Predicting Appropriate Hospital Admission of Emergency Department Patients with Bronchiolitis: Secondary Analysis

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Abstract

Background: In children below age two, bronchiolitis is the most common reason for hospitalization. Each year in the United States, bronchiolitis causes 287,000 emergency department visits, 32%-40% of which result in hospitalization. Due to a lack of evidence and objective criteria for managing bronchiolitis, clinicians often make emergency department disposition decisions on hospitalization or discharge subjectively, leading to large practice variation. Our recent study provided the first operational definition of appropriate hospital admission for emergency department patients with bronchiolitis, and showed that 6.08% of emergency department disposition decisions for bronchiolitis were inappropriate. An accurate model for predicting appropriate hospital admission can guide emergency department disposition decisions for bronchiolitis and improve outcomes, but is yet to be built.

Objective: The objective of this study is to fill the gap and build a reasonably accurate model for predicting appropriate hospital admission.

Methods: Using Intermountain Healthcare data from 2011-2014, we developed the first machine learning classification model to predict appropriate hospital admission for emergency department patients with bronchiolitis.

Results: Our model achieved an accuracy of 90.66% (=3,242/3,576, 95% CI: 89.68%-91.64%), a sensitivity of 92.09% (=1,083/1,176, 95% CI: 90.33%-93.56%), a specificity of 89.96% (=2,159/2,400, 95% CI: 88.69%-91.17%), and an area under the receiver operating characteristic curve of 0.960 (95% CI: 0.954-0.966). We pointed out possible improvements to the model to guide future research on this topic.

Conclusions: Our model has good accuracy for predicting appropriate hospital admission for emergency department patients with bronchiolitis. With further improvement, our model could serve as a foundation for building decision support tools to guide disposition decisions for children with bronchiolitis presenting to emergency departments.

Keywords: Bronchiolitis; appropriate hospital admission; emergency department; predictive model; machine learning

1. Introduction

Bronchiolitis is an inflammation of the bronchioles, the smallest air passages in the lungs, mainly seen in children below age two [1]. More than 1/3 of children have been diagnosed with bronchiolitis by age two [1]. In children below age two, bronchiolitis causes 16% of hospitalizations and is the most common reason for hospitalization [2-5]. Each year in the United States, bronchiolitis leads to approximately 287,000 emergency department (ED) visits [6], 128,000 hospitalizations [2], and US $1.73 billion of total inpatient cost (2009) [2].

Figure 1. The operational definition of appropriate hospital admission for emergency department patients with bronchiolitis.

About 32%-40% of ED visits for bronchiolitis result in hospitalization [7-9]. Current clinical guidelines for bronchiolitis [10, 11] acknowledge that due to a lack of evidence and objective criteria for managing bronchiolitis, clinicians often make ED disposition decisions on hospitalization or discharge subjectively [4, 12]. This uncertainty in bronchiolitis management leads to large practice variation [3, 12-23], increased iatrogenic risk, suboptimal outcomes, and wasted healthcare resources resulting from unnecessary admissions and unsafe discharges [15, 21, 24]. Around 10% of infants with bronchiolitis encounter adverse events during hospital stay [25]. By examining the distributions of multiple relevant attributes of ED visits for bronchiolitis and using a data-driven method to determine two threshold values, we recently developed the first operational definition of appropriate hospital admission for ED patients with bronchiolitis [26]. As shown in Figure 1, appropriate admissions cover both necessary admissions (actual admissions that are necessary) and unsafe discharges. Appropriate ED discharges cover both safe discharges and unnecessary admissions. Unsafe discharges are defined based on early ED returns. Unnecessary admissions are defined based on no more than brief exposure to certain major medical interventions listed in Figure 1. Brief exposure was defined as 6 hours and was chosen conservatively based on the median duration of major medical interventions received by a
subset of patients who tended to have been admitted unnecessarily. Based on the operational definition, we showed that 6.08% of ED disposition decisions for bronchiolitis were inappropriate [26].

So far, several models have been built for predicting hospital admission in ED patients with bronchiolitis [7-9, 27-29]. As our review paper [30] pointed out, these models have low accuracy and incorrectly assume actual ED disposition decisions are always appropriate. An accurate model for predicting appropriate hospital admission can guide ED disposition decisions for bronchiolitis and improve outcomes. This model, which is yet to be built, would be particularly useful for less experienced clinicians, including those who are junior and those in general practice seeing children infrequently [31]. The current study’s objective is to build the first model to predict appropriate hospital admission for ED patients with bronchiolitis. The dependent variable of the appropriate ED disposition decision is categorical and has two possible values: appropriate admission and appropriate ED discharge. Accordingly, the model uses clinical and administrative data to conduct binary classification.

2. Methods

Study design and ethics approval

In this study, we performed secondary analysis of retrospective data. The Institutional Review Boards of the University of Washington Medicine, University of Utah, and Intermountain Healthcare reviewed and approved this study, and waived the need for informed consent for all patients.

