Predicting Need for Hospitalization in Acute Pediatric Asthma

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Objectives: To develop and validate predictive models to determine the need for hospitalization in children treated for acute asthma in the emergency department (ED).

Methods: Prospective cohort study of children aged 2 years and older treated at 2 pediatric EDs for acute asthma. The primary outcome was successful ED discharge, defined as actual discharge from the ED and no readmission for asthma within 7 days, versus need for extended care. Among those defined as requiring extended care, a secondary outcome of inpatient care (>24 hours) or short-stay care (<24 hours) was defined. Logistic regression and recursive partitioning were used to create predictive models based on historical and clinical data from the ED visit. Models were developed with data from 1 ED and validated in the other.

Results: There were 852 subjects in the derivation group and 369 in the validation group. A model including clinical score (Pediatric Asthma Severity Score) and number of albuterol treatments in the ED distinguished successful discharge from need for extended care with an area under the receiver-operator characteristic curve of 0.89 (95% confidence interval [CI], 0.87–0.92) in the derivation group and 0.92 (95% CI, 0.89–0.95) in the validation group. Using a score of 5 or more as a cutoff, the likelihood ratio positive was 5.2 (95% CI, 4.2–6.5), and the likelihood ratio negative was 0.22 (95% CI, 0.17–0.28). Among those predicted to need extended care, a classification tree using number of treatments in the ED, clinical score at end of ED treatment, and initial pulse oximetry correctly classified 63% (95% CI, 56–70) of the derivation group as short stay or inpatient, and 62% (95% CI, 55–68) of the validation group.

Conclusions: Successful discharge from the ED for children with acute asthma can be predicted accurately using a simple clinical model, potentially improving disposition decisions. However, predicting correct placement of patients requiring extended care is problematic.

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Much of the morbidity of asthma, the most common chronic disease of childhood, is related to acute exacerbations, with an estimated 700,000 to 1.6 million emergency department (ED) visits annually among children younger than 18 years.[1–4] Traditionally, children treated for acute asthma on an emergency basis faced 2 possible dispositions: hospital admission or discharge to home in the care of the parent. Of children treated in an ED for an acute asthma exacerbation, the proportion admitted to the hospital reported in the literature ranges from 1.2% to 53%.[5–16] The initial disposition decision may not be made correctly. A varying proportion of hospital admissions for asthma have been found to be *inappropriate*.[17–19] Moreover, some children discharged from the ED will relapse; in a multicenter pediatric study, the relapse rate was 10%.[20]

Recently, many EDs have incorporated short-stay units (SSUs), where patients may receive more intensive inpatient level care for a brief period (typically less than 24 hours).[21] The cost-effectiveness of such alternatives depends at least in part on accurate identification of those likely to benefit.

Several studies have attempted to ascertain criteria to predict correctly the need for hospitalization after ED treatment of asthma,[6–9,11,22,23] and one has tried to identify patients successfully treated in an SSU,[21] but we are unaware of any other study to date that has examined the full spectrum of disposition decisions available in current practice. Moreover, most prior work has used actual disposition, without using explicit criteria for whether that disposition was correct. The purpose of this study was to develop a clinical prediction model, using explicit criteria for appropriateness, to assign an accurate disposition (successful discharge, SSU, or inpatient care) for children with acute asthma.

METHODS

Study Subjects and Setting

This was a prospective study conducted over a 12-month period at 2 urban pediatric EDs. Data from 1 ED were used to derive the predictive models, and the second site, in a different city, was used for validation. Children aged 24 months through 18 years inclusive with acute asthma were eligible (children aged 12–23 months were also enrolled at the validation site). Acute asthma was defined as wheezing or

respiratory distress requiring treatment with inhaled bronchodilator in a patient with a previous physician diagnosis of asthma or prior history of wheezing treated with inhaled bronchodilators. Patients with the following exclusion criteria were considered ineligible: respiratory failure requiring immediate intubation; other chronic cardiorespiratory disease (eg, cystic fibrosis, congenital heart disease); an ED visit for the same illness in the prior 7 days; no English- or Spanish-speaking caretaker. The sampling scheme differed at the 2 institutions. At the derivation site, a simple random sample of days throughout the study period was selected, and all eligible patients seen in the ED during these study days were approached for enrollment. To ensure an adequate number of admitted patients in the smaller validation sample, stratified sampling was used at the validation site: all patients who were admitted (either inpatient or SSU) during the study period were included, as was a 20% sample of those discharged to home.

Both participating EDs are located in freestanding children's hospitals, in an inner-city location, and are staffed by pediatric emergency physicians. Asthma management guidelines based on the National Heart, Lung, and Blood Institute Expert Panel recommendations were in place at both EDs during the study period.[24] Both EDs had an SSU for care up to 24 hours, but it was not in operation during the entire study period at the derivation site.

The study was reviewed and approved by the institutional review boards at both institutions. Informed consent was obtained for participation.

Measurements

Candidate predictor variables, selected based on expert opinion and relevant literature, included historical features and ED clinical assessments and treatments (Appendix A). Information on historical features was abstracted from asthma-specific charts used at each ED, and from data forms given directly to parents at the start of treatment. Data included demographics, details about current symptoms, asthma history, access to care, and maintenance and current asthma medication use. Physical examination findings were assessed by nursing and respiratory therapy personnel and recorded on respiratory flow charts. Clinical assessments at the start of treatment and at the time of disposition were abstracted, including a previously validated 4-item clinical score, the Pediatric Asthma Severity Score.[25] Peak expiratory flow rate (PEFR) was measured in children aged 6 years and older. Information about ED treatment was also collected. When continuously nebulized albuterol was administered, each hour of nebulization was counted as equal to 3 intermittent treatments according to the dosing protocols in use at each ED.

