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Title of Manuscript: A Machine-Learning Approach to Predicting Need for Hospitalization for Pediatric Asthma Exacerbation at the Time of Emergency Department Triage.

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Contribution

S.J.P. J.M.C, and D.B.C. conceptualized and designed the study, supervised the analysis, drafted the initial manuscript, and reviewed and revised the manuscript.

D.B.C. carried out the analyses, and reviewed and revised the manuscript.

All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

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Abstract:

Objectives: Pediatric asthma is a leading cause of emergency department (ED) utilization and hospitalization. Earlier identification of need for hospitalization could triage patients more efficiently to high- or low-resource ED tracks. While past prediction models and asthma scores have relied solely on clinical data to predict asthma disposition in children, inclusion of other types of data might improve prediction models. Our objective was to compare the performance of four common machine-learning approaches, incorporating clinical data available at the time of triage with information about weather, air pollution, neighborhood characteristics, and community viral load to predict need for hospitalization in pediatric asthma.

Methods: Retrospective analysis of patients ages 2-18 years seen at two urban pediatric EDs with asthma exacerbation over four years. Asthma exacerbation was defined as receiving both albuterol and systemic corticosteroids. We included patient features, measures of illness severity available in triage, weather features, and CDC influenza patterns. We tested four models: decision trees, logistic regression, random forests, and gradient boosting machines. For each model, 80% of the dataset was used for training and 20% was used to validate the models. The area under (AUC) the receiver operator characteristic (ROC) curve was calculated for each model.

Results: There were 29,354 patients included in the analyses; mean age of 7.0 years (SD 4.3), 42% female, 77% non-Hispanic black, 76% public insurance. The AUCs for each model were: decision tree 0.68 (95%CL 0.65-0.75), logistic regression 0.82 (95% CL 0.81-0.82), random forests 0.82 (95% CL 0.81-0.83), and gradient boosting machines 0.85 (95% CL 0.84-0.86). In the lowest quintile of risk, only 1% of patients required hospitalization; in the highest quintile this rate was 54%. After patient vital signs and acuity information, weather-related features were the most important for predicting hospitalization.

Conclusions: The gradient boosting machines model was the most successful at predicting need for hospitalization at the time of triage in pediatric patients presenting with asthma exacerbation. The addition of weather data significantly improved the performance of this model.

Introduction

Seven million children in the United States have asthma.¹ Pediatric asthma accounts for 2% of all emergency department visits or 700,000 visits each year.^{1,2} Asthma is also the most common reason for hospitalization in children, accounting for 6% of all pediatric hospitalization.³ Furthermore, hospitalization is the largest contributor to health care cost associated with pediatric asthma.⁴ Earlier identification of need for hospital level care could reduce cost by reducing ED boarding time,⁵ triaging patients more efficiently to high- or low-resource ED tracks,⁶ or allow safe discharge of patients who don't require hospitalization.

Several asthma severity scores have attempted to predict hospitalization. Most are better at predicting safe discharge from the hospital rather than making an early determination of need for hospitalization.⁷⁻¹⁸ Traditional prediction models and asthma scores have relied solely on clinical data and response to treatment.⁷⁻¹⁸ Asthma, however, is a heterogeneous disease with many phenotypes, each with a different set of environmental, genetic, and clinical factors.¹⁹ Qui et al documented an association of asthma-related hospitalization with regional temperature fluctuation.²⁰ In addition to weather changes, other well-documented environmental triggers for asthma include dust, pollen, pollution, and cockroach dander.²¹⁻²³ Seasonal variation of pediatric asthma exacerbation, with peaks occurring in September related to the start of school and increased passage of viral infections, has also been shown.^{24,25} Additionally, viral detection with fever¹⁴ and seasonal influenza²⁶ are associated with need for hospitalization in pediatric asthma.

Machine learning easily enables the inclusion of large amounts of data beyond clinical information available in the electronic health record (EHR). Allowing a computer to learn a predictive function, mapping many different types of inputs to the desired output, machine learning is ideally suited for complex, multidimensional data, and may discover interactions that humans might not consider when developing models. Finally, machine-learning models can improve over time by re-calibrating each time more data are entered.

