table 8: Machine learning algorithms and scopes applied in literature

Algorithm or Scope	Studies
Regression algorithms	[52][57][59][75][81][99]
Time series	[48][49][51][60][68][69][81][88][92][95][96][97][99][100]
Neural networks	[49][51][54][55][56][61][65][69][72][77][85][88][89][95][98]
Next neighbor analysis	[74][75][87][99]
Statistical analysis	[53][58][66][76][83][91]
Continuous monitoring	[50][63][67][70][71][73][78][82][93]

The analysis found an area of opportunity with new technologies, such as Kolmogorov-Arnold networks ([104]) which were previously used only in study [79], fuzzy logic ([105]) which was applied in studies [88] and [90]; and finally the extended version of the long and short-term memory algorithms ([106]), which, being a technology developed in 2024, with libraries recently published.

Q03. How can the optimal population sample size be determined and appropriate sampling techniques selected to ensure the validity and reliability of data analyses on the risk of contagion of respiratory diseases in enclosed spaces?

The studies were conducted in enclosed spaces such as bedrooms and living rooms, with populations ranging from 1 to 20 people. It is proposed that tests be carried out with varying numbers of people to verify the correlation between the number of people and the potential risk.

Q04. How can an efficient and secure data storage infrastructure be designed and implemented that is capable of handling large volumes of data related to the risk analysis of respiratory diseases?

The studies used various infrastructures and storage mechanisms; the use of relational database models and distributed infrastructures with monitoring systems and web platforms is highlighted.

Q05. What are the most effective interventions for mitigating the risk of transmission of respiratory once it has been identified, and how can their effectiveness be evaluated through data analysis?

Studies mention the importance of ventilating enclosed spaces, social distancing, and leaving the space once it becomes dangerous.

Q06. How can data collection mechanisms be designed and optimized to maximize the quality and usefulness of the data collected for analyzing the risks of transmission of respiratory diseases like COVID-19?

There are various solutions, including using microcontroller circuits and readily available development boards. It is worth noting that [93], [97], and [103] used Arduino and commercial sensor kits for data acquisition.

Q07. What advanced analytical methods and data analysis tools can be applied to improve the ability to predict and manage the risks of transmission of respiratory diseases?

In all articles, real-time analysis was performed by comparing values within ranges, either at the back end of the measurement reception system, or within the device itself.

3.11 Theoretical link with the research objectives

Based on a review of the literature and findings reported in previous studies, it was determined that the most relevant indoor air pollutants are carbon dioxide (CO_2), particulate matter (PM2.5 and PM10), and total volatile organic compounds (TVOCs), which have been established as the main indicators of indoor air quality in the previous study [107]. Ozone, hydrogen dioxide, and carbon monoxide will not be considered in this experiment, as the study will focus on indoor environments without industrial activity.

It was confirmed that, according to the search conducted, no other research in Mexico has focused on defining indoor air quality using prediction techniques based on artificial intelligence or machine learning. This represents an important area of opportunity for the development of new knowledge, both with traditional algorithms —linear regression, random forest and gradient boosting machines (GBM)— and with emerging approaches —Kolmogorov-Arnold Networks (KAN), extended LSTM (xLSTM) and fuzzy logic—.

4 Proposed Solution

The proposed solution is an Internet of Things (IoT)–based solution combined with machine learning techniques in a big data platform, for the monitoring and analysis of indoor air quality. The selection of variables considered in the system was primarily supported by the findings of the literature review, which identified the most relevant environmental and operational factors influencing indoor pollutant behavior. Additionally, this selection was further validated by the successful implementation and experimental results reported in previous studies [1], [2], [3], [4], and [13], which demonstrated the effectiveness of these variables for modeling, prediction, and risk assessment in indoor environments.

The variables fall into two groups:

I. Input variables: temperature (°C), relative humidity (%), population density (people per cubic meter), door status (open or closed), natural ventilation (active or inactive), and normal or mechanical ventilation (active or inactive).

II. Output variables: CO_2 (ppm), PM2.5 (µg/m^3), PM10 (µg/m^3), and TVOC (ppb).

Measurements of the environmental values (relative humidity and temperature) and the output pollutant values (CO_2, PM2.5, PM10, and TVOC) are proposed in intervals of five minutes. Room occupation, and ventilation variables are proposed to be obtained from logs, or inputs given by the users in a web interface or mobile application.

