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Predicting Resource Utilization in Burn Treatment

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Introduction

Disasters have a multitude of causes, ranging from environmental events (earthquakes, volcanoes, forest fires) to man-made incidents (bombs, arson, explosions, gas leaks). As many as 20–30% of injuries resulting from a mass casualty event involve burns. (1) Burn care is currently concentrated in a relatively small number of highly specialized centers due to the need for high intensity care. As a result, even a “small” burn disaster consisting of 10–20 patients can overwhelm local medical systems. As such, planning for burn incidents is a necessary aspect of disaster preparedness for all hospitals. Appropriate planning requires knowledge of injury treatment and an understanding of resource requirements after burn injury.

Burn injury treatment is distinguished from other traumatic injuries by its intensity, extent, and duration. Unlike other forms of trauma, burn patients require prolonged hospitalization (approximately 1 day per percent burn) and additional material and personnel support to address both the wounds and the metabolic derangements that accompany burn injury. The supplies needed to care for a burn wound have been the focus of most disaster planning, but burn treatment involves multiple other resources, such as ventilator support, blood products, antimicrobials, and surgical interventions. There is a vast array of literature on initial burn management, but less is known about the resource utilization for the entire hospitalization. Appropriate disaster preparedness planning, as well as military planning, must account for both initial and ongoing resource requirements after the event. Burn centers are likely to be unavailable for months after an incident; hence, preparations need to be made for prolonged hospital care of the burn patient in other locations.

The American Burn Association (ABA) National Burn Repository (NBR), consisting of data from multiple burn centers, contains data on resource utilization after burn injury and may represent the best source of information for preparedness planning. The purpose of this paper is to develop and test predictive models for resource utilization after burn injury to better inform disaster preparedness and military planning efforts.

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Methods

The NBR contains outcomes, patient, and injury characteristics for patients admitted to burn centers for treatment of burns and related medical conditions. We obtained the American Burn Association's 2009 release of the NBR containing of 286,293 admission records to obtain data related to current treatment and outcomes for burn care. To focus on recent burn care and outcomes, we restricted our analysis to admissions in 2000 or later (210,683). We dropped records missing information on survival to discharge (12,226), age (5,441), burn size (42,545), inhalation injury (12,861), or length of hospital stay (4,471). We also removed 6,530 records with unreliable information (e.g., total burn surface area greater than 100, records from facilities with questionable ages or mortality rates), 23,084 records associated with readmissions, 3,690 records of patients with non-burn injuries, and 3,218 records identified as probable duplicates. (2) This screening left 95,579 records of initial hospital visits (admissions and outpatient visits). From this data set, we selected records with valid entries for number of operative procedures (47,792), total operating room visits (48,068), ICU days (77,511), and ventilator days (78,652) in analyzing each of these resource use variables.

Statistical Analysis

In order to develop and evaluate predictive models, for each resource use variable, we split the data into two approximately equally-sized sets by randomly dividing records from each facility in half. One half, designated as the training set, was used to evaluate the effect of predictors on each response variable and develop a predictive model. Model performance then was assessed by applying it to the other half of the data designated as the test set. The four outcomes modeled were number of operative procedures, number of operating room visits, duration of mechanical ventilation, and duration of intensive care unit (ICU) care.

The majority of burn patients have relatively minor burns that do not require any operative procedures, intensive care or artificial ventilation. As a result, the four resource use variables contained a large proportion of zeros, indicative of no resource use (Table 1). Further, a small number of patients had substantial resource use (e.g., a large number of operations or long ICU stay), resulting in highly right-skewed distributions. To capture these unique data features, we used a hurdle model. (3) The hurdle model consists of two parts – a binary component and a count component. The binary component models the probability of a zero value, i.e., the probability of the patient not using a resource. The count component models the level of resource use given that the patient has any resource use.

