Gleaning Data From Disaster: A Hospital-Based Data Mining Method To Studying All-Hazard Triage After A Chemical Disaster

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Abstract

Objective—The objective of this paper is to describe the methods of evaluating currently available triage models for their efficacy in appropriately triaging the surge of patients after an all-hazards disaster.

Design—We developed a method for evaluating currently available triage models using extracted data from medical records of the victims from the Graniteville chlorine disaster.

Setting—On January 6, 2005, a freight train carrying three tanker cars of liquid chlorine was inadvertently switched onto an industrial spur in central Graniteville, South Carolina. The train then crashed into a parked locomotive and derailed. This caused one of the chlorine tankers to rupture and immediately release ~60 tons of chlorine. Chlorine gas infiltrated the town with a population of 7,000.

Participants—This research focuses on the victims who received emergency care in South Carolina.

Results—With our data mapping and decision tree logic, we were successful in employing the available extracted clinical data to estimate triage categories for use in triage effectiveness research.

Conclusions—The methodology outlined in this paper can be used to assess the performance of triage models after a disaster. The steps are reliable and repeatable and can easily be extended or applied to other disaster datasets.

INTRODUCTION

Mass casualty triage describes the process to classify and prioritize victims according to predetermined severity algorithms to ensure the greatest survivability within a context of

limited resources. However, there is a paucity of literature evaluating mass casualty triage models and no gold standard for measuring the effectiveness of information decision support data used in response to mass casualty incidents.[1-4] Only one of the triage models currently used for mass casualty triage decision support has been tested under mass casualty conditions and validated by outcome data.[5] Only three studies included assessments of incidents involving chemicals.[6-8]

Mass casualty events include natural, unintended and deliberate incidents that occur with little or no warning and have the potential to produce large numbers of casualties that can overwhelm existing healthcare facilities and resources[4]. Effective and timely management of mass casualties is dependent upon valid triage tools and models that provide decision support for emergency responders[9-13]. Because mass casualty incidents do not lend themselves to randomized, controlled, experimental trials, the science of disaster medical research is often anecdotal, observational, and more descriptive than analytical.[14-32] The study of mass casualty incidents requires special procedures for data collection storage and analysis.[33] The ability to collect accurate, timely and valid data at the time of an incident is difficult. Methods rely predominately on detailed observational field notes, collecting and analyzing data produced by responding agencies, and mass media sources such as photography and video.[33] Methods employed after an incident include interviews and surveys which pose potential bias and recall errors.

OBJECTIVES

The main objective of this research is to use observed health outcome data from a large chlorine leak to analyze victim assessment using the four most frequently used triage models and to compare the modeled classification to observed patient outcomes. Specifically, the decision tree for four popular triage systems (Simple Triage and Rapid Treatment [START], [14,34,35] Emergency Severity Index [ESI],[36-41] Sort, Assess, Life Saving Interventions Treatment and/or Transport [SALT],[42-43]

Chemical/Biological/Radiological/Nuclear Mass Casualty Triage System [CBRN])[6] are modeled using data extracted from victim records to produce a predicted outcome for each triage model. The triage model outcome is then compared to the observed health effect severity level for each victim. The objective of this paper is to describe a successful approach to collect, extract, and analyze clinical data for disaster-related triage effectiveness research.

The purpose of this paper is to describe the selection and use of secondary data analysis methods to accurately capture the data used for triage decisions at the time of a large chlorine leak that occurred in Graniteville, South Carolina in 2005. The research methods described in this paper show the potential use of well designed secondary analysis methods to improve mass casualty research.

RESEARCH DESIGN AND METHODS

Study Population

On January 6, 2005, a freight train carrying tanker cars of liquid chlorine was inadvertently switched onto an industrial spur in the center of Graniteville, South Carolina, where it crashed into a parked locomotive. The train then derailed and one of the heavily damaged chlorine tankers was ruptured, immediately releasing approximately 60 tons of the 90 tons of chlorine it was carrying. Within minutes, the dense chlorine gas infiltrated the surrounding town with a population of over 7,000. Many people fled the town before they were overcome by the chlorine. Yet nine people died, 72 were hospitalized in nine regional hospitals, 840 were treated as outpatients, and 220 experienced immediate health problems, but did not receive any immediate medical care.[44] Others experienced health problems only associated with the psychological trauma of the disaster. We know of 1,384 victims of this event. This study focuses on the observed clinical data collected at the time of the chlorine leak incident to determine if the criteria modeled in the four most frequently used triage systems accurately predict the severity of respiratory signs/symptoms necessitating medical intervention at the hospitals. This disaster site is located in South Carolina near the border of Georgia.[7,8]

This research applies an all hazards approach to study the validity of four triage models using physiological measurements, signs/symptoms, exposure severity ratings and medical outcome categories collected in six chlorine leak datasets. This is a retrospective study using data extracted from medical records of chlorine disaster victims. Specifically, mass casualty data were abstracted by the South Carolina Department of Health and Environmental Control (SC DHEC) in conjunction with the Centers for Disease Control and Prevention (CDC) from hospital records of victims who received medical care after the 2005 chlorine release in Graniteville, South Carolina[8]. Due to the scale of the disaster, medical chart abstraction was limited to both the hospitalized patients and those who were treated multiple times in the emergency room because it was assumed that those patients would have been hospitalized in the absence of a surge and if there were beds available. Our first step was creating a merged de-identified research dataset from these abstracted data that included the needed input data for each triage model, the patients' clinical outcome, demographics, and other elements which were useful for developing an improved triage model. Then, the required data for each triage model were mapped to the collected data. The logic of the triage decision tree was then coded in Statistical Analysis System (SAS) software producing the predicted clinical outcome categories for each triage model. Observed patient outcome categories were derived from the clinical treatment records using the duration of required medical care and severity of reported injury.[7,8] The predicted triage model outcome categories were then compared to the observed patient clinical outcome categories.

Table 1 includes data points for the adult triage models used in our study to assess mass casualty patients and the priority categories assigned to these assessments.

Wenck, et al.[7] used medical care as the medical outcome measure in their epidemiologic surveillance after the event. They used nine medical outcome categories to classify the duration of hospitalization and need for intensive care support for patients who received care

following the Graniteville chlorine exposure. The nine medical outcome categories and the relationship of the outcome category and the triage system classification are described in Table 2. These observed medical outcome categories (Observed Outcome Category – OUTCOMECAT) provide a suitable measure of medical outcome for our study.

The SC DHEC datasets include information on patients hospitalized in nine hospitals, (n=71) examined as outpatients during the first few days after the accident (n=630), or those who died (n=9). The data included patients who ranged in age from 4 months to 85 years of age, were 58.9% male, 59.9% white, 35.2% black, 2.5% Hispanic and 2.4% other or unknown[37].

All data have their inherent strengths and flaws, including the datasets that we proposed to study. We analyzed data from several datasets: the hospitalized (n=71) and multiple emergency room admitted patient abstracted medical records (n=49), medical service provider reports (n=630), the health registry (n=958), voluntary health screenings (3 datasets, n=259, n=69, and n=30), and the epidemiological follow-up interviews of reportedly exposed persons (n=287, n=94). All of these dataset were collected exclusively for public health purposes, not research. Therefore, the self-reported and voluntarily collected data from the interviews and health screenings had more missing data than traditional research-specific datasets. However, because these are public health datasets, the abstracted medical records and immediate epidemiological reporting data are rather complete as to reporting compliance because hospitals and doctor's offices were required by law to report cases of chlorine associated illness to SC DHEC. However, some record keeping was not as complete as we would have liked. The surge of patients into the regional hospitals forced the clinicians to first focus on treating the patients and providing detailed clinical notes second.[45] Often there was only minimal detail provided in the clinical notes, which was understandable given the surge status at the hospitals. A standardized paper medical record abstraction form (The Graniteville Chlorine Chart Abstraction Form) was used for all medical record abstractions, and trained epidemiologists abstracted all medical records. Further details on the medical record abstraction process are found elsewhere.[8] Likewise, health screenings were comparable to the rigorous data quality obtained from similar research-based studies[44]. All data from both self-report and abstracted hospital/ doctor reported sources were duplicately entered and reviewed for quality assurance prior to being issued as the official study datasets. Of the available datasets, the following datasets were used in the study.

1) Hospitalization database. The medical records of all persons hospitalized (n=71) were abstracted. The following information were collected: demographics, clinical presentation, physical examination, laboratory, pulmonary, and radiological studies, pulse oximetry, medical treatment, medical outcome category (duration of hospitalization and need for intensive care support) and diagnosis.

2) Multiple Emergency Room Admitted Patients. The medical records of all persons seen in the emergency room multiple times (n=49) were abstracted. The rationale for abstracting these in addition to the hospitalized patient records was that these patients would have most likely been admitted under non-surge conditions rather than treated in the emergency

department, observed for several hours, and then released with instructions to return if they required further medical care. The following information was collected: demographics, clinical presentation, physical examination, laboratory, pulmonary, and radiological studies, pulse oximetry, medical treatment, medications, medical outcome category (duration of hospitalization and need for intensive care support), and diagnosis.

3) Medical Service Provider Reports. The datasest includes emergency room logs, and a rapid epidemiological assessment database. Personnel from the CDC in conjunction with the SC DHEC collected data via interviews and medical record abstraction for individuals who sought medical care. Information includes exposure information, symptoms experienced, details about decontamination and transport to medical care, preexisting cardiac or pulmonary medical conditions, and exposure severity ratings (5 point scale). Patients (n=605) were classified according to nine medical categories. Demographic characteristics of people who received medical care are stratified by primary exposure location and duration.

The data were combined so that the variables across datasets were associated with the same patient correctly.

The datasets were explored, using SAS (SAS Institute Inc., Cary, NC, USA) version 9.2 statistical software, identifying data points as candidates for the decision tree model(s). To insure data quality, the combined datasets were analyzed using visualization techniques such as histograms and statistic measures such as range, mean, median, and outliers to quantify completeness and validity of responses. Spearman correlation was used to examine the relationship between four triage outcomes with signs/symptoms variables. The Kappa statistic was used to examine the agreement between the triage models. Decision algorithms were developed to aid in the evaluation of variables where the data points appear in multiple datasets and for the case when a direct variable was not available in any of the datasets. From these results, modifications were implemented to address issues of missing values, outliers or clustering of data. This study was approved by both the Institutional Review Board of the University of South Carolina and the South Carolina Department of Health and Environmental Control. All databases were linked within the South Carolina Office of Research and Statistics, de-identified, and provided with a unique personal identification number prior to our receipt of the study data.

DETAILS USING SAS

The steps below outline a repeatable process for evaluating mass casualty data. The process addresses (1) assessment of datasets and (2) columns, providing suggestions for managing incomplete data (3) creating variables from existing data points, and (4) coding the decision tree logic for triage models.

We were fortunate that de-identified data sets were available for our use. However, we took precautions to protect the datasets at all times. The files were delivered encrypted with a password key then stored on a password protected server that was backed up nightly.

Step 1 – Analyze data sets and data points

The public health data sets collected from the Graniteville chlorine disaster were merged to generate a research dataset useful for further analysis. The data were examined for completeness and to identify data points that fulfilled the needed input data points used in the triage models. The first step was to compare the data points across the datasets and choose which ones to include for further analysis. We made a decision to focus on the data recorded by the emergency room or the hospital on the day of the incident (the incident occurred at 2:39 am). This time period best represented when triage tools were being used to assess the victims at the hospitals.

The Graniteville Chlorine Chart Abstraction Form is a multi-page document used during the data abstraction; a portion of the data points are displayed in Table 3. The form was designed such that the abstractor filled in a blank or checked a box indicating if a condition was present or not. This form was examined for useful data points to be included in the research dataset. The last column indicates if the column was a candidate for use in the triage decision tree logic or in the creation of variables required for the decision tree. Many variables were considered as candidates, but many were discarded due to the large amount of missing data. If the variable was used in the logic model or in creation of derived variables, it was noted. For example, the emergency room visit date was considered and used, hence the 'Yes / Yes' in the final column in the table below. A blank in the second column (Variable Name) indicates the abstraction form data was not present in the dataset. A blank in the third column (Further Analysis / Used) indicates the data element was not used in our analysis. Many elements on the abstraction form were not considered useful and not included in Table 3.

We used SAS procedures (proc format and proc freq) to obtain the frequency distribution for the categorical data points in the data sets and we used proc means for the numeric data points. The analysis helped identify areas of missing data and outliers, therefore, aiding in the selection of the best data points to use in the analysis.

Step 2 – Select data points

Decisions were made to use a combination of data points to build variable(s) for the triage model(s) when the required data point was not directly collected and recorded. For example, the ability to walk is an input data point for triage. However, the value for the ability to walk was not recorded in any of the datasets. Instead, the ability to walk was derived from other collected data. We assumed a person was able to walk unless he or she was intubated or was hypoxic (<90% oxygen saturation measured by pulse oximetry). Other input variables such as heart rate or respiration rate were directly available for use in the models. Table 4 outlines the input data points for each model.

Step 3 – Create new data points and manage missing data

The Graniteville abstraction form was designed to capture the information needed to perform the descriptive epidemiology for the disaster and not for research purposes. Therefore, some information required for the triage models was not explicitly collected. As a result, we collectively made data point derivation decisions based on available data if

sufficient information was available from multiple data points on the form to derive the value for the missing data point. For example, the CBRN model asks if there is evidence of toxidrome, or signs and symptoms consistent with exposure to a toxic chemical. We created a variable for chlorine exposure based on the data from the physical exam performed in the emergency department. The abstraction form has check boxes for yes/no answers to eye issues, ear/nose/throat issues, and presence of a cough, wheezing, or burning skin because these are the hallmark signs of injury resulting from chlorine exposure. If any were checked, we indicated that the victim was exposed and had evidence of toxidrome. Additionally, we considered the first symptoms and set the toxidrome status to indicate that the victim was exposed to chlorine if vomiting or nausea was reported. Our justification being swallowing mucus secreted in response to chlorine exposure in the airways can cause nausea and/or vomiting due to these mucus secretions becoming acidic after exposure to chlorine.

When applying the SALT triage tool in practice, the first responder is required to make a decision if the victim has a major hemorrhage. There was no indicator data point for a major hemorrhage on the abstraction form because the focus of the public health descriptive epidemiology was on the chlorine injuries, not any injuries from the train derailment itself. It was well known at the time that the abstraction form was designed that few people were directly injured by the derailment itself, and that such injuries were not the cause of the epidemic of illness within the community. Therefore, no data were specifically abstracted for assessing degree of traumatic injury or major hemorrhage. After examining the available notes and other data points abstracted, we decided to create a variable indicating a major hemorrhage. We looked for a specific term in the primary diagnosis variable or in the ophthalmology consult. When either variable had the text 'inj' we derived that they were injured and hemorrhaging.

The ESI triage model asks the question 'How many different resources are needed?' and the SALT triage model asks the question 'Likely to survive given current resources?' The ESI decision logic branches according to the number of resources utilized while the SALT decision logic branches if resources are available or not. We created a variable that counted the number of resources used on each victim. For example, if the victim was *not* breathing with room air we counted a resource. The methods that indicated the victim was not breathing room air were oxygen with a face mask or nasal canula, 100% oxygen with a re-breather, on Continuous Positive Airway Pressure (CPAP), or on a ventilator. We counted a resource if the victim received an EKG, a bronchoscopy, a pulmonary function test, or was on intravenous fluids. Lastly, we looked for the term 'Intubated' in the Emergency Department notes. The minimum resources a victim could have had was 0, the maximum was 6.

Evidence of pain was used in the decision logic for the ESI model. Once again, we derived a variable to indicate if the victim was in pain or not. We assumed the victim was not in pain unless we found indicators that he or she was in pain. We selected a subset of the check boxes abstracted from the physical exam performed in the Emergency Department to indicate pain was present. If any check box under the Ear, Nose, and Throat section was checked or any item under the Dermatology section was checked, we set the pain data point

to yes. Similarly, if we found text indicating burning or pain, we set the pain data point to yes.

To manage the case when a victim was immediately admitted without going through the emergency department, we substituted the corresponding admission data points (AD) for the emergency department (ED) data points. This increased the number of victims which we could classify.

Step 4 – Code decision tree

The triage models are decision trees to help emergency clinicians ascertain which patients need care first. We translated the triage decision logic into IF/THEN statements using SAS to implement the models. The diagram for the Simple Triage and Rapid Treatment (START) tool for adults (Age > 8) is provided in Figure 1 as an illustration. There is a similar diagram for children.

The first decision in the model is to determine if the victim can walk. As described earlier in the document, we derived the ability to walk. The next decision in the model is if the victim is breathing. We matched breathing to 'Respiratory rate' on the abstraction form. If the rate is 0, then the victim is assigned the classification of black. If the rate is too low or too high then the victim is classified as red. Next, the circulation is considered, specifically if a pulse is present. We chose to use the systolic blood pressure reading as an indicator for measuring capillary refill. The value of 70 was chosen as the cutoff point to match to a capillary refill of > 2 sec. The final decision for START is if the victim can follow directions. The START triage rules for the young victims, those 8 years old or less, consider only the respiratory rate in the logic. SAS code for the START and other triage trees can be provided upon request. Pseudo code for the START logic is provided below:

S.T.A.R.T. Simple Treatment and Rapid Transport

Inputs: AGE, EDFOLLOW, EDRR, EDSYSTOLIC, EDWALK

IF EDWALK = 'Y' THEN GREEN

IF AGE <=8 THEN

IF EDRR = 0 THEN BLACK

IF EDRR > 45 OR EDRR < 15 THEN RED

IF EDRR <= 45 AND EDFOLLOW = N THEN RED

IF EDRR <=45 AND EDFOLLOW = Y THEN YELLOW

IF AGE >8 THEN

IF EDRR = 0 THEN BLACK

IF EDRR > 30 OR EDRR < 10 THEN RED

IF EDRR <= 30 AND EDSYSTOLIC < 70 THEN RED

IF EDRR <= 30 AND EDSYTOL IC >= 70 AND EDFOLLOW = N THEN RED

IF EDRR <=30 AND EDSYSTOLIC >= 70 AND EDFOLLOW = Y THEN YELLOW

ELSE NOT CLASSIFIED

We evaluated version 4 of the Emergency Severity Index (ESI) triage tool. A diagram for the ESI model is provided in Figure 2.

The ESI tool applies to all ages taking into account different thresholds for the vital signs of each age category. The first assessment is whether the victim requires immediate intervention. Immediate intervention includes issues with the airway, requiring emergency medications, needs to be intubated, is in respiratory distress (oxygen concentration < 90%), has no pulse or is unresponsive. We used the derived variables respiratory distress and inability to follow directions to mean unresponsive along with oxygen saturation value < 90% for the first decision. The next assessment is whether the victim is in a high risk situation, has abnormal responsiveness (confused/lethargic/disoriented), or is in severe pain taking into consideration the vital signs of heart rate, respiratory rate and oxygen saturation. We mapped the high risk situation to having an oxygen concentration < 92%, having a high heart rate, or a high respiratory rate. The comparison values for heart rate and respiratory rate differ by age category. We mapped abnormal responsiveness to the inability to follow directions and pain to the derived pain data point. The next assessment is based on the number of resources required and if many resources are required then the vital signs for the heart rate, respiratory rate and the oxygen saturation are considered. The model has four age categories for age when considering the vital signs. The age categories are less than 3 months, between 3 months and 3 years, age 3 to 8 years, and over 8 years of age.

A diagram for the Chemical/Biological/Radiological/Nuclear (CBRN) triage tool is provided in Figure 3[41]. CBRN triage addresses primary triage for immediate action and secondary triage for decontamination. The CBRN model classifies victims into four categories (T1, T2, T3, T4) and is valid for victims over the age of 8. The first decision in the model is whether the victim can walk. If the victim can walk, the next assessment is for evidence of toxidrome to ascertain the decontamination classification. We used the derived chlorine exposure data point to indicate the evidence of toxidrome. If the victim is unable to walk, the next decision is based on the ability to breath - which is further categorized into breathing well, breathing with difficulty or not breathing. We mapped breathing with difficulty to being in respiratory distress. We mapped not breathing to having a respiratory rate of 0. Otherwise, we assumed the victim was breathing well. For victims breathing well, the next decision is based on the ability to follow directions followed by if there is evidence of toxidrome.

The SALT triage model, illustrated in Figure 4[42], has a multi step solution to victim prioritization and classification. The first step is to quickly sort the victims into groups then to assess individuals within each group giving priority to the victims that are not moving or have an obvious life-threatening situation. We did not implement the sorting in our SAS code. The first decision for the individual assessment is whether the victim is breathing. We

used the respiratory rate > 0 to indicate if the victim is breathing. The next decision is based on answers to the following questions: (1) Obeys commands or makes purposeful movements? (2) Has peripheral pulse? (3) Not in respiratory distress? (4) and Major hemorrhage controlled? We mapped the ability to obey commands to this previously mentioned derived data point, having a peripheral pulse to having a heart rate > 0 (since only heart rate was available in the abstracted data), not in respiratory distress to this previously mentioned derived data point, and we assumed all major hemorrhages were controlled. If the victim could pass the four questions, the next decision is based on the presence of minor injuries. We used the derived injury data point to determine if the victim was classified as minimal or delayed. If the victim did not pass all four questions, the next decision is based on the available resources. We mapped the derived resource data point > 0 to classify the victim as immediate or expectant. We then compared the modeled results against the derived outcome category.

DISCUSSION

The methods and steps followed for management of data, analysis of data, coding of triage decision logic can easily be followed and implemented for similar situations. The SAS implementation is provided in Appendix A and serves as a guide for other researchers to follow. Note, the creation of variables is performed in one section before the triage decision logic, making it easy to adjust the derivation logic without interfering or requiring any changes in the triage decision logic. This proved to be quite helpful as we analyzed the data and altered the rules for deriving the missing variables. The major decisions revolved around the data and the fact that similar data were found across the available datasets along with the fact that we had incomplete data, missing data and additional data points not referenced in the available documentation related to the data sets. Once we obtained answers to detailed questions regarding the datasets we were able to move forward. Using SAS to compare data with frequency distributions for the categorical data and min, max, count, average for the numeric data proved extremely helpful in data point selection.

Coding the triage logic is straight forward and likely not subject to question or accuracy. However, the derivation for missing data points required for the triage decision logic is subject to opinion. The hope is that we gain access to more complete data for the victims so we can re-run the triage decision models without derived data points. In the absence of this information, we relied on our clinical expertise to guide the decision making.

CONCLUSIONS

We conclude that the methodology outlined in this paper can be followed or extended in evaluating the performance efficacy of triage models. The steps are reliable and repeatable and can easily be extended to other triage models or applied to other datasets or data sources. Our specific research has two areas where the data has room for improvement. The first area is the reliance on secondary data in the creation of derived data points required for the triage modeling in SAS. The second area is in the reliance on using the observed outcome category as the value to compare the predicted triage model classifications to. In

both cases, secondary data was used in the creation of the variables. Ideally, we would not have to rely on derived variables at all.

Acknowledgments

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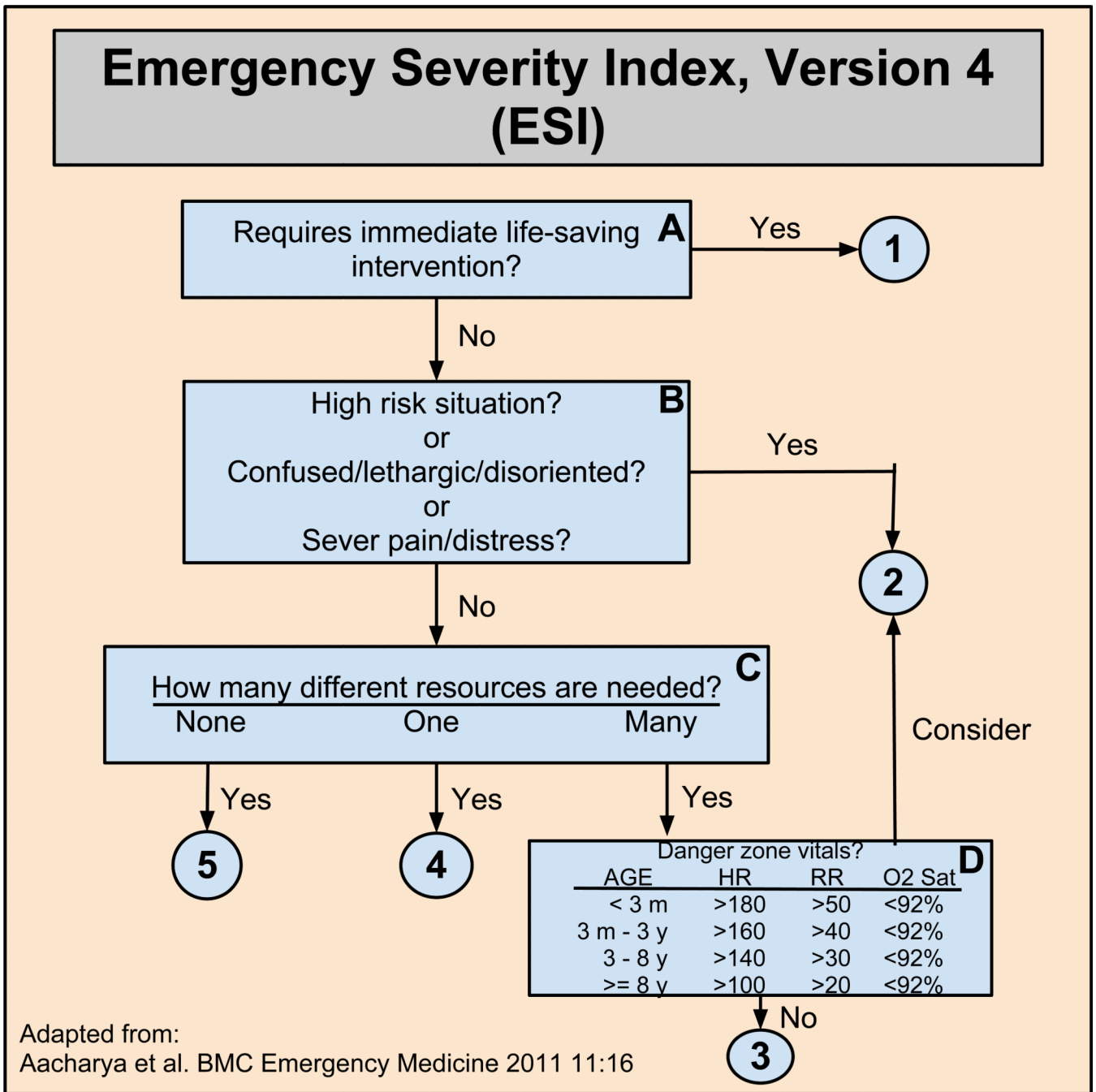
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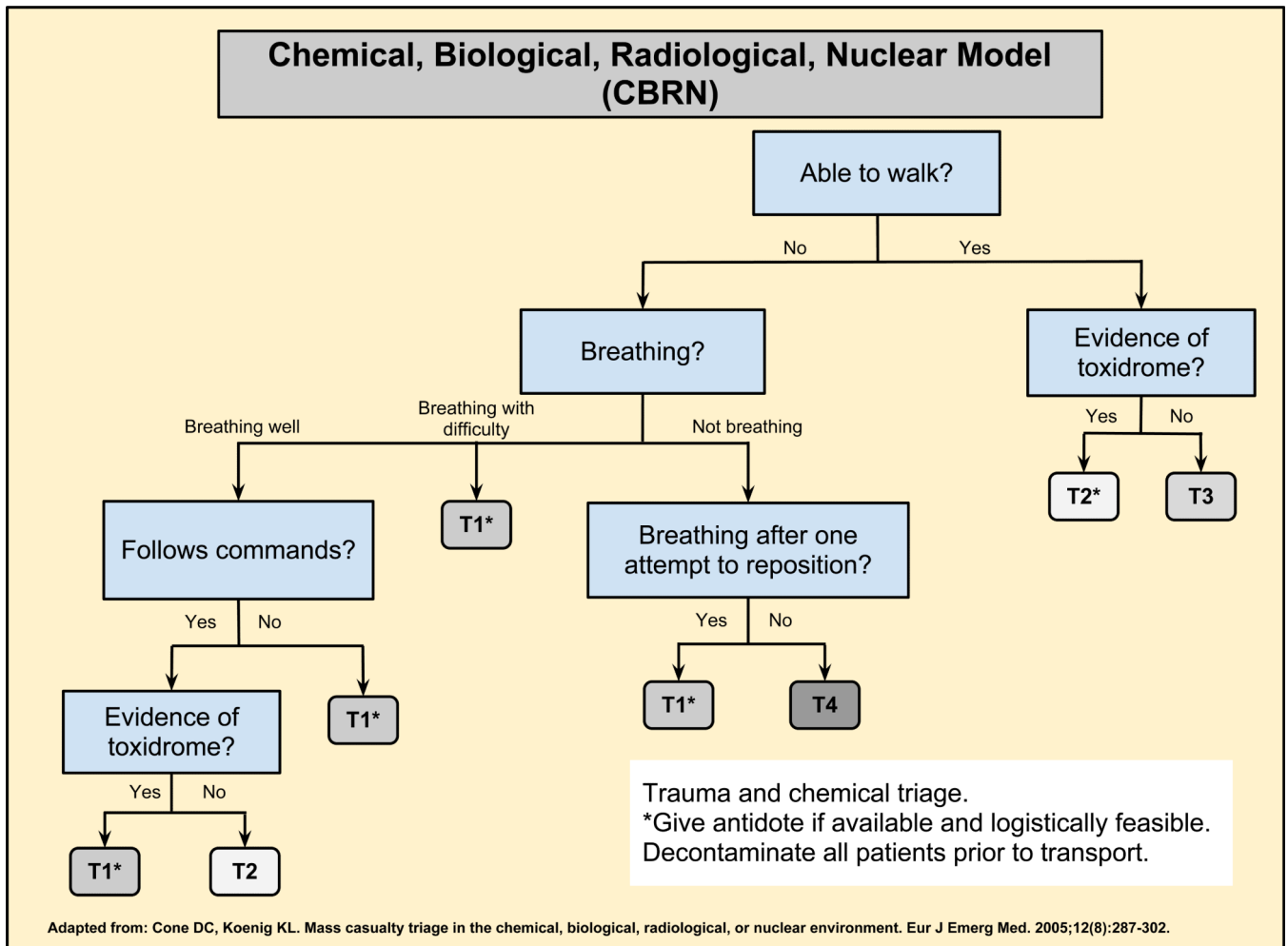
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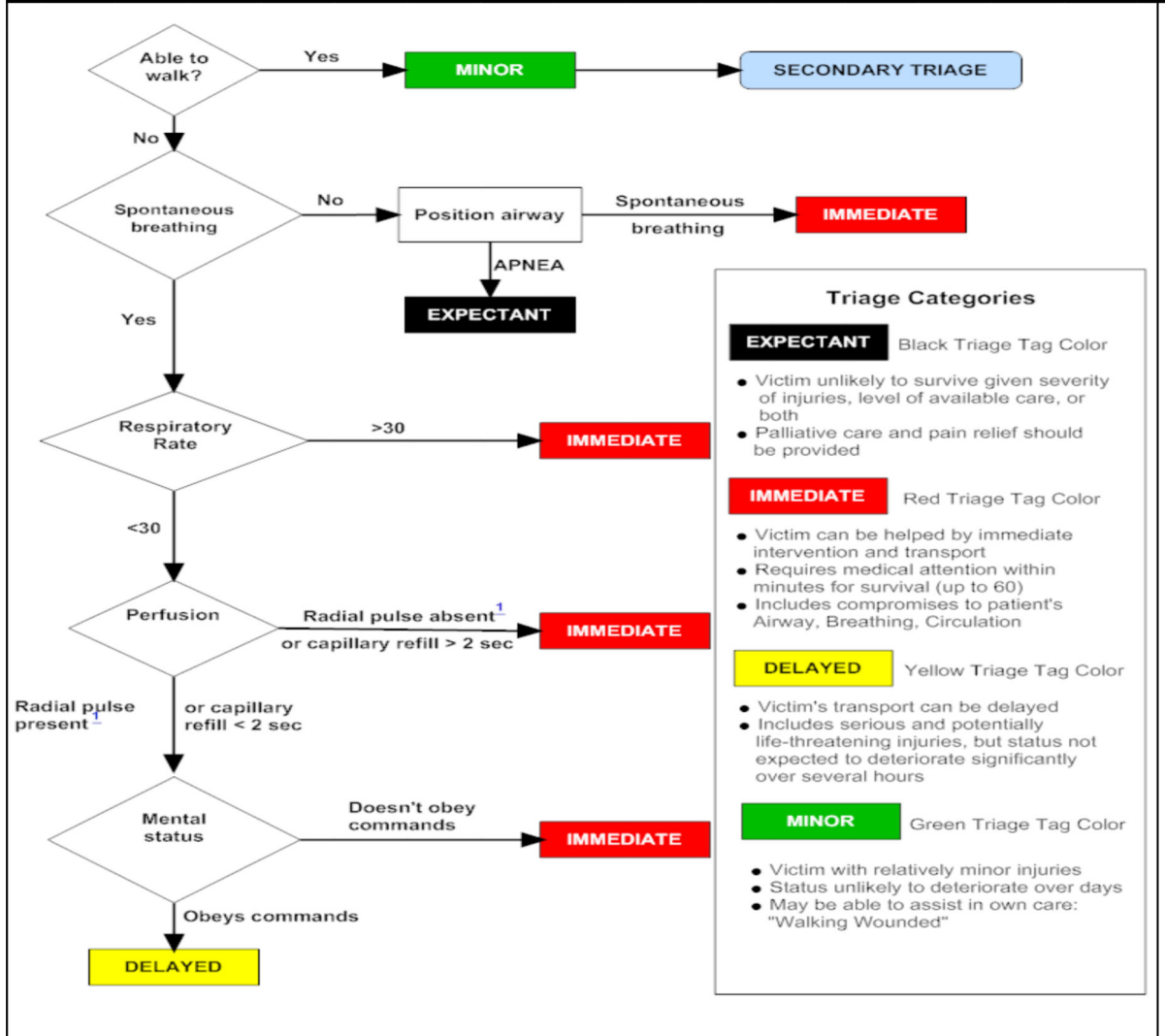
Used with permissions from Dr. Jason Carter.
http://www.jasoncartermd.com/ems/images/START_Triage_Flowsheet.jpg

Figure 1.
START Triage Tool Diagram

Emergency Severity Index, Version 4 (ESI)

A Requires immediate life-saving intervention? → Yes → (1)

No ↓

B High risk situation?
or
Confused/lethargic/disoriented?
or
Sever pain/distress? → Yes → (2)

No ↓

C How many different resources are needed?
None   One   Many

Yes ↓   Yes ↓   Yes ↓

(5)   (4)

D Danger zone vitals?

AGE	HR	RR	O2 Sat
< 3 m	>180	>50	<92%
3 m - 3 y	>160	>40	<92%
3 - 8 y	>140	>30	<92%
>= 8 y	>100	>20	<92%

Consider

No ↓

(3)

Adapted from:
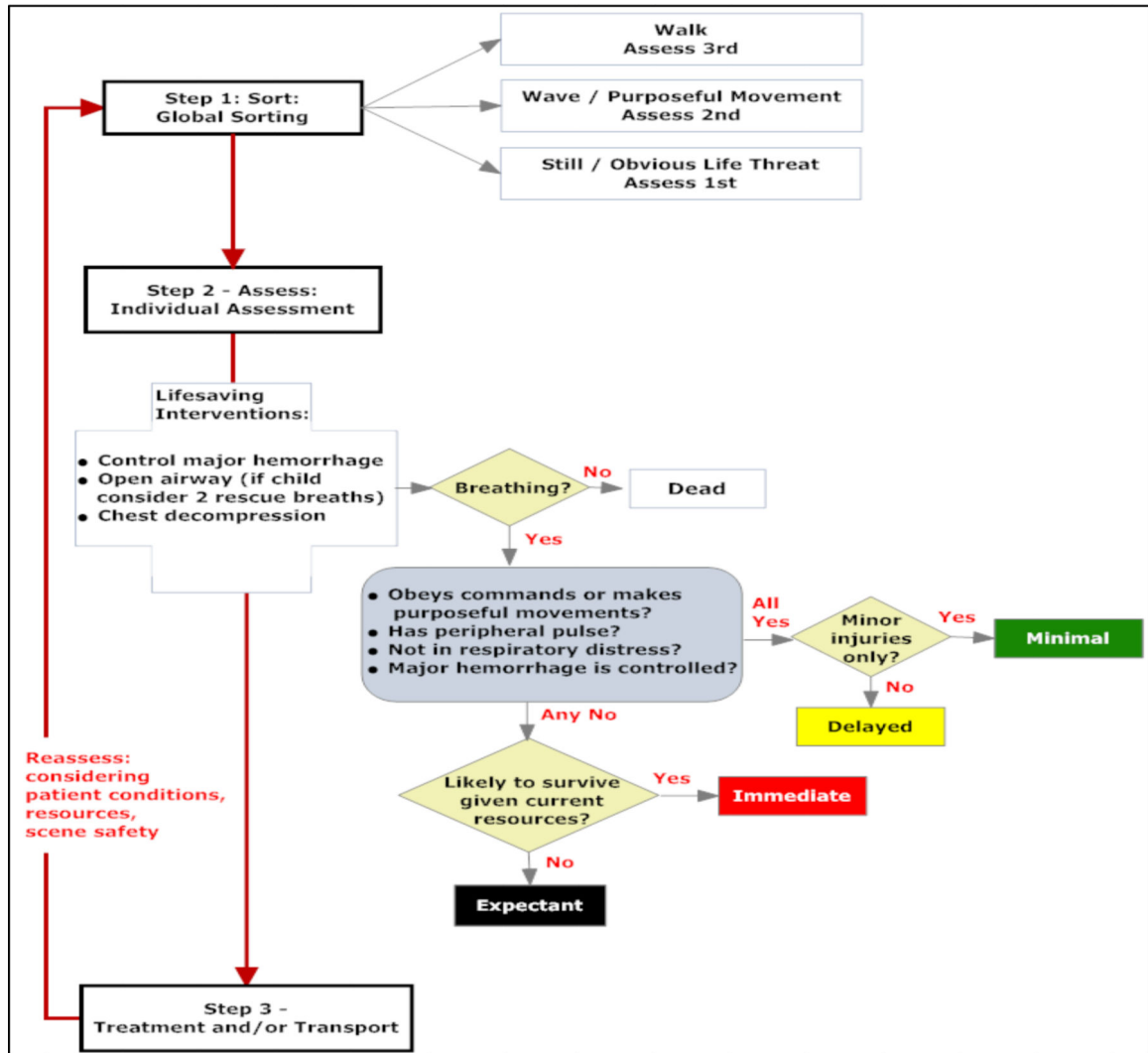Aacharya et al. BMC Emergency Medicine 2011 11:16

Figure 2.
ESI Triage Tool Diagram

Figure 3.
CBRN Triage Tool Diagram

Sort, Assess, Lifesaving Interventions, Treatment/Transport (SALT)

http://www.remm.nlm.gov/salttriage.htm

Figure 4.
SALT Triage Tool Diagram

Table 1

Summary of Triage Models, Data Points and Data Analysis Classification

TRIAGE MODELS	START	ESI	CBRN	SALT
	All ages	**All Ages**	**Adults**	**Adults**
DATA POINTS	• Respirations	• Ability to follow commands	• Ability to walk	• Ability to follow commands
	■ If > 8 years old > 30 or < 10	• # resources needed	• Ability to follow commands	• Respirations
	■ If < 8 years old > 45 or < 15	■ If < 3 months old > 180 • Pulse	• Respirations	■ > 0
		■ If > 3 months and < 3 years old > 160	• Toxidrome	• Pulse
	• Perfusion		■ Eye burning	■ > 0
	• Mental Status	■ If > 3 years old and < 8 years old > 140	■ Cough	• Respiratory distress
	– Ability to walk		■ Skin burning	
	– Ability to follow commands	■ If > 8 years old > 100	■ Wheezing	• Number of injuries
		• Respirations	■ ENT burning	
		■ If < 3 months old > 50	■ Vomiting or nausea	• # resources needed
		■ If > 3 months and < 3 years old > 40	• Injuries	
		■ If > 3 years old and < 8 years old > 30	• Decon prior to transport	
		■ If > 8 years old > 20		
		• O$_2$ Saturation		
		■ All ages < 92%		
		• Pain		
CATEGORY	• Black -Deceased	• Level 0	• T4	• Dead
	• Red - Immediate	• Levels 1 & 2	• T1	• Expectant
	• Yellow -Delayed	• Level 3 & 4	• T2	• Immediate
	• Green - Minor	• Level 5	• T3	• Minimal

Table 2

Outcome Classification For Four Triage Models

OBSERVED OUTCOME[37]	START	ESI	CBRN	SALT
Deceased	BLACK	LEVEL 0	T4	DEAD
ICU/Ventilator	RED	LEVEL 1 and 2	T1	IMMEDIATE
Hospitalized 3+ days	RED	LEVEL 1 and 2	T1	IMMEDIATE
Hospitalized 1-2 days	RED	LEVEL 1, 2 and 3	T1	IMMEDIATE
ED repeat visits	YELLOW	LEVEL 3 and 4	T2	MINIMAL
ED with significant Symptoms	YELLOW	LEVEL 3 and 4	T2	MINIMAL
ED with moderate Symptoms	YELLOW	LEVEL 3 and 4	T2	MINIMAL
ED without Symptoms	GR EEN	LEVEL 5	T3	MINIMAL
Physician office visit	GREEN	LEVEL 5	T3	MINIMAL

Table 3

Graniteville Chlorine Chart Abstraction Form Mapping

I. Demographic Information	
Questionnaire Name	**Further Analysis / Used**
Study ID #	Yes
ER Visit Date	Yes / Yes
Admission Date	Yes
ICU Admission Date	Yes
Discharge Date	Yes
ICU Discharge Date	Yes
Gender	Yes / Yes
Date of Birth	Yes / Yes
Race	Yes / Yes
II Chief Complaint	
Questionnaire Name	**Further Analysis / Used**
PULMONARY	Yes / Yes
CARDIAC	Yes
DEMATOLOGIC	Yes
OPTHALMOLOGIC	Yes
EAR, NOSE, THROAT	Yes
OTHER	Yes
III. Past Medical History and Symptoms	
Questionnaire Name	**Further Analysis / Used**
MEDICATIONS	Yes
HISTORY OR PREVIOUS HOSPITALIZATION FOR PULMONARY DISEASE	Yes
IV. Data from Emergency Room	
Questionnaire Name	**Further Analysis / Used**
Date	Yes / Yes
Time	Yes
Vital: Temp	Yes
BP	Yes / Yes
BP	Yes
Respiratory rate	Yes / Yes
Heart rate	Yes / Yes
Time	
O2 Sat	Yes / Yes
On room Air	Yes / Yes
On liters of O2 via nasal canula (NC) or face mask	Yes
On 100% non-rebreather (NRB)	Yes
On continuous Positive Airway Pressure (CPAP)with	Yes

I. Demographic Information	
Questionnaire Name	**Further Analysis / Used**
On ventilator with___%O2	Yes
Notes from Emergency Room	Yes / Yes
Physical Exam	
Questionnaire Name	**Further Analysis / Used**
Eye	Yes / Yes
Red	Yes
Other	Yes
Ear, Nose, Throat	Yes / Yes
Rhinorrhea	Yes
Other	Yes / Yes
	Yes / Yes
Pulmonary	Yes
Tachupnea	Yes
Cough	Yes / Yes
Cyanosis	Yes
Decreased breath sounds	Yes
Stridor	Yes
Wheezing	Yes / Yes
Crackles	Yes
Rhonchi	Yes
Intercostals retractions	Yes
Cepitus	Yes
Other	Yes
Cardiac	Yes
Tachycardia	Yes
Murmur	Yes
Dematology	Yes
Burn	Yes / Yes
Other	Yes / Yes
Data from Repeat ER Visit or Admission H&P	
Questionnaire Name	**Further Analysis / Used**
Date	Yes
Time	Yes
Vitals: Temp	Yes
Ht	Yes
Wt	Yes
BP	Yes
BP	Yes

I. Demographic Information	
Questionnaire Name	**Further Analysis / Used**
Respiratory rate	Yes / Yes
Heart rate	Yes / Yes
O2 Sat	Yes / Yes
On room Air	Yes
On liters of O2 via nasal canula (NC) or face mask	Yes
On 100% non-rebreather (NRB)	Yes
On continuous Positive Airway Pressure (CPAP)with	Yes
On ventilator with ___%O2	Yes
Ventilator other	Yes
Physical Exam	
Questionnaire Name	**Further Analysis / Used**
Eye	Yes
Red	Yes
Other	Yes
Ear, Nose, Throat	Yes
Other	Yes
Pulmonary	Yes
Tachupnea	Yes
Cough	Yes
Cyanosis	Yes
Decreased breath sounds	Yes
Stridor	Yes
Wheezing	Yes
Crackles	Yes
Rhonchi	Yes
Intercostals retractions	Yes
Cepitus	Yes
Other	Yes / Yes
Cardiac	Yes
Tachycardia	Yes
Dermatology	Yes
Other	Yes
Outcomes	
Questionnaire Name	**Further Analysis / Used**
Outcome	Yes
Chlorine exposure	Yes
Other Disease	
Primary Diagnosis	Yes / Yes

I. Demographic Information	
Questionnaire Name	**Further Analysis / Used**
Tests/Procedures	
Questionnaire Name	**Further Analysis / Used**
EKG Date	Yes / Yes
Brochoscopy 1ST Date	Yes / Yes
Pulmonary Date	Yes / Yes
Consults	
Questionnaire Name Further Analysis / Used	
Pulmonology Yes	
Dermatology Yes	
Opthalmology Yes / Yes	
Abstracted Information Not on Graniteville Abstraction Form but included in Dataset	
Abstracted Data	**Further Analysis / Used**
Victim transportation method	Yes / Yes
Repeat admission boolean	
First Symptoms	Yes / Yes
Outcome Category	Yes / Yes
Decontamination Location	Yes
ICU boolean	Yes
Number of days in ICU	Yes
Hospitalized	Yes
Days in hospital	Yes
Person exposed	Yes
Distance in miles from site	Yes

TABLE 4

Clinical Data Points Used For The Decision Logic In Each Triage Model

Data Point	DESCRIPTION	START	ESI	CBRN	SALT
AGE	Age in years on date of incident	x	x	x	x
CHLORINE EXPOSURE[*]	Evidence of toxidrome (chlorine)			x	
FOLLOWS DIRECTIONS[*]	Ability to follow directions	x	x	x	x
HEART RATE	Heart rate		x		x
O2 SATURATION	O₂ Saturation		x		
RESPIRATORY DISTRESS	Evidence of respiratory distress			x	x
RESPIRATORY RATE	Respiration rate	x	x	x	x
SYSTOLIC BLOOD PRESSURE	Systolic pressure	x			
ABLE TO WALK[*]	Ability to walk	x		x	
INJURY OR HEMORRHAGE[*]	Major hemorrhage or severe injury				x
NUMBER OF RESOURCES[*]	Number of medical resources required for care		x		x
PAIN[*]	Evidence of pain		x		

[*] Indicates that this data point was derived from several other recorded data points.