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# Machine Learning Models for Predicting Pediatric Hospitalizations Due to Air Pollution and Humidity: A Retrospective Study

Zohar Barnett-Itzhaki[1,2] | Vered Nir[3,4] | Almog Kellner[2] | Ofir Biton[2] | Shir Toledano[2] | Adi Klein[3,4]

[1]Ruppin Research Group in Environmental and Social Sustainability, Ruppin Academic Center, Emek Hefer, Israel | [2]Faculty of Engineering, Ruppin Academic Center, Emek Hefer, Israel | [3]Department of Pediatrics, Hillel Yaffe Medical Center, Hadera, Israel | [4]Bruce Rappaport Faculty of Medicine, Technion–Israel Institute of Technology, Haifa, Israel

**Correspondence:** Vered Nir (verednr@yahoo.com)

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## ABSTRACT

**Background:** Exposure to air pollution and meteorological conditions, such as humidity, has been linked to adverse respiratory health outcomes in children. This study aims to develop predictive models for pediatric hospitalizations based on both environmental exposures and clinical features.

**Methods:** We conducted a retrospective analysis of 2500 children (aged 1–18) who presented with respiratory symptoms at the emergency department, during 2016–2017. Air pollution data, including NOx and $NO_2$ concentrations, and relative humidity (RH) were collected from nine monitoring stations and were cross-referenced with the children's residential locations to assess their specific exposure level. Statistical tests, including Chi-square and Wilcoxon tests, were used to analyze the data. Machine learning models, specifically Random Forest (RF) and eXtreme Gradient Boosting (XGBoost), were developed to predict the children's hospitalizations.

**Results:** Boys were more likely to be hospitalized than girls (60.6% vs. 39.4%, $p = 4.31e\text{-}06$). Hospital visits peaked during winter ($p = 3.56e\text{-}37$). Increased emergency room visits were statistically significantly associated with highly polluted days ($p = 0.038$). Hospitalized children were exposed to lower RH (median 64.9%) compared to nonhospitalized children (median 69.4%, $p = 0.005$). The RF and XGBoost models were reliable, with accuracy rates of 0.7–0.98, Precision scores of 0.88–0.99, and AUC scores of 81%–99%. Key features included temperature, NOx levels, RH, and exposure to $SO_2$.

**Conclusion:** This study investigates the effects of air pollution and humidity on pediatric respiratory health. The models developed offer valuable tools for predicting hospitalizations and are intended to support public health planning and resource allocation.

## 1 | Introduction

Air pollution refers to the presence of gases and particles in the air, exposure to which is associated with health risks. Air pollution includes, inter alia, Particulate Matter (PM), Nitric Oxides (NOx), Sulfur Dioxide ($SO_2$), Ozone ($O_3$), and carbon monoxide (CO). According to the World Health Organization (WHO), air pollution is associated with 6.7 million premature deaths annually [1].

Zohar Barnett-Itzhaki and Vered Nir contributed equally to this article.

Particulate matter (PM) refers to a mixture of solid particles and liquid droplets in the air. These particles vary in size and composition and are categorized based on their diameter. The primary PM include coarse particles ($PM_{10}$), with diameters up to 10 μm, and fine particles ($PM_{2.5}$), smaller than 2.5 μm [2–4]. PM originates from natural sources, such as dust storms, wildfires, and sea spray, as well as anthropogenic sources, such as industrial emissions, vehicle exhaust, and combustion of fossil fuels [3, 4]. The chemical composition of PM is diverse, including elements such as carbon, sulfates, nitrates, metals, and organic compounds [3, 4].