The probability density function for a hurdle model is

$$f(y; x, z, \beta, \gamma) = \begin{cases} f_{zero}(0; z, \gamma) & \text{if } y=0, \\ (1 - f_{zero}(0; z, \gamma)) \cdot f_{count}(y; x, \beta) / (1 - f_{count}(0; x, \beta)) & \text{if } y > 0 \end{cases}$$

where $f_{count}(y; x, \beta)$, the count component, is a distribution for count data left truncated at 1 and $f_{zero}(0; x, \gamma)$ is the binary component. We used a negative binomial distribution for the count component ($f_{count}(y; x, \beta)$) to accommodate overdispersion and for the binary part (f_{zero}

$(0; x, \gamma)$ a binomial distribution with a logistic link (4). Note that $1 - f_{zero}(0; x, \gamma)$ is the probability of a patient requiring any resource use. Model parameters for the effects of the predictors are designated as γ for the binary component and β for the count component.

With a hurdle model, the mean resource use for a patient with the covariates specified by z_i and x_i is given by

$$\log(\mu_i) = x_i^T \beta - \log(1 - f_{count}(y; x_i, \beta)) + \log(1 - f_{zero}(0; z_i, \gamma)).$$

The mean response encompasses both the probability of any resource use ($1 - f_{zero}(0; z, \gamma)$) and the level of resource use given that there is some resource use,

$x_i^T \beta - \log(1 - f_{count}(0; x_i, \beta))$. As such it represents the average level of resource use that would be expected for patients with the given covariates. The mean resource use *given* that the patient has some resource use, is the conditional mean and is given by

$$\log(\mu_i | y_i > 0) = x_i^T \beta - \log(1 - f_{count}(0; x_i, \beta)).$$

A generalized estimating equation approach was used to estimate the effect of predictors on each response variable. Models were fit using maximum likelihood estimation. Then, to account for clustering of patients by facility, robust standard errors were calculated and used to determine significance, defined as $p\text{-value} < 0.05$. Models were fit in R version 3.0.1 (5) (R Core Team 2013) via the package `pscl` (6,7). Robust standard errors were calculated using the `clrobustse` function available at <http://staff.washington.edu/dhuh/index.cgi/code.code>.

Using the training set, we evaluated the effect of TBSA, age, the presence of inhalation injury (Inhale), the proportion of the burn that was full thickness (PropFull) and developed predictive models for each resource use variable. TBSA was converted to a categorical variable of 10% increments. Age also was categorized as [0, 2], (2, 13], [13, 18], [18, 30], and then in 10-year increments to 90. For each resource use variable, we included TBSA, age, Inhale, and PropFull as predictors in both the binary and count components of the model.

Model fit was assessed by comparing the estimated number of patients receiving each number of operative procedures, operating room visits, or stay durations (e.g., the number of patients with two operating room visits or the number of patients with and ICU stay of three days) to observed values. We used a bootstrap procedure (8) to estimate confidence intervals. In conducting the bootstrap, facilities were resampled in order to preserve the correlation structure among patients from the same facility (9). Model parameters were estimated using each bootstrap sample and the bootstrapped parameter estimates used to predict responses for the entire training set. We used 1,000 bootstrap samples to estimate 95% confidence intervals. This procedure was also used to develop confidence intervals for estimates for the test set.

Results

The training and test sets had similar patient characteristics (Table 1). For all resource use variables (operating room visits, number of operations, mechanical ventilation use, ICU use), the majority of the patients did not use any of the resources (Table 1). Mortality was low, 3–4%. The average TBSA was about 10% and the average patient age about 30 years. Interestingly, a greater percentage of patients in the data sets used to model ICU days and ventilator days had inhalation injury than in the data sets used to analyze operative procedures and total OR visits. To analyze operative procedures and total OR visits, data from 52 and 53 facilities was available, respectively. For ICU and ventilator days, 79 and 77 facilities were represented, respectively.

Training Set

Number of Operative Procedures and Total OR Visits—Both the probability of having any operative procedures and the total number of operative procedures were significantly related to TBSA, age, and PropFull. The presence of inhalation injury was only a significant factor for the number of operations and not the probability of having an operation (Table 2). Modeling results for total OR visits were similar and the same predictors were significant for total OR visits as for the number of operative procedures.

Increasing TBSA initially increased both the probability of a patient requiring an operation and the number of procedures received, but both declined at high TBSA (Figure 1). With respect to TBSA, patients with TBSA of 40–50% had the highest probability of requiring at least one operation and at least one OR visit. As TBSA increased further, these probabilities declined dramatically. The estimated number of operations showed a similar pattern but peaked at (70–80%) for the number of operations and 60–70% for the number of OR visits (Figure 2). Both the probability of any operation and the expected number of operations significantly increased with PropFull (Table 2). Similar relations were observed for total OR visits.

