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Emergency Department Pediatric Readiness Among US Trauma Centers: A Machine Learning Analysis of Components Associated with Survival

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Abstract

Objective: We used machine learning to identify the highest impact components of emergency department (ED) pediatric readiness for predicting in-hospital survival among children cared for in US trauma centers.

Summary Background Data: Emergency department (ED) pediatric readiness is associated with improved short- and long-term survival among injured children and part of the national verification criteria for US trauma centers. However, the components of ED pediatric readiness most predictive of survival are unknown.

Methods: This was a retrospective cohort study of injured children < 18 years treated in 458 trauma centers from 1/1/2012 through 12/31/2017, matched to the 2013 National ED Pediatric Readiness Assessment and the American Hospital Association survey. We used machine learning to analyze 265 potential predictors of survival, including 152 ED readiness variables, 29 patient variables, and 84 ED- and hospital-level variables. The primary outcome was in-hospital survival.

Results: There were 274,756 injured children, including 4,585 (1.7%) who died. Nine ED pediatric readiness components were associated with the greatest increase in survival: policy for mental health care (+8.8% change in survival), policy for patient assessment (+7.5%), specific respiratory equipment (+7.2%), policy for reduced-dose radiation imaging (+7.0%), physician competency evaluations (+4.9%), recording weight in kilograms (+3.2%), life support courses for nursing (+1.0% to 2.5%), and policy on pediatric triage (+2.5%). There was a 268% improvement in survival when the five highest impact components were combined.

Conclusion: ED pediatric readiness components related to specific policies, personnel, and equipment were the strongest predictors of pediatric survival and worked synergistically when combined.

MINI-ABSTRACT

We used machine learning to evaluate 152 different components of ED pediatric readiness, which identified nine measures with the greatest associated improvement in survival, including certain policies, personnel, and equipment. Combining high impact components of ED pediatric readiness had synergistic impact on survival.

Keywords

children; trauma centers; emergency department; readiness; survival

INTRODUCTION

The National Pediatric Readiness Project (NPRP) was created as a national quality improvement initiative to address the highly variable care of children in emergency departments (EDs)[1] and to ensure that all EDs are adequately prepared to care for acutely ill and injured children.[2] This initiative is particularly relevant for trauma centers because unintentional injury is the leading cause of death and years of potential life lost among children.[3, 4] Even among major Level I-II trauma centers, the levels of ED pediatric readiness are variable,[5, 6] yet high ED pediatric readiness is associated with improved short- and long-term survival among children treated in trauma centers.[6, 7] Consequently, the “readiness” of trauma centers to care for children has gained increased attention, with ED pediatric readiness recently integrated into the national guidelines for trauma center verification.[8]

The six domains of ED pediatric readiness include administration and coordination, personnel and competencies, quality improvement, patient safety, policies and procedures, and equipment and supplies.[9] Key aspects of these domains are included in a composite measure called the “weighted Pediatric Readiness Score” (wPRS),[10] which is associated with survival among injured children treated in trauma centers.[6, 7] However, there are more than 150 individual components of ED pediatric readiness[9] and research detailing which specific components are responsible for the survival benefit remain sparse. Trauma centers seeking to raise their level of ED pediatric readiness must prioritize the implementation of different components, particularly if they have limited resources. A recent study was the first to explore which aspects of ED pediatric readiness were associated with survival.[11] Using observed-to-expected mortality ratios for trauma centers, having both physician and nurse pediatric emergency care coordinators (PECCs), comprehensive quality improvement processes, and the necessary resuscitation supplies were associated with better-than-expected survival.[11] However, the associations were not consistent across all analyses and the hospital-level models had limited power to assess the large number of ED readiness components.

Machine learning (ML) is a methodology that can be useful in identifying patterns in large amounts of data, identify predictors relevant to those patterns, and perform analytical model building from these data. As a subset of artificial intelligence, ML functions without many of the constraints inherent to traditional statistical models. Unlike conventional statistical modeling, ML makes minimal assumptions about the data-generating processes and can be effective even when the data are gathered outside a carefully controlled experimental design, in the presence of non-linear interactions, and with high dimensional data. The feasibility and effectiveness of ML are supported theoretically and empirically.[12–14] Machine learning is increasingly being used in the fields of emergency care and trauma based on its flexible applications, prediction capability, and ability to process a large number of variables considered for risk prediction.[15–18]

In this study, we used ML to identify individual components of ED pediatric readiness associated with improved survival among injured children cared for in US trauma centers, including the potential benefit of combining components. We sought to create a prioritized roadmap for trauma centers seeking to raise their level of ED pediatric readiness.