The primary outcome of interest was patient disposition at the end of the ED visit. As previously noted, actual disposition decisions may be made incorrectly. We defined our outcomes according to the need for each level of care using objective criteria. Patients in need of supplemental oxygen and frequent inhaled bronchodilators (3 hours or less between treatments) were considered to require hospital care, whereas those requiring less frequent treatments were capable of being cared for at home. For patients admitted to the hospital or SSU, clinical assessments were performed at 12 and 24 hours after the start of treatment in the ED. Frequent bronchodilators were considered unnecessary if the patient had no or minimal wheezing, and no or minimal work of breathing, at least 3 hours after administration of an inhaled bronchodilator. The child must also have had an oxygen saturation of 94% or greater as measured by pulse oximetry while breathing room air. Children who were judged by their treating clinician as needing treatment less than 3 hours after the prior bronchodilator treatment were also classified as a failure and therefore needing hospital-level care.

All patients were contacted by telephone 2 weeks after the ED visit. Relapse was defined as a return to the ED for unscheduled care within 7 days of the initial visit because of persistent or worsening symptoms, with the patient admitted to the hospital at the subsequent ED visit.

Three groups of children were thus objectively defined and prospectively differentiated based on the patient's actual disposition at the time of the ED visit and data collected at subsequent follow-up. These groups are defined in Table 1. We also combined the categories of short stay and hospitalization together to create a composite outcome of need for extended care.

Analysis

Relative risk and 95% confidence intervals (CIs) were calculated to determine the individual association between each potential predictor variable and the outcome of need for extended care in the derivation population. Those variables with a significant association with the outcome, as indicated by $P < 0.15$ for the χ^2 test, were retained as candidates for the predictive models.

Two different modeling strategies were used and are briefly described here (details of the modeling strategies are shown in Appendix B). In the first approach, we used multiple logistic regression to generate a model to distinguish patients who were successfully discharged versus those needing some form of extended care. Recursive partitioning[26–28] was then used to further categorize those predicted to need extended care into those needing hospitalization and those eligible for short stay. In the second approach, we attempted to classify all patients into one of the 3 outcome categories using only recursive partitioning. For the recursive partitioning analyses, we

TABLE 1. Outcome Definitions

Outcome Classification	Definition
Capable of discharge	Discharged to home from ED, and no relapse within 7 d
Eligible for short stay	Admitted to hospital or SSU from ED and either actually discharged within 24 h and no relapse or not discharged but meeting criteria for discharge at 12 or 24 h
Needing hospitalization	Either admitted to hospital or SSU and not actually discharged or meeting criteria for discharge within 24 h or relapsed within 7 d

assumed that the consequences of making an error in 1 direction (ie, predicting someone needs hospitalization when they are really eligible for short stay) are the same as for an error in the opposite direction; this is defined as a misclassification cost ratio of 1. However, in sensitivity analyses, we tested the effect of changing this over a range of values from 1 to 3.

The performance of the logistic regression model was measured by calculating the area under the receiver-operator characteristic (ROC) curve, and the sensitivity and specificity at the optimal cut point. For recursive partitioning, we calculated the proportion of patients assigned correctly to each category, with 95% CIs. For both modeling strategies, the model was developed using only the derivation sample, and then validated by measuring performance in the other sample.

Our sample size was based on the ability to calculate sensitivity and specificity of the resulting rules with a desired degree of precision. Assuming an admission rate of 30% and a sensitivity of 0.80 or more, we determined we would need 833 derivation subjects, yielding 250 admitted patients, to calculate the sensitivity with a CI width of ±0.05.

Analyses were conducted using Stata 8.0 (Stata Corp, College Station, Tex) and Classification and Regression Tree ([CART] Salford Systems, San Diego, Calif).

RESULTS

Characteristics of Study Subjects and ED Treatment

A total of 1379 eligible patients were seen at the 2 EDs during the study period, and 1221 were successfully enrolled. The details of patient enrollment, disposition, and demographics are provided in Table 2. Although both patient populations are largely poor and minority, there are differences in the ethnic/racial composition between the 2 sites, reflecting the different source populations.

Most patients (63%) had mild intermittent asthma, using the National Heart, Lung, and Blood Institute severity classification. A greater proportion (25%) of patients at the validation ED were categorized as moderate or severe persistent asthma compared with the derivation sample (14%), most likely because of the oversampling of admitted patients at the validation site. A minority of children at both hospitals reported being followed by an asthma specialist (16%–17%) or using controller medications (26%–35%).

Compliance with ED treatment guidelines was good, with 80% of the patients at the derivation site and 89% at the validation site treated in complete accordance with the recommendations. This included 93% to 97% compliance with steroid recommendations and 81% to 95% compliance with inhaled bronchodilators, defined as 3 treatments within first hour if no complete response (if the criterion is relaxed to 3 treatments within 90 minutes, compliance was >95% in both EDs). Although the guidelines do not specifically recommend the use of ipratropium bromide, 35% of children were treated with it. The PEFR was not measured in 35% of those children 6 years and older, in whom it is recommended. However, even when PEFR was attempted in this age group, we found a high rate (35%) of inability to perform PEFR, limiting the usefulness of this information.[29] The PEFR was therefore dropped from consideration as a predictor variable.