The health impacts of PM are significant and well-documented. Fine particles ($PM_{2.5}$) can penetrate deep into the respiratory tract, reaching the alveoli and even entering the bloodstream. This can lead to a range of adverse health effects, including respiratory and cardiovascular diseases, exacerbations of asthma, chronic obstructive pulmonary disease, and increased mortality [2, 4, 5]. The World Health Organization (WHO) has established air quality guidelines to mitigate these health risks by recommending limits on PM concentrations [3]. Multiple studies have demonstrated that both short-term and long-term exposure to various air pollutants are significantly associated with increased rates of hospitalizations and emergency department visits for respiratory diseases in children.

A systematic review by de Souza et al. found that short-term exposure to $PM_{2.5}$, $PM_{10}$, $NO_2$, $SO_2$, and $O_3$, even at concentrations below current health-based guidelines, was significantly correlated with increased risk of outpatient visits and hospitalizations for respiratory diseases in children [6]. Similarly, a meta-analysis by Nhung et al. reported that short-term exposure to ambient air pollution markers such as $PM_{2.5}$, $PM_{10}$, $NO_2$, $SO_2$ and CO was associated with increased hospitalization rates for pneumonia in children, with excess risk percentages ranging from 0.9% to 2.9% per 10 μg/m$^3$ or 10 ppb increase in pollutant concentration [7].

In Vietnam, Nguyen et al. demonstrated that increases in $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, and $O_3$ concentrations were associated with higher odds of hospital admissions for respiratory diseases among children, with PM metrics and $NO_2$ being particularly linked to admissions for pneumonia and bronchitis [8]. These findings are consistent across various geographic locations, including Canada [9], Brazil [10], and China [11–13].

Humidity is also associated with pediatric hospitalization due to respiratory infections. Several studies have demonstrated this relationship, particularly focusing on conditions such as pneumonia, bronchiolitis, and respiratory syncytial virus (RSV) infections [1, 3, 14–16].

In this study we analyzed the association between exposure factors (air pollutants and humidity) and healthcare outcomes: emergency room visits and hospitalizations due to respiratory symptoms among children in Israel. In addition, we developed machine learning models to predict hospitalization based on exposure to air pollutants and humidity. We hypothesized that increased exposure to air pollution is associated with a higher likelihood of hospitalization due to respiratory symptoms.

## 2 | Methods

### 2.1 | Ethics

The study was approved by the Institutional Review Board Ethics Committee of Hillel Yaffe Medical Center (HYMC-69-15). Due to the retrospective nature of this paper, the local ethics committee approved a consent waiver.

### 2.2 | Data

We analyzed data of over 2500 patients aged 1 to 18 years old who sought medical care for respiratory symptoms at the emergency room of "Hillel Yaffe" hospital in Hadera, Israel during 2016 and 2017. Medical charts of patients were reviewed on the SAP system (the computerized data system that was used at the time). Inclusion criteria were based on ICD-9 diagnoses of 15 respiratory diagnoses (the full list can be found in Supporting Information 1).

Air pollution data was collected from nine monitoring stations across the Sharon area between 2016 and 2017. These stations measured various contaminants, including NOx and $NO_2$, in addition to relative humidity (RH), and temperature. Data was collected on a 5 min resolution. Missing RH and temperature data were imputed using data from the Israel Meteorological Service [17] based on data from proximate locations at the relevant times. Missing air pollutant values were filled in using the median of the data from the previous 4 h. We integrated patient data with air pollution measurements taken 6 h before hospital arrival.

Data on gender distribution was taken from the Central Bureau of Statistics [18].

### 2.3 | Statistical Tests

Chi-square goodness of fit test was used to compare the number of boys and girls hospitalized due to respiratory symptoms, in comparison to their distribution in the population. Chi-squared test was used to compare the number of hospitalization between seasons.

Due to the difference in the importance of viral infections and bronchiolitis as primary causes of respiratory morbidity, the data was divided into two age groups: up to 2 years of age and over 2 years of age.