Patient population

Our patient cohort consisted of children below age two with ED visits for bronchiolitis in 2013-2014 at any of the 22 Intermountain Healthcare hospitals. Intermountain Healthcare is the largest healthcare system in Utah, with 22 hospitals and 185 clinics delivering ~85% of pediatric care in Utah [32]. Like our prior paper [26], we adopted the approach used in Flaherman et al. [33-35] to capture as many ED visits for bronchiolitis as possible. This approach included patients with an ED or hospital International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) primary discharge diagnosis code of bronchiolitis or bronchitis (466.x), viral pneumonia (480.x), adenoviral infection (079.0), rhinovirus infection (079.3), respiratory infection due to influenza (487.0 or 487.1), respiratory syncytial virus (079.6), H1N1 influenza (488.1, 488.11, or 488.12), influenza due to identified avian influenza virus (488.0, 488.01, or 488.02), or influenza due to novel influenza A (488.81 or 488.82). Any of these discharge diagnosis codes, rather than only the discharge diagnosis code of bronchiolitis, could be assigned to an ED visit for bronchiolitis. In addition, this approach included all patients with any of the above as a non-primary diagnosis code, as long as the ICD-9-CM primary diagnosis code is any of the following: apnea (786.03), shortness of breath (786.05), tachypnea (786.06), wheezing (786.07), other respiratory abnormalities (786.09), cough (786.2), fever (780.60 or 780.61), acute nasopharyngitis (460), acute upper respiratory infections (465.x), other specified viral infection (079.89), urinary tract infection (599.0), pneumonia unspecified organism (486), unspecified viral infection (079.99), volume depletion (276.5x), or respiratory failure (518.81 or 518.82) [26]. The ED visits for bronchiolitis captured by this approach in 2013-2014 are the focus of our study.

Data set

From Intermountain Healthcare’s enterprise data warehouse, we extracted a clinical and administrative data set containing information of our patient cohort’s inpatient stays, ED visits, and outpatient visits at Intermountain Healthcare in 2011-2014. Recall that our patient cohort included children below age two with Intermountain Healthcare ED visits for bronchiolitis in 2013-2014. By starting the data set in 2011, we ensured that for each ED visit by a patient below age two for bronchiolitis in 2013-2014, the data set included the patient’s complete prior medical history recorded within Intermountain Healthcare and necessary for computing features (a.k.a. independent variables).

Features

The 35 candidate patient features fall into two disjoint categories:

1. **Category 1** includes all known predictors of hospital admission in ED patients with bronchiolitis, which were consistently recorded at Intermountain Healthcare facilities and available as structured attributes in our data set [30, 31]. These 15 predictors are: age in days, gender, heart rate, respiratory rate, peripheral capillary oxygen saturation (SpO2), temperature, co-infection, rhinovirus infection, enterovirus infection, history of bronchopulmonary dysplasia, history of eczema, prior intubation, prior hospitalization, prematurity, and dehydration. For any vital sign that was recorded more than once during the ED visit, we used its last value as its feature value. Among all recorded values, the last value most closely reflected the patient’s status at ED disposition time.

2. **Category 2** consists of 20 features suggested by our team’s clinical experts BS, MJ, and FN: race, ethnicity, insurance category (public, private, or self-paid or charity), the ED visit’s acuity level (resuscitation, emergent, urgent, semi-urgent, or non-urgent), chief complaint, number of consults called during the ED visit, number of lab tests ordered during the ED visit, number of radiology studies ordered during the ED visit, number of X-rays ordered during the ED visit, length of ED...
stay in minutes, hour of ED disposition, whether the patient is current with his/her immunizations, diastolic blood pressure, systolic blood pressure, weight, wheezing (none, expiratory, inspiratory and expiratory, or diminished breath sounds), retractions (none, one location, two locations, or three or more locations), respiratory syncytial virus infection, language barrier to learning, and whether the patient has any other barrier to learning. For either attribute of wheezing and retractions that was recorded more than once during the ED visit, we used its last value as its feature value. Among all recorded values, the last value most closely reflected the patient’s status at ED disposition time.

Based on the timestamp, all candidate features were available as structured attributes in our data set before ED disposition time. We used them to build predictive models.

Data analysis

Data preparation

For each ED visit by a patient below age two for bronchiolitis in 2013-2014, we used our previously developed operational definition of appropriate admission [26] (see Figure 1) to compute the dependent variable’s value. For each numerical feature, we examined its data distribution, used its upper and lower bounds given by our team’s ED expert MJ to identify invalid values, and replaced each invalid value with a null value. All temperatures <80 Fahrenheit or >110 Fahrenheit, all weights >50 pounds, all systolic blood pressure values equal to 0, all SpO2 >100%, all respiratory rates >120 breaths/minute, and all heart rates <30 or >300 beats/minute were regarded as physiologically impossible and invalid. To make all of the data on the same scale, we standardized each numerical feature by first subtracting its mean and then dividing by its standard deviation. We focused on two years of data for ED visits for bronchiolitis (2013-2014). Data from the first year (2013) were used to train predictive models. Data from the second year (2014) were used to evaluate model performance, reflecting use in practice.

Performance metrics

As shown in Table 1 and the formulas below, we used six standard metrics to measure model performance: accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and Area Under the receiver operating characteristic Curve (AUC). For instance, false negative (FN) is the number of appropriate admissions that the model incorrectly predicts to be ED discharges. Sensitivity measures the proportion of appropriate admissions that the model identifies. Specificity measures the proportion of appropriate ED discharges that the model identifies.

\[
\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \\
\text{sensitivity} = \frac{TP}{TP + FN}, \\
\text{specificity} = \frac{TN}{TN + FP}, \\
\text{positive predictive value} = \frac{TP}{TP + FP}, \\
\text{negative predictive value} = \frac{TN}{TN + FN}.
\]

Table 1. The error matrix.

| Predicted admission | Appropriate admission | Appropriate emergency department discharge |
|---------------------|-----------------------|--------------------------------------------|
| true positive (TP)  | false positive (FP)   |
| false negative (FN)| true negative (TN)    |

For the six performance metrics, we conducted 1,000-fold bootstrap [36] to compute their 95% confidence intervals. On each bootstrap sample of the 2014 data, we computed our model’s performance metrics. For each of the six performance metrics, its 2.5th and 97.5th percentiles in the 1,000 bootstrap samples specified its 95% confidence interval.

To show the sensitivity-specificity tradeoff, we plotted the receiver operating characteristic curve. The calibration of a model refers to how well the predicted probabilities of appropriate admission match with the fractions of appropriate admissions in subgroups of ED visits for bronchiolitis. To show model calibration, we drew a calibration plot [36]. There, a perfect calibration curve would coincide with the diagonal line. In addition, we used the Hosmer-Lemeshow goodness-of-fit test [36] to evaluate model calibration.

Classification algorithms

We used Weka [37], a widely used open-source machine learning and data mining toolkit, to build machine learning classification models. Winning most data science competitions [38], machine learning studies computer algorithms that learn from data, such as random forest, support vector machine, and neural network. Weka integrates many commonly used machine learning algorithms and feature selection techniques. We considered all 39 machine learning classification algorithms in the standard Weka package, and adopted our previously developed automatic machine learning model selection method [39] and the training data of 2013 to automatically select the algorithm, feature selection technique, and hyper-parameter values among all of the applicable ones. In a machine learning algorithm, hyper-parameters are the parameters whose values are traditionally


set by the machine learning software user manually before model training. An example of a hyper-parameter is the number of decision trees used in a random forest classifier. Our automatic machine learning model selection method [39] uses the Bayesian optimization (a.k.a. response surface) methodology to automatically explore numerous combinations of algorithm, feature selection technique, and hyper-parameter values, and performs 3-fold cross validation to select the final combination maximizing the AUC. Compared to the other five performance metrics accuracy, sensitivity, specificity, PPV, and NPV, AUC has the advantage of not relying on the cut-off threshold for deciding between predicted admission and predicted ED discharge.

**Demographic and clinical characteristics of our patient cohort**

Tables 2 and 3 show the demographic and clinical characteristics of our patient cohort: children below age two who had ED visits for bronchiolitis in 2013 and 2014, respectively. The characteristics are mostly similar between both years. About 40.78% (=1,640/4,022) and 38.26% (=1,368/3,576) of ED visits for bronchiolitis ended in hospitalization in 2013 and 2014, respectively. About 35.80% (=1,440/4,022) and 32.89% (=1,176/3,576) of ED visits for bronchiolitis are labelled appropriate hospital admission in 2013 and 2014, respectively.

**Table 2.** Demographic and clinical characteristics of children under age two who had emergency department visits at Intermountain Healthcare hospitals for bronchiolitis in 2013.

| Characteristic                      | Emergency department visits ($n = 4,022$) | Emergency department visits discharged to home ($n = 2,382$) | Emergency department visits ending in hospitalization ($n = 1,640$) |
|-------------------------------------|-------------------------------------------|-------------------------------------------------------------|---------------------------------------------------------------|
| **Age**                             |                                           |                                                             |                                                               |
| <2 months                           | 518 (12.88%)                              | 211 (8.86%)                                                 | 307 (18.72%)                                                  |
| 2 to <12 months                     | 2,424 (60.27%)                            | 1,498 (62.89%)                                              | 926 (56.46%)                                                  |
| 12 to 24 months                     | 1,080 (26.85%)                            | 673 (28.25%)                                                | 407 (24.82%)                                                  |
| **Gender**                          |                                           |                                                             |                                                               |
| Male                                | 2,369 (58.90%)                            | 1,414 (59.36%)                                              | 955 (58.23%)                                                  |
| Female                              | 1,653 (41.10%)                            | 968 (40.64%)                                                | 685 (41.77%)                                                  |
| **Race**                            |                                           |                                                             |                                                               |
| American Indian or Alaska native    | 51 (1.27%)                                | 26 (1.09%)                                                  | 25 (1.52%)                                                    |
| Asian                               | 49 (1.22%)                                | 20 (0.84%)                                                  | 29 (1.77%)                                                    |
| Black or African American           | 124 (3.08%)                               | 78 (3.27%)                                                  | 46 (2.80%)                                                    |
| Native Hawaiian or other Pacific islander | 321 (7.98%)                           | 160 (6.72%)                                                 | 161 (9.82%)                                                   |
| White                               | 2,940 (73.10%)                            | 1,784 (74.90%)                                              | 1,156 (70.49%)                                                |
| Unknown or not reported             | 537 (13.35%)                              | 314 (13.18%)                                                | 223 (13.60%)                                                  |
| **Ethnicity**                       |                                           |                                                             |                                                               |
| Hispanic                            | 1,321 (32.84%)                            | 826 (34.68%)                                                | 495 (30.18%)                                                  |
| Non-Hispanic                        | 2,687 (66.81%)                            | 1,549 (65.03%)                                              | 1,138 (69.39%)                                                |
| Unknown or not reported             | 14 (0.35%)                                | 7 (0.29%)                                                   | 7 (0.43%)                                                    |
| **Insurance**                       |                                           |                                                             |                                                               |
| Private                             | 2,436 (60.57%)                            | 1,338 (56.17%)                                              | 1,098 (66.95%)                                                |
| Public                              | 1,422 (35.36%)                            | 933 (39.17%)                                                | 489 (29.82%)                                                  |
| Self-paid or charity                | 164 (4.08%)                               | 111 (4.66%)                                                 | 53 (3.23%)                                                    |
| Asthma                              | 207 (5.15%)                               | 72 (3.02%)                                                  | 135 (8.23%)                                                   |
| Chronic complex condition [40]      | 296 (7.36%)                               | 60 (2.52%)                                                  | 236 (14.39%)                                                  |