Our objective was to compare the performance of four common machine-learning approaches, combining clinical data available at the time of triage with information about weather, air pollution, neighborhood characteristics, and community viral load to predict need for hospitalization in pediatric asthma.

Methods

Study Design

We performed a retrospective analysis of all patients evaluated for asthma exacerbation in the pediatric emergency department. The hospital institutional review board approved this study.

Study Setting and Population

We included all patient visits age 2 to 18 years with asthma exacerbation evaluated at two urban pediatric emergency departments affiliated with a single Children's Hospital between January 1, 2012 and December 31, 2015. This Children's Hospital is a large, academic, tertiary care center and serves a predominantly African American population. The ED treats approximately five to seven thousand ED visits for asthma each year, with approximately 15% resulting in admission.²⁷

Acute asthma exacerbation was defined as having received a beta-agonist and systemic corticosteroids. Patients who received diphenhydramine were excluded to avoid inclusion of patients being treated for severe allergic reaction or anaphylaxis.

Study Protocol and Measures

The outcome of interest was hospitalization. Admission criteria for asthma are standardized and include the need for at least Q2h treatments with beta-agonists, inability to tolerate oral fluids, or hypoxia. Conceptually, need for hospital level care is a measure of severity of illness.

Because our focus was early prediction of the need for hospitalization, exposure variables of interest were those potentially available at the time of triage. We abstracted the following from the electronic health record (EHR): demographic information (including patient sex, age, race and ethnicity), patient acuity at triage [measured by the Emergency Severity Index (ESI)], as well as the first recorded measurement of (weight, oxygen saturation, heart rate, and respiratory rate). The ESI rates a patient's urgency on a 5-point scale, with 1 being the most urgent.²⁸

We also included data potentially available at the time of triage from other publicly available data sources. We accessed climate data made available by the weather station at the local airport.²⁹ For each patient, we computed the maximum, minimum, mean, and range of the dry bulb temperature, hourly visibility, relative humidity, wind speed, and station pressure over the 24, 48, 168, and 336 hours prior to their ED visit. We used community viral load data from the CDC (Centers for Disease

Control)³⁰ to compute the mean percentage weighted influenza-like illness (ILI), percentage unweighted ILI, and ILI total over the one, two, and four week period prior to the ED visit.

We also included information on home environment and socioeconomic status (SES) from the American Community Survey (ACS).³¹ Using each patient's zip code, we extracted the percentage of people below the poverty line and the breakdown of types of housing units available in that zip code.

Data Analysis

To develop our models, we randomly split the data into an 80% training dataset and a 20% test dataset. Once the dataset was split, each feature was normalized so that it would have a zero mean and unit standard deviation in the training dataset. Normalization is required for logistic regressions with L1 (LASSO or least absolute shrinkage and selection operator) regularization so that all variables have the same magnitude range. The normalizing coefficients were then applied to the training dataset.

The training dataset was used to train each of the four models: classification trees, logistic regressions with L1 (LASSO) regularization, random forests, and gradient boosting machines. For each type of model, we optimized the hyperparameters using one hundred iterations of randomized search, evaluating the results using a three-fold cross-validation. Once the optimal parameters were selected, we trained each model on the complete training dataset.

We chose four common machine learning classification algorithms to model hospital admission. Briefly, classification trees use recursive partitioning to classify subjects based on a binary outcome. Binary logistic regression models the probability of a binary outcome using odds ratios for each predictor. LASSO regularization prevents overfitting by penalizing complex models based on the parameter estimates. Random forests create multiple independently trained classification trees using random subsets of the data and features and combine their predictions to produce a single estimate. Gradient boosting machines are similar to random forests but each new model is specifically chosen to improve the aggregate prediction for all data points over the previous model rather than generated independently. All of these models were used for *supervised* learning, meaning that the outcome was provided in the training set. In contrast, unsupervised machine learning is used to determine associations of variables without a known outcome (e.g. word clouds).