METHODS

Study Design:

We performed a retrospective cohort study that was reviewed and approved by Institutional Review Boards at Oregon Health and Science University and the University of Utah School of Medicine, which waived the requirement for informed consent. We used the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) cohort study guidelines.[19]

Study Setting:

We included 458 trauma centers (Levels I – IV, adult and pediatric) across the US that submit pediatric data to the National Trauma Data Bank (NTDB). Data from these hospitals were collected using the National Trauma Data Standard,[20] which uses standardized inclusion criteria and data fields to capture information on initial ED presentation, physiology, injury severity, procedures, intensive care, and clinical outcomes.

Patient Population:

The study population was injured children < 18 years meeting NTDB inclusion criteria (an injury diagnosis with hospital admission, inter-hospital transfer, or injury-related death in a participating trauma center[21]) from January 1, 2012 through December 31, 2017, matched at the hospital level to the 2013 NPRP assessment and the 2014 American Hospital Association (AHA) data.[22, 23] We based our analysis on the readiness of the trauma center ED providing the initial care for each child. For children subsequently transferred to another trauma center, we matched available records from the second hospital using probabilistic linkage.[24] We excluded children who were dead on arrival, missing the initial ED record (e.g., children treated initially in non-trauma center EDs), missing hospital disposition, or treated in EDs without matched NPRP or AHA data (eFigure 1). To provide stable estimates and to minimize bias, the primary sample included trauma centers that cared for at least 50 injured children over the 6-year period and experienced at least one death.

Emergency Department Pediatric Readiness:

The components of ED readiness are aligned with national ED guidelines for children and represent factors that can be implemented in all EDs, regardless of hospital type, inpatient services, or other hospital-specific factors. We included 152 different components of ED pediatric readiness from the six domains, as measured in the 2013 NPRP assessment.[9] The NPRP assessment was a national 55-question assessment of EDs providing emergency care 24 hours per day seven days per week.[25] Nurse managers from 4,146 U.S. EDs completed the assessment from January 1 through August 31, 2013.[9] We matched the NPRP assessment to the initial trauma center ED record using hospital name, address, and zip code. For NPRP questions with multiple subcomponents, we divided each subcomponent into a separate predictor.

Variables:

In addition to the 152 components of ED pediatric readiness, we evaluated patient factors and additional ED and hospital factors. Patient-level variables (29) included: demographics (age, sex, and race), comorbidities, mechanism of injury, mode of arrival, initial ED physiology (systolic blood pressure [SBP] and Glasgow Coma Scale [GCS] score), emergent airway intervention, blood transfusion, Abbreviated Injury Scale (AIS) score,[26] Injury Severity Score (ISS),[26, 27] surgical procedures, and inter-hospital transfer. To maximize information for airway interventions, blood transfusions, and surgical procedures, we used a combination of abstracted NTDB data fields and ICD-9/10 procedure codes, categorized using the Agency for Healthcare Research and Quality Clinical Classification System (CCS).[28] We then mapped CCS categories to standardized operative domains for trauma (brain, spine, neck, chest, abdominal-pelvic, and orthopedic), airway interventions, and blood transfusion.

In addition, we included 84 fixed (i.e., not easily modifiable) ED- and hospital-level variables from NTDB, the NPRP assessment, and the AHA survey to consider the impact of these factors on pediatric survival. These variables included adult trauma level I – IV, pediatric trauma level I – IV, ED and inpatient pediatric volumes, the presence of a separate pediatric ED, total licensed hospital beds, hospital ownership and accreditation, inpatient pediatric resources, specialty services for children, and broader hospital resources for children.

Outcomes:

The primary outcome was in-hospital survival. To assess the performance of predictor variables, we used the area under the receiver operating characteristic curve (AUC), sensitivity, and specificity. To calculate the percent survival increase for each component of ED pediatric readiness, we set the predictor variable to its two values (0, 1) and analyzed the model for each value using the validation dataset (detailed below). For example, if S0 = the number of patients predicted to survive when a certain ED policy was not implemented and S1 = the number of patients predicted to survive when the policy was implemented, the percent increase in survival predicted by implementing the ED policy was:

$$\%\ \text{change} = \frac{(S1 - S0)}{S0}$$

Thus, a policy with S0 = 868 and S1 = 944 would generate a percent change in survival of 8.76%

Statistical Analysis:

Using a structure approach for supervised ML in the healthcare setting,[29] we analyzed 265 unique variables (152 ED readiness, 29 patient, and 84 ED/hospital) using several ML software programs (Keras v2.4.3,[30] Tensorflow v2.4.1,[31] Scikit-learn v0.24.1,[32] and Scipy v1.6.2[33]). We initially divided the data into a validation dataset (randomly selected 20% of deaths and an equivalent number of survivors), with the remainder of sample used for training and testing the models. We initiated the ML analysis using an unrestricted parent sample of 752 trauma centers (n = 290,419 children, eFigure 1) to test and compare four types of models (logistic regression, support vector machine classification [SVM], random forest, and neural net) using 5-fold cross-validation to train and test the models.[13, 14] Because survivors and deaths were unbalanced (i.e., more survivors than deaths), we compared multiple techniques to balance the sample, including over-sampling, under-sampling, hybrid over/under-sampling, and the mini-batch technique to balance the classes.[34, 35] Using 50/50 class split mini-batch dataset balancing,[36, 37] a logistic regression model outperformed SVM, random forest, and neural network models. We used restricted samples of the data to test for bias caused by low volume trauma centers with no deaths, high volume hospitals over-represented in the sample, and children with low severity of injury. The sample with the least biased estimates and similar predictive performance to the larger parent sample included hospitals with ≥ 50 children and at least one death, which formed the primary analytic sample (458 trauma centers, n = 274,756 children, eFigure 1).

