Hospital-based Medicine: Clinical & HSR

Tuesday, August 11  2:30-4:00 pm EDT

Moderators
Sunitha Kaiser
Eyal Cohen

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<th>Abstract</th>
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<th>Presenting Author</th>
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<td>Pediatric Readmission Risk Modeling Using Clinical and Sociodemographic Factors</td>
<td>Lauren Solan</td>
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<tr>
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<td>Validation of a Childhood Pneumonia Prognostic Tool for Use in Emergency Care Settings in the United States</td>
<td>Derek Williams</td>
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Note: Schedule subject to change based on presenter availability.
**CONTROL ID:** 3375532

**TITLE:** Pediatric Readmission Risk Modeling Using Clinical and Sociodemographic Factors

**PRESENTER:** Lauren Solan

**AUTHORS (LAST NAME, FIRST NAME):** Solan, Lauren¹; Fortuna, Robert J.³; Thevenet-Morrison, Kelly²; Kittel, Julie²; van Wijngaarden, Edwin²; Halterman, Jill⁴

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**CURRENT CATEGORY:** Hospital-based Medicine

**CURRENT SUBCATEGORY:** None

**KEYWORDS:** readmission risk, sociodemographics, electronic health record.

**SESSION TITLE:** Hospital-based Medicine: Clinical & HSR | Hospital-based Medicine: Clinical & HSR

**SESSION TYPE:** Webinar|Platform

**ABSTRACT BODY:**

**Background:** Pediatric readmissions are burdensome to families and health care systems. Identifying predictors of risk may guide interventions to decrease readmissions. Prediction of readmission risk is often based on clinical factors alone although sociodemographic variables play an important role in pediatric healthcare and outcomes. However, these variables are not commonly available in the electronic health record (EHR) and are not routinely included in risk prediction.

**Objective:** To validate a previously studied adult-based readmission risk model in a prospective pediatric cohort, and to build a new pediatric readmission risk model that includes both clinical and sociodemographic factors.

**Design/Methods:** We enrolled a prospective cohort of caregivers of hospitalized patients <18 years of age, excluding newborns, and asked caregivers to complete an electronic survey assessing sociodemographic variables. A previously-studied adult-based readmission risk assessment tool was validated in this prospective cohort using receiver operator characteristic (ROC) analyses. We then performed principal component analyses (PCA) and stepwise methods on survey responses to create novel sociodemographic variables for use in logistic regression and ROC analyses, determined their association with 30-day readmissions and created a new pediatric risk assessment tool.

**Results:** We enrolled 343 caregivers (response rate 67%); 31 patients (9%) experienced a 30-day readmission. Those who did and did not experience a readmission had similar demographic characteristics. ROC analyses validated the application of the adult-based risk assessment tool in our prospective pediatric cohort, maintaining a statistically significant area under the curve (AUC) of 0.7. Logistic regression analyses yielded 3 additional predictors of readmission: delaying medical care, caregivers with depressive symptoms, and confidence in patient/physician interactions (Figure 1). Incorporating these variables into the previously validated model strengthened the model’s predictive capacity (AUC = 0.78) (Figure 2) and resulted in a new pediatric readmission risk assessment model.

**Conclusion(s):** An adult-based readmission risk model yielded a moderate predictive capacity for 30-day readmissions within our pediatric prospective cohort. The addition of sociodemographic variables strengthened the predictive nature of the model. Inclusion of sociodemographic variables within the EHR is an important step to support predictive analytic risk assessments and guide interventions to reduce readmissions.
BACKGROUND: We previously developed a prognostic tool that accurately estimates risk for severe outcomes in children hospitalized with pneumonia.

OBJECTIVE: To prospectively validate our prognostic tool in a new population of children presenting for emergency care.