TABLE 2. Patient Characteristics

	Derivation Site	Validation Site
Enrollment, no. (%)		
Patients eligible	976	403
Patients refused	77 (7.9)	18 (4.5)
Patients missed	20 (2)	16 (3.9)
Patients enrolled	852 (90.1)*	369 (91.6)
Disposition, no. (%)		
Admitted (inpatient or SSU)	274 (32)	230 (62.3)
Discharged	578 (68)	139 (37.7)
Successful d 14 follow-up	784 (89.2)	322 (87.3)
Age, y		
Mean (+SD)	7.0 ± 4.3	5.9 ± 4.3
Median (interquartile range)	6.0 (3–10)	5.0 (2–9)
Sex, % female	38	41
Race/ethnicity, no. (%)		
White	66 (7.8)	86 (23.3)
African American	765 (89.9)	58 (15.7)
Hispanic	7 (0.8)	222 (60.2)
Asian/Pacific Islander	1 (0.1)	1 (0.3)
Native American	0	2 (0.5)
Other†	12 (1.4)	0
Insurance type, no. (%)		
Commercial fee-for-service	34 (4.2)	13 (3.5)
Commercial managed care	170 (20.7)	107 (29)
Traditional medical assistance	23 (2.8)	26 (7.1)
Medicaid managed care	555 (67.7)	209 (56.6)
Self-pay/none	36 (4.4)	14 (3.8)
Usual source of primary care, no. (%)		
Private physician's office	358 (43.6)	163 (44.2)
Hospital-based clinic	386 (47)	154 (41.7)
Community health center	54 (6.6)	40 (10.8)
None	24 (2.8)	12 (3.3)

*Records were missing for 27 enrolled patients, and these were excluded from subsequent analysis.

†Other includes those self-identified as none usually because of mixed race/ethnicity.

Disposition

Of 272 derivation site patients admitted to the hospital initially, 76 met the criteria for capable of early discharge. Of these, 64 were actually discharged from the hospital within 24 hours (5 within 12 hours and 59 between 12 and 24 hours), and another 12 were still in the hospital but had no or minimal symptoms at least 3 hours after the last bronchodilator treatment and could therefore have been managed at home. Only 15 patients (3% of those discharged from the ED) returned for unscheduled care and were subsequently admitted, meeting our definition of relapse. Of these, two thirds

TABLE 3. Adjusted OR for Predictors of Successful Discharge From the ED

Variable	Adjusted OR	95% CI	*P*
History of fever	0.50	0.22–1.11	0.09
History of URI symptoms	0.28	0.10–0.76	0.01
No. albuterol treatments in ED (OR for each additional treatment)	0.34	0.21–0.54	<0.001
Final clinical score (OR for each additional point)	0.39	0.28–0.55	<0.001
Initial pulse oximetry reading	1.43	1.20–1.69	<0.001

OR indicates odds ratio.

occurred within the first 24 hours after the initial ED visit. Thus, a total of 565 (67%) patients were classified as successful discharge, 76 (9%) were eligible for short stay, and 211 (24%) needed hospitalization. Among the 230 patients initially admitted to the validation hospital (either directly to the inpatient unit or to the 23-hour observation unit), 120 were discharged within 24 hours and another 15 were considered capable of early discharge. However, of these 135, 6 returned and were readmitted later, leaving 129 meeting the definition of eligible for short stay and 101 as needing inpatient care. Of the 139 patients discharged to home at the time of the initial ED visit, none relapsed within the 2-week follow-up period.

Predicting Successful Discharge

In the first stage of the analysis, we used logistic regression modeling to predict which patients could be successfully discharged from the ED, and which would require extended care (either SSU or inpatient). Using data from the derivation sample, 24 of the 33 candidate predictor variables passed the univariate screening (Appendix A). Both the initial and final clinical score were significantly associated with the need for extended care. On a priori clinical grounds, we chose to retain only the final clinical score (ie, at the time of disposition) in the subsequent models. This decision was also supported by the greater predictive ability of final score. In addition, both initial and final pulse oximetry were associated with the need for further care. Because the patient's disposition at both institutions is determined in part by the pulse oximetry at the time of disposition according to protocol—all patients with a reading of less than 94% at the final assessment are admitted—it would be difficult to separate the predictive value of this variable. We therefore selected the pulse oximetry value at presentation to the ED for consideration in the prediction models; final pulse oximetry was substituted for initial pulse oximetry in sensitivity analyses.

The remaining 22 variables were entered into a multiple logistic regression. 713 subjects (82%) had complete data on all candidate variables and were included in the modeling. Five of these variables had a significant ($P < 0.1$) independent association with successful discharge. The adjusted odds ratio and 95% CIs for these 5 are shown in Table 3.

To develop a predictive model that is practical for clinical use, we wished to have the most parsimonious model possible and one with a simple additive nature. We developed additive linear models including successive variables, starting with the most significant variables. Because the regression coefficients were of similar magnitude for all variables, unit weighting was used for all. However, the coefficient for pulse oximetry was positive (the higher the pulse oximetry, the greater the likelihood of successful discharge), whereas all others were negative, indicating an inverse relationship. Therefore, for pulse oximetry, the number of points less than 100% was included in the linear models. The 5 models considered were:

- Model 1: final 4-point clinical score
- Model 2: clinical score + number of albuterol treatments given in the ED
- Model 3: model 2 + initial pulse oximetry (points below 100%)
- Model 4: model 3 + history of upper respiratory infection (URI) symptoms
- Model 5: model 4 + history of fever

The discriminative ability of the models was similar for all models (AUC, 0.89–0.90), except for the simplest model that included only the final clinical score (AUC, 0.84). We therefore focused on model 2, which is the simplest model that maintains adequate predictive ability. The ROC plot for model 2 is shown in Figure 1 (derivation AUC, 0.89). When the model was applied to the validation sample, the discriminant ability remained high (AUC, 0.92). At the optimal cutoff of 5 points or more, the sensitivity of the model for predicting successful discharge was 0.82 (95% CI, 0.76–0.86) in the derivation set and 0.90 (95% CI, 0.85–0.93) in the validation set. Specificity was 0.84 (95% CI, 0.81–0.87) and 0.80 (95% CI, 0.72–0.86) in the derivation and validation sets, respectively. The likelihood ratio positive (LR) was 5.2 (95% CI, 4.2–6.5), and the LR negative was 0.22 (95% CI, 0.17–0.28) in the derivation population compared with an LR positive of 4.5 (95% CI, 3.2–6.4) and an LR negative of 0.13 (95% CI, 0.08–0.19) in the validation population.