Model performance was measured on the accuracy in predicting hospitalization in the test dataset. For each model, we computed an area under the receiver operating characteristic (ROC) curve, AUC. We then measured calibration by reporting observed admissions versus expected admissions for each decile of predicted risk.

Results

There were 36,080 ED visits for patients with a diagnosis of asthma who were treated with beta agonists and systemic corticosteroids. 6,726 (18.6%) were excluded because they were missing initial weight, vital signs, insurance, weather or SES data (Figure 1). Thus, there were 29,254 ED visits included in the analyses. Overall, the mean age was 7 (SD 4.3) years, 42% (12,329) were female, 77% (22,603) were non-Hispanic Black, and 76% (22,309) had public insurance. 5251 (17.9%) of patient visits resulted in hospitalization. (Table 1)

The AUCs for each model were 1) decision tree: 0.68 (95%CL 0.65-0.75), 2) logistic regression: 0.82 (95% CL 0.81-0.82), 3) random forests: 0.82 (95% CL 0.81-0.83), and 4) gradient boosting machines: 0.85 (95% CL 0.84-0.86). Figure 2 shows the AUC curves for each model. Using the gradient boosting machines model, in the lowest quintile of risk, only 1% of patients required hospitalization; in the highest quintile this rate was 54%. After patient vital signs and acuity information, weather-related features were the most important for predicting asthma admission. (Figure 3) Housing, SES, and community level of influenza at the time of the ED visit did not have large effects in the final model. It is possible that these features did not have a high enough geographic resolution to measure poverty status or viral load in the patient's actual community. Figure 4 depicts the calibration of the gradient boosting model. Overall, the model performed well comparing observed to expected admissions.

Table 1. Characteristics of the Study Population By Disposition Outcome

	All (Column%)	Admitted (Row%)	Discharged (Row%)
ED Visits for Asthma	29254	5251 (18%)	24103 (82%)
Variable			
Mean Age (SD in years)	7.0 ($\pm$ 4.3)	7.1 ($\pm$ 4.4)	7.0 ($\pm$ 4.2)
Race/Ethnicity			

Non-Hispanic Black	22603 (77%)	3666 (70%)	18888 (78%)
Hispanic	4863 (17%)	941 (18%)	3922 (16%)
White	930 (3%)	390 (7%)	540 (2%)
Other	1007 (3%)	254 (5%)	753 (3%)
Gender			
Female	12329 (42%)	2235 (43%)	10097 (42%)
Male	17022 (58%)	3016 (57%)	14006 (58%)
Insurance Status			
Public	22220 (76%)	3618 (69%)	18602 (77%)
Other	7134 (24%)	1633 (31%)	5501 (23%)

Table 2. Comparison of Model Performance

Model	AUC	95% confidence interval
Decision Tree	0.68	0.65-0.75
Logistic Regression	0.82	0.81-0.82
Random Forests	0.82	0.81-0.83
Gradient Boosting Machines	0.85	0.84-0.86