Age did not affect the probability of OR visits or any operative procedures as strongly as TBSA, but like TBSA there were curvilinear relationships between patient age and the probability of having an operative procedure or an OR visit. Very old (70+ years old) and very young (0–2 years old) patients were less likely to have an operation than other age groups. However, the expected number of operations and OR visits tended to increase with increasing age. Inhalation injury only significantly impacted the number of operative procedures and the number of OR visits, increasing these slightly relative to patients without inhalation injury, but did not have a significant effect on the probability of having at least one operation or OR visit (Figure 2).

The model for the number of OR visits fit the data well and better than the model for the number of operative procedures (Figure 3). The 95% confidence limits for the number of patients experiencing each number of OR visits covered the true value in most cases (Figure 3). In contrast, the model for the number of operative procedures substantially over-estimated the number of patients receiving one operation and under-estimated the number receiving two operations (Figure 3). Interestingly, the observed number of patients receiving

only one operation ($n = 736$) was much smaller than the number receiving two operative procedures ($n = 4,562$) followed by continuing declines in the number of patients receiving larger numbers of operations. This aspect of the data likely resulted in a poor fit of the negative binomial distribution to the counts. In addition to the discrepancy in the number of patients receiving one and two operations, the model tended to over-estimate the number of patients receiving 5 to 9 operations.

ICU Days—Burn size significantly affected the probability of a patient being admitted to the ICU and the duration of the ICU stay (Table 2). The probability of a patient requiring ICU care increased with TBSA up to a burn size of 70% and then leveled off (Figure 4). Unlike the number of operative procedures and total OR visits, the probability of any ICU care did not decline substantially at very large burn sizes. Length of stay in the ICU was highest for patients with intermediate-sized burns (TBSA = 40–80%) (Figure 5). The proportion of full thickness burn only significantly affected the length of ICU stay and not the probability of requiring ICU care (Table 2).

Increasing age generally increased the number of ICU days and the probability of any ICU stay (Figures 4 & 5). However, children aged 13–18 years had the shortest ICU stay and lowest probability of any ICU stay (Table 2). Older patients (> 40 years old) had significantly longer ICU stays and higher probabilities of requiring ICU care than younger patients (Table 2). Inhalation injury significantly affected both the probability of ICU care and its duration (Figures 4 & 5; Table 2). The odds of requiring ICU care were 5.65 (95% C.I. [3.73, 8.54]) times greater for a patient with inhalation injury than a patient without inhalation injury. The model fit the observed data reasonably well although there was a tendency for the model to overestimate the number patients with ICU stays of 3 to 7 days (Figure 6).

Ventilator Days—The presence of an inhalation injury strongly and significantly affected the probability that a patient would require mechanical ventilation (Table 2; Figure 4). The odds of requiring mechanical ventilation was nearly 30 times (Odds ratio = 29.9 [95% C.I. (20.7, 43.2)]) greater for a patient with inhalation injury than a patient without inhalation injury. The total length of time on a ventilator also was greater for patients with inhalation injury (Figure 5).

As with the other resource use variables, the probability of being on a ventilator was significantly related to burn size (Table 2). Patients with burn sizes of 50% or more carried the highest probability of requiring mechanical ventilation (Figure 4). Like ICU days, the probability of mechanical ventilation declined modestly at the highest burn sizes (Figure 4). Duration on a ventilator was greatest for patients with intermediate burns sizes (40 to 70%) with shorter durations for patients with smaller or larger burns (Table 2; Figure 5).

Increasing age significantly increased the probability of mechanical ventilation (Figure 5) but was not a strong predictor of the length of time on a ventilator; only three age categories were significant (Table 2). The proportion of full thickness burn increased both the probability of a patient requiring a ventilator and the length of time on a ventilator (Table 2). The model adequately predicted the number of patients requiring none or one day on a

ventilator but tended to overestimate the number of patients requiring 2 to 9 ventilator days (Figure 6). For longer ventilator day durations, the model tended to underestimate the number of patients (not shown).

Application to Test Set—We then applied the models developed with the training set to a test set. When applied to the test set, all four models performed similarly to their performance with the training set. For number of operative procedures, the predicted number of patients not having any operative procedures was very close to the observed value but like the training set results, the number receiving one and two operations was under and over-estimated respectively (Figure 3). For larger numbers of operations, the model tended to overestimate. Predictions of the total OR Visits were better and in most cases, the 95% confidence limits encompassed the observed value. For the number of ICU days and number of days on a ventilator, the models tended to overestimate the number of days patients would require for short durations (Figure 6) but then to overestimate longer durations (not shown).

Discussion

We used the NBR, one of the largest national databases for burn injury, to investigate factors impacting resource and to develop predictive models for treating burn patients. We found burn characteristics (size and severity), inhalation injury and patient age to be significant predictors of the four resource use variables considered – number of operative procedures, total operating room visits, length of stay in ICU and length of time on a ventilator. Age, inhalation injury, burn size, and burn severity have been associated with increased mortality in many studies. (10–15) However, studies of resource utilization after burn injury have been limited to length of stay and are primarily based on single center data or on hospital charges. (16, 17)

TBSA had a strong and complex effect on all of the resource use variables. For the number of operative procedures and total OR visits, both the probability that a patient would require any resource use and the level of use increased with TBSA up to a point but then declined at very high TBSA levels. The decline at high TBSA levels reflects the differential resource by survival status. Most patients with large burns who succumb to their injuries do so within a short period of time. In fact, the NBR data show that of the patients that died, 25% did so within one day of hospital admission and 50% succumbed within 1 week. Few operations are performed on patients that are severely injured and that die within a short period of time of hospital admission. Hence the probability of any operation and the number of operative procedures performed declines at high TBSA.

The number of days in the ICU and length of time on a ventilator responded similarly to changes in TBSA. However, unlike the relationship between TBSA and the number of operative procedures, the probability of any ICU care and the probability of mechanical ventilation did not decline at high TBSA levels but rather remained at or near 100%. This different dynamic reflects that while severely injured patients are not likely to be subjected to operations, they nonetheless would receive appropriate critical care likely including mechanical ventilation. The level of resource use of patients with massive burns (>80%) is

lower than for smaller major burns (50–80%) because death shortly after admission decreases duration of ICU and ventilator needs.

The most resource intensive group is aged 50–70 years with moderate-sized major burns (TBSA = 50–80%) and inhalation injury. Patients with these characteristics have a moderate probability of surviving their injuries, but due to injury severity and patient age prolonged intensive care is required. In the event of a mass casualty situation, resource utilization by this group of patients may become problematic. In recent military conflicts, non-combatants with burn sizes >50% were placed into the expectant care category and treated with analgesics due to the high mortality and resource needs. (18) Comorbidities common in this age group can also complicate and prolong recovery. Patients with more severe burns (TBSA > 80%) have a high probability of dying which reduces their resource use while those with less severe burns (TBSA < 50%) do not require as intensive or prolonged care. Similarly for age, older patients are more likely to succumb to the injury while younger patients likely recover faster.

Although the dynamics of the models qualitatively reflect the effects of the predictors on each resource use variable, the model estimates deviated from observed values in both the training and test sets in the number of operative procedures. This is likely due to treatment variability between centers or in differences in the how individual hospitals define an operative procedure. Notably, few patients had only one operative procedure while much larger numbers had two operations which resulted in the poor fit of the truncated negative binomial distribution. Ventilator days tended to overestimate short-term ventilator need (e.g., < 10 days) but underestimated prolonged mechanical ventilation. For all variables though, the models did well at predicting the number of patients that would require any resources.

The models can be used to estimate three parameters of interest – 1) the probability of any resource use, 2) the unconditional expected level of resource use and 3) the conditional expected level of resource use. The unconditional expected level of resource use represents the overall level of resource use taking into account both the probability of *any* use and the level of use given some. The conditional expectation is the level of use *given* the patient has some resource use. In Appendix A, we show how to estimate each of these parameters.

Mortality predictors and resource utilization predictors share several factors, including the effects of age, inhalation injury, and burn size. However, the factors predicting resource utilization demonstrate different patterns in several key areas. For example, an increase in burn size increases mortality. However, in estimating length of stay, ventilator support duration, or number of operations, the extent of burn has variable effects. Resource utilization increases until the burn reaches a nonsurvivable level (>80% TBSA); at this point resource utilization actually decreases due to patient death. As such burn size has a “ceiling” effect on resource use. A key question in a mass casualty scenario is how to determine how many and which patients in high resource use categories will be resuscitated. Triage criteria have been developed but may require modification depending on the extent of the disaster. (19)

In fitting these models, we used all patients regardless of survival status. Although resource use tended to decline for severely injured patients, for the few patients that survive severe burns, their resource use is very high. Because we included all patients, predictions from these models are best suited for use at the hospital level in planning overall resource use based on the hospital's patient population. The models could also be helpful for disaster planning because they can be used to predict resource requirements taking into account both the probability of any resource use which is influenced by survival and the level of use if any is needed.

Predicting resource needs after burn injury has implications for disaster preparedness, military planning, and day-to-day operations of burn centers. Recognition of how factors variably effect mortality prediction vs. resource utilization will be essential in disaster planning and hospital operations.

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Appendix A

Hospital administrators and clinicians may want to use these models to estimate three different parameters for patients with given characteristics (age, TBSA, proportion of burn that is full thickness, and presence of inhalation injury). These parameters are 1) the probability of any resource use, 2) the estimated mean level of resource and 3) the estimated mean level of resource use given that the patient has some resource use. The following details how to calculate each of these outcomes.

Probability of Any Resource Use

The probability of any resource use is modeled by the binary component of the models. A binomial distribution with a logistic link was used for this component. Let π_i be the probability that a patients with covariates z_i does not use any of the resource of interest. Then, π_i can be estimated from the equation

$$\log \frac{\hat{\pi}_i}{1 - \hat{\pi}_i} = z_i^T \hat{\gamma}$$

where $\hat{\pi}_i$ is the estimated probability of no resource use for a patient with covariates z_i and $\hat{\gamma}$ are the appropriate estimated coefficients from Table 2. The probability of any resource use then is given by

$$1 - \hat{\pi}_i = 1 - \frac{e^{z_i^T \hat{\gamma}}}{1 + e^{z_i^T \hat{\gamma}}}$$

For age and TBSA, z_i are group indicator variables rather than the actual observed values, inhalation injury is 1 if present and PropFull is the proportion of the burn that was full thickness. For a patient that is 20 years old, with a 50% burn of which 10% is full thickness (i.e., total full thickness burn is 5%) and no inhalation injury,

$z_i^T \hat{\gamma} = -1.533 + 0.902 + 0.583 + 0.1 \times 1.815$ using the coefficients from Table 2.

Mean Level of Resource Use

The estimated log scale mean response is given by

$$\log(\mu_i) = x_i^T \beta - \log(1 - f_{count}(0; x_i, \beta)) + \log(1 - f_{zero}(0; z_i, \gamma))$$

The mean response is the estimated average resource use of a patient with the covariates specified by z_i and x_i . It encompasses both the probability of any resource use ($1 - f_{zero}(0; z_i, \gamma)$) and the level of resource use given that there is some resource use

$x_i^T \beta - \log(1 - f_{count}(0; x_i, \beta))$. As such it represents the overall average level of resource use that would be expected for patients with the given covariates. Estimating the overall average level of resource necessitates estimating both the probability of resource use and the level of use given any use. $(1 - f_{zero}(0; z_i, \gamma))$ is the probability of any resource use and is estimated as $1 - \hat{\pi}_i$ as shown above. $x_i^T \beta - \log(1 - f_{count}(0; x_i, \beta))$ is the mean of count component (i.e, the truncated negative binomial) on the log scale given some resource use. $f_{count}(0; x_i, \beta)$ is the probability of a zero value from the untruncated negative binomial distribution. $f_{count}(0; x_i, \beta) = \Pr(y=0) = (1 + \alpha\theta)^{-\frac{1}{\alpha}}$ where α is the scale parameter and θ , the mean of the untruncated negative binomial, is $e^{-x_i^T \beta}$. Thus, to estimate the overall average level of resource use

1. Estimate $\hat{\theta} = e^{-x_i^T \hat{\beta}}$
2. Estimate $f_{count}(0; x_i, \hat{\beta}) = \Pr(y=0) = (1 + \hat{\alpha}\hat{\theta})^{-\frac{1}{\hat{\alpha}}}$
3. Estimate $f_{zero}(0; z_i, \hat{\gamma}) = \hat{\pi}_i = 1 - \frac{e^{z_i^T \hat{\gamma}}}{1 + e^{z_i^T \hat{\gamma}}}$
4. Estimate $\log(\hat{\mu}_i) = \log(\hat{\theta}_i) - \log(1 - f_{count}(0; x_i, \hat{\beta})) + \log(1 - f_{zero}(0; z_i, \hat{\gamma}))$

Mean Level of Resource Use Given Some Use

The mean level of resource use given some resource use is the mean of the truncated negative binomial and can be estimated with the following equation.

$$\log(\hat{\mu}_i | \hat{\mu}_i > 0) = \log(\hat{\theta}_i) - \log(1 - f_{count}(0; x_i, \hat{\beta}))$$

A **B** **Figure 1.**

Predicted probability of at least one operation (A) and at least one operating room visit (B)
The proportion of the burn that was full thickness was fixed at 50% and no inhalation injury was assumed.

Figure 2.

Predicted number of operations with (A) and without (B) inhalation injury and predicted number of operating room visits with (C) and without (D) inhalation injury. The proportion of the burn that was full thickness was fixed at 50%.

Figure 3.

Predicted versus observed number of patients receiving 1 to 9 operative procedures (A & B) and number of patients with 1 to 9 total operating room visits (C & D) for the training and test sets. Error bars are 95% confidence limits derived from bootstrap resampling. Asterisks indicate observed values for the training and test sets.

Figure 4. Predicted probability of at least one day in ICU without (A) and with (B) inhalation injury and predicted probability of at least one day on a ventilator without (C) and with (D) inhalation injury. The proportion of the burn that was full thickness was fixed at 50%.

Figure 5. Predicted length of ICU stay (days) without (A) and with (B) inhalation injury and predicted number of ventilator days without (C) and with (D) inhalation injury. The proportion of the burn that was full thickness was fixed at 50%.

Figure 6.

Predicted versus observed number of patients in intensive care for 1 to 9 days (A & B) and on a ventilator for 1 to 9 days (C & D) for the training and test sets. Error bars are 95% confidence limits derived from bootstrap resampling. Asterisks indicate observed values for the training and test sets.

Table 1

Summary statistics for the training and test sets for each resource use. For TBSA, age, and the proportion of the burn that is full thickness, summaries are the mean $\pm$ standard deviation with the interquartile range (IQR) shown below.

Resource	% Zeros ^a	Mortality	TBSA (%)	Age	Inhalation Injury	Prop. Full Thickness
<i>No. Operative Procedures</i>						
Training Set (n=23,881)	61.05%	3.96%	9.6 $\pm$ 13.6 [IQR: 2, 11]	29.0 $\pm$ 22.9 [IQR: 4.5, 44.2]	7.88%	0.23 $\pm$ 0.37 [IQR: 0, 0.40]
Test Set (n=23,911)	60.76%	3.73%	9.5 $\pm$ 13.4 [IQR: 2, 11]	28.8 $\pm$ 23.0 [IQR: 4.4, 44.6]	7.42%	0.22 $\pm$ 0.36 [IQR: 0, 0.37]
<i>Total OR Visits</i>						
Training Set (n=24,019)	60.94%	3.87%	9.5 $\pm$ 13.4 [IQR: 2, 11]	29.1 $\pm$ 22.9 [IQR: 6.4, 46.1]	7.61%	0.22 $\pm$ 0.37 [IQR: 0, 0.38]
Test Set (n=24,049)	60.93%	3.82%	9.6 $\pm$ 13.5 [IQR: 2, 11]	28.8 $\pm$ 23.0 [IQR: 6.2, 45.8]	7.70%	0.23 $\pm$ 0.37 [IQR: 0, 0.40]
<i>ICU Days</i>						
Training Set (n=38,734)	62.48%	4.64%	10.1 $\pm$ 14.2 [IQR: 2, 12]	30.7 $\pm$ 23.0 [IQR: 9.1, 47.3]	9.86%	0.22 $\pm$ 0.37 [IQR: 0, 0.38]
Test Set (n=38,777)	62.63%	4.66%	10.2 $\pm$ 14.3 [IQR: 2, 12]	30.3 $\pm$ 23.0 [IQR: 8.7, 46.8]	9.68%	0.22 $\pm$ 0.37 [IQR: 0, 0.38]
<i>Ventilator Days</i>						
Training Set (n=39,306)	84.05%	4.61%	10.0 $\pm$ 14.2 [IQR: 2, 11.5]	30.7 $\pm$ 22.9 [IQR: 9.5, 47.1]	9.64%	0.22 $\pm$ 0.37 [IQR: 0, 0.38]
Test Set (n=39,346)	83.77%	4.76%	10.1 $\pm$ 14.3 [IQR: 2, 11.5]	30.7 $\pm$ 22.9 [IQR: 9.6, 47.1]	9.93%	0.22 $\pm$ 0.36 [IQR: 0, 0.35]

^a% Zeros is the percentage of the records with no resource us.

Table 2

Estimated coefficients $\pm$ standard error for the full model for each resource variable. The baseline TBSA category is 0–10% and the baseline age category is 0–2 years old. These categories are represented by the intercepts.

	Number Operations	Total OR Visits	ICU Days	Ventilator Days
COUNT COMPONENT				
Intercept	0.349 $\pm$ 0.106**	−1.633 $\pm$ 1.634	0.505 $\pm$ 0.449	0.586 $\pm$ 0.304
TBSA Category				
(10–20%]	0.565 $\pm$ 0.043**	0.852 $\pm$ 0.221**	0.760 $\pm$ 0.110**	0.621 $\pm$ 0.067**
(20–30%]	1.062 $\pm$ 0.073**	1.512 $\pm$ 0.351**	1.260 $\pm$ 0.149**	1.044 $\pm$ 0.106**
(30–40%]	1.471 $\pm$ 0.091**	1.989 $\pm$ 0.437**	1.667 $\pm$ 0.155**	1.369 $\pm$ 0.090**
(40–50%]	1.662 $\pm$ 0.099**	2.190 $\pm$ 0.522**	1.943 $\pm$ 0.148**	1.568 $\pm$ 0.087**
(50–60%]	1.871 $\pm$ 0.091**	2.339 $\pm$ 0.494**	1.912 $\pm$ 0.156**	1.653 $\pm$ 0.111**
(60–70%]	2.085 $\pm$ 0.129**	2.579 $\pm$ 0.516**	1.846 $\pm$ 0.146**	1.514 $\pm$ 0.127**
(70–80%]	2.151 $\pm$ 0.120**	2.280 $\pm$ 0.459**	1.858 $\pm$ 0.202**	1.476 $\pm$ 0.191**
(80–90%]	1.927 $\pm$ 0.224**	2.402 $\pm$ 0.556**	1.474 $\pm$ 0.194**	1.305 $\pm$ 0.232**
(90–100%]	1.550 $\pm$ 0.281**	1.868 $\pm$ 0.481**	0.784 $\pm$ 0.316*	1.020 $\pm$ 0.334**
Age Category				
(2–13)	0.127 $\pm$ 0.050*	0.443 $\pm$ 0.124**	−0.054 $\pm$ 0.093	−0.128 $\pm$ 0.118
[13–18)	0.174 $\pm$ 0.052**	0.567 $\pm$ 0.142**	−0.143 $\pm$ 0.114	−0.368 $\pm$ 0.170*
[18–30)	0.079 $\pm$ 0.101	0.442 $\pm$ 0.117**	0.032 $\pm$ 0.111	−0.003 $\pm$ 0.144
[30–40)	0.093 $\pm$ 0.097	0.385 $\pm$ 0.149**	0.027 $\pm$ 0.105	−0.043 $\pm$ 0.136
[40–50)	0.113 $\pm$ 0.097	0.527 $\pm$ 0.132**	0.262 $\pm$ 0.102*	0.183 $\pm$ 0.124
[50–60)	0.246 $\pm$ 0.106*	0.648 $\pm$ 0.202**	0.459 $\pm$ 0.123**	0.275 $\pm$ 0.141
[60–70)	0.152 $\pm$ 0.119	0.677 $\pm$ 0.179**	0.618 $\pm$ 0.105**	0.586 $\pm$ 0.167**
[70–80)	0.208 $\pm$ 0.101*	0.581 $\pm$ 0.169**	0.817 $\pm$ 0.114**	0.437 $\pm$ 0.186*
[80–90]	0.134 $\pm$ 0.129	0.739 $\pm$ 0.233**	0.789 $\pm$ 0.115**	0.276 $\pm$ 0.189
Inhalation Injury	0.339 $\pm$ 0.068**	0.594 $\pm$ 0.281*	0.695 $\pm$ 0.111**	0.516 $\pm$ 0.074**
Prop. Full Thickness	0.558 $\pm$ 0.129**	0.960 $\pm$ 0.441*	0.821 $\pm$ 0.168**	0.441 $\pm$ 0.134**
α (scale parameter)	0.4328	2.1249	3.0694	4.4072
BINARY COMPONENT				
Intercept	−1.533 $\pm$ 0.596**	−1.496 $\pm$ 0.610*	−1.487 $\pm$ 0.263**	−4.161 $\pm$ 0.154**
TBSA Category				
(10–20%]	0.521 $\pm$ 0.198**	0.515 $\pm$ 0.207*	1.018 $\pm$ 0.108**	1.384 $\pm$ 0.070**
(20–30%]	0.892 $\pm$ 0.237**	0.820 $\pm$ 0.273**	1.736 $\pm$ 0.179**	2.381 $\pm$ 0.094**
(30–40%]	0.865 $\pm$ 0.314**	0.748 $\pm$ 0.237**	2.089 $\pm$ 0.276**	3.386 $\pm$ 0.117**