The first tests integrated the IAQM-128W 8-in-1 Wi-Fi Air Quality Monitor sensor described in [108] incorporating the library for UART integration with the computer. The first option features internal data storage and export functionality via proprietary software compatible up to Windows 10.

Other tests utilized the Carefor CF-20 Air Quality Detector for CO_2, PM2.5, PM10, TVOC, HCHO, AQI, Temp, Humidity with Data Report ([109]), which stores data internally in comma-separated values (CSV) format and allows direct export via USB connection.

After those concept tests, an IoT system is proposed, using the Databot sensor described in [110] and the PMS5003 particulate matter sensor, described in [111], integrated with an Internet of Things system using a Raspberry Pi development board. This import system was implemented as part of the project, for the study [3], with an estimated cost below USD 500, making it a comparatively low-cost alternative for indoor air quality monitoring, while other methods exist to verify data authenticity from different sources.

Following the preliminary analysis, a technical solution was defined for the execution of machine learning models and their integration as services to be consumed by the monitoring system, which was implemented using the Apache Spark Big Data technology ([112]). This platform enables the processing of large volumes of data through distributed computing schemes, facilitating efficient model execution in scalable environments. At this stage, Random Forest and Gradient-Boosted Tree models were implemented, selected for their ability to handle multiple variables and capture non-linear relationships in complex indoor scenarios. These models were also considered as a foundation for future implementations; specifically, for the CO_2 case, the use of advanced techniques such as time series analysis with recurrent neural networks (RNNs) and Kolmogorov–Arnold networks is envisioned to further improve temporal modeling and predictive performance.

The software versions used were Java 8 and Apache Spark 3.4.0. For this implementation, a distributed architecture based on a Hadoop cluster was employed, consisting of three machines running Ubuntu 20.04 LTS (Focal Fossa): one configured as the Master Node and two as Slave Nodes. Each machine was equipped with 8 GB of RAM, an Intel Core i7 processor, and 1 TB of storage, operating in a distributed manner through the HDFS file system and the YARN parallel execution framework.

The experiment involved loading data through a symbolic link to a storage server using Minio technology ([113]), an open-source and self-hosted alternative compatible with the Amazon Web Services S3 API. This approach made it possible to emulate a data ingestion workflow similar to those used in cloud computing environments. The experiment was executed through a web browser using the Hadoop web interface, accessed remotely from a laptop via the Mozilla Firefox browser.

Building on the results of this experiment, an architectural approach is proposed for deployment in buildings and local indoor environments such as residential spaces and offices, without requiring leased cloud infrastructure. The self-hosted and modular nature of the evaluated components enables the system to be implemented on local servers or embedded computing platforms, operating entirely within a local area network.

Figure 2 presents the local architecture diagram used for model execution and integration with the monitoring system.

