Prediction of Pediatric Critical Care Resource Utilization for Disaster Triage

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Objectives: Pediatric protocols to guide allocation of limited resources during a disaster lack data to validate their use. The 2011 Pediatric Emergency Mass Critical Care Task Force recommended that expected duration of critical care be incorporated into resource allocation algorithms. We aimed to determine whether currently available pediatric illness severity scores can predict duration of critical care resource use.

Design: Retrospective cohort study.

Setting: Seattle Children's Hospital.

Patients: PICU patients admitted 2016–2018 for greater than or equal to 12 hours ($n = 3,206$).

Interventions: None.

Measurements and Main Results: We developed logistic and linear regression models in two-thirds of the cohort to predict need for and duration of PICU resources based on Pediatric Risk of Mortality-III, Pediatric Index of Mortality-3, and serial Pediatric Logistic Organ Dysfunction-2 scores. We tested the predictive accuracy of the models with the highest area under the receiver operating characteristic curve (need for each resource) and R^2 (duration of use) in a validation cohort of the remaining one of three of the sample and among patients admitted during one-third of the sample and among patients admitted during surges of respiratory illness. Pediatric Logistic Organ Dysfunction score calculated 12 hours postadmission had higher predictive accuracy than either Pediatric Risk of Mortality or Pediatric Index of Mortality scores. Models incorporating 12-hour Pediatric Logistic Organ Dysfunction score, age, Pediatric Overall Performance Category, Pediatric Cerebral Performance Category, chronic mechanical ventilation, and postoperative status had an area under the receiver operating characteristic curve = 0.8831 for need for any PICU resource (positive predictive value 80.2%, negative predictive value 85.9%) and area under the receiver operating characteristic curve = 0.9157 for mechanical ventilation (positive predictive value 85.7%, negative predictive value 89.2%) within 7 days of admission. Models accurately predicted greater than or equal to 24 hours of any resource use for 78.9% of patients and greater than or equal to 24 hours of ventilation for 83.1%. Model fit and accuracy improved for prediction of resource use within 3 days of admission, and was lower for noninvasive positive pressure ventilation, vasoactive infusions, continuous renal replacement therapy, extracorporeal membrane oxygenation, and length of stay.

Conclusions: A model incorporating 12-hour Pediatric Logistic Organ Dysfunction score performed well in estimating how long patients may require PICU resources, especially mechanical ventilation. A pediatric disaster triage algorithm that includes both likelihood for survival and for requiring critical care resources could minimize subjectivity in resource allocation decision-making. (*Pediatr Crit Care Med* 2020; XX:00–00)

Key Words: algorithms; disasters; organ dysfunction scores; pediatric intensive care units; resource allocation; triage

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Resources to care for a surge of critically ill or injured children during a disaster may be limited, creating an imbalance between needs and available resources (1, 2). Up to 30% of hospitalized disaster victims require intensive care, and fewer pediatric critical care resources are available per capita compared with adults (2, 3). In 2011, the Pediatric Emergency Mass Critical Care (PEMCC) Task Force recommended that hospitals be able to triple their usual PICU

capacity for 10 days without external assistance (4), and the 2014 American College of Chest Physicians (CHEST) guidelines suggested that hospitals be able to expand critical care resources by 200% above baseline in a crisis response (5). Most institutions are unable to stockpile sufficient quantities of resources such as ventilators to satisfy these guidelines (4).

There is thus a need for an ethically sound, widely accepted, and well-validated approach for allocation of scarce resources for children during a disaster (1, 4, 6). Although pediatric providers are divided on the use of protocols for triage decisions (7), both the PEMCC Task Force and CHEST guidelines recommend that objective protocols rather than ad hoc clinical judgment be used to determine allocation of limited resources during crises (1, 8). Several pediatric illness severity scores have been evaluated for ventilator-triage protocols; however, only the Pediatric Logistic Organ Dysfunction (PELOD) score (9) fulfills all criteria deemed important for use in a triage algorithm (10).

A major limitation to the use of PELOD (11, 12) and other pediatric scoring systems (10, 13) in a disaster is that they have primarily been validated to predict mortality; however, very few children would reach a mortality probability threshold that would suggest limitation of resources if a triage algorithm was based solely on mortality (4). The PEMCC Task Force proposed that a scoring system be developed that identifies patients likely to require an extended duration of critical care in order to survive (4).

A triage protocol that incorporates likelihood of resource need and duration may maximize lives saved by identifying children most likely to benefit from scarce resources (4). Subjective triage decision-making may result in variation between clinicians in their estimates of which patients might benefit from resources, and may be influenced by unconscious bias (1). Although "first-come first-served" and lottery system approaches have also been proposed to allocate limited resources, these do not target resources at patients who would benefit the most and could result in excess mortality (1, 14). In a model of a pandemic, overall pediatric survival was greater when triage thresholds based on probability of death and duration of ventilation were used compared with a first-come first-served approach (15). Most experts agree that it is ethically appropriate and preferable in a disaster setting to prioritize treatment of the greatest number of patients (1, 14).

We thus aimed to determine how well currently available pediatric illness severity scores are able to predict need for and duration of critical care resource use. Prediction of both mortality and resource use would facilitate development of a triage algorithm incorporating the central principles recommended by the PEMCC Task Force for pediatric disaster resource allocation.