	Number Operations	Total OR Visits	ICU Days	Ventilator Days
COUNT COMPONENT				
(40–50%]	0.902 ± 0.214**	0.744±0.188**	2.157 ±0.304**	3.988±0.174**
(50–60%]	0.538 ± 0.260*	0.468±0.336	2.188 ±0.448**	4.511±0.241**
(60–70%]	0.548 ± 0.326	0.058±0.343	2.403 ±0.447**	4.647±0.349**
(70–80%]	−0.208 ± 0.323	−0.115±0.274	2.143 ±0.456**	4.628±0.356**
(80–90%]	−0.492 ± 0.235*	−0.664±0.219**	2.400 ±0.409**	4.574±0.335**
(90–100%]	−1.636 ± 0.360**	−1.899±0.340**	1.524 ±0.406**	4.106±0.486**
Age Category				
(2–13)	0.384 ± 0.068**	0.307±0.077**	0.061 ±0.083	0.153±0.131
[13–18)	0.491 ± 0.068**	0.482±0.077**	−0.044 ±0.151	0.379±0.198
[18–30)	0.583 ± 0.192**	0.642±0.191**	0.275 ±0.239	0.653±0.133**
[30–40)	0.662 ± 0.201**	0.607±0.204**	0.395 ±0.244	0.762±0.143**
[40–50)	0.779 ± 0.207**	0.767±0.216**	0.448 ±0.230	0.839±0.156**
[50–60)	0.771 ± 0.202**	0.679±0.237**	0.539 ±0.223*	1.024±0.160**
[60–70)	0.684 ± 0.202**	0.621±0.203**	0.716 ±0.235**	1.355±0.167**
[70–80)	0.479 ± 0.268	0.425±0.256	1.077 ±0.242**	1.508±0.159**
[80–90]	0.072 ± 0.252	−0.002±0.258	1.138 ±0.232**	1.545±0.169**
Inhalation Injury	−0.239 ± 0.245	−0.188±0.219	1.731 ±0.211**	3.398±0.188**
Prop. Full Thickness	1.815 ± 0.477**	1.872±0.446**	0.255 ±0.166	0.780±0.111**

**
p < 0.01

*
p < 0.05