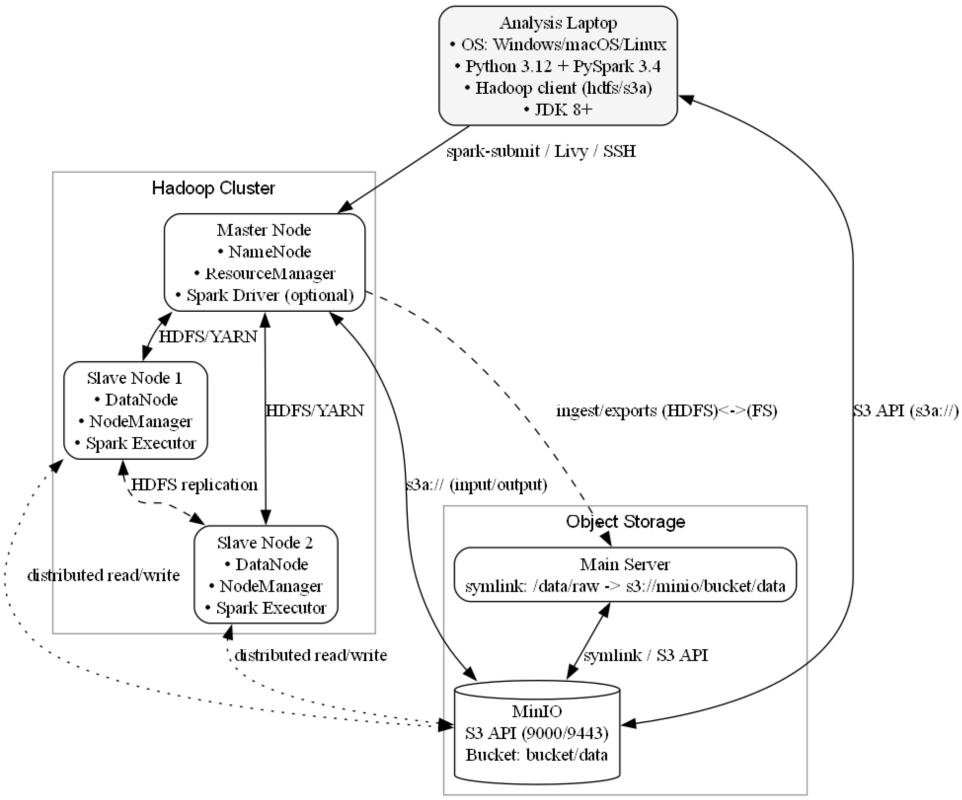

Figure 2. Proposed architecture

The workflow of this architecture encompasses an implemented process for data integration, processing, and validation, enabling the use of the models in real time. This workflow also includes a continuous model re-evaluation stage triggered by the arrival of new data, allowing forecasts to be progressively refined and improved. The sequence begins with a connection to the MinIO storage service, where data are accessed through a symbolic link hosted on a master server that redirects to the MinIO bucket, effectively simulating a cloud storage environment within a local infrastructure.

Data loading is performed through the PySpark interface to access files in CSV format. The processed results are subsequently stored in the cluster's HDFS using a partitioned Parquet format, optimizing query performance and data management. Based on these datasets, forecasting is performed using the machine learning models associated with each pollutant, enabling the identification of potential risk scenarios related to indoor air quality in the evaluated environment. In addition to real-time forecasting, the workflow also considers periodic model retraining as new data become available, allowing the models to adapt to changing indoor conditions and improve their predictive accuracy over time.

In order to operationalize the proposed models and facilitate their integration into real-world applications, this work proposes exposing the analytical capabilities through a REST-based service architecture. This approach enables the deployment of the described infrastructure either on a dedicated on-premises server or using cloud computing technologies, allowing flexibility in terms of scalability, availability, and maintenance. In alignment with the findings of the literature review, data storage is proposed using a relational database schema, structured around time-stamped measurements associated with specific indoor locations. This design supports traceability, efficient querying, and longitudinal analysis of environmental conditions, which are essential for monitoring trends and assessing evolving risk scenarios.

These services are intended to be consumed by a web-based platform that leverages modern digital technologies to provide an accessible and user-oriented interface. In the medium term, the platform is envisioned to support end users by delivering notifications related to potential indoor air quality risks, along with real-time recommendations aimed at mitigating adverse exposure scenarios.

Using the data acquisition system previously described, a dataset was generated to support the experimental analysis of indoor air quality conditions.

The dataset consists of 135,371 records and includes environmental, occupancy, ventilation, and pollutant-related variables. Specifically, the monitored variables include temperature, humidity, people density, normal ventilation, natural ventilation, door status, CO_2, PM2.5, PM10, TVOC.

Figure 3 show the distribution of each variable in the last dataset, which includes the measurements of previous studies in this project, and new ones of the same locations in the Mexican states of Puebla and Morelos.