To analyze the effect of exposure to air pollutants on medical conditions, we conducted several statistical tests. Due to the non-normal distribution of the air pollutant concentrations, we used the nonparametric one-sided Wilcoxon non-paired tests. This test was used to compare the number of arrivals to the emergency room on days with no or little air pollution "clean days" ($n = 30$) to the arrivals in "polluted days" ($n = 53$) in the years 2016–2017. This comparison was conducted for all of the days combined, as well as separately for winter (November to February), for summer (June to September) and for autumn/spring (the remaining months). To define “polluted” and “clean” days on a national level, we focused on five cities representing different areas in Israel: Jerusalem, Be'er Sheva, Ra'anana, Tel Aviv, and Kiryat Ata and calculated the average daily $PM_{2.5}$ concentration in monitoring stations located at these cities. Polluted days on the national level were defined as days in which $PM_{2.5}$ levels were at or above the 90th percentile ($PM_{2.5} \geq 25.73\ \mu g/m^3$) in at least four of the five cities, while “clean” days were defined as days when $PM_{2.5}$ levels were at or below the 10th percentile ($PM_{2.5} \leq 9.3\ \mu g/m^3$) in at least four out of the five cities.

To investigate the impact of air pollution and meteorological conditions on hospital admissions, we conducted Wilcoxon non-paired tests to compare the temperature, RH, and air pollutant concentrations 6 h before arrival between hospitalized and nonhospitalized groups. These analyses included only 2016 data, since the 2017 data lacked essential information such as patient address and physician recommendations for hospitalization. In addition, patients living in distant areas or those without nearby stations were excluded from these analyses.

All statistical analyses were performed using Python (version 3.11.0).

## 2.4 | Models

The prediction models were developed using only 2016 data (as essential information was missing from the 2017 data). Data was normalized using min-max normalization. To avoid multicollinearity, columns with high correlations ($r > 0.5$) were removed, so that only one representative column was left.

To address missing values, we employed two approaches: (a) deletion of rows with missing values, and (b) column-based deletion - first identified which column's removal would result in the fewest remaining rows with missing values, subsequently remove that column and then deleting any rows that still contained missing values. Data was divided into two groups: infants up to the age of two and infants and children older than 2 years.

To predict whether a patient arriving at the emergency room hospital due to respiratory symptoms will be hospitalized, we employed two classification models: Random Forests (RF) and eXtreme Gradient Boosting (XGBoost): RF is an ensemble learning algorithm that constructs multiple decision trees during training, and outputs the class which is the majority vote of the individual trees. Each tree is trained on a different subset of the training data, enhancing the model's robustness and generalization capabilities. XGboost is a machine learning algorithm that iteratively builds decision trees. In each step, it focuses on correcting the errors made by the previous tree, by fitting a new tree to the residuals (errors) of the prior model. This approach minimizes the loss function and leads to a more robust final model. XGBoost employs regularization techniques to control model complexity and prevent overfitting.

The models were optimized using grid search to fine-tune hyperparameters and enhance performance. The models were evaluated using cross-validation and Grid-search to ensure robustness and accuracy. By incorporating feature importance analysis, we identified key features influencing hospitalization, providing valuable insights for healthcare decision-making. Models' performances were evaluated using several evaluation metrics: (a) Accuracy - representing the proportion of correctly classified instances out of the total instances. (b) precision - measures the proportion of true positive predictions among all positive predictions. (c) recall - measures the proportion of true positive predictions among all actual positives, (d) F1 Score - the harmonic mean of precision and recall, providing a balance between the two metrics, and (e) AUC (Area Under the Curve) Score - measures the area under the Receiver Operating Characteristic (ROC) curve, which plots the true positive rate against the false positive rate at various threshold settings. The AUC score provides an aggregate measure of performance across all classification thresholds, making it a robust metric for evaluating models, especially when the data set is imbalanced.

$$Accuracy = \frac{TP + TN}{Total\ Instances}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Where: TP = true positives, FP = False positives, TN = true negatives.