**Table 3.** Demographic and clinical characteristics of children under age two who had emergency department visits at Intermountain Healthcare hospitals for bronchiolitis in 2014.

| Characteristic                      | Emergency department visits ($n = 3,576$) | Emergency department visits discharged to home ($n = 2,208$) | Emergency department visits ending in hospitalization ($n = 1,368$) |
|-------------------------------------|-------------------------------------------|-------------------------------------------------------------|---------------------------------------------------------------|
| **Age**                             |                                           |                                                             |                                                               |
| <2 months                           | 454 (12.70%)                              | 186 (8.42%)                                                 | 268 (19.59%)                                                  |
| 2 to <12 months                     | 2,079 (58.14%)                            | 1,379 (62.45%)                                              | 700 (51.17%)                                                  |
| 12 to 24 months                     | 1,043 (29.17%)                            | 643 (29.12%)                                                | 400 (29.24%)                                                  |
| **Gender**                          |                                           |                                                             |                                                               |

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Based on the $\chi^2$ twosample test, for the 2013 data, the ED visits discharged to home and those ending in hospitalization showed the same distribution for gender ($P = .49$) and different distributions for race ($P < .001$), ethnicity ($P = .01$), and insurance category ($P < .001$). For the 2014 data, the ED visits discharged to home and those ending in hospitalization showed the same distribution for gender ($P = .94$) and race ($P = .61$), and different distributions for ethnicity ($P < .001$) and insurance category ($P < .001$). Based on the Cochran-Armitage trend test [41], for both the 2013 and 2014 data, the ED visits discharged to home and those ending in hospitalization showed different distributions for age ($P < .001$).

3. Results

Our automatic machine learning model selection method [39] chose the random forest classification algorithm. Random forest can naturally handle missing feature values. Our model was built using this algorithm and the 33 features shown in Table 4. These features are sorted in descending order of their importance values, which were automatically computed by the random forest algorithm in Weka based on average impurity decrease. In general, the features related to the patient’s history are ranked lower than those reflecting the patient’s status in the current ED visit. This intuitively makes medical sense. Two candidate patient features, ethnicity and the ED visit’s acuity level, were not used in our model because they did not increase model accuracy.

| Feature | Feature importance based on average impurity decrease |
|---------|------------------------------------------------------|
| Hour of ED disposition | 0.42 |
| Age in days | 0.40 |
| Whether the patient has any other barrier to learning | 0.39 |
| Length of ED stay in minutes | 0.38 |
| Number of lab tests ordered during the ED visit | 0.37 |
| Heart rate | 0.37 |
| Diastolic blood pressure | 0.36 |
| Gender | 0.35 |
| Temperature | 0.35 |
| Respiratory rate | 0.34 |
| Number of radiology studies ordered during the ED visit | 0.34 |
| Insurance category | 0.34 |
| Number of X-rays ordered during the ED visit | 0.34 |
| Systolic blood pressure | 0.34 |
| Weight | 0.33 |
| Chief complaint | 0.32 |
Figure 2 shows the receiver operating characteristic curve of our model. Weka uses 50% as its default probability cutoff threshold for making binary classifications. Table 5 shows the error matrix of our model. Table 6 compares our model and the ED clinician’s disposition decision. Our model achieved an accuracy of 90.66% (=3,242/3,576, 95% CI: 89.68%-91.64%), a sensitivity of 92.09% (=1,083/1,176, 95% CI: 90.33%-93.56%), a specificity of 89.96% (=2,159/2,400, 95% CI: 88.69%-91.17%), an AUC of 0.960 (95% CI: 0.954-0.966), a PPV of 81.80% (=1,083/1,324, 95% CI: 79.67%-83.80%), and an NPV of 95.87% (=2,159/2,252, 95% CI: 95.00%-96.65%). If we removed the insurance category feature, our model achieved a lower accuracy of 90.32% (=3,230/3,576, 95% CI: 89.37%-91.28%), a lower sensitivity of 90.22% (=1,061/1,176, 95% CI: 88.30%-91.79%), a specificity of 90.38% (=2,169/2,400, 95% CI: 89.15%-91.57%), an AUC of 0.960 (95% CI: 0.955-0.966), a PPV of 82.12% (=1,061/1,292, 95% CI: 79.94%-84.15%), and a lower NPV of 94.97% (=2,169/2,284, 95% CI: 93.97%-95.78%). In comparison, the ED clinician’s disposition decision achieved an accuracy of 93.68% (=3,350/3,576, 95% CI: 92.87%-94.49%), a sensitivity of 98.55% (=1,159/1,176, 95% CI: 97.85%-99.24%), a specificity of 91.29% (=2,191/2,400, 95% CI: 90.05%-92.46%), an AUC of 0.949 (95% CI: 0.942-0.956), a PPV of 84.72% (=1,159/1,368, 95% CI: 82.83%-86.69%), and an NPV of 99.23% (=2,191/2,208, 95% CI: 98.86%-99.59%).

| Feature                                      | Value  |
|----------------------------------------------|--------|
| SpO2                                         | 0.32   |
| Wheezing                                     | 0.32   |
| Retractions                                  | 0.29   |
| Number of consults called during the ED visit| 0.28   |
| Whether the patient is current with his/her immunizations | 0.27   |
| Race                                         | 0.27   |
| Enterovirus infection                        | 0.25   |
| Respiratory syncytial virus infection        | 0.24   |
| Co-infection                                 | 0.24   |
| Prior hospitalization                        | 0.22   |
| Prior intubation                             | 0.22   |
| Dehydration                                  | 0.20   |
| Language barrier to learning                 | 0.20   |
| Rhinovirus infection                         | 0.20   |
| Prematurity                                  | 0.18   |
| History of bronchopulmonary dysplasia        | 0.16   |
| History of eczema                            | 0.15   |
Table 5. The error matrix of our predictive model.