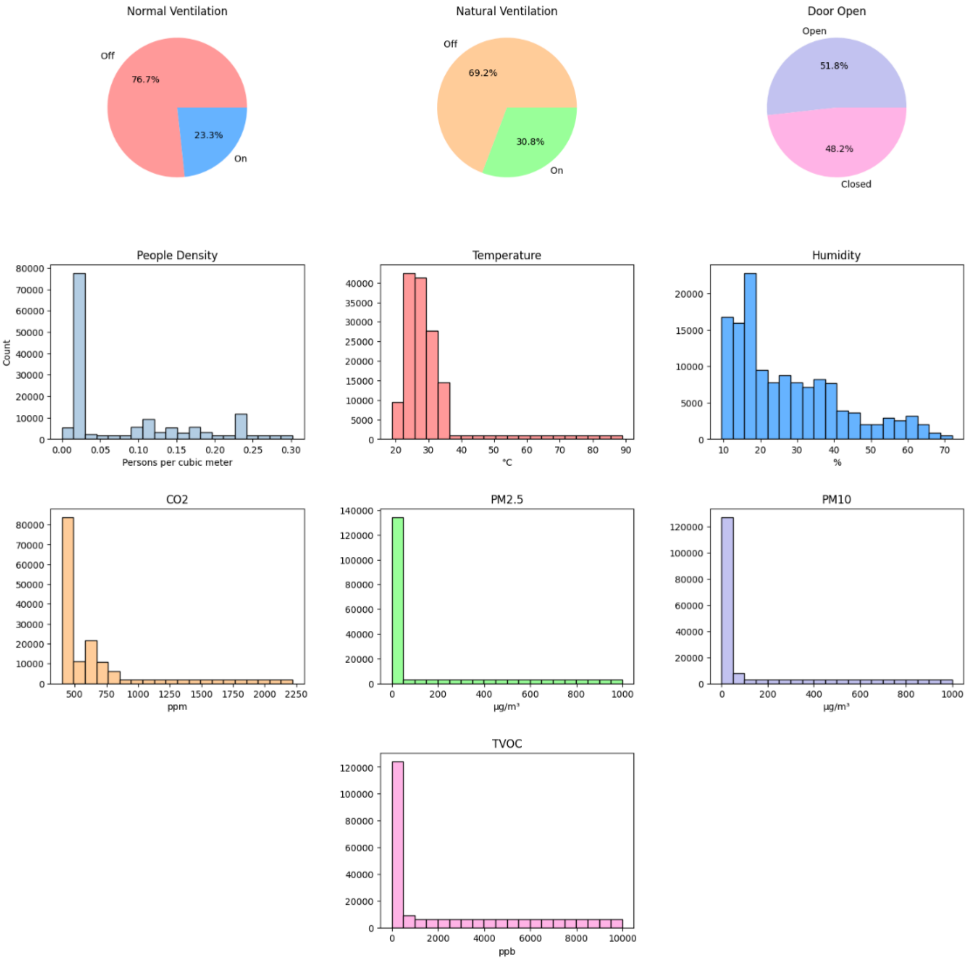

Figure 3. Dataset Distribution

Table 9 describes the locations the measurements took place, with their volume in cubic meters, used for the people density calculation for Machine Learning models. These variations in indoor volume allowed the dataset to represent different spatial conditions, occupancy scenarios, and ventilation contexts.

Table 9: Measurement Locations

Location	Volume in Cubic Meters
Classrooms of the University Computing Center	157.95
Microbiology Laboratory	200
Medicine Laboratory	200
Bioengineering Laboratory	157.5
Biology Laboratory	225
Classroom located in the University Computing Center	80
Classroom located in the University Computing Center	157.95
Office of the Faculty of Engineering	13.249
Room located in Puebla	27.6
Room located in Morelos	53.76

Machine Learning algorithms implemented with Spark were replicated. For this stage, the dataset was divided into training and validation subsets, using 80% of the dataset for model training, and 20% of the data for. The selected output variables were CO_2, PM2.5, PM10, and TVOC, while the remaining variables in the dataset were used as input features.

The replicated experiments considered Random Forest and Gradient Boosting Machine models to estimate each pollutant independently. Model performance was evaluated using common regression metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and the coefficient of determination (R^2), as displayed in Table 10.

Table 10: Model Training Results

Evaluation Metric	CO_2 (ppm)		PM2.5 (μg/m³)		PM10 (μg/m³)		TVOC (ppb)	
	RF	GBM	RF	GBM	RF	GBM	RF	GBM
MAE	24.7030	29.8854	4.6321	5.1677	6.5136	4.9113	35.0180	39.6130
RMSE	47.8651	51.4498	7.2472	7.6253	9.7738	12.9697	54.5967	58.4256
MSE	2291.0703	2647.0874	52.5226	58.1455	95.5281	168.2142	2980.8002	3413.5562
R2	0.847	0.823	0.792	0.759	0.729	0.614	0.8777	0.8310

These results show that the use of a larger data volume contributed to improving the perceived performance of the models, particularly for CO_2. In previous experiments with fewer records, CO_2 had been identified as one of the most difficult variables to describe due to its variability and its sensitivity to occupancy, ventilation conditions, and indoor dynamics.

However, with the expanded dataset, the models achieved a better representation of CO_2 behavior, suggesting that the inclusion of more observations and scenarios improved the learning process and the predictive capacity for this pollutant.