DESIGN/METHODS: The previously developed prognostic tool uses ordinal logistic regression to estimate risk for severe (invasive mechanical ventilation or shock requiring vasoactive medications); moderate (intensive care admission without severe features); or mild (children without moderate or severe features) disease using clinical, laboratory, and radiologic predictor data collected at the time of presentation. Two versions of the tool were created, one using 10 predictors based on expert consensus (Expert) and the other using 9 predictors available as coded data fields in the electronic health record (EHR). For this study, we prospectively enrolled children (2mo to <18yr) with clinical and radiographically-confirmed pneumonia presenting for emergency care at two US children’s hospitals between September 2017 and May 2019. Predictor data for each tool was collected at presentation. In-hospital outcomes were assessed through chart review following discharge. Discriminative ability of each tool was measured using concordance (c-statistic) and compared to concordance estimated from the original development cohort. Calibration plots were created to contrast observed vs predicted probabilities for moderate or severe pneumonia.

RESULTS: There were 995 children included in the Expert tool and 593 children in the EHR tool (fewer children included due to missing white blood cell count data). Baseline characteristics and outcome frequencies are detailed in Table 1. Discriminative ability of both tools was good, with identical discrimination when compared to performance in the development cohort (Table 2). Both tools also demonstrated excellent calibration (Figure 1). Median (interquartile range)
The predicted probability for moderate or severe pneumonia was 0.13 (0.06, 0.29) for the Expert tool and 0.22 (0.10, 0.41) for the EHR tool; predicted probabilities were significantly higher for those experiencing these outcomes compared to children with the mild outcome (Figure 2).

Conclusion(s): Both the Expert and EHR prognostic tools accurately estimate risk for severe outcomes among children with pneumonia presenting for emergency care. Next steps include testing the clinical effectiveness of these validated tools in a forthcoming randomized controlled trial.
Background: Positive blood cultures lead to unnecessary interventions when results are due to a contaminant. Biomolecular assays can identify contaminants but they are costly and do not detect all nonpathogenic bacteria.

Objective: To: 1. Estimate true bacteremia risk with a predictive model that uses clinical factors and time-to-positivity (TTP), and; 2. Compare its performance with the <24-hour rule (reference standard).

Design/Methods: This is a matched cohort study of infants who were brought to the emergency departments at two children’s hospital from January 2014-December 2018. Inclusion criteria consisted of age 0-90 days, temperature >38°C, and collection of a blood culture. Infants with positive blood cultures were matched 1:2 with infants with negative bloods culture based on age and sex. Informed by the literature, 10 variables (Table 1) were used to develop a predictive model using a random forest (RF) classification algorithm. Tuning parameters were chosen by cross-validated area-under-the receiver operating characteristic curve (AUC). For negative blood cultures, a TTP of 130 hours was used. The main outcome was true bacteremia, defined as growth of a single pathogen that was treated clinically as an infection. Using five-fold cross-validation, four folds were used for training. The fifth fold consisted only of infants with a positive blood culture and was used for testing. AUC, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) were calculated. Results were compared with the <24-hour rule as the reference standard in which a TTP of <24 hours was used as the sole predictor.

Results: Of 173 febrile infants, 59 had a positive blood culture and 22 had true bacteremia. The AUCs for the 24-hour rule and RF model were 0.72 (95% CI 0.64-0.8) and 0.97 (95% CI 0.93-1), respectively. At a risk threshold of 0.19 for the RF model, the sensitivity was 1 (95% CI 1-1), specificity was 0.865 (95% CI 0.757-0.973), PPV was 0.815 (95% CI 0.710-0.956), and NPV was 1 (95% CI 1-1) compared with 1 (95% CI 1-1), 0.432 (95% CI 0.270-0.595), 0.512 (95% CI 0.449-0.595), and 1 (95% CI 1-1), respectively, for the <24-hour rule.

Conclusion(s): Findings from this multi-site study suggest that easily obtained clinical risk factors can be used to enhance the risk estimate of true bacteremia in infants with positive blood cultures. Formatted as a risk calculator, this tool could be used to safely avoid further treatment when true bacteremia risk is sufficiently low.
Background: Tens of thousands of well-appearing febrile infants 7-60 days old are hospitalized annually to rule out bacterial meningitis and bacteremia (invasive bacterial infection, IBI). Current approaches to suspected IBI in febrile infants rely on traditional linear modeling techniques which use a small number of variables and face limitations due to missing data and scant observations. However, most infants present with a vast number of clinically relevant factors.