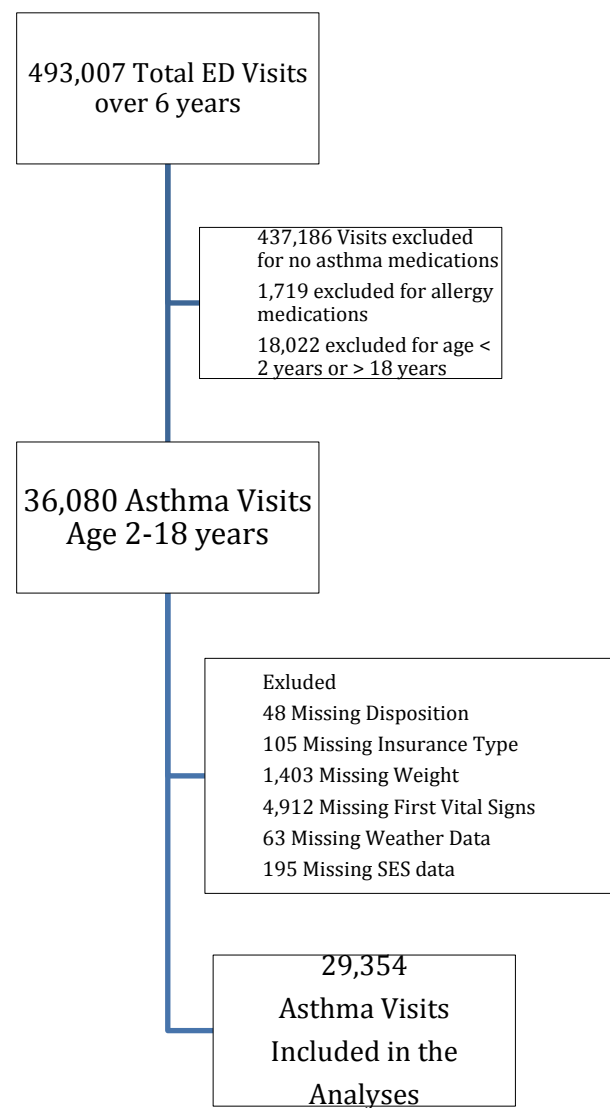
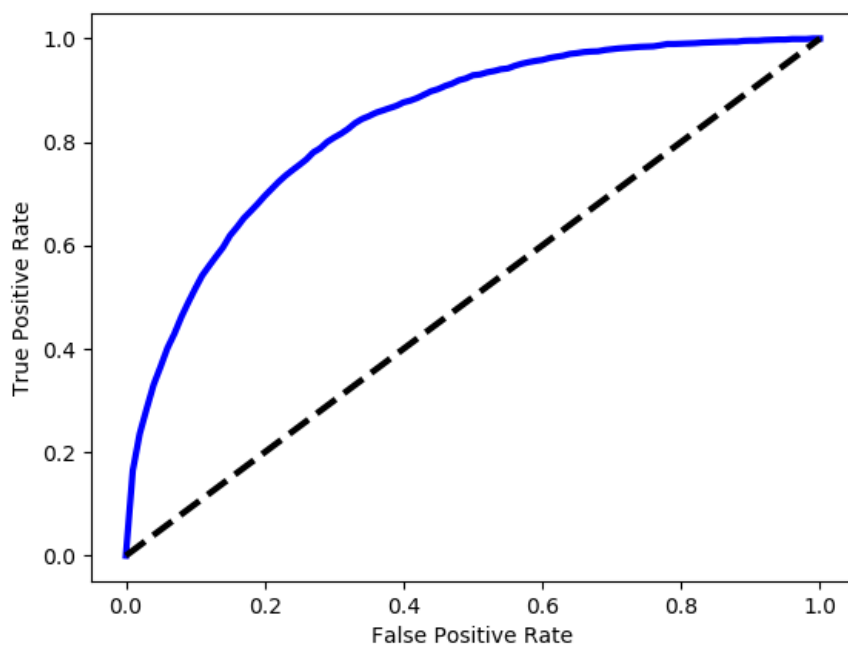


Figure 1. Flow Diagram for Visits Included in Analysis



	Sensitivity	Specificity
99%	99.1%	14.6%
95%	95.1%	45.3%
5%	35.6%	95.0%
1%	17.6%	99.0%
Minimum	26.3%	97.9%

Figure 2. AUC for each model. A) Decision Tree B) Gradient Boosting C) Logistic Regression D) Random Forest. [red line represents ranges (25%, 75%)]