MATERIALS AND METHODS

Study Design
After Institutional Review Board review, we conducted a retrospective cohort study to evaluate the accuracy of the Pediatric Risk of Mortality (PRISM) III (16), Pediatric Index of Mortality (PIM) 3 (17), and PELOD-2 (11) scores in predicting need for and duration of critical care resource use among patients admitted to the Seattle Children's Hospital PICU. We developed models assessing the association between PRISM, PIM, and serial PELOD scores with need for and duration of multiple PICU resources. Predictive models were evaluated both in the general PICU population to assess generalizability and during weeks with a surge in viral respiratory illnesses to assess performance with high hospital census and a predominance of one illness type to simulate a disaster scenario.

Setting and Participants
Seattle Children's Hospital is a freestanding academic children's hospital with 38 PICU beds. We included all patients admitted to the PICU for greater than or equal to 12 hours from January 12, 2016, to January 15, 2018, including those who did not survive to discharge. Patients were included regardless of diagnosis, reason for admission, or whether the admission was a repeat PICU admission. Patients in the hospital's cardiac and neonatal ICUs were not included as other illness severity scores are more commonly used in these populations. We excluded patients transferred from another ICU (to assess scores at time of initial critical care need) and patients who left against medical advice (to assess true duration of need).

Illness Severity Scores
We queried the electronic health record (EHR) and Virtual Pediatric Systems (VPS) database (18) for PRISM, PIM, and serial PELOD scores (**Table 1**). At our institution, VPS nurses calculate a PRISM-III score from the first 12 hours of data postadmission and a PIM-3 from the first 1 hour of data postadmission. A PELOD-2 score is automatically calculated and recorded in the EHR every 12 hours based on data from the prior 12 hours. PRISM-III (16) and PIM-3 (17) have been validated to predict mortality risk, and PELOD-2 has been validated for prediction of organ dysfunction severity and mortality (19, 20).

Covariates
We limited covariates to those easily obtained at hospital presentation to be relevant for use during a disaster: age, baseline Pediatric Overall Performance Category (POPC) and Pediatric Cerebral Performance Category (PCPC) scores (21), need for chronic continuous invasive mechanical ventilation via tracheostomy, and postoperative admission. We collected information on primary diagnosis but did not include it as a covariate in order to develop models agnostic to specific diagnoses.

Outcomes
We used VPS to determine the cumulative duration of mechanical ventilation, noninvasive positive pressure ventilation (NIPPV) with continuous positive airway pressure or bilevel positive airway pressure but not high-flow nasal cannula, continuous renal replacement therapy (CRRT), and extracorporeal membrane oxygenation (ECMO) for each patient, as well as PICU length of stay (LOS). We used the EHR to determine the cumulative duration of any vasoactive infusion.

TABLE 1. Characteristics of the Pediatric Risk of Mortality, Pediatric Index of Mortality, and Pediatric Logistic Organ Dysfunction Scores

Score Characteristic	Pediatric Risk of Mortality-III	Pediatric Index of Mortality-3	Pediatric Logistic Organ Dysfunction-2
When calculated at Seattle Children's Hospital	12 hr after PICU admission	1 hr after PICU admission	Every 12 hr
Automated calculation possible	Yes	No	Yes
Number of variables	17	8	10
Score components	Systolic blood pressure	Pupillary reaction	Glasgow Coma Score
	Heart rate	Elective admission	Pupillary reaction
	Temperature	Mechanical ventilation	Lactate
	Pupillary reflexes	Base excess	Mean arterial pressure
	Glasgow Coma Score	Systolic blood pressure	Creatinine
	Acidosis	Fio_2/Pao_2	Pao_2
	pH	Post-procedure	$Paco_2$
	Total co_2	Diagnosis risk category	Invasive ventilation
	Pao_2		WBC count
	$Paco_2$		Platelet count
	Glucose		
	Potassium		
	Creatinine		
	Blood urea nitrogen		
	WBC count		
	Prothrombin time/partial thromboplastin time		
	Platelet count		
Score range	0–74	Unrestricted negative number to unrestricted positive number	0–33
Scale	Intermittent	Continuous	Continuous
Worse prognosis	Higher score	Higher score	Higher score
Validated to predict	Mortality risk	Mortality risk	Severity of organ dysfunction
			Mortality risk

Our primary outcomes were need for and cumulative duration of any of the five resources within 7 days after PICU admission. Our secondary outcomes were need for and cumulative durations of each individual resource and PICU LOS within 7 days after PICU admission. During model validation, we also assessed the ability of the 7-day models to predict need for and duration of each resource within 3 and 14 days after PICU admission.

Statistical Analysis

Model Development: Base Models. We randomly selected two-thirds of the total cohort to constitute a development cohort and one-third to constitute a validation cohort (22). Using the development cohort, we performed logistic regression analyses to determine associations between PRISM, PIM, and serial PELOD scores calculated 6, 12, and 24 hours after admission with the odds of requiring any resource and each of the five resources within 7 days after admission (**Fig. 1**). We compared the area under the receiver operating characteristic curve (AUROC) for each analysis to assess the ability of each score to discriminate between patients who did and did not require each resource.