Objective: To assess the feasibility of a next-generation risk prediction tool using a nationally representative, contemporary patient population and machine learning techniques.

Design/Methods: 126 hospitals contributed data on well-appearing febrile infants aged 7-60 days 12/2015-12/2017. A limited set of features were available for algorithm development including infant age group (7-30 or 31-60 days), gender, history of prior infection, presence of abnormal inflammatory markers, urinalysis, respiratory symptoms, and diagnosis of IBI. The Rochester criteria was approximated using inflammatory marker, history of infection, and urinalysis data. Boosted regression trees were used to identify patterns among infants that were related to the presence of IBI. Model development used a random subset of 50% of infants; prediction accuracy was described with the remaining 50% using ROC curves. Infants with a predicted probability of IBI lower than the median predicted probability of IBI were labeled as low risk. Test characteristics were then compared to those of the approximate Rochester criteria (ARC).

Results: 21,624 encounters were included; 10,000 were used to construct the IBI risk assessment algorithm, 11624 were used to validate the algorithm and compare with the ARC. The ARC identified 5618 (48%) of infants as low risk, 208 (3.7%) had IBI. Of 6003 (52%) identified as non-low risk by the ARC, 770 (12.8%) had IBI, resulting in a sensitivity of 78.7%, specificity of 50.8% and AUC of 0.65. The boosted regression tree algorithm identified 6733 (58%) of infants as low risk, 225 (3.3%) had IBI. Of 4891 (42%) identified as non-low risk, 753 (15.3%) had IBI, resulting in a sensitivity of 77.0%, specificity of 61.1%, and AUC of 0.691.

Conclusion(s): A next-generation algorithm using large-scale data and machine learning techniques can outperform
current risk stratification criteria for well-appearing febrile infants. Development of a future algorithm based on a broader array of variables may allow for individualized IBI risk prediction.

(No Image Selected)
Background: Post-hospitalization follow-up visits are frequently prescribed and have been proposed and used as a quality metric in the setting of bronchiolitis. The benefits and harms of this practice are uncertain.

Objective: To determine whether an as-needed post-hospitalization follow-up visit is non-inferior to a scheduled post-hospitalization follow-up visit with respect to reducing anxiety among parents of children hospitalized for bronchiolitis.

Design/Methods: We conducted a randomized controlled trial (NCT03354325) involving children under 24 months old who were hospitalized for bronchiolitis at one of four hospitals (two children’s hospitals and two community hospitals). Children with chronic conditions were not considered for enrollment. Participants were randomized to a scheduled follow-up visit within 4 days of discharge or an as-needed follow-up visit, in which parents were instructed to follow-up if the child’s symptoms did not resolve or worsened. The primary outcome was parental anxiety 7 days after hospital discharge, measured using the anxiety portion of the Hospital Anxiety and Depression Scale (HADS); range 0 to 28 points, with higher scores indicating greater anxiety. Thirteen additional pre-specified secondary outcomes were assessed.

Results: The primary outcome was available for 268 (88%) of 303 randomized patients (Figure 1). Demographic and
Clinical characteristics were well-balanced between groups (Table 1). Eighty-two percent of children in the scheduled group attended a scheduled post-hospitalization visit compared to 19% of children in the as-needed group (absolute difference 63%, 95% CI 53-72%; Table 2). The mean 7-day parental anxiety score was 3.9 among the as-needed follow-up group and 4.2 among the scheduled follow-up group (absolute difference -0.3 points, 95% CI -1.0 to 0.7), with the upper bound of the 95% CI within the pre-specified non-inferiority margin of 1.1 points. Among patients in the as-needed group, 9% received a new medication, compared to 16% of patients in the scheduled group (absolute difference -7%, 95% CI -15 to 1%). New ambulatory medications prescribed after hospital discharge included antibiotics (n=22; 19 for acute otitis media), albuterol (n=7), and inhaled corticosteroids (n=6).