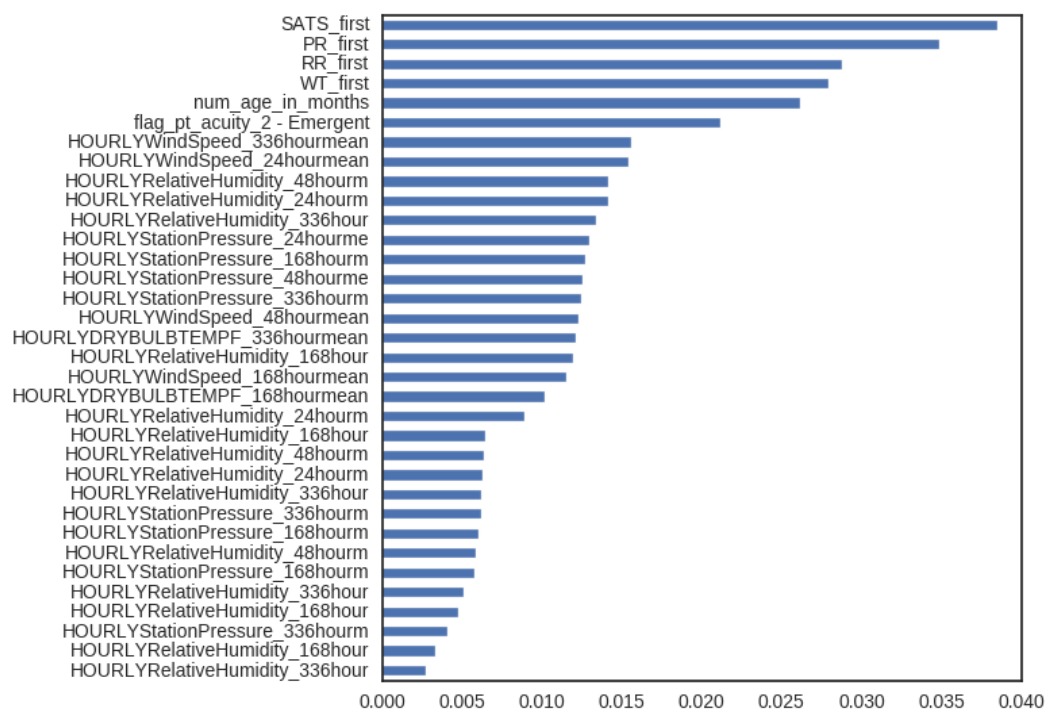


Figure 3. Feature Weights and Contributions to Gradient Boosting Model (Note: Figure only includes top features contributing to the model)

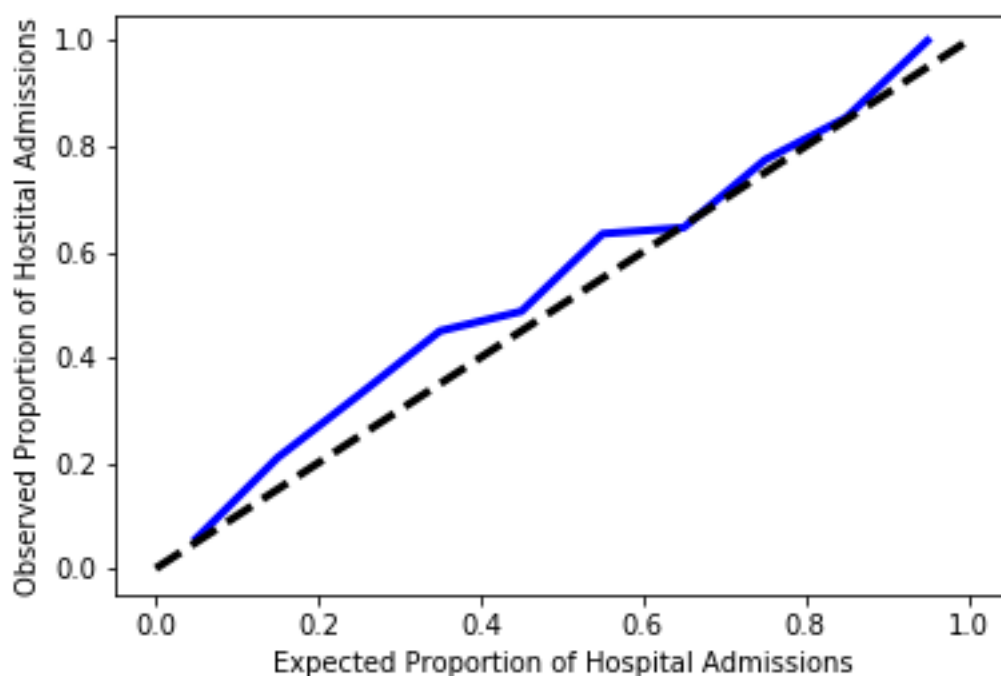


Figure 4. Calibration Plot for observed admissions versus expected admissions by decile of predicted risk. The dotted black line depicts perfect calibration.