We then performed linear regression analyses evaluating associations between PRISM, PIM, and serial PELOD scores with the cumulative duration of any resource use and each individual resource and PICU LOS within 7 days after admission. We compared the adjusted R^2 value for each analysis to
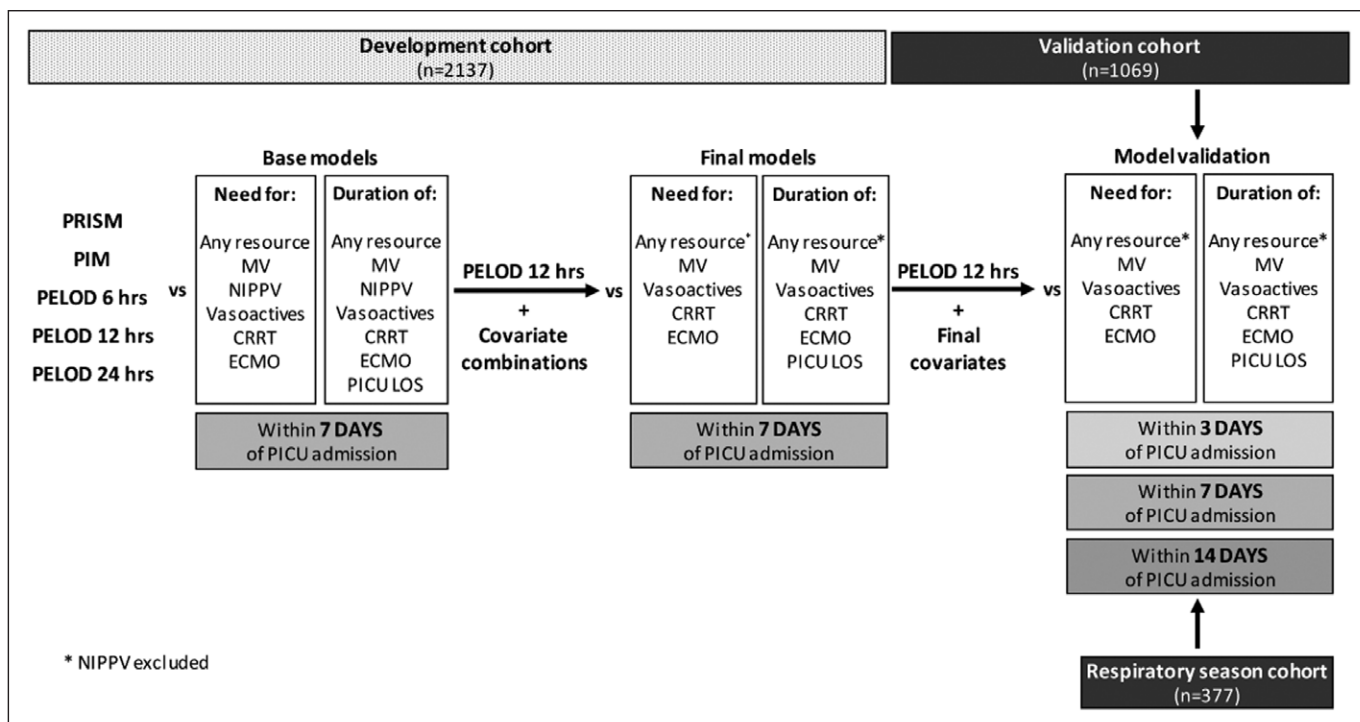
Figure 1. Flow diagram of model development and validation process. CRRT = continuous renal replacement therapy, ECMO = extracorporeal membrane oxygenation, LOS = length of stay, MV = mechanical ventilation, NIPPV = noninvasive positive pressure ventilation, PELOD = Pediatric Logistic Organ Dysfunction, PIM = Pediatric Index of Mortality, PRISM = Pediatric Risk of Mortality.

evaluate the ability of the score to explain the variability in the duration of each resource.

Model Development: Final Models. Using the exposure variable with the highest AUROC and R^2 values for our primary outcomes of need for and duration of any resource (determined to be 12-hr PELOD score), we systematically added covariates into the models. We first tested models incorporating 12-hour PELOD plus each covariate individually, then tested combinations of covariates, and finally added transformations of continuous and categorical covariates.

For the logistic regression models, we compared models with different covariates and variable interactions using the AUROC curve to determine the best final model fit for the association between 12-hour PELOD plus covariates and need for any resource within 7 days. For the linear regression models, we systematically added covariates and nested transformations of each variable and used the adjusted R^2 value to determine the best final model fit for the association between 12-hour PELOD plus covariates and duration of any resource within 7 days. We repeated the process for each of the individual resources.

Model Validation. We tested each of the best-fitting final models for need for and duration of each resource within 3, 7, and 14 days of PICU admission in the validation cohort. To determine the accuracy of prediction for the logistic regression analyses for need for each resource, we contrasted the AUROC of each 3-, 7-, and 14-day model in the development cohort with the AUROC in the validation cohort, assessed calibration using the Hosmer-Lemeshow chi-square test, and determined the positive predictive value (PPV) and negative predictive value (NPV)

of each prediction compared with whether patients actually required each resource within 3, 7, or 14 days. For the linear regression analyses of duration of each resource, we contrasted the adjusted R^2 value of each 3-, 7-, and 14-day model in the development cohort with the adjusted R^2 value in the validation cohort. We then calculated the percent agreement between the predicted duration and the actual duration for requiring each resource for greater than or equal to 12 and greater than or equal to 24 hours, and calculated the PPV and NPV for requiring each resource for greater than or equal to 12 and greater than or equal to 24 hours.

Respiratory Season Cohort. To evaluate model performance during times with a surge of viral respiratory illnesses, we obtained weekly hospital census data and viral respiratory testing results. We calculated the percentage of patients testing positive for any viral respiratory illness for each week during the study period, and determined if patients were admitted during weeks with greater than 25% of patients testing positive (**Supplemental Digital Content 1**, http://links.lww.com/PCC/B329). We then repeated the process of testing the best-fitting final models from the development cohort for need for and duration of each resource within 3, 7, and 14 days of PICU admission in the subset of patients in the validation cohort who were admitted during the respiratory season.