|                                | Appropriate admission | Appropriate emergency department discharge |
|--------------------------------|-----------------------|-------------------------------------------|
| Predicted admission            | 1,083                 | 241                                       |
| Predicted emergency department discharge | 93                    | 2,159                                     |

Table 6. A comparison of our model and the emergency department clinician’s disposition decision.

|                                | Accuracy  | Sensitivity | Specificity | AUC      | PPV      | NPV      |
|--------------------------------|-----------|-------------|-------------|----------|----------|----------|
| Our model                      | 90.66%    | 92.09%      | 89.96%      | 0.960    | 81.80%   | 95.87%   |
| The emergency department      | 93.68%    | 98.55%      | 91.29%      | 0.949    | 84.72%   | 99.23%   |

Figure 3 shows the calibration plot of our model by decile of predicted probability of appropriate admission. The Hosmer-Lemeshow test showed imperfect calibration of the predicted probabilities and the actual outcomes ($P < .001$). When the predicted probability is $<0.5$, our model tends to overestimate the actual probability. When the predicted probability is $>0.5$, our model tends to underestimate the actual probability.

Figure 3. The calibration plot of our model by decile of predicted probability of appropriate admission.

4. Discussion

Principal results

We developed the first machine learning classification model to accurately predict appropriate hospital admission for ED patients with bronchiolitis. Our model is a significant improvement over the previous models for predicting hospital admission in ED patients with bronchiolitis [7-9, 27-29]. Our model has good accuracy, with five of the six performance metrics achieving a value $\geq 90\%$ and the other achieving a value $>80\%$. Although our model attained a 3.02\% lower accuracy than Intermountain Healthcare clinicians’ ED disposition decisions (90.66\% vs. 93.68\%), we still view our model as a step forward with great potential. Within 0.01 second, our model can output the prediction result for a new patient. With further improvement to boost its accuracy and automatically explain its prediction results [42, 43], our model could be integrated into an electronic health record system and become the base of a decision support tool to help make appropriate ED disposition decisions for bronchiolitis. At that time, a clinician could use the model’s output as a point of reference when considering the disposition decision. This could provide value, improve outcomes, and reduce healthcare costs for bronchiolitis regardless of whether our future final model can achieve a higher accuracy than Intermountain Healthcare clinicians’ ED disposition decisions. Our faith in this stems from the following considerations:

(1) Intermountain Healthcare has several collaborative partnerships among its EDs and hospitals to facilitate coordination of pediatric specialty care, and has completed multiple quality improvement projects for bronchiolitis management. About 52.16\% (=3,963/7,598) of ED visits for bronchiolitis within Intermountain Healthcare occur at a tertiary pediatric hospital with an ED staffed by pediatric-specific clinicians. On average, the ED disposition decisions for bronchiolitis made at
Intermountain Healthcare could be more accurate than those made at some other healthcare systems, especially those systems with general practice physicians or fewer pediatricians working in their EDs. Our model can be valuable for those systems, if it reaches a higher accuracy than the clinicians’ ED disposition decisions made at those systems. There is some evidence indicating this possibility. Most inappropriate ED disposition decisions are unnecessary admissions [26]. In our data set, 14.36% of hospital admissions from the ED were deemed unnecessary [26]. In the literature [44, 45], this percentage is reported to be larger and between 20%-29%. To understand our model’s value for other systems, additional studies need to be conducted using those systems’ data. This is an interesting area for future work.

(2) Figure 4 shows the degree of missing values of each feature with missing values. Figure 5 shows the probability mass function of the number of features with missing values in each data instance. In our data set, several attributes have numerous missing values because those values were either recorded on paper or occasionally undocumented, and therefore were not available in Intermountain Healthcare’s electronic health record system. In particular, wheezing and retractions values were missing for 73.56% (=5,589/7,598) of ED visits for bronchiolitis. Systolic and diastolic blood pressure values were missing for 46.49% (=3,532/7,598) of ED visits for bronchiolitis. This could lower model accuracy. In the future, these attributes are expected to be recorded more completely in Intermountain Healthcare’s newly-implemented Cerner-based electronic health record system. After re-training our model on more complete Intermountain Healthcare data from future years, we would expect its accuracy to increase. In addition, multiple other healthcare systems like Seattle Children’s Hospital have been using the Cerner electronic health record system to record these attributes relatively completely for many years. Our model could possibly achieve a higher accuracy if trained on those systems’ data. Both of these are interesting areas for future work.

Figure 4. The degree of missing values of each feature with missing values.

Figure 5. The probability mass function of the number of features with missing values in each data instance.
When making ED disposition decisions for bronchiolitis, clinicians often face some level of uncertainty and would prefer to obtain a second opinion given by a reasonably accurate predictive model, particularly if some technique is used to automatically explain the model’s prediction results. For this, we can use our prior method [42, 43] to automatically provide rule-based explanations for any machine learning model’s classification results with no accuracy loss.

When reporting the performance metrics, we used the default cut-off threshold Weka chose for deciding between predicted admission and predicted ED discharge. Different healthcare systems could emphasize differing performance metrics and give divergent weights to false positives and false negatives. As is the case with predictive modeling in general, a healthcare system can always adjust the cut-off threshold based on the system’s preferences.