Discussion

Using data available at triage, we developed four machine learning approaches to model the risk of hospitalization for an acute exacerbation of childhood asthma. The gradient boosting model performed best, with an AUC of 0.85. In addition to being accurate and precise, the model is clinically sensible, incorporating, in descending order of importance, oxygen saturation, pulse rate, respiratory rate, weight, age, and triage acuity, followed by weather variables. Calibration showed good agreement between observed and predicted admissions. (Figure 4)

Machine learning has several advantages over traditional multivariable modeling. First, machine learning can uncover meaningful interactions that may not occur to the human investigator. For example, we were surprised to discover that tachycardia is more important than tachypnea, and weight is more important than triage acuity (Figure 3). These would not have been likely hypotheses in developing a traditional logistic regression model for acute asthma. Nevertheless, they are physiologically plausible and likely represent new knowledge about variable interactions that were discovered by using machine learning. Second, machine learning can be used easily to perform iterative recalibration of models over time as new data are provided. We plan to provide future data to this machine learning algorithm to improve our model over time. Finally, machine learning can be incorporated into clinical workflow and can provide dynamic modeling of risk. Inclusion of post treatment vital signs or information about retractions, for example, can be used to provide additional information about risk assessment over time during an ED visit.

The performance of this model is promising especially given the efficiency with which it was developed. A previous model of risk of hospital admission, the Pediatric Risk of Admission (PRISA) score, took investigators approximately 2 years and hundreds of hours of data abstraction and modeling to achieve similar performance (AUC 0.85). PRISA incorporated additional data beyond triage, including worst vital signs and lab results.³² In contrast, the model presented in this paper took approximately 100 hours of data abstraction and modeling and achieved an AUC of 0.85 using only data available in triage. This bodes well for future model development using machine learning based on data from the EHR.

A mathematic model of admission risk with an AUC of 0.85 is not useful for making admission decisions for individual patients. However, such performance could be used to initially triage patients to low urgency versus high urgency areas of the ED, for example. In the lowest risk quintile, the likelihood of hospitalization is only 1%. Arguably, these patients could be treated differently than patients in the highest risk quintile, who have a probability of admission of 54%. Such an approach could be used to improve the use of resources to optimize ED efficiency. A model with this level of performance could also be used to compare groups of patients to ensure similar severity for clinical trials or quality assessment, for example.

Limitations

This study has several limitations. First, this study was performed at a single institution. It is likely that an admission model would be different at other hospitals and in cities with different weather patterns. The principles of model development would be similar. The future of machine learning is likely to include individualized site-specific models to improve accuracy. Second, we did not validate the necessity of hospitalization. It is possible that some patients were hospitalized unnecessarily. Therefore, we are modeling physician behavior. Given the large dataset including the practice of many providers over multiple years, the effect of individual bias on admitting practices and those due to non-clinical reasons on the model is likely minimal. Additionally, criteria for admission for asthma are well standardized at our institution. Third, as a retrospective study based on EHR data, we were limited to the data available. Potentially important information on progression of illness or non-clinical reasons (social, cultural, other) for hospitalization was not considered. We did not mine documents for specific text, for example. These limitations are common when conducting retrospective studies on data collected for a different purpose. Future use of natural language processing and coding could allow extraction of more detailed data regarding presence of respiratory viral symptoms or level of severity. Finally, weather features and CDC influenza patterns were not available at the zip code level and models assume the patient was at the address given to registration to determine prior exposures.