To narrow the number of predictor variables (feature selection), we compared the predictive performance of models with 5, 10, 20, 30, 40, and 50 predictors using the largest magnitude variable weights (beta values) from the logistic regression model class separation equation and maximum relevance minimum redundancy.[38] We sought to preserve ≥ 95% of the baseline prediction obtained from all 265 variables using a smaller number of variables. We included all types of variables (ED readiness, ED/hospital, and patient) in the feature selection process to identify the most predictive variables without preconceived biases or assumptions. We retained the 50 highest impact predictors and used the held-out validation dataset to calculate the final predictive estimates.

To evaluate the significance of each component of ED pediatric readiness, we tested each variable in the validation dataset for overall percent change in predicted survival when present versus absent. For the ED pediatric readiness components most predictive of improved survival, we also estimated the survival impact of combining components. Finally, for the highest impact components of ED pediatric readiness, we estimated their association with survival among children with varying levels of injury severity (ISS 0–8, 9–15, 16–24, and > 24). A detailed explanation of the machine learning methods is included in the Supplemental Digital Content.

For handling missing values, we used multiple imputation[39, 40] to reduce bias and preserve the sample size. We have shown the validity of multiple imputation for trauma data.[41–43] We generated 10 multiply imputed datasets[44] using chained equations, as implemented by Stata's "mi impute chained" command,[45, 46] then combined the results accounting for within- and between-dataset variance.[40]

RESULTS

Among 832 trauma centers with matched ED pediatric readiness data, we included 458 trauma centers that cared for 274,756 children in the primary analysis (eFigure 1). Among the 458 trauma centers, the median wPRS was 84.7 (IQR 69.1–95.1, range 32.2–100). Emergency department and hospital characteristics of the 458 trauma centers are included in Table 1. Of the 274,756 children, 4,585 (1.7%) died during their hospital stay. The median age was 10 years (IQR 4–15), 35.7% were female, 13.7% had ISS ≥ 16, and the most common mechanism of injury was fall (37.6%). Patient characteristics are summarized in eTable 1.

The predictive performance metrics for domain-level components of ED pediatric readiness are listed in Table 2. The domains of policies, procedures, and protocols (AUC 0.61) and personnel (AUC 0.62) had the highest prediction performance for survival. Among the 265 variables considered for feature selection, we identified the 50 highest impact predictors that preserved predictive performance compared to the full model (AUC 0.98 vs. 0.99, sensitivity 93.7% vs, 96.8%, and specificity 96.1% vs. 94.6%). The 50 predictors included 25 ED pediatric readiness variables, 18 patient variables, and 7 hospital variables (Table 3). Patient variables were more predictive of survival than ED and hospital variables. Comparison of models that included the 25 ED pediatric readiness and 7 hospital variables versus models in which these two groups of predictors were separate showed that the 25 ED readiness variables had similar prediction to the combined model (AUC 0.62 versus 0.62). There were nine ED pediatric readiness variables and 4 hospital variables associated with statistically significant improved survival (Table 4).

We estimated the impact of coupling the nine components of ED pediatric readiness associated with improved survival, as compared to the effect of each single component (Figure 1). Combining two components had a synergistic effect on survival. For example, when trauma centers had a policy on mental health care (+8.8% change in survival) *and* a policy for patient assessment and reassessment (+7.5% change), there was a combined 21.5% increase in survival. Similarly, when a policy for reduced-dose radiation imaging (+7.0% change) was present with physician competency evaluations (+4.9% change), there was a 24.0% increase in survival. Components of ED pediatric readiness with smaller individual impact showed minimal additional increases in survival when combined.

In Figure 2, we estimated the impact of combining more than two high impact components of ED pediatric readiness. Combining three, four, or five high impact components of ED pediatric readiness showed greater synergy for improving survival than with two factors. Among trauma centers with policies for mental health care and patient assessment and reassessment (+21.5% combined change in survival), the addition of infant non-rebreather masks (+7.2% individual change), a policy on reduced-dose radiation imaging (+7.0% individual change), and physician competency evaluations (+4.9% individual change) resulted in 268.0% cumulative improvement in survival. Combining ED readiness components with incrementally lower impact had smaller combined improvements in survival. Figure 2 illustrates the importance of selecting specific components of ED pediatric readiness to combine. Table 5 quantifies the estimated improvement in survival when using different combinations of ED pediatric readiness components.