Sensitivity Analysis

Both the PELOD-2 and the PIM-3 include mechanical ventilation as an element in score calculation, while PRISM-III does not. We conducted a sensitivity analysis to evaluate the ability of each score to predict subsequent need for mechanical

TABLE 2. Characteristics of PICU Admissions Included in the Study

Patient Characteristic	n (%), n = 3,206
Age, yr, median (IQR)	4.8 (1.2–12.7)
Male gender	1,735 (54.1)
Race	
Non-Hispanic White	1,587 (49.5)
Non-Hispanic Black	186 (5.8)
Hispanic	556 (17.3)
Asian	316 (9.9)
Other/mixed/unknown	561 (17.5)
Baseline Pediatric Overall Performance Category score	
1 Normal	856 (26.7)
2 Mild disability	573 (17.9)
3 Moderate disability	1,425 (44.5)
4 Severe disability	352 (11.0)
Baseline Pediatric Cerebral Performance Category score	
1 Normal	2,206 (68.8)
2 Mild disability	298 (9.3)
3 Moderate disability	390 (12.2)
4 Severe disability	312 (9.7)
Chronic mechanical ventilation	144 (4.5)
Primary admission diagnosis	
Respiratory	903 (28.2)
Infectious	366 (11.4)
Craniofacial/otolaryngology	364 (11.4)
Neurologic	340 (10.6)
Oncologic	246 (7.7)
Cardiovascular	163 (5.1)
Neurosurgery	146 (4.6)
Injury/poisoning	146 (4.6)
Other medical	289 (9.0)
Other surgical	243 (7.6)
Postoperative admission	1,061 (33.1)
Pediatric Risk of Mortality III score, median (IQR)	0 (0–4); range 0–40
Pediatric Index of Mortality-3 score, median (IQR)	−4.97 (−6.14 to −4.54); range −8.23 to +3.78
12-hr Pediatric Logistic Organ Dysfunction score, median (IQR)	3 (2–5); range 0–24
PICU resource use within 7 d	
Any resource	1,460 (45.5)
Mechanical ventilation	820 (25.6)
Noninvasive positive pressure ventilation	570 (17.8)
Vasoactive infusions	430 (13.4)
Continuous renal replacement therapy	73 (2.3)
Extracorporeal membrane oxygenation	22 (0.7)
PICU length of stay, d, median (IQR)	2 (1–4)
PICU mortality	66 (2.1)

IQR= interquartile range.

ventilation among patients not currently ventilated at the time of score calculation. Models were adjusted for age, POPC, PCPC, and postoperative status.

RESULTS

There were 3,206 PICU admissions included in the study. Respiratory illnesses were the most common reason for admission (28.2%), and 33.1% of admissions were postoperative. Median PRISM-III, PIM-3, and 12-hour PELOD-2 scores were low but with wide ranges represented across the cohort. Forty-five percent of admissions required any PICU resource within 7 days after admission, including 25.6% requiring mechanical ventilation, 17.8% NIPPV, 13.4% vasoactive infusions, 2.3% CRRT, and 0.7% ECMO (**Table 2**).

Model Development: Base Models

Of the five primary exposures assessed (PRISM, PIM, and PELOD at 6, 12, and 24 hr postadmission), 12-hour PELOD had the highest AUROC (0.8434) for use of any PICU resource and the second-highest R^2 value (0.2288) behind 24-hour PELOD (0.2526) for duration of any resource within the first 7

days (**Supplemental Digital Content 2**, http://links.lww.com/PCC/B330). Model fit was best for need for and duration of mechanical ventilation, with 12-hour PELOD having the highest AUROC (0.8667) and second-highest R^2 (0.1843) behind 24-hour PELOD (0.2048). Balancing model fit with usefulness for triage decision-making, we selected 12-hour PELOD as the base exposure to use for final model development. Given that there was almost no association between 12-hour PELOD score and need for or duration of NIPPV, we did not include NIPPV in final model development and removed it from calculation of total resource use.

Model Development: Final Models

After the addition of covariates and variable interactions to 12-hour PELOD, the logistic regression model with the best fit for need for any resource within 7 days of admission (AUROC = 0.8722) included age, POPC, PCPC, chronic mechanical ventilation, and postoperative status as covariates (**Supplemental Digital Content 3**, http://links.lww.com/PCC/B331). Of the individual resources, need for mechanical ventilation had the best fit (AUROC = 0.9009) after addition of age,

TABLE 3. Validation of Final Logistic Regression Models for Prediction of Need for Each PICU Resource

Resource	Development Cohort	Validation Cohort			Respiratory Season Cohort		
	AUROC	AUROC	PPV (%)	NPV (%)	AUROC	PPV (%)	NPV (%)
Any resource, d							
3	0.8858	0.8970	80.3	85.7	0.9304	80.7	89.7
7	0.8722	0.8831	80.2	85.9	0.9162	79.6	89.2
14	0.8702	0.8834	79.6	86.7	0.9162	79.6	89.2
Mechanical ventilation, d							
3	0.9180	0.9299	86.1	90.5	0.9475	85.3	93.5
7	0.9009	0.9157	85.7	89.2	0.9253	87.0	92.5
14	0.8992	0.9093	85.8	89.4	0.9253	87.0	92.5
Vasoactive infusions, d							
3	0.8149	0.8476	55.6	88.7	0.8977	56.3	91.7
7	0.8103	0.8356	57.1	88.2	0.8783	60.0	91.4
14	0.8060	0.8337	56.8	88.1	0.8783	60.0	91.4
Continuous renal replacement therapy, d							
3	0.8728	0.8667	42.9	98.0	0.9420	80.0	98.7
7	0.8676	0.8626	42.9	97.8	0.9386	80.0	98.6
14	0.8538	0.8525	42.9	97.7	0.9386	80.0	98.6
Extracorporeal membrane oxygenation, d							
3	0.8160	0.8698	0	99.3	0.9309	0	99.1
7	0.8068	0.8390	0	99.3	0.9076	0	99.2
14	0.7934	0.8212	0	99.3	0.9076	0	99.2

AUROC = area under the receiver operating characteristic curve, NPV = negative predictive value, PPV = positive predictive value.