In the case of PM2.5 and PM10 the results suggest that a broader range of indoor scenarios was incorporated into the analysis. Although these variables remain complex due to their dependence on environmental conditions, ventilation patterns, and possible external or activity-related sources, the expanded dataset provides a more robust basis for repeated experimentation.

Building on the previous experimental results, the prediction outputs are integrated into a fuzzy logic-based risk assessment module.

The implemented algorithm evaluates the estimated or measured concentrations of CO_2, TVOC, PM2.5, and PM10 through the fuzzy membership functions defined in study [12], classifying each pollutant into linguistic risk levels: low, moderate, high, or very high. Figure 4 shows the described membership functions.

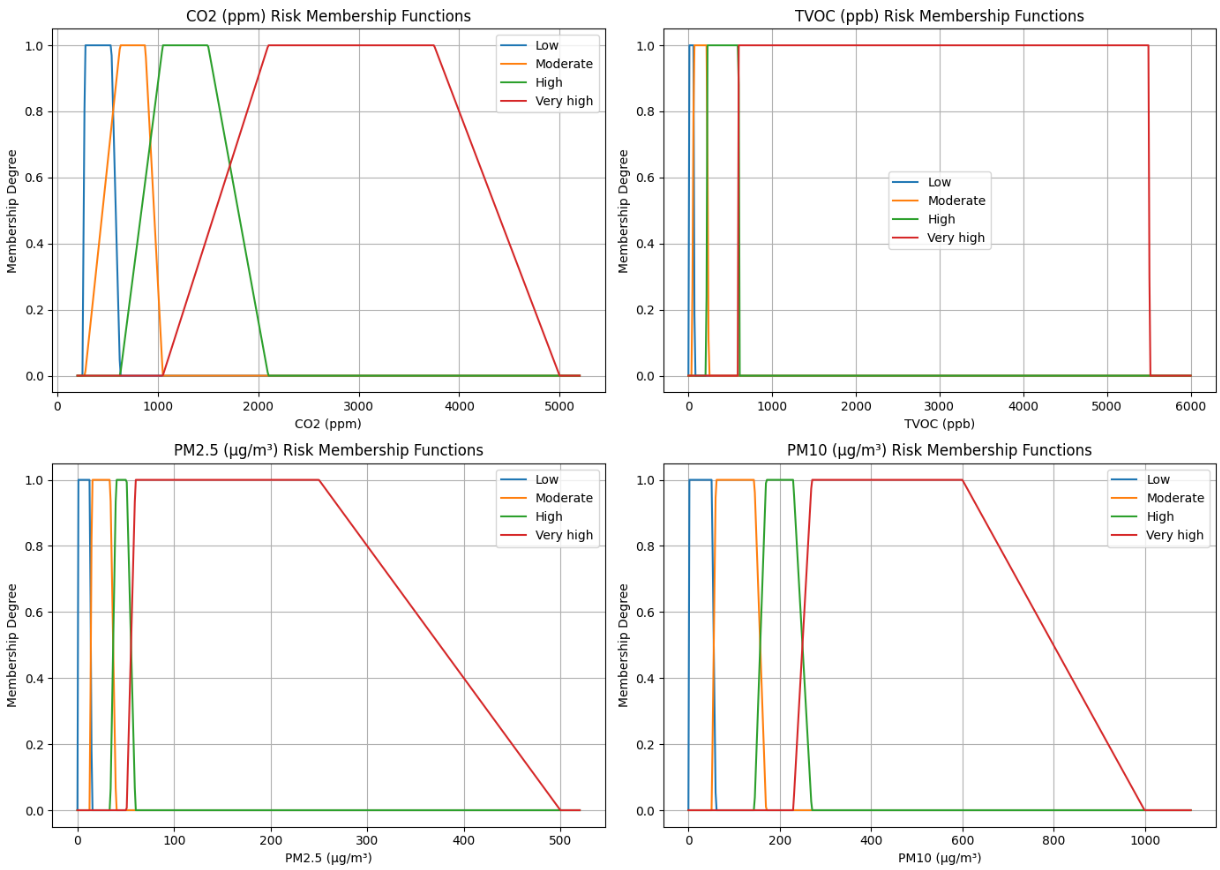

Figure 4. Risk Level Membership Functions

After calculating the membership level associated with each pollutant, the system assigns an individual risk category and then aggregates the final indoor air quality risk by selecting the highest risk level among all evaluated pollutants.