Conclusions

We were able to develop a machine-learning model for predicting hospital admission for pediatric asthma using only data available at the time of triage. Discrimination and calibration were similar to previous models incorporating data beyond triage. The gradient boosting machines model was the most accurate at predicting need for admission. The addition of weather data significantly improved the performance, but community viral load and socioeconomic variables did not contribute further improvement. These models could be used for differential triage of low-risk patients and high-risk patients as a strategy to improve efficiency. Study of these models in real-time, to evaluate the dynamic power of multidimensional machine learning for predicting which patients are at high risk for admission at the time of ED triage, is warranted.

References

1. Akinbami LJ, Moorman JE, Bailey C, Zahran HS, King M, Johnson CA, et al. Trends in asthma prevalence, health care use, and mortality in the United States, 2001-2010. NCHS Data Brief 2012(94):1-8.
2. Akinbami LJ, Moorman JE, Garbe PL, Sondik EJ. Status of childhood asthma in the United States, 1980-2007. Pediatrics 2009;123 Suppl 3:S131-45.
3. Agency for Healthcare Research and Quality. HCUPnet, Healthcare Cost and Utilization Project Rockville, MD: Agency for Healthcare Research and Quality; 2012 Estimates calculated from the 2012 HCUP Nationwide Emergency Department Sample (NEDS). Available at: <http://hcupnet.ahrq.gov> Accessed Date (May 6, 2018).
4. Barnett SB, Nurmagambetov TA. Costs of asthma in the United States: 2002-2007. J Allergy Clin Immunol 2011;127(1):145-52.
5. Barak-Corren Y, Fine AM, Reis BY. Early Prediction Model of Patient Hospitalization From the Pediatric Emergency Department. Pediatrics 2017;139(5):e20162785.
6. Peck JS, Benneyan JC, Nightingale DJ, Gaehde SA. Predicting emergency department inpatient admissions to improve same-day patient flow. Acad Emerg Med 2012;19(9):E1045-54.
7. Alnaji F, Zemek R, Barrowman N, Plint A. PRAM score as predictor of pediatric asthma hospitalization. Acad Emerg Med 2014;21(8):872-8.
8. Gorelick M, Scribano PV, Stevens MW, Schultz T, Shults J. Predicting need for hospitalization in acute pediatric asthma. Pediatr Emerg Care 2008;24(11):735-44.
9. Kerem E, Tibshirani R, Canny G, Bentur L, Reisman J, Stein R et al. Predicting the need for hospitalization in children with acute asthma. Chest 1990;98(6):1355-61.
10. Keahey L, Bulloch B, Becker AB, Pollack CV Jr, Clark S, Camargo CA Jr. Initial oxygen saturation as a predictor of admission in children presenting to the emergency department with acute asthma. Ann Emerg Med 2002;40(3):300-7.
11. Keogh KA, Macarthur C, Parkin PC, Stephens D, Arseneault R, Tennis O. et al. Predictors of hospitalization in children with acute asthma. J Pediatr 2001;139(2):273-7.