Finally, we estimated the survival benefit of the five highest impact ED readiness components by injury severity (eTable 2). Compared to the full sample (all injury severities), the effect of these ED pediatric readiness components was greatest among children with minor and moderate injuries (ISS 0–15), representing 86.3% of children in the sample.

DISCUSSION

We show that specific components of ED pediatric readiness had the highest estimated impact on survival among children treated in US trauma centers. These components included specific policies (mental health care, patient assessment/reassessment, and reduced-dose radiation imaging), use of a validated pediatric triage tool, availability of certain respiratory equipment, physician competencies, recording weight in kilograms, and certain training courses for nurses. These findings may provide a roadmap for US trauma centers seeking to raise their level of ED pediatric readiness in a prioritized manner. When implemented together, these components showed substantial synergy for improving pediatric survival.

The highest impact components of ED pediatric readiness came primarily from the domains of policies/procedures and personnel, which target diverse and critical aspects of pediatric trauma care. Our results suggest that an implementation strategy that includes specific components of ED readiness may provide synergistic impact. That is, the presence of a single policy, piece of equipment, or provider training may be limited. To recognize their full potential for improving survival, these factors should be implemented together. The presence of a PECC alone was not a major predictor of survival, which contrasts with a previous study showing better-than-expected survival when physician and nurse PECCs were present in trauma centers.[11] However, PECCs are integral to the development and implementation of essentially all aspects of ED pediatric readiness, including policies, procedures, quality improvement, patient safety initiatives, appropriate equipment, and provider training. When evaluated in direct comparison to all other individual components of ED pediatric readiness, the direct impact of PECCs on survival was attenuated. This finding reflects the unique role of PECCs in implementing and facilitating the many components of ED pediatric readiness, thereby influencing survival through these components. Such an explanation may reconcile findings from a previous study showing the survival benefit of PECCs[11] and our findings. When we tested the highest impact components of ED readiness among children with differing levels of injury severity, the largest influence was among children with minor and moderate injuries, representing a group where modifiable aspects of emergency care may have a larger relative impact on survival compared to patient-level factors.

The mechanisms by which these components of ED pediatric readiness exert their influence on survival is likely multifactorial. While the biologic plausibility for how certain policies (e.g., mental health care and reduced-dose radiation imaging) improve short-term survival may seem unclear, there are several potential explanations. First, the components of ED readiness likely function through complex mechanisms to lower mortality, rather than having a direct effect. Implementing different aspects of ED readiness contributes to a culture of increased provider awareness, familiarity, skills, and processes of care focused on the unique needs of children. This collective shift can change the quality of care over time, which may ultimately lower mortality. The development of policies can also change systems of care and the way providers practice, with effects beyond those of the immediate policy. For example, mental health care and reduced-dose radiation imaging policies are typically developed through partnerships with non-ED service lines (e.g., psychiatry, social work, radiology, hospital administration, surgery, and inpatient services), which creates a collective awareness about caring for children and the potential for spillover effects.

Similarly, recording weight in kilograms seems like a small factor related to accurate drug dosing for children, but this aspect of care impacts pediatric resuscitation (e.g., fluid dosing, blood dosing and administration, sedation), increases the precision of care for children, and involves multiple other services (e.g., inpatient pharmacy, informatics, general pediatrics, trauma). The concept that specific components of ED readiness affect survival through a collective change in the culture and awareness of caring for children is further supported by our findings of optimal survival when the components are present together. That is, there appears to be a synergistic effect of implementing multiple aspects of ED pediatric readiness that is greater than the sum of the individual parts. It is also possible that these components of ED readiness are proxy measures for other aspects of care that work to improve survival. For the mental health policy, it is possible that attention to the mental health of children in the ED addresses a previously under-recognized aspect for optimizing trauma outcomes. Suicide is the second leading cause of death among adolescents[3] and a previous study showed that self-harm was one of the most common causes of death among children discharged from trauma centers.[7] Furthermore, among injured children who die after arriving to a trauma center, death occurs early (median 3.1 hours from arrival),[7] placing increased focus on care in the ED. The attention paid to refining and adapting care for children likely exerts its influences through a variety of mechanisms.

Our study has several limitations. The study was limited to trauma centers participating in NTDB and caring for a minimum number of children, which likely reflects higher performing hospitals. In addition, certain aspects of ED pediatric readiness and hospitals may have served as surrogate measures for other aspects of care associated with survival. We excluded children classified as dead on arrival, but recognize that there is variability in classifying such patients across trauma centers and the potential for misclassification.[47] In addition, older adolescents are often cared for on adult trauma services, so the inclusion of children under 18 years may have represented a mix of adult and pediatric inpatient trauma services.