POPC, PCPC, and chronic mechanical ventilation. Fit of the final models was less strong for need for vasoactive infusions (AUROC = 0.8103), CRRT (AUROC = 0.8676), and ECMO (AUROC = 0.8068).

After addition of covariates to 12-hour PELOD and variable transformation, the linear regression model with the best fit for duration of any PICU resource within 7 days of admission ($R^2 = 0.2993$) included age, POPC, PCPC, chronic mechanical ventilation, and postoperative status (**Supplemental Digital Content 4**, http://links.lww.com/PCC/B332). Duration of mechanical ventilation had the best fitting model of the individual resources ($R^2 = 0.2888$) and included age, PCPC, and chronic mechanical ventilation. Model fit was less strong for duration of vasoactive infusions ($R^2 = 0.2291$), CRRT ($R^2 = 0.0534$), ECMO ($R^2 = 0.0102$), and PICU LOS ($R^2 = 0.1410$).

Model Validation

Need for Resource Use. The final model for prediction of need for any resource within 7 days of admission performed well in the validation cohort (AUROC = 0.8831) compared with the development cohort (**Table 3**). The Hosmer-Lemeshow chi-square value was 8.22 ($p = 0.3417$). The model predicted greater than 50% probability of resource use (0.53; 95% CI, 0.51–0.58) at a 12-hour PELOD score of 5, and greater than 95% probability (0.97; 95% CI, 0.95–0.98) at a 12-hour PELOD score of 10 (**Fig. 2**). Relative to actual need, the PPV of the model was 80.2% and NPV was 85.9%. There was no difference in predictive accuracy for need for resources within 3 or 14 days of admission.

The final model for prediction of need for mechanical ventilation within 7 days performed better in the validation cohort (AUROC = 0.9157) than the development cohort, with a Hosmer-Lemeshow chi-square value of 2.93 ($p = 0.4022$), PPV of 85.7%, and NPV of 89.2% (Table 3). The model predicted greater than 50% probability of ventilator use (0.58; 95% CI, 0.55–0.62) at a 12-hour PELOD score of 6, and greater than 95% probability (0.96; 95% CI, 0.94–0.97) at a 12-hour PELOD score of 10 (Fig. 2). Model performance was slightly improved for prediction of ventilator need within 3 days of admission.

The 7-day models for vasoactive infusions and ECMO performed better in the validation cohort than the development cohort, while the 7-day model for CRRT performed slightly worse in the validation cohort (Table 3). Predictive accuracy was moderate for need for vasoactive infusions and poor for CRRT and ECMO. Accuracy for all three models was similar for prediction of resource use within 3 and 14 days of admission. The models predicted increasing probability of resource use with higher PELOD scores for all three resources (Fig. 2).

Duration of Resource Use. The final model for duration of any PICU resource within 7 days performed better in the validation cohort ($R^2 = 0.3403$) than the development cohort (**Table 4**). The mean predicted duration of resource use within 7 days increased continuously to a 12-hour PELOD score of 18 (mean, 4.3 d; 95% CI, 3.9–4.7 d) then declined (**Fig. 3**). The model accurately predicted whether patients would require greater than or
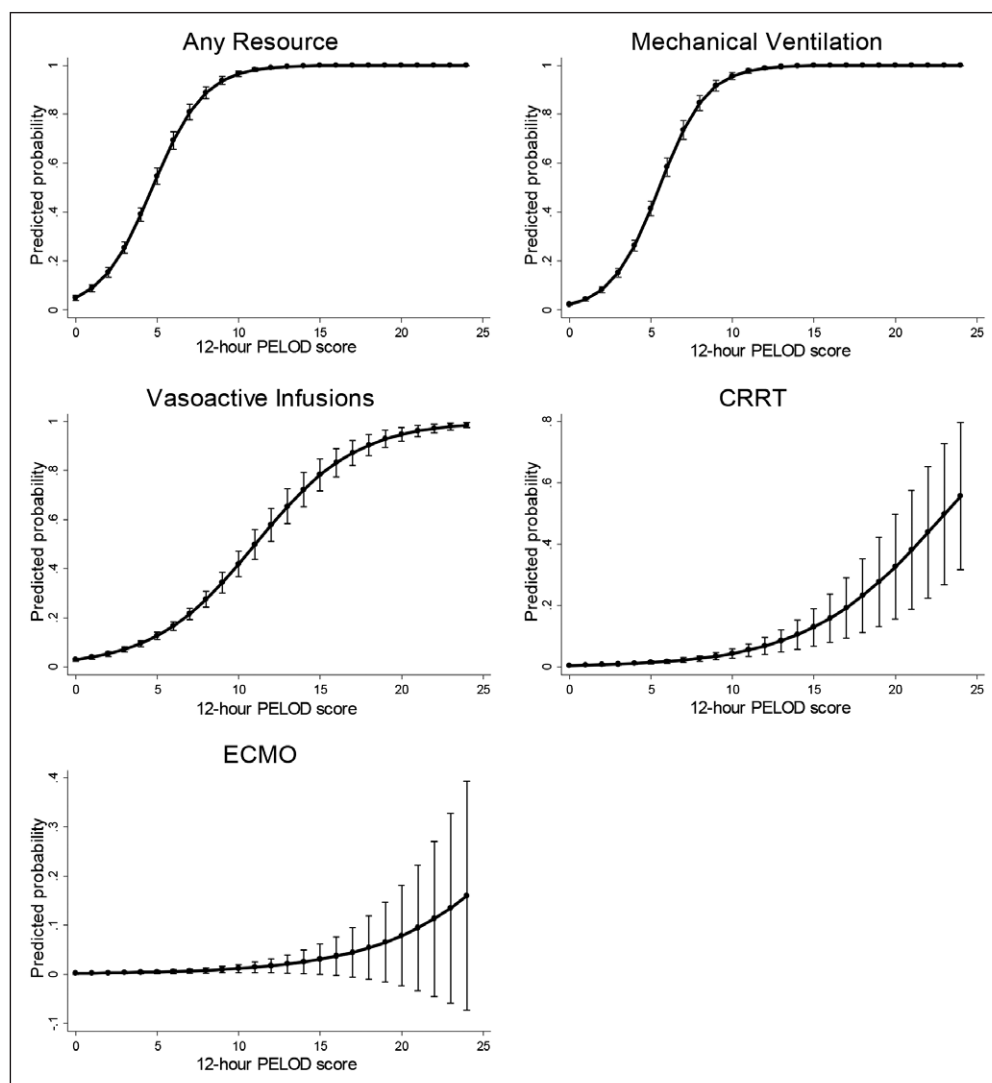