**Comparison with prior work**

Previously, researchers had constructed several models to predict hospital admission in ED patients with bronchiolitis [7-9, 27-29]. Table 7 gives a comparison of these previous models with our model. Compared to our model that predicts the appropriate ED disposition decision, the previous models are much less accurate and incorrectly assume actual ED disposition decisions are always appropriate. Our model uses many more patients’ data, many more predictive features, and a more sophisticated classification algorithm than the previous models. As is the case with predictive modeling in general, all of these help improve our model’s accuracy.

**Table 7.** A comparison of our model and several previous models for predicting emergency department disposition decisions for bronchiolitis. “-” means that the performance metric is unreported in the original paper describing the model.

| Model            | Number of ED visits | Method for building the model | Features included in the final model                                                                 | Accuracy | Sensitivity | Specificity | AUC  | PPV | NPV  |
|------------------|---------------------|-------------------------------|--------------------------------------------------------------------------------------------------------|----------|-------------|-------------|------|-----|------|
| Our model        | 7,599               | random forest                 | as listed in the Results section                                                                     | 90.66%   | 92.09%      | 89.96%      | 0.960| 81.80% | 95.87%|
| Walsh et al. [27]| 119                 | neural network ensemble       | age, respiratory rate after initial treatment, heart rate before initial treatment, oxygen saturation before and after initial treatment, dehydration, maternal smoking, increased work of breathing, poor feeding, wheezes only without associated crackles, entry temperature, and presence of both crackles and wheezes | 81%      | 78%         | 82%         | -    | 68%  | 89%  |
| Marlais et al. [7]| 449                 | scoring system               | age, respiratory rate, heart rate, oxygen saturation, and duration of symptoms                          | -        | 74%         | 77%         | 0.81 | 67%  | 83%  |
| Destino et al. [28]| 195                | single variable              | the Children’s Hospital of Wisconsin respiratory score                                                | -        | 65%         | 65%         | 0.68 | -    | -    |
| Laham et al. [8]   | 101                 | logistic regression          | age, need for intravenous fluids, hypoxia, and nasal wash lactate dehydrogenase concentration        | 80%      | 81%         | 77%         | 0.87 | 88%  | 66%  |
| Corneli et al. [9] | 598                 | decision tree                | oxygen saturation, the Respiratory Distress Assessment Instrument score computed from wheezing and retractions, and respiratory rate | -        | 56%         | 74%         | -    | -    | -    |
| Walsh et al. [29]  | 300                 | logistic regression          | age, dehydration, increased work of breathing, and heart rate                                         | -        | 91%         | 83%         | -    | 62%  | -    |

Some aspects of our findings are similar to those of previous studies. In our data set, 39.59% (=3,008/7,598) of ED visits for bronchiolitis ended in hospitalization. This percentage is within 32%-40%, the range of hospital admission rates in ED visits for bronchiolitis reported in the literature [7-9].

**Limitations**
This study has several limitations:

(1) This study used data from a single healthcare system, Intermountain Healthcare, and did not test our results’ generalizability. In the future, it would be desirable to validate our predictive models on other healthcare systems’ data. We are reasonably confident in our results, as our study was conducted in a realistic setting for finding factors generalizable to other US healthcare systems. “Intermountain Healthcare is a large healthcare system with EDs at 22 heterogeneous hospitals spread over a large geographic area, ranging from community metropolitan and rural hospitals attended by general practitioners and family doctors with constrained pediatric resources to tertiary care children’s and general hospitals in urban areas attended by sub-specialists. Each hospital has a different patient population, geographic location, staff composition, scope of services, and cultural background” [26].

(2) Despite being an integrated healthcare system, Intermountain Healthcare does not have complete clinical and administrative data on all of its patients. Our data set missed information on patients’ healthcare use that occurred at non-Intermountain Healthcare facilities. Including data from those facilities may lead to different results, whereas we do not expect this to significantly change our results. Intermountain Healthcare delivers ~85% of pediatric care in Utah [32]. Hence, our data set is reasonably complete with regard to capturing bronchiolitis patients’ healthcare use in Utah.

(3) Our operational definition of appropriate hospital admission is imperfect and ignores factors such as patient transportation availability, preference of the patient’s parents, and hour of ED disposition [26]. Many of these factors are often undocumented in patient records. For some hospital admissions from the ED that were regarded as unnecessary based on our operational definition, the original admission decisions could be made because of these factors.

(4) Besides those used in the paper, there could be other features that can help improve model accuracy. Finding new predictive features is an interesting area for future work.

5. Conclusions
Our model can predict appropriate hospital admission for ED patients with bronchiolitis with good accuracy. In particular, our model achieved an AUC of 0.960, whereas an AUC ≥0.9 is considered outstanding discrimination [46]. With further improvement, our model could be integrated into an electronic health record system to provide personalized real-time decision support for making ED disposition decisions for bronchiolitis. This could help standardize care and improve outcomes for bronchiolitis.

Authors’ contributions
GL was mainly responsible for the paper. He conceptualized and designed the study, performed literature review and data analysis, and wrote the paper. BLS, MDJ, and FLN provided feedback on various medical issues, contributed to conceptualizing the presentation, and revised the paper. SH took part in retrieving the Intermountain Healthcare data set and interpreting its detected peculiarities.

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Conflicts of interest
None declared.

