

## 1 (O-I4) Changes in Pediatric Emergency Department Visits After Arrival of COVID-19

Barnet Eskin, MD, PhD; Neena Joy, DO; John R. Allegra, MD, PhD

**Objectives:** Our goal was to examine the changes in pediatric ED visits after the arrival of COVID-19.

**Background:** Coronavirus 2019 (COVID-19) arrived in the New York metropolitan area in early March 2020. Shortly thereafter, total emergency department (ED) visits markedly decreased likely due to public health mandates and fear of contracting COVID-19. Our goal was to examine the changes in pediatric ED visits after the arrival of COVID-19.

**Methods:** Design: retrospective cohort. Setting: EDs of 8 hospitals within 150 miles of New York City. Hospitals were teaching and non-teaching in rural, suburban, and urban settings. Annual ED volumes ranged from 30,000-122,000. Population: Consecutive ED visits for patients ages 0-21 years, for the period from March 1–November 30 in 2019-2022, as COVID-19 emerged in early March 2020. Protocol: We tallied total pediatric ED visits for the time periods in each year. We calculated the percent changes from the base year, 2019, for each of the years 2020-2022 along with 95% confidence intervals (CI).

**Results:** The database contained a total of 332,504 visits: 110,210 in 2019, 55,270 in 2020, 71,570 in 2021, and 93,512 in 2022. Average age by year ranged from a low of 8.8 years in 2022 to a high of 10.5 years in 2020. The percentage of female patients ranged from a low of 47% in 2022 to a high of 49% in 2020. The percent changes in visits from 2019 were as follows: -49.9% (95% CI, -49.6, -50.2%); -35.1% (CI -34.8, -35.3%); and -15.2% (-14.9, -15.4%), for the years 2020, 2021 and 2022, respectively.

**Conclusion:** The number of pediatric ED visits changed after arrival of COVID-19. There was a marked decrease in 2020. This decrease was partially reversed in 2021 and 2022, although the visits did not reach their pre-pandemic levels. Since public health mandates have been relaxed, we speculate that failure to return to the pre-pandemic number of visits was likely due to preferential use of other sources of care, including doctor's offices, urgent care centers, and telemedicine.

## 2 (O-T2) Predicting High-risk Emergency Department Bounce-backs: A Natural Language Processing Approach to Provider Notes

Derick D. Jones, MD/MBA; Katie Sebald, PA; Pavan Thaker, MS; Moein Enayati, PhD

**Objectives:** Emergency department (ED) provider notes

can be used to predict high-risk ED bounce-backs using natural language processing machine-learning techniques.

**Background:** ED 72-hour return visits are a marker for high-risk patient visits and can be a surrogate marker for lapses in the quality of care at the index visit.<sup>1</sup> Published risk factors for bounce-backs resulting in hospitalization include age, public insurance, and end-stage renal disease among others.<sup>2</sup> While structured data from the medical record has been analyzed for factors associated with high-risk bounce-backs, there is a paucity of evidence analyzing the large volume of unstructured data that is contained in provider notes and that lend additional insight into the features associated with high-risk bounce-backs.

**Methods:** The authors analyzed patient encounters in the Mayo Clinic Midwest EDs from May 4, 2018– September 30, 2022. ED encounters were included if the repeat ED visit was within 72 hours and resulted in a disposition of admission, hospital observation, expired, send to the operating room, send to the catheterization lab, and transfer to another healthcare facility. ED encounters were excluded if the patient was not discharged on the index visit or experienced an irregular departure (eloped, left without being seen, left against medical advice). Notes from different provider types documenting on the same encounter were combined. Machine-learning methods used included text cleaning, TFIDF and count vectorization, creation of 1 to 3 n-grams, splitting data into test and training set, model fitting using support vector classifiers and logistic regression. Model explainability techniques include LIME (local interpretable model-agnostic explanations) and SHAP (Shapley additive explanations).

**Results:** A total of 397,125 patients among 639,693 encounters were eligible for inclusion. Of these, 10,094 (2.5%) resulted in a 72-hour bounce-back with a concerning disposition. Prediction accuracy on the concerning bounce-back cohort achieved 67% accuracy, precision of 68%, recall of 71%, and an area under the receiver operative curve (AUROC) of 71%. After applying SHAP, the top 10 text features associated with the concerning repeat visits include “return,” “discharged,” “significant,” “ed,” “pending,” “iv,” “mild,” “plan,” “discussed,” and “care.”

**Conclusion:** Natural language processing techniques applied to ED provider notes can be used to predict high-risk bounce-backs as surrogate markers for gaps in quality of care. Furthermore, NLP machine-learning explainability techniques give insight into the types of terminologies that are associated with high-risk bounce-backs. These features can be combined with previously studied risk factors for high-risk bounce-backs to increase prediction accuracy and generate comprehensive clinical phenotypes of ED patients at risk for these serious outcomes.

**References:** 1. Shy BD, Shapiro JS, Shearer PL et al. (2015). A conceptual framework for improved analyses of 72-hour return cases. *Am J Emerg Med*, 33(1), 104-107. 2. Gabayan GZ, Asch