- Accepted Article
12. Mehta SV, Parkin PC, Stephens D, Keogh KA, Schuh S. Oxygen saturation as a predictor of prolonged, frequent bronchodilator therapy in children with acute asthma. *J Pediatr* 2004;145(5):641-5.
 13. Arnold DH, Gebretsadik T, Moons KG, Harrell FE, Hartert TV. Development and internal validation of a pediatric acute asthma prediction rule for hospitalization. *J Allergy Clin Immunol Pract* 2015;3(2):228-35.
 14. Ducharme FM, Zemek R, Chauhan BF, Gravel J, Chalut D, Poonai N et al. Factors associated with failure of emergency department management in children with acute moderate or severe asthma: a prospective, multicentre, cohort study. *Lancet Respir Med* 2016;4(12):990-8.
 15. Ducharme FM, Chalut D, Plotnick L, Savdie C, Kudirka D, Zhange X et al. The Pediatric Respiratory Assessment Measure: a valid clinical score for assessing acute asthma severity from toddlers to teenagers. *J Pediatr* 2008;152(4):476-80, 80 e1.
 16. Geelhoed GC, Landau LI, Le Souef PN. Evaluation of SaO₂ as a predictor of outcome in 280 children presenting with acute asthma. *Ann Emerg Med* 1994;23(6):1236-41.
 17. Gouin S, Robidas I, Gravel J, Guimont C, Chalut D, Amre D. Prospective evaluation of two clinical scores for acute asthma in children 18 months to 7 years of age. *Acad Emerg Med* 2010;17(6):598-603.
 18. Gorelick MH, Stevens MW, Schultz TR, Scribano PV. Performance of a novel clinical score, the Pediatric Asthma Severity Score (PASS), in the evaluation of acute asthma. *Acad Emerg Med* 2004;11(1):10-8.
 19. Lemanske RF, Jr., Busse WW. Asthma: clinical expression and molecular mechanisms. *J Allergy Clin Immunol* 2010;125(2 Suppl 2):S95-102.
 20. Qiu H, Yu IT, Tse LA, Chan EY, Wong TW, Tian L. Greater temperature variation within a day associated with increased emergency hospital admissions for asthma. *Sci Total Environ* 2015;505:508-13.
 21. Szeffler SJ, Gergen PJ, Mitchell H, Morgan W. Achieving asthma control in the inner city: do the National Institutes of Health Asthma Guidelines really work? *J Allergy Clin Immunol* 2010;125(3):521-6; quiz 527-8.

- Accepted Article
22. Kattan M, Stearns SC, Crain EF, Stout JW, Gergen PJ, Evans R et al. Cost-effectiveness of a home-based environmental intervention for inner-city children with asthma. *J Allergy Clin Immunol* 2005;116(5):1058-63.
 23. Gruchalla RS, Pongracic J, Plaut M, Evans R, Visness CM, Walter M et al. Inner City Asthma Study: relationships among sensitivity, allergen exposure, and asthma morbidity. *J Allergy Clin Immunol* 2005;115(3):478-85.
 24. Johnston NW, Johnston SL, Duncan JM, Greene JM, Keadze T, Keith PK et al. The September epidemic of asthma exacerbations in children: a search for etiology. *J Allergy Clin Immunol* 2005;115(1):132-8.
 25. Maffey AF, Barrero PR, Venialgo C, Fernandez F, Fuse VA, Saia M et al. Viruses and atypical bacteria associated with asthma exacerbations in hospitalized children. *Pediatr Pulmonol* 2010;45(6):619-25.
 26. Gerke AK, Yang M, Tang F, Foster ED, Cavanaugh JE, Polgreen PM. Association of hospitalizations for asthma with seasonal and pandemic influenza. *Respirology* 2014;19(1):116-21.
 27. Asthma Surveillance in DC Emergency Departments. Available at: http://childrensnational.org/giving/~media/cnhs-site/files/departments/impactdc/impact-dc-surveillance-20022011_website-compatibility-mode.ashx?la=en.), Accessed date (May 14, 2018).
 28. Emergency Severity Index (ESI): A Triage Tool for Emergency Department Care Agency for Healthcare Research and Quality. Available at: <https://www.ahrq.gov/sites/default/files/wysiwyg/professionals/systems/hospital/esi/esihandbk.pdf>. Accessed date (June 10, 2018)
 29. Station Data Inventory, Access & History: Washington Reagan National Airport. Available at: <https://www.ncdc.noaa.gov/cdo-web/datasets/GHCND/stations/GHCND:USW00013743/detail>. Accessed date (May 14, 2018).
 30. FluView Interactive. Available at: <https://www.cdc.gov/flu/weekly/fluviewinteractive.htm>. Accessed date (May 14, 2018).

- Accepted Article
31. American Community Survey. Available at: <https://www.census.gov/programs-surveys/acs> Accessed date (May 14, 2018)
 32. Chamberlain JM, Patel KM, Ruttimann UE, Pollack MM. Pediatric risk of admission (PRISA): a measure of severity of illness for assessing the risk of hospitalization from the emergency department. *Ann Emerg Med* 1998;32(2):161-9.