Figure 2. Predicted probability of need for PICU resources within 7 d of PICU admission by 12-hr Pediatric Logistic Organ Dysfunction (PELOD) score based on final logistic regression models. *Bars* represent 95% CIs. CRRT = continuous renal replacement therapy, ECMO = extracorporeal membrane oxygenation.

TABLE 4. Validation of Final Linear Regression Models for Prediction of Duration of Use of Each PICU Resource

Resource	Development Cohort R^2	Validation Cohort							Respiratory Season Cohort						
		R^2	12 hr			24 hr			R^2	12 hr			24 hr		
			%[a]	PPV	NPV	%[a]	PPV	NPV		%[a]	PPV	NPV	%[a]	PPV	NPV
Any resource, d															
3	0.4024	0.4493	79.7	59.8	91.9	84.2	74.2	86.5	0.4860	82.5	62.0	94.2	87.3	80.0	88.6
7	0.2993	0.3403	71.3	49.9	92.6	78.9	56.8	90.4	0.4016	72.2	49.5	95.2	82.2	59.0	92.7
14	0.2198	0.2538	63.0	43.2	93.5	74.9	50.9	91.4	0.3241	66.1	44.3	96.2	79.3	53.5	94.9
Mechanical ventilation, d															
3	0.4157	0.4384	84.5	57.5	95.8	89.3	72.8	91.5	0.4417	84.9	57.7	96.2	89.4	72.5	91.4
7	0.2888	0.3168	75.5	45.5	96.3	83.1	50.2	94.4	0.3586	78.3	49.0	96.6	83.6	50.0	95.0
14	0.2112	0.2299	69.6	40.1	96.4	79.0	44.4	95.5	0.3018	62.3	35.1	97.0	80.6	45.5	95.1
Vasoactive infusions, d															
3	0.2259	0.2808	85.8	46.7	92.4	87.5	61.1	88.5	0.2700	90.5	53.9	94.7	89.9	60.0	90.3
7	0.2291	0.2511	82.5	41.1	94.0	87.0	53.3	90.2	0.1956	87.0	42.4	95.3	89.4	50.0	91.4
14	0.1881	0.1388	82.5	36.0	94.4	88.9	56.3	90.9	0.1617	83.8	36.7	96.3	89.7	51.6	93.1
Continuous renal replacement therapy, d															
3	0.0561	0.0470	98.1	0	98.1	98.9	0	98.9	0.1077	98.4	40.0	98.7	99.0	0	99.0
7	0.0534	0.0523	96.7	22.1	98.3	98.0	9.1	98.3	0.0819	97.0	16.7	98.7	98.7	42.9	99.0
14	0.0476	0.0480	91.7	11.7	98.4	97.3	26.0	98.5	0.0520	93.7	15.6	99.4	98.1	23.1	99.0
Extracorporeal membrane oxygenation, d															
3	0.0126	0.0173	99.6	0	99.6	99.7	0	99.7	0.0233	99.4	0	99.4	99.4	0	99.4
7	0.0102	0.0101	99.4	0	99.4	99.4	0	99.4	0.0137	99.3	0	99.3	99.3	0	99.3
14	0.0070	0.0062	99.3	0	99.3	99.4	0	99.4	0.0103	99.3	0	99.3	99.3	0	99.3
PICU length of stay, d															
3	0.1425	0.1608	NA	NA	NA	70.1	70.1	100	0.1757	NA	NA	NA	71.9	71.9	66.7
7	0.1410	0.1489	NA	NA	NA	70.3	70.3	75.0	0.1573	NA	NA	NA	72.2	72.2	66.7
14	0.1287	0.1378	NA	NA	NA	70.9	70.9	70.0	0.1574	NA	NA	NA	73.7	73.4	83.3

NA = not applicable, NPV = negative predictive value, PPV = positive predictive value.