We used ML methods to identify components of ED pediatric readiness with the greatest impact on survival in trauma centers. These methods represent a constellation of many techniques and model types that offer large flexibility and versatility without many of the restrictions of traditional statistical models. However, data quality, quantity, consistency, and missingness can affect the results. In addition, the results can be influenced by the model learning and prediction methods. The analyses were done by analysts experienced in ML methods who used standardized routines for model selection, balancing the dataset (i.e., deaths vs. survivors), testing for and minimizing bias, feature selection (narrowing the number of predictor variables without sacrificing prediction accuracy), testing the significance of predictors, and estimating the impact of each component on pediatric survival. The analysts did not have preconceived ideas about the potential importance of different variables, which reduced another potential source of bias. Our study team was interdisciplinary and included multiple types of clinicians and methodologists, which added another level of rigor, quality checks, and interpretation of the results. While we employed multiple strategies to reduce bias and ensure validity of the results, it is possible that the results could be different using a different approach to the analysis.

Finally, we used the 2013 NPRP assessment of ED pediatric readiness, as these were the most recent data available at the time of this analysis. The NPRP assessment was repeated in 2021, yet these data are not yet available for analysis, nor are the 2021 NTDB patient-level data. It is possible that the readiness of individual EDs and the importance of certain readiness factors have changed over time. While we believe that our findings should be confirmed in future studies using more contemporary data, ED pediatric readiness is part of current trauma center verification processes,[8] with active assessment and implementation ongoing in US trauma centers. Combined with the results from another recent study,[11] we believe these findings provide data-driven, prioritized guidance to trauma centers seeking to raise their level of ED pediatric readiness.

In summary, we show that certain components of ED pediatric readiness were the strongest predictors of improved pediatric survival in US trauma centers. These components included specific policies, certain respiratory equipment, physician competencies, safety measures, and resuscitation training. The combination of ED readiness components had a synergistic impact on survival. These findings provide a roadmap for implementing ED pediatric readiness in US trauma centers.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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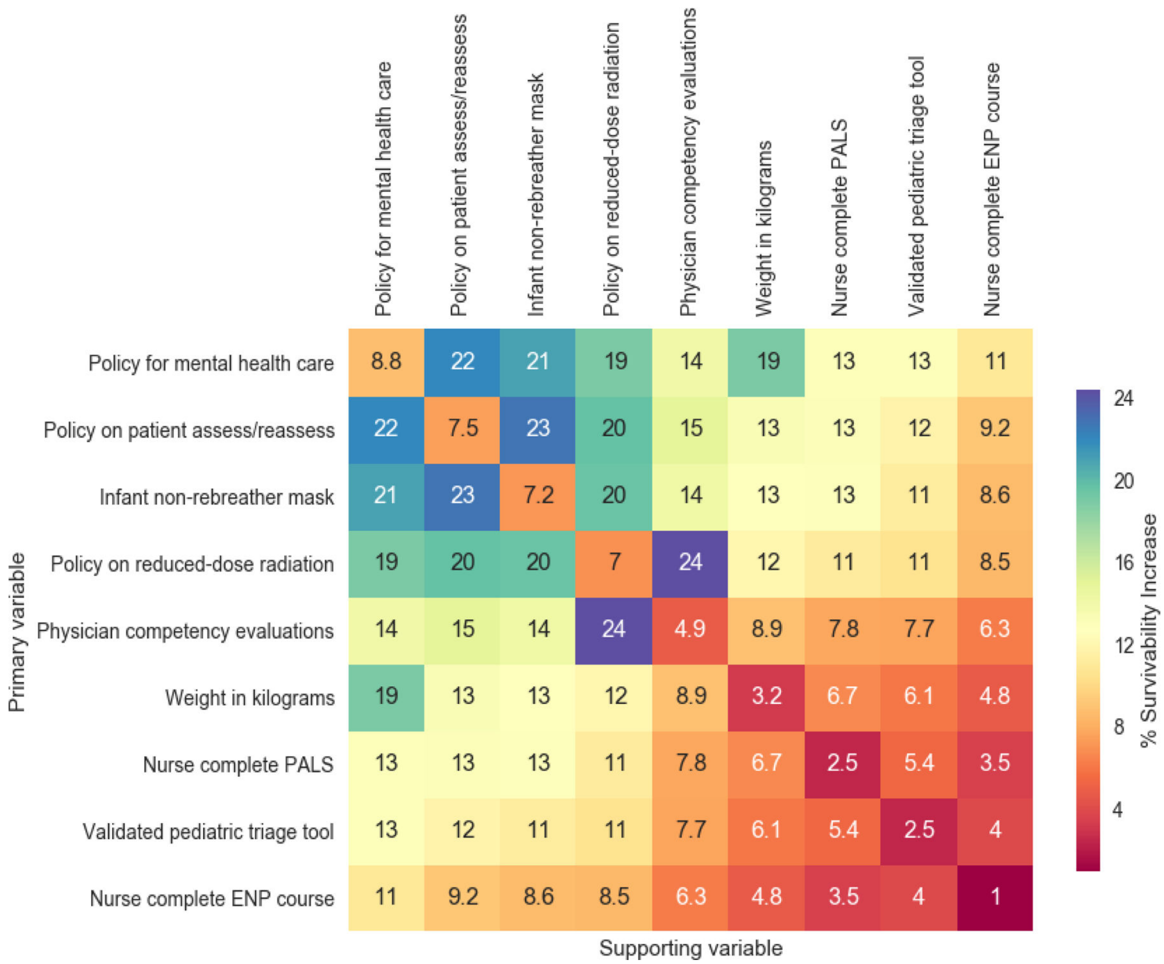