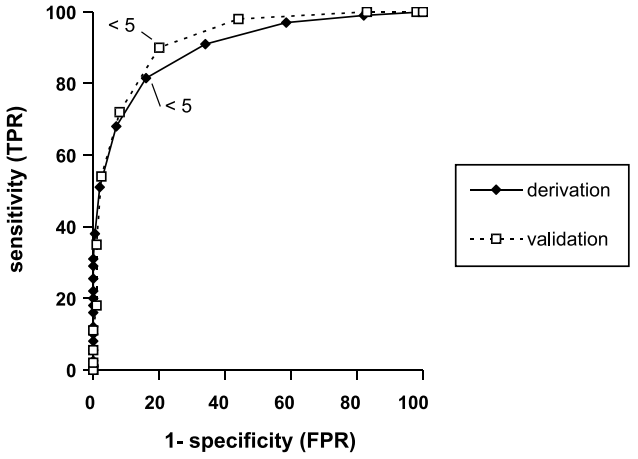

FIGURE 1. Receiver-operator characteristic curve for predicting successful discharge from the ED.

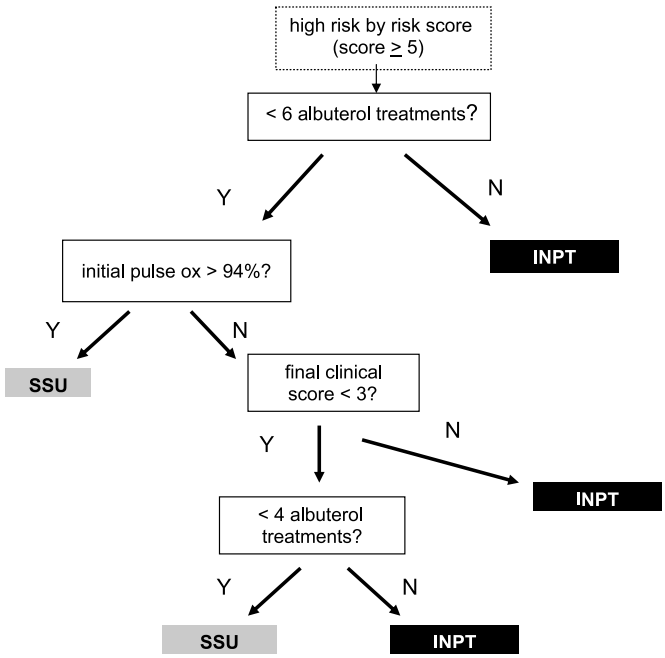

FIGURE 2. Recursive partitioning tree for predicting ED disposition in patients considered high risk by linear risk score.

Predicting Overall Disposition

Using the previously mentioned prediction model 2, patients with a risk score of 5 points or more were categorized as high risk of needing extended care. Recursive partitioning was used to generate a classification tree to divide these high-risk patients as eligible for SSU or needing inpatient care. All of the previously mentioned predictor variables were considered as candidate splitters. The optimal tree included 4 decision nodes using 3 variables: number of albuterol treatments administered in the ED, clinical score at the time of disposition, and presence of hypoxia (pulse oximetry <94%) at the start of the visit. The classification tree is shown in Figure 2, and the classification success rates are shown in Table 4. Overall, 64% (95% CI, 57%–71%) of the derivation patients predicted by the risk model to need extended care were correctly assigned to SSU or inpatient, as were 66% (95% CI, 59%–73%) of the validation patients.

TABLE 4. Classification of Patients Identified as High Risk by Prediction Model

		Predicted		
Derivation set		Inpatient	SSU	Total
Actual	Inpatient	95 (58%)*	70	165
	SSU	8	44 (85%)	52
		Predicted		
Validation set		Inpatient	SSU	Total
Actual	Inpatient	48 (58%)	35	83
	SSU	32	80 (71%)	112

*Figure in parentheses represents the percentage of subjects actually in the category that was correctly classified by the model (ie, true positive rate, or sensitivity).

TABLE 5. Overall Results of Combined Risk Score/Recursive Partitioning Predictions

		Predicted			
Derivation		Discharge	SSU	Inpatient	Total
Actual	Discharge	394 (88%)*	52	2	448
	SSU	19	44 (62%)	8	69
	Inpatient	31	70	95 (48%)	196
		Predicted			
Validation		Discharge	SSU	Inpatient	Total
Actual	Discharge	103 (80%)	24	2	129
	SSU	19	80 (61%)	32	131
	Inpatient	3	35	48 (56%)	86

*Figure in parentheses represents the percentage of subjects actually in the category that was correctly classified by the model (ie, true positive rate, or sensitivity).

The overall results of the combined prediction model/recursive partitioning analysis are shown in Table 5. The patients who were categorized as low risk by the regression model are predicted to be able to be successfully discharged. Few patients who in fact needed inpatient treatment would be sent home from the ED using this rule; a large percentage of the *false-negatives*—that is, patients predicted to be able to be discharged to home but actually requiring extended care—were patients who were capable of being sent home after less than 24 hours. On the other hand, 16% to 20% of patients who in fact could have been safely sent home from the ED would unnecessarily be kept for extended care (ie, fairly high false-positive rate). Among the 713 derivation sample patients who had complete data to permit risk stratification, this strategy achieved an overall correct classification of 75% (95% CI, 71%–78%). The percentage of patients in the validation set correctly classified was slightly lower at 67% (95% CI, 62%–72%).

In an alternative recursive partitioning analysis, the first step of using the linear risk score to identify those likely to need extended care was eliminated, and all patients were

TABLE 6. Results of Predicting Disposition by Recursive Partitioning Alone

		Predicted			
Derivation		Discharge	SSU	Inpatient	Total
Actual	Discharge	467 (83%)*	91	7	565
	SSU	15	43 (57%)	18	76
	Inpatient	29	64	118 (56%)	211
		Predicted			
Validation		Discharge	SSU	Inpatient	Total
Actual	Discharge	98 (71%)	33	8	138
	SSU	18	75 (56%)	42	135
	Inpatient	3	31	61 (64%)	95

*Figure in parentheses represents the percentage of subjects actually in the category that was correctly classified by the model (ie, true positive rate, or sensitivity).

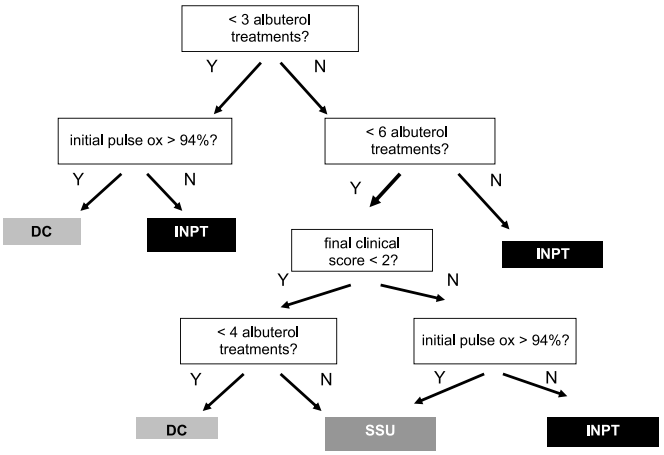

FIGURE 3. Pure recursive partitioning tree to predict ED disposition.

entered into a CART model with a trichotomous outcome. A tree with 3 predictor variables was generated: hypoxia at the beginning of the visit, number of albuterol treatments given in the ED, and clinical score at the end of the visit. The results of this analysis are shown in Table 6 and Figure 3. The overall correct classification rates are 74% (95% CI, 71%–77%) for the derivation set and 64% (95% CI, 59%–69%) for the validation set. Note that because CART uses alternative splitting strategies to classify patients when information required to determine the split at a node is missing (similar to imputation of data in logistic regression), the table includes results for all patients. When the analysis was repeated including only those patients with complete data on the splitting nodes, the results were virtually identical.

Sensitivity Analyses

Varying the misclassification cost ratio from 1 to 3 in the recursive partitioning models did not change the overall correct classification rates substantially. Substituting final pulse oximetry for initial pulse oximetry in the CART analyses led to a minimal increase in correct classification. Using the combined risk score/recursive partitioning approach, the rate of overall correct classification in the derivation population was 75% using initial pulse oximetry versus 76% using final oximetry; the rates were 67% and 69%, respectively, for the validation population. The same differences were observed with the pure recursive partitioning strategy.

DISCUSSION

Although a large number of variables were found to be associated with the need for extended care (vs successful discharge to home directly from the ED), many were not independently associated after adjustment for other variables. Note that we do not claim that these are not risk factors for the outcome of interest, but merely that they do not substantially enhance the ability to predict; the goal of this study was to develop the most parsimonious risk score possible. We were in fact able to develop a prediction score using only 2 variables—final clinical score at the time of disposition and number of albuterol treatments given in the ED—that predicted accurately those patients who could be discharged successfully to home from the ED without relapse versus those requiring further care in the hospital. The overall discriminant ability of this score was very good, with an area under the ROC curve of 0.89 in the derivation population. In more clinically relevant terms, use of a score of 5 or more points to identify those at high risk of needing extended care had a sensitivity of 82% and specificity of 84%. Thus, in this population, 75% of those considered high risk actually needed extended care (positive predictive value), and 89% of the low risk patients were successfully discharged (negative predictive value). More importantly, the model validated extremely well, with an area under the curve of 0.92 in the validation sample.

Our results are supported by prior studies documenting primary associations of clinical examination findings after acute treatment with hospitalization in pediatric asthma.[16] Compared with other predictive models, our risk score performed extremely well.[6–9,11,21–23] No other proposed model has been able to achieve the same combination of high sensitivity and specificity, and those few studies that included an independent validation sample did not validate nearly as well. Why we were able to predict so accurately is unclear, but we can make some speculations. First, we used data about the patients available at the time of disposition, not at the beginning of the visit. One other study that used post-treatment data also performed reasonably well, although the results were not validated.[23] Within our own study, we found end-of-visit clinical data correlated much better with this outcome than did information obtained before treatment was initiated. As previously noted, we also included relapse in our definition of needing further care. It is possible that patients who relapse, if they are indeed more severely ill, and are incorrectly discharged from the ED despite clinical evidence of this severity of illness, would represent *false-positives* in studies where they are counted as *successfully discharged*—that is, they would be considered high risk on the basis of severity of clinical appearance but would be counted in the less severe outcome group. In contrast, such patients would have been correctly identified as high risk and included in the more severe outcome category in our study. However, it is equally plausible that patients who are discharged and relapsed are discharged because their clinical picture is misleading. In this case, they would have been considered *false-negatives* in our study. Given the relatively small number of relapsed patients in the current study, their correct or incorrect characterization is unlikely to explain the high predictive ability of our risk model but could explain the problems encountered in other studies.

In contrast to the excellent performance in distinguishing those patients successfully discharged from the ED with those needing further care, we were unable to assign patients accurately to short-stay (<24 hours) versus inpatient (≥24 hours) care. Two different strategies—selection of children at high risk for needing some type of extended care (based on the previously mentioned risk score) and then predicting need for SSU or inpatient care among this subset; and using recursive partitioning to assign all patients to outpatient,

SSU, or inpatient treatment—resulted in approximately 50% to 65% of patients correctly categorized as SSU or inpatient. Considering the overall forecasting ability, the accuracy of the 2 prediction strategies was for 74% to 75% of the derivation patients and 64% to 67% for the validation patients.

This relative difficulty in predicting the duration of additional treatment needed parallels actual clinical experience. Several studies of inpatients showed that approximately 20% to 30% of such patients were discharged within 24 hours.[30–32] Conversely, a variable percentage of patients admitted to an SSU or observation unit will subsequently require admission for prolonged treatment. At one of the study hospitals, an SSU was in operation throughout the study period. Of 140 patients initially admitted to the SSU, 30 (21%) were subsequently admitted to the inpatient unit, whereas 21 (23%) of 90 of those admitted to the inpatient ward directly from the ED were discharged in less than 24 hours. These results are similar to those reported by Gouin and Patel,[21] who noted that 21 (31%) of 68 children with asthma admitted to an observation unit required transfer to an inpatient ward. Miescier et al,[33] in another institution, found an inpatient admission rate of 25% among children with asthma initially admitted to an observation unit. In contrast, Browne[34] noted that only 4% to 6% of children admitted to SSUs at 2 Australian hospitals were transferred to inpatient care. Although asthma was a common diagnosis in this study, the inpatient transfer rates for children with asthma were not reported separately. Among children admitted to the observation unit, Miescier et al[33] found that 3 factors—need for supplemental oxygen at the end of ED treatment, female sex, and fever—were associated with increased risk of subsequent inpatient admission; however, the accuracy of prediction based on these factors was not determined. Similar to our study, Gouin and Patel[21] found no clinical predictive factors that could accurately identify those SSU patients needing subsequent inpatient care. The inaccuracy of placement decisions may be an important limiting factor in the cost-effectiveness of such SSUs.

There are several potential limitations to this study. The first is potential misclassification of the outcomes. Among patients actually kept for extended care, the use of objective criteria for need for in-hospital services was intended to minimize misclassification of patients (ie, SSU vs inpatient) caused by variations in actual practice. However, we are unable to say with certainty that patients kept for extended care would not have done as well at home; for this, we must still rely to some extent on the judgment of the clinician. Similarly, we do not know whether some patients discharged to home might have met criteria for needing inpatient care, but did not seek such care and therefore were not identified. We have previously shown that parent report of patient status after discharge correlates very well with evaluation after discharge by a home care respiratory therapist,[35] indicating that any such misclassification of discharged patients would not substantially change our results.

The rate of relapse in our study was low (3%) compared with other studies in the literature. We used a more restrictive definition of relapse, which depended not only on a return for unscheduled care but admission to the hospital at the second visit. We chose this definition because we wished to reduce bias caused by differences in the care-seeking behavior of different individuals and availability of primary care for continued follow-up asthma treatment. However, this makes comparison of our results with those some other studies problematic.

Clinical assessments were performed at the start and end of treatment. However, the timing of the final assessment varied according to the intensity of treatment provided. For example, some patients received treatment for only 1 hour or less, whereas others were treated for up to 4 hours in the ED. Thus, we cannot make a recommendation concerning an assessment at a specific point in time (eg, after 90 minutes of treatment). Other investigators have similarly examined assessments or treatment provided over the course of the ED stay rather than at certain time points, in keeping with actual practice.[8,20] Moreover, at both study EDs, ED treatment is limited to 4 hours, and in most cases less than 3 hours, so variability in timing of the final disposition is likely to be relatively modest.

We chose to use multiple logistic regression and recursive partitioning to develop predictive models. Such techniques have some advantages: they have been well studied, clinicians are increasingly familiar with them, software is readily available to conduct analyses, and they have been shown to allow the development of valid clinically useful prediction tools. It is possible that other modeling strategies, such as neural network modeling, might have led to an improved ability to predict. However, such techniques are not yet in widespread use. Moreover, neural network models are not well suited to bedside decision making without computer support and may validate to other populations less well than models developed using other strategies.[36]

Finally, although the 2 study sites differ in important respects (eg, ethnicity of patients, location, resources available), there are substantial similarities. Both serve predominantly poor, minority, urban populations in the northeast, and both are pediatric-specific facilities. It is therefore possible that our findings may not be generalizable to other quite different practice settings. In this respect, we are encouraged by the similarity in some of the results between our study and a prior multicenter study of relapse, which included 44 different EDs across the country.[20]

We conclude that reasonably accurate prediction of the need for further care after an initial period of ED treatment can be made based on the clinical score and the number of treatments provided. Such information may be useful to acute-care providers who are attempting to identify patients in whom discharge to home may be unsafe. It is unclear, however, whether such rule-based decisions would actually improve the quality of care. Moreover, decisions about the duration of that care and the placement of patients in SSUs versus regular inpatient units are frequently incorrect, and we were unable to develop a tool to improve the accuracy of these decisions. Further study is needed to evaluate the clinical and economic consequences of inaccurate patient disposition after ED treatment; specifically, the impact of inaccurate assignment on the cost-effectiveness of SSUs.

REFERENCES

1. Newacheck PW, Halfon N. Prevalence, impact, and trends in childhood disability due to asthma. *Arch Pediatr Adolesc Med*. 2000;154:287–293.
2. Crain EF, Weiss KB, Bijur PE, et al. An estimate of the prevalence of asthma and wheezing among inner-city children. *Pediatrics*. 1994; 94(3):356–362.
3. Crain EF, Weiss KB, Fagan MJ. Pediatric asthma care in US emergency departments, current practice in the context of the National Institutes of Health guidelines. *Arch Pediatr Adolesc Med*. 1995;149:893–901.
4. Moorman JE, Rudd RA, Johnson CA, et al. National surveillance for asthma—United States, 1980–2004. *MMWR Surveill Summ*. 2007; 56(8):1–54.
5. Gergen PJ, Weiss KB. Changing patterns of asthma hospitalization among children: 1979 to 1987. *JAMA*. 1990;264(13):1688–1692.
6. Ownby DR, Abarzua J, Anderson JA. Attempting to predict hospital admission in acute asthma. *Am J Dis Child*. 1984;138:1062–1066.
7. Silver RB, Ginsburg CM. Early prediction of the need for hospitalization in children with acute asthma. *Clin Pediatr*. 1984;23(2):81–84.
8. Skoner DP, Fischer TJ, Gormley G, et al. Pediatric predictive index for hospitalization in acute asthma. *Ann Emerg Med*. 1987;16(1):25–31.
9. Kerem E, Canny G, Tibshirani R, et al. Clinical-physiologic correlations in acute asthma in childhood. *Pediatrics*. 1991;87(4):481–486.
10. Bishop J, Carlin J, Nolan T. Evaluation of the properties and reliability of a clinical severity scale for acute asthma in children. *J Clin Epidemiol*. 1992;45(1):71–76.
11. Kerem E, Tibshirani R, Canny G, et al. Predicting the need for hospitalization in children with acute asthma. *Chest*. 1990;98:1355–1361.
12. Bishop J, Nolan T. Pulse oximetry in acute asthma. *Arch Dis Child*. 1991;66:724–725.
13. Mayefsky JH, El-Shinaway Y. The usefulness of pulse oximetry in evaluating acutely ill asthmatics. *Pediatr Emerg Care*. 1992;8(5): 262–264.
14. Geelhoed GC, Landau LI, LeSouef PN. Evaluation of SaO2 as a predictor of outcome in 280 children presenting with acute asthma. *Ann Emerg Med*. 1994;23:1236–1241.
15. Loughheed MD, Garvey N, Chapman KR, et al. The Ontario Asthma Regional Variation Study: emergency department visit rates and the relation to hospital rates. *Chest*. 2006;129:909–917.
16. Pollack CV, Pollack ES, Baren JM, et al. A prospective multicenter study of patient factors associated with hospital admission from the emergency department among children with acute asthma. *Arch Pediatr Adolesc Med*. 2002;156:934–940.
17. MacFaul R, Glass EJ, Jones S. Appropriateness of paediatric admission. *Arch Dis Child*. 1994;71:50–58.
18. Perrin JM, Homer CJ, Berwick DM, et al. Variations in rates of hospitalization of children in three urban communities. *N Engl J Med*. 1989;320(8):1183–1187.
19. Payne SM, Donahue C, Rappo P, et al. Variations in pediatric pneumonia and bronchitis/asthma admission rates. Is appropriateness a factor? *Arch Pediatr Adolesc Med*. 1995;149(2):162–169.
20. Emerman CL, Cydulka RK, Crain EF, et al. Prospective multicenter study of relapse after treatment for acute asthma among children presenting to the emergency department. *J Pediatr*. 2001;138:318–324.
21. Gouin S, Patel H. Utilization analysis of an observation unit for children with asthma. *Pediatr Emerg Care*. 1999;15:79–83.
22. Ducharme FM, Kramer MS. Relapse following emergency treatment for acute asthma: can it be predicted or prevented? *J Clin Epidemiol*. 1993;46(12):1395–1402.
23. Schuh S, Johnson D, Stephens D, et al. Hospitalization patterns in severe acute asthma in children. *Pediatr Pulmonol*. 1997;23:184–192.
24. National Heart, Lung, and Blood Institute. *Expert Panel Report 2: Guidelines for the Diagnosis and Management of Asthma: Clinical Practice Guidelines. NIH pub. no. 97-4051*. Bethesda, MD: National Institutes of Health; 1997.
25. Gorelick MH, Stevens MW, Schultz TR, et al. Performance of a novel clinical score, the Pediatric Asthma Severity Score (PASS), in the evaluation of acute asthma. *Acad Emerg Med*. 2004;11:10–18.
26. Breitman L, Friedman J, Olshen R, et al. *Classification and Regression Trees*. Pacific Grove, CA: Wadsworth; 1984.
27. Steinberg D, Colla P. *CART: Tree-Structured Non-Parametric Data Analysis*. San Diego, CA: Salford Systems; 1995.
28. McConnochie KM, Roghmann KJ, Pasternack J. Developing prediction rules and evaluating observation patterns using categorical clinical markers: two complementary procedures. *Med Decis Making*. 1993; 13(1):30–42.
29. Gorelick MH, Stevens MW, Schultz TR, et al. Difficulty in obtaining peak expiratory flow measurements in children with acute asthma. *Pediatr Emerg Care*. 2004;20:22–26.
30. Baker MD. Pitfalls in the use of clinical asthma scoring. *Am J Dis Child*. 1988;142:183–185.
31. Roth A. Hospital admissions of young children for status asthmaticus in Honolulu, Hawaii, 1986 to 1989. *Ann Allergy*. 1993;71:533–536.
32. Willert C, Davis AT, Herman JJ, et al. Short-term holding room treatment of asthmatic children. *J Pediatr*. 1985;106(5):707–711.
33. Miescier MJ, Nelson DS, Firth SD, et al. Children with asthma admitted to a pediatric observation unit. *Pediatr Emerg Care*. 2005;21:645–649.
34. Browne GJ. A short-stay or 23-hour ward in a general and academic children's hospital: are they effective? *Pediatr Emerg Care*. 2000; 16:223–229.
35. Gorelick MH, Stevens MW, Schultz TR. Comparability of acute asthma severity assessments by parents and respiratory therapists. *Arch Pediatr Adolesc Med*. 2002;156:1199–1202.
36. Tu JV. Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. *J Clin Epidemiol*. 1996;49:1225–1231.

APPENDIX A. Univariate Association of Clinical Variables With Successful Discharge From ED

Predictor Variables	Relative Risk (95% CI)	*P*
Sociodemographic data		
Age, y	1.06 (1.03–1.10)	0.001
Male sex	0.99 (0.9–1.1)	0.79
Season		
Winter (reference category)	1	
Spring	0.82 (0.56–1.18)	0.28
Summer	0.73 (0.49–1.08)	0.12
Fall	0.82 (0.47–1.42)	0.47
History of current illness		
Duration of symptoms, d	1.0 (0.94–1.06)	0.90
Presence of URI symptoms	0.90 (0.8–1.0)	0.08
Report of fever	0.91 (0.8–1.0)	0.07
Sought care with another provider before ED visit	0.92 (0.83–1.01)	0.085
Asthma history		
Any visits for acute asthma in past year	0.94 (0.83–1.07)	0.33
Three or more visits for acute asthma in past year	0.9 (0.8–1.03)	0.11
Any hospitalizations for asthma in past year	0.78 (0.70–0.87)	<0.0001
History of ICU admission	0.74 (0.61–0.89)	0.0002
History of intubation	0.91 (0.66–1.26)	0.53
Followed by asthma specialist	0.93 (0.81–1.07)	0.27
History of prematurity as reported by parent	0.96 (0.83–1.10)	0.55
Asthma severity (NAEPP classification) (RR for each level of severity above 1)	0.87 (0.73–1.03)	0.095
Asthma severity (NAEPP classification)		
Mild intermittent	1 (reference category)	
Mild persistent	0.98 (0.67–1.44)	0.92
Moderate persistent	0.90 (0.55–1.48)	0.68
Severe persistent	0.46 (0.23–0.92)	0.03
Medical care access		
Source of primary care (private physician office vs clinic/none)	1.01 (0.92–1.12)	0.79
Medical insurance (commercial vs medical assistance/none)	0.93 (0.83–1.05)	0.24
Asthma medications		
Baseline use of inhaled albuterol		
No use	1 (reference category)	
PRN use only	0.8 (0.55–1.17)	0.25
Regular use	0.45 (0.28–0.74)	0.002
Current use above baseline	0.92 (0.84–1.01)	0.10
Use of controller medication	0.78 (0.67–0.89)	0.0001
Systemic steroids in past 4 wk	0.82 (0.70–0.96)	0.006
Systemic steroids at the time of the ED visit	0.85 (0.70–1.03)	0.07
ED Assessment		
Fever in ED	0.87 (0.73–1.03)	0.08
Pulse oximetry less than 94% in room air, initial	0.15 (0.09–0.25)	<0.0001
Pulse oximetry less than 94% in room air, at disposition	0.03 (0.01–0.10)	<0.0001
4-Item score, initial	0.51 (0.45–0.57)	<0.0001
4-Item score, at disposition	0.31 (0.26–0.37)	<0.0001
ED Treatment		
No. albuterol treatments in the ED	0.32 (0.26–0.38)	<0.001
Use of ipratropium in the ED	0.52 (0.45–0.59)	<0.0001
Steroids given in the ED	0.72 (0.66–0.79)	<0.0001
Treatment for less than 1 hour in the ED	1.43 (1.30–1.58)	<0.0001
Treatment according to guidelines in the ED	1.23 (1.07–1.42)	0.0016

ICU indicates intensive care unit; NAEPP, National Asthma Education and Prevention Program; PRN, pro re nata (as needed); RR, relative risk.

APPENDIX B

Prediction Model Development

Two different modeling strategies were used. The first approach was a 2-step process, with patients first categorized as able to be discharged versus needing some form of extended care (either SSU or inpatient), and then those at high risk of needing extended care were subsequently categorized as needing hospitalization or eligible for SSU. For the first step, we used multiple logistic regression, with the outcome of needing extended care. Those candidate predictor variables that passed the univariate screening process (ie, univariate relative risk with a $P < 0.15$) were entered into the logistic regression model. This modeling was done only with subjects from the derivation population. To simplify the model, we retained all variables with a significant adjusted association with the outcome as indicated by a $P \leq 0.1$ by the Wald test. These variables were then included in a simple additive linear score, with points assigned to each variable proportional to that variable's coefficient in the logistic regression model. At each possible cutoff of the score, the sensitivity and specificity for detecting the outcome at that cutoff were calculated, with 95% confidence intervals, as were the positive and negative predictive values. A receiver-operator characteristic curve was plotted, and the overall ability of the scores to discriminate between those with and without the outcome was assessed by the area under the receiver-operator characteristic curve (AUC). We then applied the model to patients from the validation sample and calculated sensitivity, specificity, and AUC in this population for comparison.

For the second step, patients categorized by the logistic regression model as needing extended care were then classified into one of the outcome categories of SSU or inpatient using recursive partitioning.[26–28] In this method, the best predictor of the outcome is identified, and its presence or absence is used to split the sample into 2 groups, with relatively high and low probability of a given outcome, respectively. This process is repeated in a sequential stepwise fashion until further partitioning is not possible. The result is a tree diagram, with terminal nodes representing subgroups of patients with a specific pattern of predictors and a certain probability of the outcome of interest. The Classification and Regression Tree, a computer program developed to perform recursive partitioning analysis, also "prunes" the tree by recombining subgroups if classification error is not increased. This process was used to partition patients into the 2 outcome categories previously mentioned. The tree was generated using the derivation population and cross-validated in the other sample.

Several parameters require specification for the CART modeling. The first is the prior probability of the final outcome classes. In our data set, the ratio of outcomes was different in the 2 populations because of the way patients were selected. In the combined data set, however, the relative frequencies of the 3 outcomes were similar. We therefore instructed the program to generate models assuming equal prior probabilities. The second parameter is the misclassification cost ratio (MCR). This refers to the relative cost of making an error in classification. For example, if one believes that it is twice as bad, or costly, to falsely classify someone as needing admission when she could be discharged as the other way around, one would assign an MCR of 2. Our baseline analysis assumed equal misclassification costs (MCR, 1), but we repeated the various analyses varying the MCR from 1 to 3 for each outcome.

The performance of the CART model was measured by calculating the proportion of patients assigned correctly to each category, with 95% confidence intervals.

In the second approach, we used only recursive partitioning to classify patients into one of the 3 outcome categories. For this analysis, all candidate variables that passed the univariate screening were considered as potential predictors. We used the same methods for recursive partitioning previously described.

Analyses were conducted using Stata 8.0 (Stata Corp, College Station, Tex) and CART (Salford Systems, San Diego, Calif).