[a]Percentage of patients for whom model accurately predicted at least 12 hr or 24 hr of resource use.

equal to 12 hours of resource use for 71.3% of patients and greater than or equal to 24 hours for 78.9% of patients. Prediction was improved for duration of resource use within 3 days of admission ($R^2 = 0.4493$, 79.7% 12-hr accuracy, 84.2% 24-hr accuracy).

Of the individual resources, model fit was best for prediction of 7-day ventilator duration, with a higher R^2 value in the validation cohort ($R^2 = 0.3168$) than the development cohort (Table 4). The mean predicted duration of mechanical ventilation peaked at a PELOD score of 17 (3.7 d; 3.3–4.0 d) then declined (Fig. 3). The model accurately predicted greater than or equal to 12 hours of ventilator use in 75.5% of patients and greater than or equal to 24 hours in 83.1%. Model fit improved

for prediction of ventilator duration within 3 days of admission ($R^2 = 0.4384$, 84.5% 12-hr accuracy, 89.3% 24-hr accuracy).

Models to predict duration of vasoactive infusions, CRRT, ECMO, and PICU LOS all performed similarly to slightly better in the validation cohorts than the development cohorts (Table 4). Duration of vasoactive infusions had the best fit (7-d $R^2 = 0.2511$). Model fit was poor for the other resources. Predicted duration continuously increased to a PELOD score of 24 for both infusions and CRRT and peaked followed by decline for ECMO and LOS (Fig. 3).

Respiratory Season Cohort. Of the admissions included in the study, 1,127 (35.2%) occurred during weeks with a surge in viral respiratory illnesses. Each of the final models from the
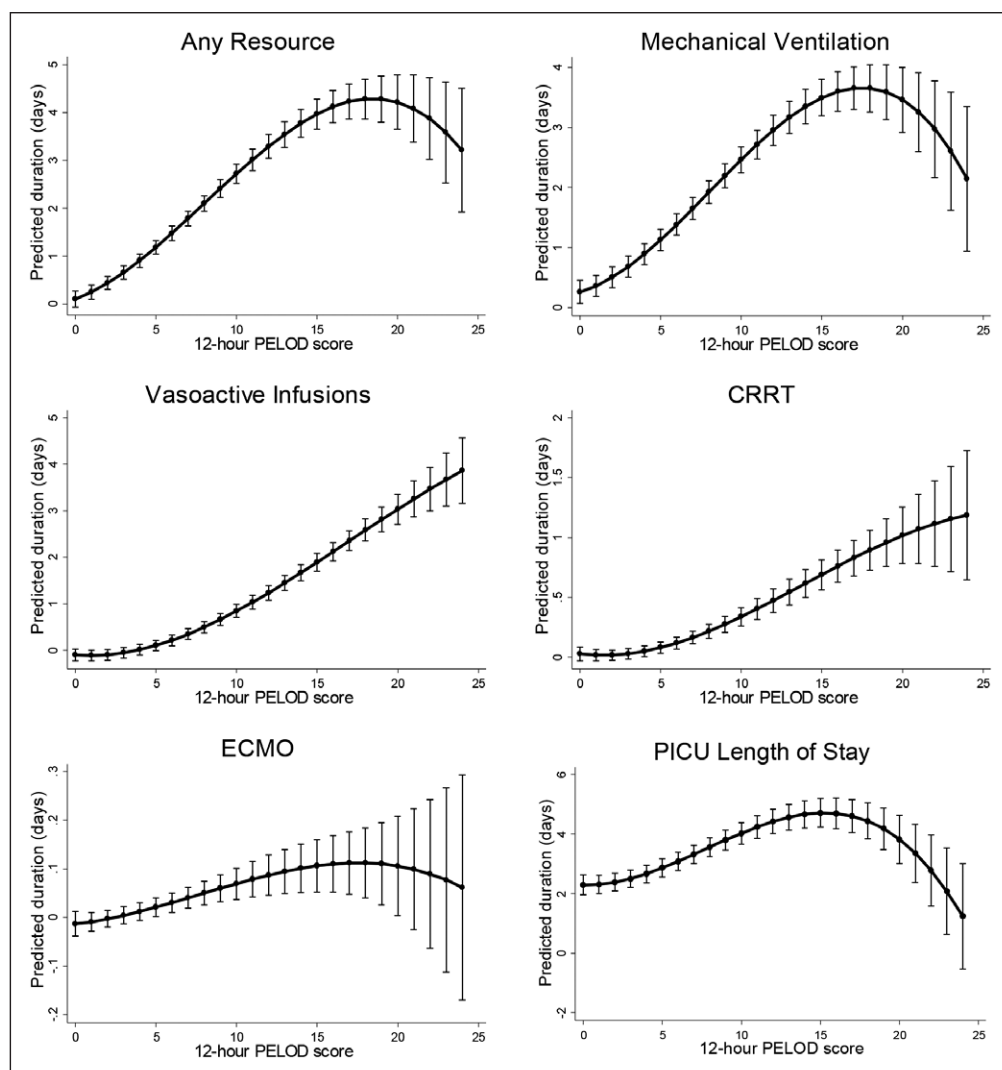
Figure 3. Predicted mean duration of use of PICU resources within 7 d of PICU admission by 12-hr Pediatric Logistic Organ Dysfunction (PELOD) score based on final linear regression models. *Bars* represent 95% CIs. CRRT = continuous renal replacement therapy, ECMO = extracorporeal membrane oxygenation.

subsequent need for ventilation within 7 days in the validation cohort was 0.7271 for 12-hour PELOD, 0.6993 for PRISM, and 0.7353 for PIM.