# 3 | Results

## 3.1 | Participants

An analysis of 1090 emergency department visits for respiratory symptoms in 2016 found that babies under the age of two represented the majority. (41.6%) (Figure 1). The mean age of the studied population was 5.52 years old (median = 3 years). Boys exhibited a statistically significantly higher proportion of emergency department visits compared to girls (60.1% vs 39.9%, $p = 4.2e\text{-}05$), and higherhospital admission rates due to respiratory symptoms (60.6% vs. 39.4%, $p = 4.31e\text{-}06$). The main complaint was respiratory (the full list is in sup. Text 1), and 452 (41.5%) of the children arriving to emergency department were hospitalized (Table 1).

## 3.2 | The Association Between Exposure to Air Pollutants and Arrivals to Emergency Room Due to Respiratory Symptoms, on a National Level

The association between exposure to air pollution and arrivals to emergency room due to respiratory symptoms in 2016 and 2017 was studied by comparing the number of arrivals on

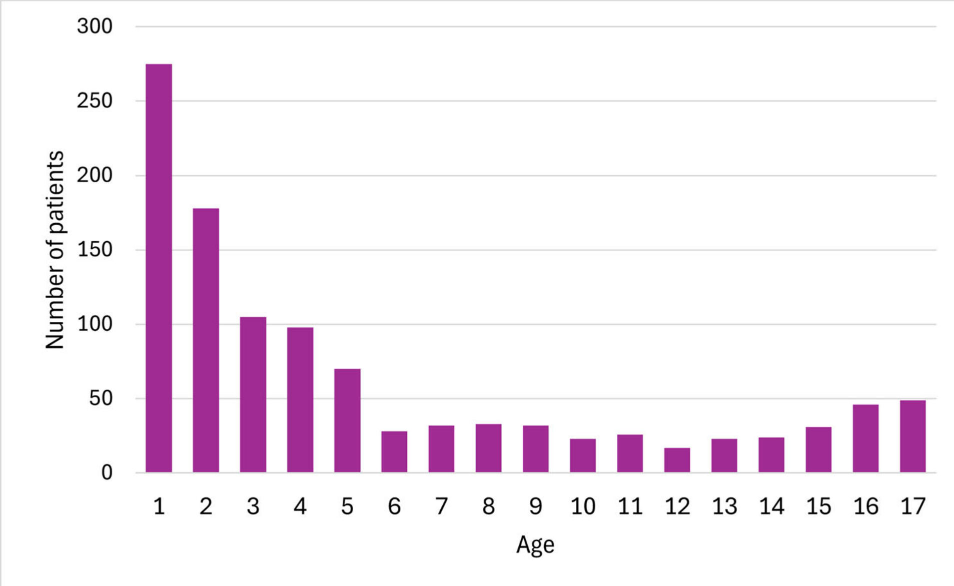


**FIGURE 1** | Age distribution of patients who visited the emergency room for respiratory symptoms in 2016. [Color figure can be viewed at wileyonlinelibrary.com].

highly polluted days (53 days) to the arrivals on non-polluted days (30 days). There were statistically significant more arrivals on highly polluted days (mean = 4.8 arrivals) in comparison to the arrivals on non-polluted days (mean = 3.4 arrivals, $p = 0.019$), suggesting that poor air quality is associated with increased hospital arrivals due to respiratory symptoms. Analyzing arrivals on polluted versus non-polluted days by season further supports our findings. In winter, there were significantly more arrivals on highly polluted days (mean = 5.37, $n = 27$) compared to non-polluted days (mean = 3.6, $n = 18$, $p = 0.012$). Similarly, in spring and autumn, arrivals were significantly higher on polluted days (mean = 4.33, $n = 24$) than on non-polluted days (mean = 3.1, $n = 10$, $p = 0.046$). In summer, only two polluted days and only two non-polluted day were recorded, preventing statistical analysis.

### 3.3 | The Association Between Exposure to Humidity and Hospitalization Due to Respiratory Symptoms

We compared the average levels of humidity (RH) to which the children were exposed 6 h before their arrivals to emergency room due to respiratory symptoms, between children hospitalized and children that were not hospitalized. Children that were hospitalized were exposed to lower humidity (RH) (median of 64.9%) in comparison to nonhospitalized children (median exposure of 69.4%, $p = 0.005$).

#### 3.3.1 | Models for Predicting Hospitalization in Children Due to Respiratory Symptoms

Feature selection resulted in 50 features for the children models and 52 features for the babies' models, including dummy variables of months (see list of features in Supporting Information Table 1).

We employed two Random Forest (RF) models: for babies (younger than 2 years old - BABY-RF), and for children of age 2+ (CHILD-RF). Analysis of the both CHILD-RF and the BABY-RF models, indicated that temperature, the mean NOx and $SO_2$ levels 6 h preceding the patient arrival, and the RH 6 h preceding the patient arrival, were the most significant contributing factors (Figure 2a,b). Wilcoxon test revealed that higher hospitalization rates were in days with lower RH ($p = 0.005$).

We employed two XGBoost (XG) models: for babies (younger than 2 years - BABY-XG), and for children of age 2+ (CHILD-XG). The XGBoost model for infants younger than 2 years old (BABY-XG) further emphasized the impact of both respiratory complaints (cough/Haemoptysis), and environmental factors (RH 6 h preceding the patient arrival) as the most influential factors, along with a history of gastrointestinal diseases, patient arrival on September, and additional complaints such as vomiting/nausea, and febrile seizure (Figure 2c).

The XGBoost model for children (CHILD-XG)'s most important features were complaints of cough/Haemoptysis, weakness/apathy/drowsiness, headache and abdominal pain (Figure 2d).

All models were reliable with good performances: accuracy rates of 0.7–0.98, The RF models' F1 scores were 0.76 (for children) and 0.98 for babies with AUC of 99%, 100% (accordingly). The XG models for babies yielded good result (F1 of 0.7 and AUC of 87%). However, while the XG model for children achieved a good precision of 0.92, it had a problematic recall of 0.25, making it less reliable, see (Table 2).

## 4 | Discussion

In this retrospective study, we examine the relationship between pediatric respiratory emergency department visits and

TABLE 1 | Demographic and clinical characteristics of the studied population.

| Variable | Category | Value/count (%) |
|---|---|---|
| Age | 0–2 years | 453 (41.6%) |
| | 2–5 years | 203 (18.6%) |
| | 5–8 years | 130 (11.9%) |
| | 8–11 years | 88 (8.1%) |
| | 11–14 years | 66 (6.1%) |
| | 14–18 years | 150 (13.8%) |
| Sex (ER visits) | Boys | 655 (60.1%) |
| | Girls | 435 (39.9%) |
| Hospitalized | Total | 452 (41.5%) |
| | Boys hospitalized | 274 (60.6%) |
| | Girls hospitalized | 178 (39.4%) |
| Patient's complaints[a] | Cough, Haemoptysis | 656 (60.2%) |
| | Fever | 593 (54.4%) |
| | Shortness of breath, difficulty breathing, choking, cyanosis | 547 (50.2%) |
| | Runny nose, congestion, post-nasal drip (PND) | 338 (31%) |
| | Vomiting, nausea | 226 (20.1%) |
| | Stridor, barking cough, persistent cough | 215 (19.7%) |
| | Weakness, apathy, drowsiness | 74 (6.8%) |
| | Abdominal pain | 67 (6.1%) |
| | Diarrhea | 66 (6.1%) |
| | Throat inflammation, sore throat | 60 (5.5%) |
| | Chest pain, chest discomfort | 50 (4.6%) |
| | Headache | 38 (3.5%) |
| | Hoarseness | 14 (1.3%) |
| | Febrile seizure | 14 (1.3%) |
| | Ear inflammation, ear pain | 14 (1.3%) |
| | chills | 13 (1.3%) |
| | Choking | 11 (1%) |

[a]Some of the patients had more than one complaint.

hospitalizations and air pollution characteristics. Based on our findings, we developed predictive models to estimate pediatric hospitalizations related to air pollution.

Our findings indicated a number of notable findings:

We observed higher frequency of respiratory pediatric hospitalizations in winter compared to summer. This pattern is primarily driven by the seasonality of RSV, influenza and other respiratory viruses. RSV, a leading cause of bronchiolitis and pneumonia in young children, typically peaks during the winter months. According to a study analyzing RSV-associated hospitalizations in the United States, the highest rates of hospital and ICU admissions occur in the winter and early spring [19]. Similarly, a study from Buenos Aires, Argentina, found that RSV and influenza A virus (IA) infections peaked during the coldest months, further supporting the winter predominance of respiratory hospitalizations [20]. Additionally, a study from Denmark highlighted that the highest hospitalization incidence for respiratory infections in children under 5 years old occurred during the winter months, particularly from November to January [21]. This seasonal trend is consistent across various geographic regions and is influenced by factors such as temperature and humidity, which affect viral transmission dynamics.

We found that children who were admitted to the hospital were exposed to lower humidity levels than those who did not require hospitalization during the 6 h prior. This is also in accordance with existing data: Sloan et al. demonstrated that infant bronchiolitis, primarily due to RSV, shows a seasonal pattern influenced by fluctuations in temperature and humidity. Their findings indicate that lower humidity levels can contribute to the early onset and longer duration of bronchiolitis epidemics [16]. Aganovic et al. modeled the impact of indoor relative humidity on the infection risk of various respiratory viruses. They found that lower indoor humidity levels

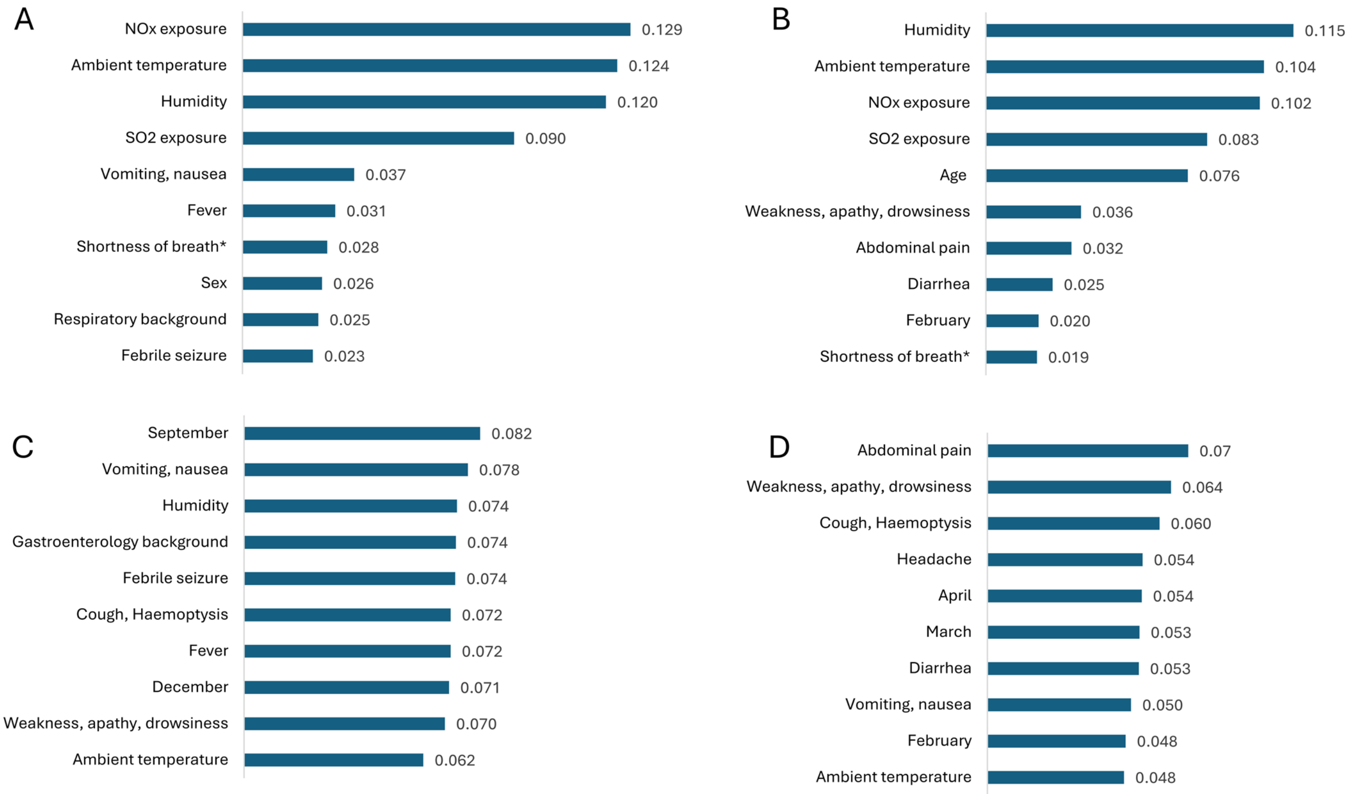


**FIGURE 2** | The most important features of the models: (A) Random forest – babies, (B) Random forest – children, (C) XGBoost – babies, and (D) XGBoost – children. Shortness of breath* - Shortness of breath, difficulty breathing, choking, cyanosis. [Color figure can be viewed at wileyonlinelibrary.com].

**TABLE 2** | Performance evaluation of the models.

| **Model** | | | | |
|---|---|---|---|---|
| **Measure** | **BABY-RF** | **BABY-XG** | **CHILD-RF** | **CHILD-XG** |
| Accuracy | 0.98 | 0.77 | 0.85 | 0.7 |
| Precision | 0.99 | 0.88 | 0.99 | 0.92 |
| Recall | 0.96 | 0.58 | 0.62 | 0.25 |
| F1 score | 0.98 | 0.7 | 0.76 | 0.39 |
| AUC | 99% | 87% | 99% | 81% |

*Note:* BABY-RF - random forest model for babies' data set (0–2 years old). BABY-XG - XGBoost model for babies' data set (0–2 years old). CHILD-RF - random forest model for children data set (≥ 2 years old). CHILD-XG - XGBoost model for children data set (≥ 2 years old).

increase the infection risk for viruses like rhinovirus and adenovirus, highlighting the importance of maintaining optimal indoor humidity levels to reduce infection risk [22].

As for the association between air pollution and pediatric respiratory emergency visits, there were significantly more visits on highly polluted days Our findings are in accordance with previous existing literature. Air pollutants affect lung immune responses and inflammatory reactions, which may underlie the increased risk for respiratory infections [23]. Numerous studies have demonstrated that short- and long-term exposure to air pollution is connected to respiratory morbidity [24–26]. As we aimed to develop a tool to assist in short term resource planning, we used a cutoff of 6 h. In pediatric population unspecified acute upper respiratory infections were associated with $O_3$ within 2–6 h and $NO_2$ within 1 h [27].

The primary focus of this study is to leverage machine learning for predicting hospitalizations and identifying key factors contributing to patient admissions. Current efforts are directed toward developing and integrating clinical decision support systems that provide objective criteria to assist healthcare professionals. Previous studies have demonstrated that machine learning models can support healthcare providers in making hospitalization decisions by utilizing medical records, demographic data, and symptoms [28–30].

In this study, we take this approach a step further by incorporating external factors into our predictive models. Beyond demographic features, we integrate exposure to air pollutants and meteorological conditions, aiming to enhance the accuracy and applicability of hospitalization predictions.

The models we developed to predict pediatric respiratory hospitalizations revealed distinct patterns in feature importance across different age groups: For babies and for children aged two and older, the Random Forest models identified temperature, mean NOx and $SO_2$ levels 6 h before arrival, and relative humidity (RH) 6 h before arrival as the most significant features that predict hospitalization. These results are in line with the aforementioned statistical results and emphasize that environmental factors play a crucial role in respiratory health outcomes for this age group.

The XGBoost models provided further insights, emphasizing the importance of respiratory diseases and symptoms: For infants under 2 years old, in addition to RH 6 h preceding the patient arrival, the model identified respiratory complaints (cough/Haemoptysis) as the primary factors influencing hospitalizations, along with other complaints and a history of gastrointestinal diseases. This underscores the heightened vulnerability of infants to respiratory infections and their significant impact on health outcomes. For children aged three and older, the XGBoost model also pointed to cough/Haemoptysis, headache, abdominal pain and weakness, as the most important features. Overall, most of the models demonstrated high reliability with accuracy rates, indicating robust performance in predicting pediatric respiratory hospitalizations.

These models present intriguing possibilities. As temperature, humidity, and air pollution levels can be predicted, it may be possible to identify in advance days in which more patients are expected to visit the emergency room and require hospitalization (e.g., days with lower RH). This may allow hospitals, for example, to allocate resources, such as staffing, medical supplies, and equipment more efficiently; manage wait times and optimize patient flow; improve emergency preparedness; reduce operational costs; and improve clinical decision making.

Above all, in our opinion, our data emphasizes the influence of environmental factors on children's health and thus the crucial importance of directing more resources to reduce air pollution.

While this study provides valuable insights, several limitations should be acknowledged. First, this study is retrospective in its design and therefore exposed to selection bias. Further validation using prospective datasets may address this limitation. Second, our data were extracted from a database (SAP system), were limited data that could be retrieved from it. Third, considering the fact that this study is a single-center study, the difference between cases of hospitalization and cases of non-hospitalization may be affected by the center's admission policy. Fourth, while our data set is extensive, it is based on data collected in 2016–2017 and may not fully capture recent trends. Additionally, the lack of external validation and the absence of sensitivity analyses for missing data may limit its generalizability. Furthermore, the high accuracy and AUC scores reported suggest a potential risk of overfitting, emphasizing the need for further validation to ensure model robustness. In addition, while we considered key features, we did not account for long-term exposure effects or interactions between variables, which may influence the observed outcomes. Despite these limitations, our study offers important contributions to the field by leveraging long-term data and applying machine learning and advanced data science tools. Addressing these limitations in future research will further refine and strengthen the insights derived from similar studies.

In summary, our study explores the relationship between exposure to air pollutants and humidity and the likelihood of emergency medical visits for pediatric respiratory health issues. Our findings supported the development of prediction models for hospital admissions, aimed at enhancing public health planning and resource allocation. Further prospective randomized trials are needed to validate our results and improve these models.

## Author Contributions

**Zohar Barnett-Itzhaki:** conceptualization, methodology, writing – original draft, writing – review and editing, software, formal analysis, resources. **Vered Nir:** conceptualization, investigation, writing – original draft, methodology, writing – review and editing, software, formal analysis, resources, project administration. **Almog Kellner:** investigation, writing – review and editing, software, formal analysis, data curation. **Ofir Biton:** investigation, writing – review and editing, validation, formal analysis, software, data curation. **Shir Toledano:** investigation, validation, software, formal analysis, data curation. **Adi Klein:** conceptualization, investigation, funding acquisition, writing – original draft, methodology, formal analysis, writing – review and editing, project administration, supervision, resources.

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## Conflicts of Interest

The authors declare no conflicts of interest.

## Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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### Supporting Information

Additional supporting information can be found online in the Supporting Information section.