Figure 1.

Percent increase in survival when emergency department pediatric readiness components were implemented together versus separate (n = 274,756).

*Results are from a model of the 50 highest impact predictor variables (patient, ED pediatric readiness, and hospital) for in-hospital survival. The 9 predictors included in the figure are the components of ED pediatric readiness that predicted increased survival with statistical significance, in order of decreasing impact on survival.

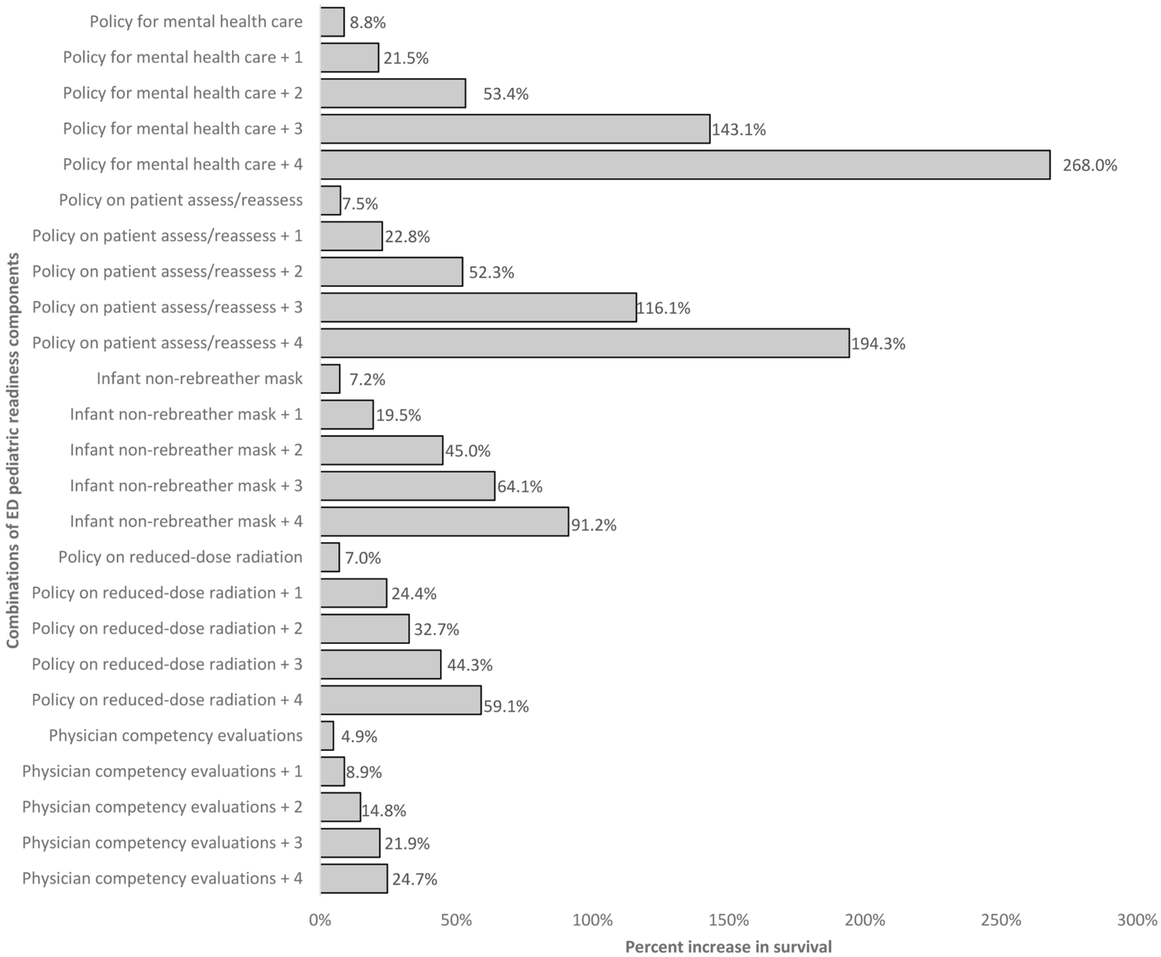

Figure 2.