In this context, the forecasting errors observed in the Machine Learning models can be considered acceptable for the proposed monitoring strategy, since they do not substantially displace the predicted values across the fuzzy logic threshold ranges used to determine whether an alert should be generated.

Figure 5 shows the risk distribution determined from the dataset using the fuzzy logic assessment approach.

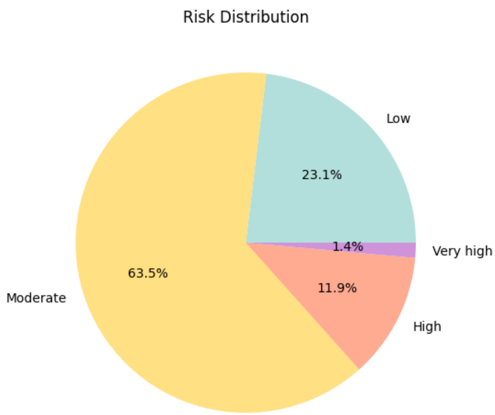

Figure 5. Risk Level Distribution

Overall, these metrics and experiments illustrate how the infrastructure of the proposed technical solution would operate to implement a real-time indoor air quality monitoring and alert system, with the integration of data acquisition, Machine Learning prediction models, and fuzzy logic-based risk assessment.

5 Discussion

The findings of this study reinforce the evidence reported in the literature regarding the adverse health effects associated with exposure to CO_2, TVOC, PM2.5, and PM10 in indoor environments. Elevated CO_2 concentrations in enclosed spaces have been consistently linked to symptoms such as fatigue, drowsiness, and reduced cognitive performance, as well as more severe outcomes including cardiovascular alterations. At higher levels, acute effects such as dizziness, nausea, disorientation, and, in extreme cases, asphyxiation may occur. Even at moderate concentrations, CO_2 has been shown to negatively affect academic and occupational performance by impairing concentration and energy levels.

Similarly, exposure to TVOC is associated with immediate discomfort, including irritation of the eyes, nose, and throat, and headaches. Prolonged exposure can result in damage to vital organs and the central nervous system. From an environmental perspective, TVOC also contribute to the formation of smog and ozone depletion, indirectly exacerbating respiratory conditions in urban settings. With respect to particulate matter, the literature highlights a wide range of health impacts, from respiratory irritation to more severe outcomes such as lung inflammation, vascular alterations, increased susceptibility to respiratory infections in children, and dermatological effects including premature aging and inflammatory skin conditions.

In parallel with these findings, this work advances a technical methodology for defining indoor air quality risk environments based on an extensive review of documented health impacts associated with pollutant exposure. The proposed approach addresses both short- and medium-term risks through the integration of time series analysis, regression models, and neural networks to identify behavioral patterns and emerging trends in pollutant concentrations. Additionally, fuzzy logic is incorporated to model potential and existing risk scenarios, enabling the representation of uncertainty and variability inherent to indoor environments.

Furthermore, the findings are consistent with the relevance of existing knowledge-based regulations, which already recognize the importance of particulate matter thresholds, occupancy conditions, and spatial characteristics in indoor environments. For example the Mexican standard NOM-182-SEMARNAT-2019, described in [8] defines risk-level ranges for particulate matter, while the complementary technical standard for architectural projects in Mexico City [114] establishes occupancy-related criteria based on indoor area, considering 18.5 m^2 per person for residential areas, 9.3 m^2 per person for offices, and 1.9 m^2 per person for schools and universities. Similarly, building regulations also consider room height as a relevant factor for indoor environmental conditions, with minimum values of 2.3 meters in Mexico City, between 2.3 and 2.5 meters in Puebla, and 2.7 meters in the state of Morelos [115]. Therefore, the knowledge obtained from the proposed monitoring system and data-driven analysis can contribute, in the long term, to expanding best practices for ensuring indoor air quality by incorporating additional evidence regarding people density per cubic meters, relative humidity, temperature, and their combined influence on pollutant behavior in enclosed spaces.

Daily measurements collected across multiple indoor settings with varying occupancy levels support the development and validation of the proposed algorithms. These data-driven components are complemented by the implementation of an automated monitoring system capable of generating real-time risk alerts and recommending corrective actions aimed at protecting occupant health. The application of machine learning and advanced data analysis techniques in this context demonstrates the feasibility of leveraging emerging technologies to enhance indoor air quality management.