List of abbreviations
AUC: Area Under the receiver operating characteristic Curve
ED: emergency department
FN: false negative
FP: false positive
ICD-9-CM: International Classification of Diseases, Ninth Revision, Clinical Modification
NPV: negative predictive value
PPV: positive predictive value
SpO2: peripheral capillary oxygen saturation
TN: true negative
TP: true positive
References

1. Zorc JJ, Hall CB. Bronchiolitis: recent evidence on diagnosis and management. Pediatrics 2010;125(2):342-9. PMID:20100768
2. Hasegawa K, Tsugawa Y, Brown DF, Mansbach JM, Camargo CA Jr. Trends in bronchiolitis hospitalizations in the United States, 2000-2009. Pediatrics 2013;132(1):28-36. PMID:23733801
3. Mansbach JM, Emond JA, Camargo CA Jr. Bronchiolitis in US emergency departments 1992 to 2000: epidemiology and practice variation. Pediatr Emerg Care 2005;21(4):242-7. PMID:15824683
4. Parker MJ, Allen U, Stephens D, Lalani A, Schuh S. Predictors of major intervention in infants with bronchiolitis. Pediatr Pulmonol 2009;44(4):358-63. PMID:19283838
5. Shay DK, Holman RC, Newman RD, Liu LL, Stout JW, Anderson LJ. Bronchiolitis-associated hospitalizations among US children, 1980-1996. JAMA 1999;282(15):1440-6. PMID:10535434
6. Hasegawa K, Tsugawa Y, Brown DF, Mansbach JM, Camargo CA Jr. Temporal trends in emergency department visits for bronchiolitis in the United States, 2006 to 2010. Pediatr Infect Dis J 2014;33(1):11-8. PMID:23934206
7. Marlais M, Evans J, Abrahamson E. Clinical predictors of admission in infants with acute bronchiolitis. Arch Dis Child 2011;96(7):648-52. PMID:21339199
8. Laham FR, Trott AA, Bennett BL, Kozinetz CA, Jewell AM, Garofalo RP, Piedra PA. LDH concentration in nasal-wash fluid as a biochemical predictor of bronchiolitis severity. Pediatrics 2010;125(2):e225-33. PMID:20100751
9. Corneli HM, Zorc JJ, Holubkov R, Bregstein JS, Brown KM, Mahajan P, Kuppermann N; Bronchiolitis Study Group for the Pediatric Emergency Care Applied Research Network. Bronchiolitis: clinical characteristics associated with hospitalization and length of stay. Pediatr Emerg Care 2012;28(2):99-103. PMID:22270499
10. Scottish Intercollegiate Guidelines Network. Bronchiolitis in children. A national clinical guideline. https://www.guidelinecentral.com/summaries/bronchiolitis-in-children-a-national-clinical-guideline/. Archived at http://www.webcitation.org/6bhQvWHzA
11. Bronchiolitis Guideline Team, Cincinnati Children's Hospital Medical Center: Evidence-based care guideline for management of first time episode bronchiolitis in infants less than 1 year of age. http://www.guideline.gov/content.aspx?id=34411. Archived at http://www.webcitation.org/6bhOyjITC
12. Brand PL, Vaessen-Verberne AA. Differences in management of bronchiolitis between hospitals in the Netherlands. Eur J Pediatr 2000;159(5):343-7. PMID:10834519
13. Ducharme FM. Management of acute bronchiolitis. BMJ 2011;342:d1658. PMID:21471173
14. Behrendt CE, Decker MD, Burch DJ, Watson PH. International variation in the management of infants hospitalized with respiratory syncytial virus. Eur J Pediatr 1998;157(3):215-20. PMID:9537488
15. Chamberlain JM, Patel KM, Pollack MM. Association of emergency department care factors with admission and discharge decisions for pediatric patients. J Pediatr 2006;149(5):644-9. PMID:17095336
16. Johnson DW, Adair C, Brant R, Holmwood J, Mitchell I. Differences in admission rates of children with bronchiolitis by pediatric and general emergency departments. Pediatrics 2002;110(4):e49. PMID:12359822
17. Mallory MD, Shay DK, Garrett J, Bordley WC. Bronchiolitis management preferences and the influence of pulse oximetry and respiratory rate on the decision to admit. Pediatrics 2003;111(1):e45-51. PMID:12509594
18. Plint AC, Johnson DW, Wiebe N, Bulloch B, Pusic M, Joubert G, Watchman G, Klassen TP. Practice variation among pediatric emergency departments in the treatment of bronchiolitis. Acad Emerg Med 2004;11(4):353-60. PMID:15064208
19. Vogel AM, Lennon DR, Harding JE, Pinnock RE, Graham DA, Grimwood K, Pattemore PK. Variations in bronchiolitis management between five New Zealand hospitals: can we do better? J Paediatr Child Health 2003;39(1):40-5. PMID:12542811
20. Willson DF, Horn SD, Hendley JO, Smout R, Gassaway J. Effect of practice variation on resource utilization in infants hospitalized for viral lower respiratory illness. Pediatrics 2001;108(4):851-5. PMID:11581435
21. Willson DF, Jiao JH, Hendley JO, Donowitz L. Invasive monitoring in infants with respiratory syncytial virus infection. J Pediatr 1996;128(3):357-62. PMID:8774504
22. Wang EE, Law BJ, Boucher FD, Stephens D, Robinson JL, Dobson S, Langley JM, McDonald J, MacDonald NE, Mitchell I. Pediatric Investigators Collaborative Network on Infections in Canada (PICNIC) study of admission and management variation in patients hospitalized with respiratory syncytial viral lower respiratory tract infection. J Pediatr 1996;129(3):390-5. PMID:8804328