Bundling each of the five high impact components of emergency department pediatric readiness with other supporting components to optimize survival (n = 274,756).

*Results are from a model of the 50 highest impact predictor variables (patient, ED pediatric readiness, and hospital) for in-hospital survival. The figure shows the predicted percent increase in survival for each of the 5 highest impact components of ED pediatric readiness (in order of decreasing impact on survival) and the additional percent increase in survival when the four next most important ED readiness components were added.

Table 1.

Emergency department and hospital characteristics among 458 trauma centers.

Structural and operational characteristics:	
Trauma center level:	
I	163 (36%)
II	195 (43%)
III/IV/IV	100 (22%)
Trauma center type:	
Adult	326 (71%)
Mixed	88 (19%)
Pediatric	44 (10%)
Pediatric ward	350 (76%)
Pediatric ICU	185 (40%)
Neonatal ICU	320 (70%)
Adult ward that admits children	199 (43%)
Adult ICU that admits children	220 (48%)
Total bed size – median (IQR)	349 (IQR 235–512)
Total pediatric beds – median (IQR)	12 (IQR 0–25)
ED type:	
Mixed adults & children	312 (68%)
Separate pediatric ED (in general hospital)	84 (18%)
Children's hospital ED	43 (9%)
Other	19 (4%)
ACGME residency programs	117 (26%)
Medical school affiliation	154 (34%)
Hospital ownership and accreditation:	
Hospital owned by physicians or physician group	9 (2%)
Accreditation – Centers for Medicare and Medicaid Services	429 (94%)
Accreditation – DNV	36 (8%)
Accreditation – The Joint Commission	421 (92%)
Accreditation – Other	83 (18%)
Volume (all patient types):	
Annual pediatric ED volume – median (IQR)	10,153 (IQR 5,290–18,001)
Annual total ED volume – median (IQR)	59,728 (IQR 41,614–78,000)
Annual total admissions – median (IQR)	16,931 (IQR 11,350–24,907)
Select characteristics of ED pediatric readiness:	
wPRS median (IQR)	84.7 (69.1–95.1)
Physician - Pediatric Emergency Care Coordinator	306 (67%)
Nurse - Pediatric Emergency Care Coordinator	324 (70%)
Policy – child assessment & reassessment	387 (85%)

Structural and operational characteristics:	
Policy – reduced-dose radiation imaging	307 (67%)
Policy – triage of ill and injured children	357 (78%)
Policy – use of validated pediatric triage tool	241 (53%)
Policy – mental health and social issues	269 (59%)
QI process	308 (67%)
Safety – record all weights in kilograms	299 (65%)
Safety – notification of abnormal vitals	366 (80%)
Written inter-facility transfer guidelines	375 (82%)
Written inter-facility transfer agreements with other hospitals	320 (70%)

* wPRS = weighted Pediatric Readiness Score, range 0–100.

Table 2.

Prediction metrics for the six domains of ED pediatric readiness using data from 458 trauma centers (n = 274,756 children).

Emergency department pediatric readiness domain	AUC	Sensitivity	Specificity
Administration and Coordination: Nurse PECC*, Physician PECC*, total domain score (raw, weighted†)	0.539	0.252	0.800
Policies, procedures, and protocols: Written inter-facility guidelines and agreements, disaster plan for children, promotion of family-centered care, mental health care, transfers, triage processes, child assessment and reassessment, handling pediatric deaths, reduced-dose radiation imaging, immunizations, child maltreatment, total domain score (raw, weighted†)	0.613	0.733	0.457
Equipment and supplies: Difficult airway kit for children, pediatric sizes for airway and ventilation equipment, medication chart tape, ED staff training for supply locations, pediatric sizes for monitoring, catheters, and defibrillator, total domain score (raw, weighted†)	0.563	0.797	0.295
Personnel: All physicians board certified in EM or PEM,* physician training, mid-level providers that care for children, provider pediatric competency evaluations, provider course requirements, continuing education requirements, nursing pediatric competency evaluations, nursing course requirements, nursing continuing education requirements, total domain score (raw, weighted†)	0.623	0.653	0.525
Pediatric patient safety: Pediatric blood pressure monitoring, pre-calculated drug dosing, 24/7 access to interpreter services, weights in kilograms, pediatric pulse oximetry monitoring, vitals recorded on all children, written procedure for notifying physicians of abnormal vitals, total domain score (raw, weighted†)	0.547	0.314	0.753
Quality improvement: Pediatric patient care review process, collection and analysis of pediatric emergency care data, use of quality indicators for children, re-evaluation of performance using outcomes, plan for improvement, 100% of QI measures, total domain score (raw, weighted†)	0.573	0.728	0.391

*PECC = pediatric emergency care coordination; BVM = bag-valve mask; EM = emergency medicine; PEM = pediatric emergency medicine;

†Weighted domain scores included only those variables selected for inclusion in the “weighted Pediatric Readiness Score” (wPRS) metric and their respective weights.