In addition, security considerations were incorporated into the system infrastructure to protect both the data acquisition process and the model training environment. Access to the system was restricted through the use of credentials, while VPN rules were configured to reduce the risk of unauthorized access to the training environment and data storage services. These measures support the integrity, confidentiality, and controlled operation of the proposed system.

The proposed framework is designed to be scalable and flexible, allowing its adaptation to a wide range of indoor environments, including residential spaces, educational institutions, offices, and other commonly occupied facilities. Its modular architecture facilitates integration with sensing technologies and digital platforms, supporting broader implementation and continuous improvement. Overall, these strategies contribute to the advancement of practices for ensuring indoor air quality and promote the development of safer, healthier indoor environments.

6 Conclusions

Indoor air quality represents a critical public health concern, as exposure to pollutants such as CO_2, volatile organic compounds, and particulate matter has been shown to produce adverse health effects ranging from immediate discomfort to the development of chronic diseases. The evidence reviewed in this study, together with findings reported in prior research, underscores the importance of addressing indoor environments where individuals spend a substantial portion of their daily lives.

The results of this work demonstrate the technical feasibility of implementing an automated system for monitoring and forecasting indoor air quality using contemporary digital technologies. The proposed approach, supported by outcomes reported in previous studies, confirms that the integration of time series analysis, regression techniques, neural networks, and fuzzy logic can effectively model complex pollutant behaviors and support early risk detection. Continuous and periodic measurements enable the system to adapt to diverse indoor scenarios, allowing progressive refinement of its predictive accuracy. Overall, the proposed technological framework provides a viable, scalable, and flexible solution for improving indoor air quality management and supporting proactive health protection strategies in indoor environments.

7 Limitations

The monitored spaces, including classrooms, laboratories, offices, and residential rooms, correspond to real indoor environments used in daily activities. This provides a practical basis for evaluating indoor air quality under realistic conditions, however, since this work represents an initial phase of the project, the analysis focuses on indoor environments located in the states of Morelos and Puebla, which should be considered when interpreting the applicability of the findings to other regions of Mexico.

The study also defines risk levels based on pollutant concentration ranges reported in the literature, rather than through direct clinical follow-up of the occupants. Therefore, the proposed risk assessment should be understood as an environmental monitoring and prevention approach, not as an individual medical evaluation or diagnosis.

Finally, the implementation of the monitoring system in university facilities required authorization and institutional coordination for equipment installation and data collection. These processes may influence the duration of monitoring campaigns or access to specific spaces. Likewise, the project depends on the availability of material and infrastructure resources, including sensors, data acquisition devices, and data storage systems, which are subject to budget availability and acquisition times.

8 Future Works

Future work will focus on the application and validation of the proposed system through controlled and real-world testing scenarios, with the objective of defining best practices for indoor air quality management in Mexico. In addition, a commercial version of the proposed system will be developed, including a financial evaluation to assess its feasibility for implementation and adoption in homes and offices. These evaluations will support the development of internal routines and operational guidelines aimed at ensuring healthy indoor environments, grounded in the evidence generated by the implemented machine learning models.

The knowledge derived from data-driven analysis will be used to propose feasible and proactive actions for indoor occupants, including recommendations related to ventilation strategies, occupancy levels, and appropriate duration of stay in enclosed spaces. By translating model outputs into actionable guidance, the system seeks to support informed decision-making and promote sustainable behaviors that contribute to maintaining acceptable pollutant levels and improving overall indoor air quality.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Ethical Considerations

This study was conducted with the utmost respect for ethical standards. Measurements were taken in workspaces and living rooms under normal conditions during everyday activities, ensuring that subjects were not exposed to any risks. No experiments were conducted on animals or humans. Furthermore, the research activities did not produce any environmental pollution or harm. All procedures were designed to minimize any potential negative impacts and to prioritize the well-being and safety of all involved.

In addition, no medical records, clinical histories, diagnoses, personal identifiers, or other health-related data from occupants were collected. The study focused exclusively on environmental variables and indoor air quality indicators. Information related to occupant presence, activities, and room schedules was treated as sensitive contextual data and handled with appropriate privacy considerations to prevent individual identification and ensure its use only for research and environmental monitoring purposes.

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