23. Christakis DA, Cowan CA, Garrison MM, Molteni R, Marcuse E, Zerr DM. Variation in inpatient diagnostic testing and management of bronchiolitis. Pediatrics 2005;115(4):878-84. PMID:15805359
24. Mansbach JM, Clark S, Christopher NC, LoVecchio F, Kunz S, Acholonu U, Camargo CA Jr. Prospective multicenter study of bronchiolitis: predicting safe discharges from the emergency department. Pediatrics 2008;121(4):680-8. PMID:18381531
25. McBride SC, Chiang VW, Goldmann DA, Landrigan CP. Preventable adverse events in infants hospitalized with bronchiolitis. Pediatrics 2005;116(3):603-8. PMID:16140699
26. Luo G, Johnson MD, Nkoy FL, He S, Stone BL. Appropriateness of hospital admission for emergency department patients with bronchiolitis: secondary analysis. JMIR Med Inform 2018;6(4):e10498. PMID:30401659
27. Walsh P, Cunningham P, Rothenberg SJ, O'Doherty S, Hoey H, Healy R. An artificial neural network ensemble to predict disposition and length of stay in children presenting with bronchiolitis. Eur J Emerg Med 2004;11(5):259-64. PMID:15359198
28. Destino L, Weisgerber MC, Soung P, Bakalarski D, Yan K, Rehborg R, Wagner DR, Gorelick MH, Simpson P. Validity of respiratory scores in bronchiolitis. Hosp Pediatr 2012;2(4):202-9. PMID:24313026
29. Walsh P, Rothenberg SJ, O'Doherty S, Hoey H, Healy R. A validated clinical model to predict the need for admission and length of stay in children with acute bronchiolitis. Eur J Emerg Med 2004;11(5):265-72. PMID:15359199
30. Luo G, Nkoy FL, Gesteland PH, Glasgow TS, Stone BL. A systematic review of predictive modeling for bronchiolitis. Int J Med Inform 2014;83(10):691-714. PMID:25106939
31. Luo G, Stone BL, Johnson MD, Nkoy FL. Predicting appropriate admission of bronchiolitis patients in the emergency department: rationale and methods. JMIR Res Protoc 2016;5(1):e41. PMID:26952700
32. Byington CL, Reynolds CC, Korgenski K, Sheng X, Valentine KJ, Nelson RE, Daly JA, Osguthorpe RJ, James B, Savitz L, Pavia AT, Clark EB. Costs and infant outcomes after implementation of a care process model for febrile infants. Pediatrics 2012;130(1):e16-24. PMID:22732178
33. Flaherman VJ, Ragins AL, Li SX, Kipnis P, Masaquel A, Escobar GJ. Frequency, duration and predictors of bronchiolitis episodes of care among infants ≥32 weeks gestation in a large integrated healthcare system: a retrospective cohort study. BMC Health Serv Res 2012;12:144. PMID:22682080
34. Mittal V, Darnell C, Walsh B, Mehta A, Badawy M, Morse R, Pop R, Tidwell J, Sheehan M, McDermott S, Cannon C, Kahn J. Inpatient bronchiolitis guideline implementation and resource utilization. Pediatrics 2014;133(3):e730-7. PMID:24534398
35. Sandweiss DR, Mundorff MB, Hill T, Wolfe D, Greene T, Andrews S, Glasgow TS. Decreasing hospital length of stay for bronchiolitis by using an observation unit and home oxygen therapy. JAMA Pediatr 2013;167(5):422-8. PMID:23479000
36. Steyerberg EW. Clinical Prediction Models: A Practical Approach to Development, Validation, and Updating. New York, NY: Springer; 2009. ISBN:038777243X
37. Witten IH, Frank E, Hall MA, Pal CJ. Data Mining: Practical Machine Learning Tools and Techniques, 4th ed. Burlington, MA: Morgan Kaufmann; 2016. ISBN:0128042915
38. Kaggle homepage. https://www.kaggle.com/. Archived at http://www.webcitation.org/6oOiI4j9t
39. Zeng X, Luo G. Progressive sampling-based Bayesian optimization for efficient and automatic machine learning model selection. Health Inf Sci Syst 2017;5(1):2. PMID:29038732
40. Feudtner C, Feinstein JA, Zhong W, Hall M, Dai D. Pediatric complex chronic conditions classification system version 2: updated for ICD-10 and complex medical technology dependence and transplantation. BMC Pediatr 2014;14:199. PMID:25102958
41. Agresti A. Categorical Data Analysis, 3rd ed. Hoboken, NJ: Wiley; 2012. ISBN:9780470463635
42. Luo G. Automatically explaining machine learning prediction results: a demonstration on type 2 diabetes risk prediction. Health Inf Sci Syst 2016;4:2. PMID:26958341
43. Luo G. A roadmap for semi-automatically extracting predictive and clinically meaningful temporal features from medical data for predictive modeling. Global Transitions 2019, in press.
44. Shaw KN, Bell LM, Sherman NH. Outpatient assessment of infants with bronchiolitis. Am J Dis Child 1991;145(2):151-5. PMID:1994678
45. Shaﬁk MH, Seoudi TM, Raway TS, Al Harbash NZ, Ahmad MM, Al Mutairi HF. Appropriateness of pediatric hospitalization in a general hospital in Kuwait. Med Princ Pract 2012;21(6):516-21. PMID:22678120
46. Hosmer Jr. DW, Lemeshow S, Sturdivant RX. Applied Logistic Regression, 3rd ed. Hoboken, NJ: Wiley; 2013. ISBN:0470582472