DISCUSSION

In this 2-year study of patients with a broad range of diagnoses receiving contemporary PICU care, we found that PICU resource utilization could be accurately predicted using existing pediatric illness severity scores traditionally used to predict mortality risk. PELOD performed better than PRISM or PIM for prediction of overall resource utilization and specifically mechanical ventilation, and PELOD score calculated 12 hours after admission provided good predictive accuracy relative to other time points while balancing practicality for use in triage decision-making. With the addition of several patient factors easily obtained at admission, logistic and linear regression models based on 12-hour PELOD score were able to predict need for PICU resources within the first week of admission with a PPV of 80% and NPV of 86%, and correctly identified whether greater than or equal to 24 hours of resource use would be required for 79% of patients.

Prediction of overall PICU resource use could aid with triage of patients based on bed and nursing availability during a disaster, while prediction of the specific types of and duration of need for resources may optimize allocation of these resources. Ventilator triage is a particular area of interest given the likelihood for shortage with a large influx of patients at high risk for respiratory failure (10, 23–25). We found that models to predict ventilator need and duration of use performed better than for any other resource. The model to predict need for mechanical ventilation within 7 days of admission had an AUROC of 0.9253 with a PPV of 86% and a NPV of 89%, and accurately predicted greater than or equal to 24 hours of resource use for 83% of patients. Accuracy was even higher in the subset of patients admitted during weeks with a high proportion of viral respiratory illnesses, suggesting that the models might perform well during a respiratory pandemic.

development cohort performed better in the subset of patients from the validation cohort admitted during respiratory season than in the general validation cohort. Prediction of need for any resource within 7 days of admission had an AUROC = 0.9262 in the respiratory season validation cohort (PPV = 79.6%, NPV = 89.2%). The same trend was found for need for mechanical ventilation (AUROC = 0.9253, PPV = 87.0%, NPV = 92.5%) (Table 3). Model fit for prediction of resource duration was also better in the respiratory season validation cohort than in the general validation cohort (7-d R^2 = 0.4016, 72.2% 12-hr accuracy, 82.2% 24-hr accuracy). Duration of mechanical ventilation within 7 days had an R^2 value of 0.3586 (78.3% 12-hr accuracy, 83.6% 24-hr accuracy) (Table 4). Predictive accuracy for need for and duration of resource use was lower for vasoactive infusions, CRRT, and ECMO, and model fit was generally improved for 3-day prediction and worse for 14-day prediction.

Sensitivity Analysis. Among patients not receiving mechanical ventilation at the time of score calculation, the AUROC for

Our modeling suggests that the PELOD score may be the best of the existing pediatric illness severity scores to incorporate into a resource-allocation algorithm that accounts for both likelihood of survival and expected duration of critical care resource use. Even without considering survival as an outcome in this study, the predicted duration for total resource use, mechanical ventilation, and LOS all peaked at a PELOD score in the high teens and then fell, likely reflecting early mortality for patients with the highest PELOD scores.

The primary limitation of this study was that it was intentionally designed as a single-center retrospective study of existing pediatric scoring systems. Expansion into a larger cohort at other institutions is an essential next step in developing a final algorithm for use in pediatric disasters. Inclusion of cardiac and neonatal ICU patients will also be necessary to account for all ICU resources needed throughout a hospital. We limited covariates to those available in VPS, but predictive accuracy may be increased with inclusion of additional factors such as preexisting comorbidities or medical complexity, prior admission data, or prehospital resuscitation received. Additionally, we developed models using an a priori-determined systematic process for addition of covariates and variable transformation, but a machine-learning approach may allow more precise model development by allowing an algorithm to test all possible variable combinations to determine the best-fitting model. Finally, use of existing scores limits the flexibility of the models and limited our evaluation of the PIM and PRISM scores to their standard time of calculation at 1 and 12 hours postadmission, respectively; a modified score less reliant on laboratory values may have more utility in prehospital or emergency department settings.

In addition to multicenter model refinement and validation, it will be critical to consider ethical principles and both provider and public opinion prior to implementation of a resource-allocation score in a crisis standards of care scenario, including whether resources would be withdrawn from patients already receiving them at the time of score calculation and reassigned to other patients, and how to allocate pediatric and adult resources simultaneously. Implementation would also have to be considered in the greater context of regional resources, disproportionately affected populations, and in close collaboration with public health departments, regional healthcare partners, and healthcare coalitions rather than on an individual hospital or provider basis.

Scoring tools for any scarce resource allocation must be carefully evaluated using the best epidemiological information at the time of the disaster. No standard pediatric scoring system has yet been implemented for crisis standards of care, and special attention must be given to not overly rely on scoring systems to make decisions prematurely. We remain cautious about the utility of any score, while understanding that there could be a point when a score-based algorithm does become necessary to create an objective and transparent system for resource allocation, especially in light of the current coronavirus disease 2019 pandemic and limited critical care resource availability. A multidisciplinary and multimodal approach will be essential to develop an ethically sound and widely accepted triage tool appropriate for clinical use.

CONCLUSIONS

The PELOD score may have utility in being incorporated into a triage decision-making algorithm for pediatric critical care resource utilization during a disaster when crisis standards of care are in place. A pediatric disaster triage algorithm that includes both likelihood for survival and need for critical care resources could minimize subjectivity in resource allocation decision-making.

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