Table 3.

Prediction metrics for the 50-variable model and models restricted to patient, hospital, and ED pediatric readiness factors (n = 274,756).

Dataset	AUC	Sensitivity	Specificity
50 feature overall model	0.979	0.937	0.961
Patient features (18): • Age • Physiology (systolic blood pressure, respiratory rate, abnormal respiratory rate, Glasgow Coma Scale score) • Arrival by ambulance, prehospital cardiac arrest • Mechanism of injury • Blood transfusion, assisted ventilation or intubation • Non-orthopedic surgery, orthopedic surgery • Critical care procedures • Transfer to other hospital • Injury Severity Score • AIS scores * (head and extremity) • Length of hospital stay	0.943	0.961	0.791
ED pediatric readiness features (25): • Physician PECC * position description • Policies (mental health care, child assessment and reassessment, reduced-dose radiation imaging, child maltreatment, pediatric triage, notifying physicians of abnormal vitals) • Use of a validated pediatric triage tool • Disaster plan for children • Difficult airway kit for children • Infant non-rebreather mask • Umbilical vein catheters • Mid-level providers that care for children • Competency evaluations (physicians, nurses, mid-level providers) • Nursing course requirements (ENPC, PALS, TNCC) * • Nursing continuing education in pediatric emergencies • Nursing maintenance of specialty certification • Physician training – other • Pre-calculated drug dosing • Children weighed in kilograms, recorded in kilograms	0.620	0.661	0.521
Hospital features (7): • Full-time medical and dental residents • Total patients per year • Hospital ambulance services • Neonatal intensive care in the health system • Open physician-hospital organization • Adult inpatient unit that admits children • Neonatal ICU that admits children	0.584	0.544	0.555
ED pediatric readiness and *hospital features* (32)	0.622	0.665	0.504

* AIS = Abbreviated Injury Scale; PECC = pediatric emergency care coordination; ENPC = emergency nursing pediatric course; PALS = pediatric advanced life support; TNCC = trauma nursing core course.

Table 4.

Emergency department pediatric readiness components and hospital factors associated with increased survival (n = 274,756).

ED pediatric readiness components	Impact on survival (% change)	Hospital components	Estimated impact on survival (% change)
Policy for mental health care	8.76 +/− 0.62	Open physician-hospital organization†	12.78 +/− 0.69
Policy for patient assessment and reassessment	7.54 +/− 1.11	Neonatal ICU in-hospital	10.26 +/− 1.31
Infant non-rebreather mask	7.18 +/− 1.29	Neonatal ICU in the health system	9.65 +/− 0.60
Policy for reduced-dose radiation imaging by age or weight	7.02 +/− 0.80	Adult inpatient unit that admits children	1.39 +/− 0.74
Physician competency evaluations required	4.87 +/− 0.84		
Weight recorded only in kilograms	3.20 +/− 0.81		
Nurses required to complete Pediatric Advanced Life Support course	2.48 +/− 1.13		
Policy for use of a validated pediatric triage tool	2.45 +/− 0.78		
Nurses required to complete Emergency Nurse Pediatric course	0.97 +/− 0.84		

*Results are from a model of the 50 highest impact predictor variables (patient, ED pediatric readiness, and hospital) for in-hospital survival.

†From the American Hospital Association survey, an open physician-hospital organization is a hospital that “maintains a joint venture between the hospital and all members of the medical staff who wish to participate. The open physician-hospital organization can act as a unified agent in managed care contracting, own a managed care plan, own and operate ambulatory care centers or ancillary services projects, or provide administrative services to physician members.”[23]

Table 5.

Examples of bundles of emergency department pediatric readiness components and the estimated change in predicted survival (n = 274,756).

Example	Primary component associated with increased survival	Supportive components to further optimize survival	Estimated % change in survivability
5 components	Policy for mental health care	• Policy on patient assessment and reassessment • Infant non-rebreather mask • Reduced-dose radiation imaging by age or weight • Physician competency evaluations required	267.95 +/− 36.67
4 components	Policy for mental health care	• Policy on patient assessment and reassessment • Infant non-rebreather mask • Reduced-dose radiation imaging by age or weight	143.05 +/− 18.84
3 components	Infant non-rebreather mask	• Reduced-dose radiation imaging by age or weight • Physician competency evaluations required	44.96 +/− 2.80
2 components	Physician competency evaluations	• Reduced-dose radiation imaging by age or weight	24.36 +/− 0.33

[*] Results are from a model of the 50 highest impact predictor variables (patient, ED pediatric readiness, and hospital) for in-hospital survival. The four examples illustrate how various combinations of components of ED pediatric readiness may affect the percent increase in pediatric survival.