**Conclusion(s):** As-needed post-hospitalization follow-up for bronchiolitis is non-inferior to scheduled follow-up. In addition to empowering families to decide when and if post-hospitalization follow-up is necessary, as-needed follow-up might decrease exposure to unnecessary medications.
Background: Tobacco smoke exposure (TSE) is associated with higher rates of respiratory diseases and other causes of illness among children. Hospitalized children have higher rates of TSE, and parents who smoke may be receptive to tobacco and secondhand smoke interventions during their child’s hospitalization.

Objective: To test the efficacy of a smoking cessation intervention delivered to parents of hospitalized children.

Design/Methods: We conducted a randomized, controlled, single-blind clinical trial at Children’s Hospital Colorado. Families were recruited from 12/2014 – 5/2018 and followed for 12 months. Families with at least one parent who used tobacco were eligible for participation. Consenting parents completed an in-depth questionnaire, and urine was collected from the child and analyzed for cotinine using liquid chromatography-tandem spectrometry, with a limit of quantification
of .05 ng/mL. Intervention participants received brief motivational interviewing (MI) with an average of 3 sessions, plus provision of 14 days of free nicotine replacement therapy (NRT) if appropriate, and Quitline referral at the end of MI participation. Control participants were referred to the Quitline. Our primary outcomes were: 1) increase in smoke-free home rules, 2) change in child’s cotinine from baseline to 1 year, and 3) parental smoking cessation at 1 year. We used an intention-to-treat analysis; data was analyzed with SAS v9.4 using Chi-square and t-tests for bivariable data, and multivariable logistic and linear regression.

**Results:** Of 1989 eligible families approached, 263 enrolled in the study (13%); 149 families had follow-up data at 12 months (57%). There were no significant differences between intervention and control groups in demographics or exposures (Table 1). Overall, 25% of the intervention group parents reported being quit at 12 months, compared to 15% in the control group, however this was not significant. In a model adjusted for potential confounders, compared to control families the intervention group had no difference in report of smoke free homes, a similar increase in cotinine levels, and a trend towards more parents having quit (Table 3).

**Conclusion(s):** A smoking cessation intervention was successfully delivered to parents of hospitalized children, resulting in a 25% quit rate at 12 months. Hospitals have an opportunity to provide resources to help parents quit smoking but more efficient and effective engagement strategies still need to be developed.
Table 5: Changes compared to autonomic measures for the control and intervention groups

<table>
<thead>
<tr>
<th>Measure</th>
<th>Control</th>
<th>Intervention</th>
<th>P-value</th>
<th>P-value</th>
<th>P-value</th>
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<tr>
<td>Tension</td>
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<td>77.2%</td>
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<tr>
<td>Heart rate</td>
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<td>72.3%</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
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<tr>
<td>Arterial systolic</td>
<td>118.9%</td>
<td>118.9%</td>
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Table 6: Multivariate regression analysis on autonomic measures

<table>
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<tr>
<th>Predictor</th>
<th>Coefficient</th>
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<th>t-value</th>
<th>P-value</th>
<th>Coefficient</th>
<th>Standard Error</th>
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<td>Predictors</td>
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<tr>
<td>Age (years)</td>
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<td>0.0001</td>
<td>-0.126</td>
<td>0.218</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.126</td>
<td>0.218</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.126</td>
<td>0.218</td>
</tr>
<tr>
<td>Gender (male)</td>
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<td>0.0001</td>
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<td>0.218</td>
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<td>0.126</td>
<td>0.218</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.126</td>
<td>0.218</td>
</tr>
<tr>
<td>Smoking status (current)</td>
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<td>0.218</td>
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<td>0.0001</td>
<td>0.126</td>
<td>0.218</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.126</td>
<td>0.218</td>
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IMAGE CAPTION: