2018

A Comprehensive Reengineering Of The Hospital Emergency Triage System

Nicholas D. Boltin
University of South Carolina

A COMPREHENSIVE REENGINEERING OF THE HOSPITAL EMERGENCY TRIAGE SYSTEM

by

Nicholas D. Boltin

Bachelor of Science
Appalachian State University, 2005

Submitted in Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy in

Biomedical Engineering

College of Engineering and Computing

University of South Carolina

2018

Accepted by:

Homayoun Valafar, Major Professor

Jenay Beer, Committee Member

Joan Culley, Committee Member

Jill Michels, Committee Member

Mark Uline, Committee Member

Cheryl L. Addy, Vice Provost and Dean of the Graduate School

DEDICATION

In memory of my grandfather Charles…

This work is dedicated to my family and future generations who may be faced with the overwhelming decision of pursuing a higher education. It can be done; it should be done. No matter what happens in life, you will always look back at this moment with an appreciation for the hard work and effort you have put forth on the pursuit of knowledge. It will be scary and downright brutal at times, but you will make the greatest friends, and nothing can describe the pride you will have when you cross that finish line. Surround yourself with people who want to see you succeed, and you will be successful. Good luck and I hope you find the following pages inspirational.

ACKNOWLEDGMENTS

Firstly, I would like to express my sincere gratitude to my advisor Dr. Homayoun Valafar for the continuous support of my Ph.D. study and research, for his patience, motivation, and immense knowledge. For having the courage to say yes when all others said sorry. I could not have imagined having a better advisor and mentor to provide guidance for my research.

I am also grateful to my thesis committee members: Dr. Joan Culley, Dr. Jenay Beer, Dr. Jill Michels, and Dr. Mark Uline for their encouragement, insightful comments, and stimulating questions which gave me the incentive to widen my research from various perspectives.

A special gratitude goes out to everyone at the National Institutes of Health for providing the funding for this work.

A special thanks to Diego Valdes, a lab mate, a fellow Marine and friend for his unwavering commitment to this project and always making sure we had coffee. Without his passionate participation and input EDICT would not have been successful.

To my lab mates: Mohammed Behbooei, Linkel Boateng, Chris Bowling, James Brubaker, Helen Carr, Casey Cole, Arjang Fahim, Stephanie Irausquin, Bethany Janos, Emily Ji, Devaun McFarland, Kenneth Nesbitt, Hanin Omar, Caleb Parks, Danial Vu. Thank you for the stimulating discussions and for all the fun we have had in the last four years.

Finally, I must express my profound gratitude to my parents and family for providing me with unfailing support and continuous encouragement throughout my years of study and through the process of researching and writing this thesis. This accomplishment would not have been possible without them. Thank you.

ABSTRACT

Hospital emergency triage and specifically Mass Casualty Incidents (MCIs) are of major concern with regard to treatment and patient outcomes. Traditional emergency department triage models are oversimplified and often lead to over/under triaging of patients. Furthermore, triage models do not account for the full spectrum of different types of MCIs which often results in misclassification. In this thesis, we begin by looking at traditional triage models currently being used in hospital systems and identify several shortcomings of using these models within the context of a chemical related MCI. I will then move to describe a new approach to creating a dynamically adaptive multi-phase triage system capable of managing patients regardless of the MCI scenario. The new system utilizes modern mobile technology and is capable of deploying artificial intelligence algorithms to assist caregivers with decision making. I discuss the data analytics and machine learning techniques necessary to create deployable AI and compare these models to current resources available for emergency decision support, WISER and CHEMM-ist. Finally, I will conclude by describing the Human-Computer Interaction (HCI) design of computational software capable of quickly collecting patient data, performing data analysis and provide caregivers with decision logic and situational awareness. This patient management system has the potential to improve patient treatment and outcomes with the added advantage of being integrated into current hospital Electronic Health Records

(EHR). Current hospital resources and triage models can be easily implemented and should be considered for Emergency Department (ED) deployment.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AI .... Artificial Intelligence

ANN .... Artificial Neural Network

BDT .... Binary Decision Trees

BP .... Blood Pressure

CBRN .... Chemical, Biological, Radiological, Nuclear

CERTS .... Community Emergency Response Teams

CSAC .... Chemical Security Analysis Center

DTC .... Decision Tree Classifier

ED .... Emergency Department

EDICT .... Emergency Department Informatic Collection Tool

EHR .... Electronic Health Records

ESI .... Emergency Severity Index

HCI .... Human Computer Interaction

HIS .... Health Information Systems

HR .... Heart Rate

LSI .... Lifesaving Intervention

MCI .... Mass Casualty Incident

NATO .... North Atlantic Treaty Organization

PCA .... Principal Component Analysis

SALT......................................Sort, Assess, Lifesaving Interventions, Treatment/Transport

SpO2 .... Oxygen Saturation

SSx .... Signs & Symptoms

START...Simple Triage and Rapid Treatment

TIH...Toxic Inhalation Hazards

TSA .... Transportation Security Administration

CHAPTER 1

INTRODUCTION

BACKGROUND – HISTORICAL REVIEW OF TRIAGE

The word “Triage” originates from the French word trier, to sort. It was originally used to describe the sorting of fruits and vegetable but in its present-day sense is almost exclusively used in the health care industry. Even though this review aims to look at the Emergency Department (ED) triage system, credit must be given to the military for its historical introduction into medicine. The practice of triage arose from the necessities of war, wherein the 18th-century military surgeon Baron Dominique-Jean Larrey in Napoleon’s Imperial Guard developed the first battlefield triage rules. Before then soldiers usually relied on comrades for aid and most died from inefficient care. Larrey had a simple rule when sorting patients for treatment on the battlefield: “Those who are dangerously wounded should receive the first attention, without regard to rank or distinction. They who are injured in a less degree may wait until their brethren in arms, who are badly mutilated, have been operated on and dressed, otherwise the latter would not survive many hours; rarely, until the succeeding day”[1].

British naval surgeon John Wilson was the next major contribution to military triage. Wilson argued that focus should be given to patients for whom treatment would be most successful. Treatment should be postponed to those whose wounds were probably fatal or would be without immediate intervention[2].

In the United States during the Civil War medical services were understaffed and poorly organized. Patient treatment was on a first come first serve basis. While this did establish priority, it did not address the relative urgency or the available resources. After a deadly first year, the Union Medical Corps significantly decreased their death rate by combining triage procedures with frontline medical care and ambulance services[3].

The introduction of deadly new weapons during World War I created an unprecedented number of patients needing rapid care. A description from a military surgical manual offers insight into the triage mechanism used at the time. "A hospital with 300 or 400 beds may suddenly be overwhelmed by 1000 or more cases. It is often, therefore, physically impossible to give speedy and thorough treatment to all. A single case, even if it urgently requires attention—if this will absorb a long time—may have to wait, for in that same time a dozen others, almost equally exigent, but requiring less time, might be cared for. The greatest good of the greatest number must be the rule"[4]. This approach to triage is much different than Larrey's thought that priority should go to the most severely injured and goes beyond Wilson's proposal that the hopelessly injured cannot be treated. It insists that a critical and treatable patient should not be given priority for treatment if the time required for providing that treatment would prevent treatment for other patients with critical but less complicated injuries. This approach explicitly recognizes that, when resources are limited, some patients who could be saved may be allowed to die to save others. It is evident that historically there is a considerable debate to which triage model should be used. As we will see in the following section, this continues to be the case even today.

MODERN DEVELOPMENT OF TRIAGE MODELS

Historically it has been the development of technology that has stimulated the development of modern triage models. The introduction of advanced warfare and weapons during World War II and the Korean War gave rise to situations in which large numbers of people quickly needed medical attention. In a 1958 North Atlantic Treaty Organization (NATO), military handbook described one of the first 3-tiered triage models as follows, (1) those who are slightly injured and can return to service, (2) those who are more severely injured and in need of immediate resuscitation or surgery, and (3) the "hopelessly wounded" or dead on arrival[5]. It is believed that civilian triage and modern Emergency Department (ED) triage have been adapted from military triage systems and in 1964 Weinerman et al. published the first systematic description of civilian EDs use of triage[6]. Although Weinerman's group was looking at the social economics of EDs being used as primary care for the lower class, the group does draw the conclusion that as the tendency of patients to use EDs for nonurgent situations increases, there needs to be a triage system in place to sort which patients need care the soonest.

Emergency departments continued to evolve over the years, and so did the use of triage systems. In modern, routine on-site ED triage, triage officers, usually nurses routinely assess all patients needing treatment and try to prioritize them according to greatest need of resources. In routine triage, ED resources are typically not overwhelmed, and in general, a three-level system is used. Those who are the most severe are prioritized on the top tier, and those with minor injuries are on a first come first serve basis[1]. More recently four and five-tiered models have gained popularity for not only routine emergencies but also when hospitals EDs become overwhelmed, and resources become limited. This allows for the highest priority patients to still occupy the top, first tier, but then lower lever tiers attempt to allocate resources accordingly to less severe patients. The following sections highlight several models currently being used throughout the world.

Simple Triage and Rapid Treatment (START)

In their simplest form, triage models are decision models that help emergency personnel decide which patients need care first. Initially developed for Community Emergency Response Teams (CERTS) and firefighters after earthquakes, the START algorithm has been used in the United States since the 1980s[2]. The primary focus of START is to sort disaster victims into four different categories based on the available transportation resources at the disaster site. Minimally trained first responders should be able to triage multiple victims in under 30 seconds based on observations of respiration, perfusion, and mental status[7].

The START algorithm is shown in Figure 1.1. This first step in the model is for the responder to assess the patient's ability to walk. If the patient can walk then the patient is labeled green, a low priority level. If the patient is not walking, then the next assessment is of the patients breathing. If the patient is not breathing, the triage officer can make an attempt to open the airway. If unsuccessful then the model categorizes the patient as expectant and unlikely to survive given the severity of the injuries and/or the level of available care. However, a moral debate, given this scenario, it may not be a priority to allocate resources to transport or provide care to an expectant patient. If spontaneous breathing can be restored, then the patient is categorized as a red level, the highest priority to be evacuated for immediate care. If further assessment is possible, then the next step is to assess the patient's respiration rate, radial pulse and finally their mental status. If any of these assessments are abnormal the patient still remains in the red, immediate, category; however, if the patient vitals are normal, and their status is not expected to deteriorate significantly over the next several hours then the patient could be moved to a yellow category, in which the patients' transportation would be delayed until all immediate cases have been provided care.

Figure 1.1 START Triage Model. A modern example of a tiered triage system for assessing patient severity.

In 2009 Kahn et al. looked at the START triage model to see how it would perform with real patient data collected from a train crash in 2003[8]. They conducted a retrospective analysis of the accident with patient data that was received from local emergency departments. The START algorithm was used by paramedics who were dispatched to the scene to categorize victim acuity. Data showed that out of the 148 patient records that were reviewed, 22 were triaged as red, 68 were triaged as yellow and 58 were triaged as green. They compared this actual data to their modified Baxt criteria, which is a set of standards against which major incident triage algorithms can be tested[9]. They found that the START model over-triaged 79 of the 148 victims to higher acuity levels than needed. 2 patients were truly red, 26 patients were truly yellow, and 120 patients were truly green. By over-triaging patients, resources are taxed more heavily, first responder teams can become worn out quickly and hospitals can become overwhelmed.

Chemical, Biological, Radiological, Nuclear Model (CBRN)

CBRN is one of the first models to look at a mass casualty incident (MCI) due to a chemical, biological, radiological or nuclear event. The complexity of one of these events can be challenging to first responders and medical caregivers who do not have advanced training. CBRN events involve unique hazards that require specific education and training. In an online survey conducted in British Columbia, participants were asked about their training level of CBRN events. Of the 1028 respondents, only 63% indicated they had received either theoretical or practical training to work in a contaminated environment. Of that 63%, only 42% had received training for symptoms of nerve agents, 37% had received training for symptoms of blister agents, and 46% had received training for symptoms of asphyxiants. Only 31% of all respondents had received training for detecting radiation[10]. In the model adapted from Cone et al. seen in Figure 1.2, patients are separated not only by the severity of their trauma but taking into account exposure to some toxic chemical or Toxidrome. A toxidrome is a group of signs and symptoms that are caused by a dangerous level of toxins in the body. Triage officers first assess the patient's ability to walk then try to determine whether there is evidence of a toxidrome to ascertain the decontamination classification. If there is no evidence of a toxidrome, the patient is classified as a T3, and their injuries can be considered minor. If there is evidence of a toxidrome, then the triage officer may attempt to give an antidote if available and logistically feasible. This patient is classified as a T2, and further care may be delayed. Further evaluation of the patient's breathing and ability to follow commands identifies the additional levels a victim could be classified.

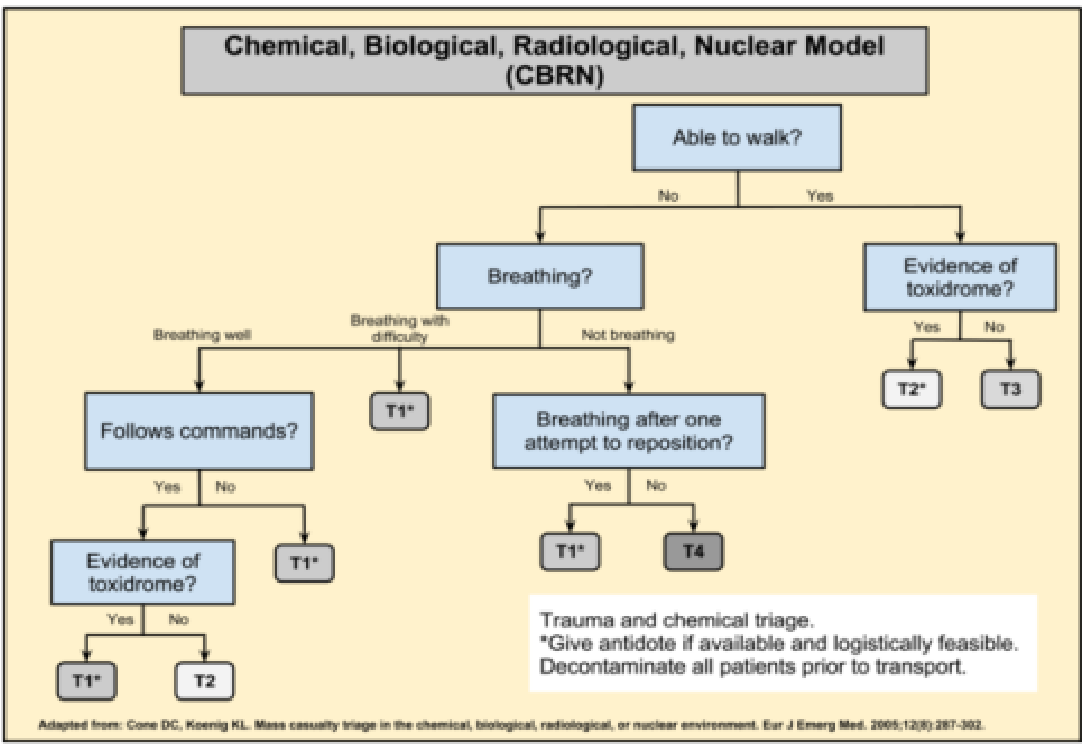


Figure 1.2 CBRN Triage Model. A triage tool used for classifying patients exposed to chemical, biological, radiological or nuclear disasters.

Table 1.1 CBRN Categories. Categories for triage classification of the Chemical, Biological, Radiological, Nuclear (CBRN) Triage model

Triage Category	**Action**
T1 – Immediate	Require lifesaving care within a short time
T2 – Delayed	Require hospitalization and prolonged surgery
T3 – Minimal	Have minor injuries
T4 - Expectant	Would not survive with optimal medical care

The CBRN model is useful in identifying the evidence of a toxidrome[11], allowing responders to implement appropriate methods for rescue, decontamination, and medical treatment. However, the model could fall short when faced with some biological responses. For instance, rapid assessment of individuals potentially exposed to specific biological or chemical substances may not be ideal. In some instances, the first indication of a problem may be delayed with the onset of illness following an exposure ranging from a few minutes to several weeks[12].

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

The SALT model is one of the most recent tools developed. In 2006, the National Association of EMS Physicians convened a workgroup to examine the science supporting the existing mass casualty triage systems and make a recommendation for adopting one of them as a national standard. The group of thirty members with various backgrounds in emergency medicine concluded that no existing triage system had enough scientific evidence to justify its universal adoption and that many had identified shortcomings in their methodologies. The workgroup instead developed the SALT model, which was based on a combination of expert opinion and the current research available for incorporating the widely accepted best practices of existing triage models[13]. Mechanisms of the SALT model are as follows. Step one is global sorting. The triage officer sorts the patients on their ability to either walk, give a purposeful movement or if they have an obvious life threat. This establishes the order in which the patients will be assessed, the obvious life threat being first and patients who can walk will be assessed last. During the assessment, the officer decides if the patient needs some sort of lifesaving intervention(LSI). If necessary, LSI is performed first before moving forward in the assessment. The next step is to give an individual assessment of the patients in the order as pre-determined by the previous step and assign one of five triage categories[14]. The criteria for each individual category are very specific and summarized in Table 1.2.

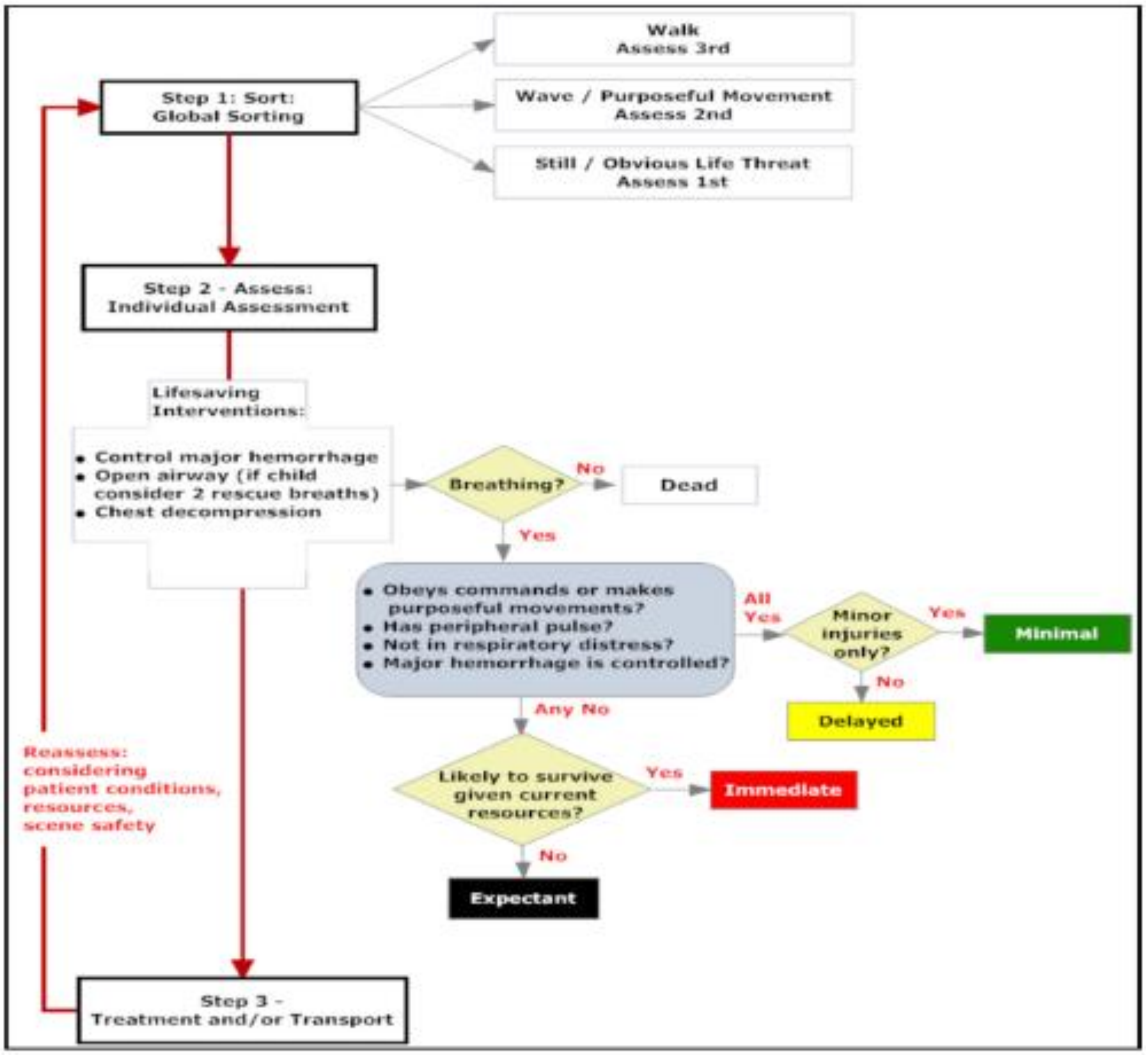


Figure 1.3 SALT Triage Model. Sort, Assess, Lifesaving Interventions, Treatment/Transport (SALT) is a modern example of a tiered triage system for assessing patient severity.

Table 1.2 SALT Triage Categories. Individual criteria for assessing patients and assigning triage categories using the SALT model.

Triage Category	**Assessment Criteria**
Dead	Patients not breathing after 1 attempt to open airway OR patient who can be identified as dead
Immediate	Patients unable to follow commands or make purposeful movements OR have no peripheral pulse OR obvious respiratory distress OR have a life-threatening external hemorrhage; provided they are **likely** to survive given the available resources
Expectant	Patients unable to follow commands or make purposeful movements OR have no peripheral pulse OR obvious respiratory distress OR have a life-threatening external hemorrhage; provided they are **unlikely** to survive given the available resources
Delayed	Patients who are able to follow commands OR make purposeful movements AND they have peripheral pulse AND not in respiratory distress AND do not have a life-threatening external hemorrhage AND they have injuries that are **not** considered minor
Minimal	Patients who are able to follow commands OR make purposeful movements AND they have peripheral pulse AND not in respiratory distress AND do not have a life-threatening external hemorrhage AND they have injuries that are considered minor

In 2009, Lerner et al. conducted a simulated mass casualty incident (MCI) to determine the accuracy of the SALT triage system. Seventy-three trainees participated in a two-day mock scenario where on day one they were taught the SALT triage system in a 30-minute lecture. On day two they were asked to assess and prioritize 28 to 30 victims. Victims included 10 to 11 moulaged manikins and 18 to 20 moulaged actors. Each victim had a card that stated the victim's respiratory effort, pulse quality, and ability to follow commands. Of the 212 victims observed, the initial triage was correct for 81%. Six percent were over-triaged, and 10% were under-triaged, and the mean triage interval was 28 seconds. The downside of this model is that the criteria for categorizing patients are very strict, and a simulated MCI does not necessarily reflect real-life situations. The simulated disaster did, however, show that the SALT system was very accurate at triaging patients and is the first model that address the concern of available resources, which is important for our next discussion on the emergency severity index.

Emergency Severity Index (ESI)

The Emergency Severity Index (ESI) is one of the most widely used hospital-based triage models in the United States. The original concept was developed by emergency physicians, Richard Wuerz and David Eitel in 1998 and by 2001 was adopted by seven hospitals. Today, the ESI model is in its 4th version[15]. Over the years, the model has undergone many reliability and validity studies and has shown that it is effective at categorizing patients[16, 17]. The ESI diagram can be seen in Figure 1.4. This tool applies to all ages and takes into account resources needed for each patient as well as different thresholds for the vital signs of each age category. The first assessment is whether the victim requires immediate lifesaving intervention, classifying the patient as a level 1, the highest and most urgent. Immediate intervention includes issues with the airway, requiring emergency medications, needs to be intubated, is in respiratory distress (oxygen saturation < 90%), has no pulse or is unresponsive. 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. The next assessment is based on the number of resources required for the individual patient. Examples of typical resources can be found in Table 1.3. If many resources are required then the vital signs for heart rate, respiratory rate, and the oxygen saturation are considered. ESI also allows for the classification of different age groups.

As seen in Figure 1.4, there are four age categories when considering the vital signs and different danger zones for vitals within each category.

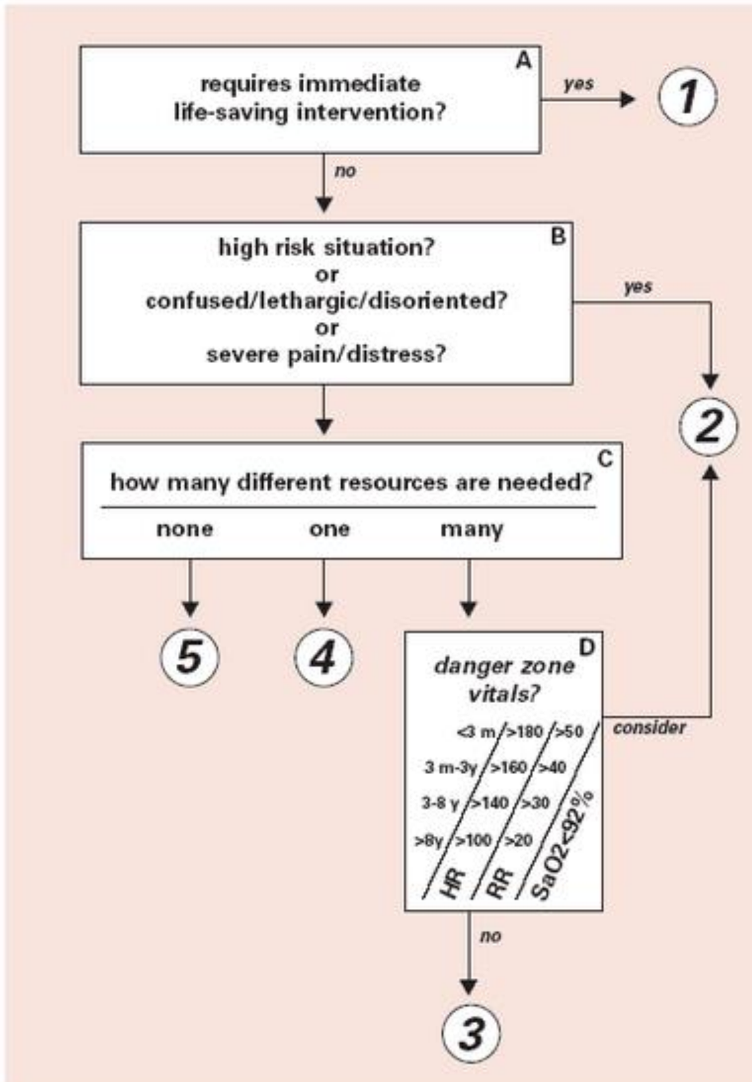


Figure 1.4 ESI Triage Model. The Emergency Severity Index is a modern example of a tiered triage system for assessing patient severity.

Table 1.3 ESI Triage Model Resources. Caregivers should count the number of different types of resources, not the individual test or X-rays.

Resources	Non-Resources
• Labs (blood, urine) • ECG, X-rays • CT-MRI-ultrasound-angiography	• History and Physical (including pelvic) • Point of care testing
• IV Fluids (hydration)	• Saline or heplock
• IV or IM or nebulized medications	• PO medications • Tetanus immunization • Prescription refills
• Specialty consultation	• Phone call to personal care physician

• Simple procedure = 1
  ○ (Lac repair, foley cath)
• Complex procedure = 2
  ○ (conscious sedation)
	• Simple wound care
	  ○ (dressings, recheck)
	• Crutches, splints, slings

In an observational cohort study Elshove-Bolk, et al. found that ESI reliably predicts the severity of a patient's condition. It also clearly identified patients who require minimal resources[18], such as a level 4 or level 5. To the contrary, a retrospective study done by van der Wulp et al. found that the elderly (65 or older) were more likely to be under-triaged as a level 4 or level 5, suggesting that the ESI model may not be sensitive to patients with important existing conditions or postoperative complications.

Motivation & Significance

Toxicology is an area of science concerned with mechanisms of action and exposure to chemical agents as a cause of acute and chronic illness. Toxicologists have been able to identify several groups of toxic agents in which harmful substances can be generally classified. They are Pesticides, Metals, Solvents/Vapors, and Radiation or Radioactive Materials. Most people can come into contact with one of these substances on a daily basis [19, 20]. For example, a person who works in an aircraft factory as a metal degreaser may be exposed to trichloroethylene (TCE exposure) daily. Another person may drive to the neighborhood bar after work and have a few drinks (ethanol exposure) and cigarettes (benzene and styrene exposure). Also, everyone may relate to stopping at a filling station for gasoline (benzene, toluene, 1,3-butadiene exposure) or the dry cleaners for laundry (tetrachloroethylene exposure). In addition, more hazardous materials are being transported every year by railway, highway, water, and air. Incidents involving hazardous material have been on an upward trend over the last ten years. According to the US Department of Transportation between 2006 and 2015, there have been 166,968 incidents involving hazardous substances, which cost taxpayers nearly 820 million dollars in damages[21]. Materials being transported on railways are a primary concern because these shipments routinely move through densely populated areas where an incident could result in loss of life, serious injury or significant environmental damage. Of particular interest, have been accidents involving materials that are poisonous, or toxic inhalation hazards (TIH materials).

Furthermore, the Center for Disease Control (CDC) has reported that the number of biological and chemical terrorism events has been on the rise for the last 10 years. The CDC states that the US is particularly vulnerable to chemical warfare due to the number of agents available to the public[22]. Recipes for preparing "homemade" agents are readily available, giving terrorists access to highly dangerous agents that can easily be engineered for mass dissemination. In the report published by the CDC, researchers recommended 1.) strengthen state and local surveillance systems for illness and injury resulting from pathogens and chemical substance, 2.) Develop new algorithms and statistical methods for searching medical databases on a real-time basis for evidence of suspicious events, and 3.) establish criteria or investigating and evaluating suspicious clusters of human disease or injury related to biological or chemical terrorism that provides situational awareness to key personnel [22]. Due to the concern for public safety, the United States spends 1.5 Billion dollars annually on emergency health preparedness. 255 million is spent every year to help prepare healthcare facilities prepare for, respond to and recover from medical emergencies like biological and chemical incidents.

In the following chapters, this thesis will outline a novel patient management system capable of providing better health preparedness and response to biological and chemical incidents. We begin by looking at several shortcomings to the traditional triage models and discuss the benefits to a dynamic triage system. We will then explore new algorithms and statistical methods capable of assisting caregivers with making decisions related to chemical events. Finally, we will conclude by describing the design of a computational software capable of investigating events by collecting patient data, quickly performing data analysis and provide key personnel with decision logic and situational awareness.

CHAPTER 2

A NEW APPROACH TO HOSPITAL TRIAGE DURING MASS CASUALTY INCIDENTS

LIMITATIONS OF TRADITIONAL MODELS IN HOSPITAL TRIAGE SYSTEMS

In the United States, the federal government spends 1.5 Billion dollars every year in emergency preparedness[23]. This money is used to fund programs such as the CDC, FEMA and the Hospital Preparedness Program (HPP)[24]. Through the HPP, 255 Million dollars is spent every year to help prepare hospitals and train emergency personnel on how to prepare for medical disasters. Funding through these programs has gone a long way to move emergency medicine forward; however, the current triage models discussed in Chapter 1 are primarily designed with a considerable emphasis on simplicity of their implementation. Previous studies indicate that no triage system is appropriate to manage a chemical release such as chlorine and their delayed or latent effects[25, 26]. In addition, there is not a nationally accepted standard model, and hospitals are free to choose whichever triage model works best for their system. In creating simplistic models, a number of other essential aspects of patient treatment and outcome are disregarded. Some of these aspects are described in the following section.

A Single Patient Model

By necessity, the current triage models described in Chapter 1 assume a single-patient model in order to simplify the triage process. This means that hospital triage models will use the same criteria to triage all patients and do not take into account patients with different signs and symptoms. However, patients exposed to the same hazardous toxidrome may exhibit very different signs and symptoms (SSx) from one another[25]. They may also exhibit additional latent symptoms that may not reveal themselves anywhere from hours to days after the exposure. None of the triage models described in Chapter 1 account for latent symptoms[26]. Therefore, a complete patient management system should be able to accommodate a broader range of patient models. An ideal patient management system should not only be able to monitor patients continuously, but also adapt and evolve to conditions within the environment. Furthermore, a more functional patient management system should provide a mechanism for interpreting an individual patient's SSx within the context of the latest information. For instance, the presence of a particular SSx may elicit a more immediate treatment in the context of a known chemical exposure (such as chlorine). An ideal system would be able to adapt to the latest information and state of the emergency for better interpretation of the SSx gathered by medical personnel. This would streamline the patient entry process thus optimizing patient care.

A Single Disaster Model

In addition to the generalization of patients, current triage models operate with a disregard for the nature of the MCI. The existing triage mechanisms equally and irrespectively apply to mass highway accidents, chemical exposures, food poisoning, or terrorist attacks to name a few. However, it is easy to argue that an optimal patient management system should not operate in a vacuum independent of the exact nature of the incident. An ideal system should be adaptive to become more optimally suited to the precise nature of the incident, as information is made available. For instance, as patients arrive at the ED and are evaluated through the patient management system, signs, and symptoms from individual patients are collected. The ideal system should then be able to evaluate the incident based on the patient population. Here the adaptive nature of the system allows for the individual patient evaluation to contribute to the discovery of the exact nature of the incident.

Current Triage Models and Hospital Resources

The ESI triage model described in Chapter 1 introduced the concept of hospital resources. Table 1.3 gives some examples of different resources however this list is too general and does not define all hospital resources. The ESI list also requires caregivers to memorize resources vs non-resources and keep track of the cost value of using individual resources. In addition, hospitals vary with the number and types of resources available. For example, a hospital in a large city may have over 100 beds available for patients (a typical measurement for hospital size), where a hospital in a rural community may only have 25 beds. An MCI is defined when a hospital's resources are exceeded or in threat of being over-run. By definition, this suggests that hospital resources are finite and should be continuously monitored, however in practice this is almost never the case [27]. The ESI model also does not account for resources that may fluctuate within the hospital such as the number of caregivers available to patients. Typically, a hospital will have a number of specialist, surgeons, and nurses on staff, however, these numbers can change throughout the day, week, or time of year. An ideal patient management system should be able to track hospital resources and be configured for individual hospitals[28]. By customizing the patient management system for each hospital, caregivers can have an accurate awareness of the resources available to allocate to patients. Notifications can also be developed to alert caregivers when resources are in danger of being over-run thus quickly identifying the possibility of an MCI event occurring.

Incomplete Patient Management System

Due to the chaotic nature of MCI, it is not entirely unexpected to encounter partially completed forms, indecipherable handwritten information. In addition, in the interest of simplicity, the current MCI triage protocols resort to simple procedures which are susceptible to mistakes and misinterpretation. Finally, the existing approaches do not aim to control the chaotic nature of an MCI by providing a global awareness of the situation (situational awareness). An ideal patient management system should be able to utilize advances in mobile technology. By introducing devices such as tablets, phones, and smartwatches a complete communication system can be developed by giving caregivers real-time global awareness and allowing them to allocate resources where necessary.

A DYNAMICALLY ADAPTIVE, MULTIPHASE APPROACH TO HOSPITAL TRIAGE

In this research project, we have developed a modernized approach to MCI management that addresses the shortcomings of the existing approaches discussed in the previous sections. Our work has incorporated emerging mobile technology with decision support and pattern recognition coupled with machine learning techniques in order to achieve its objectives. To accomplish this lofty objective, we will deploy a two-prong approach.

First, we redefine the current simplistic model of an MCI event to consist of multiple phases that take advantage of the evolving nature of an MCI event. A dynamic framework for the handling of an MCI will then allow for the development of an adaptive triage system. Typically, an MCI event starts with no to little-known information regarding the nature of the event, and it ends with full knowledge of everything that took place. Despite the gamut of the available information during the unfolding of an MCI, the triage mechanism remains static and unchanged. It is reasonable to argue that a more effective triage mechanism should take advantage of the available information in order to maximize patient outcome. Therefore, we define a three-phase model of an evolving triage mechanism that corresponds to three distinct phases of an MCI. The three phases are discussed further in the following three sections.

Chapter 5 describes a software-based intelligent system that is capable of implementing a more sophisticated orchestration of activities during an MCI. In the following sections of this chapter, we will outline the distinct operational phases of the patient management system. We will define what role technology plays in each phase to help develop a more sophisticated method for tracking and triaging patients during an MCI. Figure 2.1 shows an overview of our proposed patient management system. A central server will coordinate ED activities during an MCI by actively tracking patients. As a large number of patients arrive at the ED, general signs and symptoms can be collected through a patient kiosk system. This information is stored and analyzed by the central server. By obtaining the signs and symptoms of individual patients, the central server can assist nurses in assessing patient severity and assigning triage levels. Information regarding triage levels and patient severity can be communicated to nurses and caregivers via tablets or similar mobile devices. As the MCI develops, the central server continues to collect and analyze signs and symptoms from all the patients, thereby generating a global awareness of the MCI event and over time determining the exact nature of the MCI. Identifying the correct cause of an MCI event is very important, and while beyond the scope of this work, the central server could theoretically coordinate activities such as 1) send alerts to first responders on personal protective equipment (PPE) or decontamination protocols to deploy at the scene of the MCI, 2) send notifications to nurses on appropriate antidotes or medical procedures, and 3) refine the number and types of signs and symptoms collected at the patient kiosk system thus optimizing the assessment of patient severity. In Chapter 3 and Chapter 4, we dive deeper into the Artificial Intelligence models that can be deployed during an MCI event to assess patient severity and determine a culprit MCI. We will show how these models can be applied to an array of MCIs. However, our primary focus will be on the detection of an irritant gas and more specifically, chlorine gas.

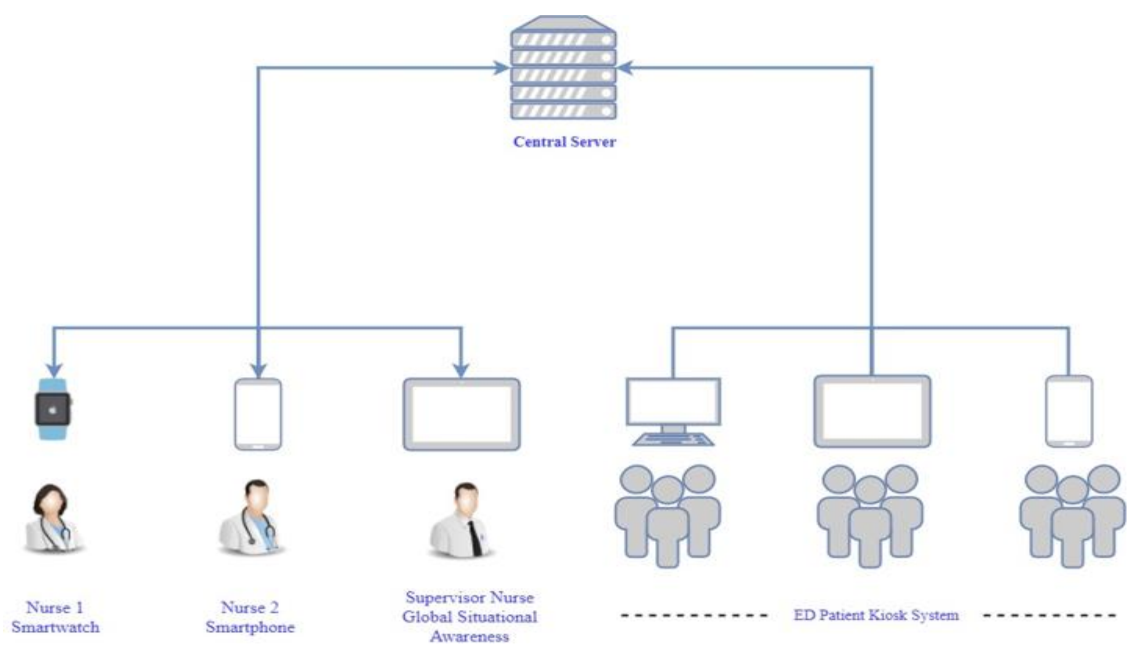


Figure 2.1 Overview of the Patient Management System. Information is collected from patients through a kiosk system and distributed to caregivers via a central server.

Phase 1: Normal Hospital Operations

In this work, we define phase 1 as the normal operational state of a hospital. During this phase, a monitoring system should be in place to detect the onset of a surge of patients into the ED. Figure 2.2 shows a diagram of the phase 1 monitoring system. Under these conditions, it is assumed that patient flow into the ED is at an acceptable rate and the hospital resource status is good. In phase 1 the ED will use its regular registration and triage process, be it ESI, START or any other triage model. In addition, there is a computational component monitoring ED operations and resources. This program would ideally be tied to the normal hospital patient registration and would be able to detect when hospital resources are in threat of being over-run. This program could be customized for each hospital depending on the hospital's available resources such as personnel, available beds, and equipment, etc. The program can then detect when one or more of these resources are in danger of being over-run. The program could be as complex as monitoring many resources before activating the next phase or as simple as monitoring the patient flow into the hospital ED. Obviously, a threshold can be different for each hospital but once that threshold is met the program can send warnings to hospital staff and trigger the transition to phase 2. Finally, the program will continue to monitor the situation for changes. If resources and patient flow fall back under the threshold, the program can alert staff and return to normal operations.

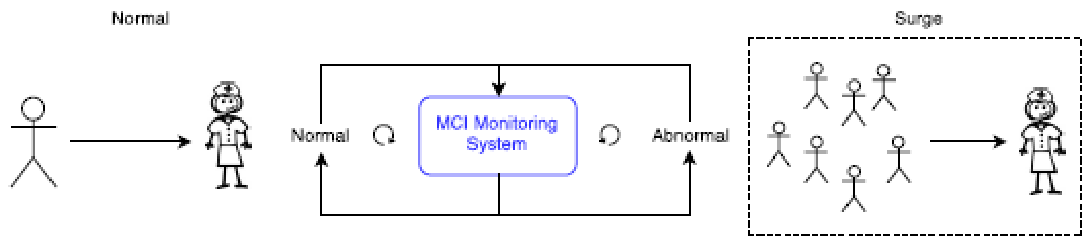


Figure 2.2 Phase 1, MCI Monitoring System. In its simplest for the new triage system can be tied into current hospital registration systems, monitor patient, and detect a patient surge or an influx of patients arriving to the ED

Phase 2: Mass Casualty Incident Detection

During phase 1, the hospital continues to operate in standard conditions with a program in the background monitoring the status of hospital resources and patient flow into the ED. While the dynamic nature of the program will allow for the monitoring of multiple resources, in its simplest form, the program can monitor the flow of patients into the ED. One of the earliest signs of an MCI is the influx of patients needing medical care. The patient flow is a value that can be measured through normal ED registration. While we recognize that this value can differ from hospital to hospital, we understand that each ED will have a threshold of patients they can receive over a given time period. When this threshold is met, the monitoring program will send hospital staff alerts that the patient flow is getting critical and advise the staff to switch to phase 2, shown in Figure 2.3. Phase 2's primary goal is to get as many patients into the data collection system as quickly as possible. To efficiently accomplish this task the first step is to barcode patients and store their values. This gives caregivers a way to track the patient through the data gathering system. Next, a primary triage is given to the patient by doing a quick visual assessment. This will allow the nurse to identify the most critical patients. Normally this assessment is done based on the ED's triage model and can range from the patient's ability to walk to the need for life-saving intervention. If the patient is determined critical, the patient is immediately removed from the triage area and given medical care. If the patient is considered non-critical, the patient is directed to one of two patient information gathering systems. Here, we envision several kiosk-type systems placed throughout the ED where non-critical patients can enter their personal information and symptoms through an interactive interface. The second information gathering system will be similar to the kiosk interface but with the assistance of hospital staff. This can help alleviate concerns of patients with disabilities. The kiosk systems will walk the patient through a program asking the most basic health questions relative to different MCIs. At first, the questions will be general in nature, but as more data is gathered, reduction techniques outlined in Chapter 4 will be deployed. This will quickly reduce the number of questions and time needed to assess a patient. The kiosk system will also gather basic vitals such as oxygen saturation, heart rate, and blood pressure. Based on the information collected at the kiosk, a computational AI model can give a suggested triage level. A nurse can then review all the information collected and the AI suggestions and provide a final triage for the patient based on the hospital's usual triage model.

Phase 3: Adapt to the Specific Mass Casualty Incident

While Phase 2 focuses on the ability to gather information from patients as quickly as possible, Phase 3 will be an adaptable model that will be able to change depending on the MCI detected. Phase 2 information is being gathered and stored but in addition, there will be a program evaluating this information and determining which type of MCI is taking place. During phase 3, the determinant of the MCI has been identified, and the ED can

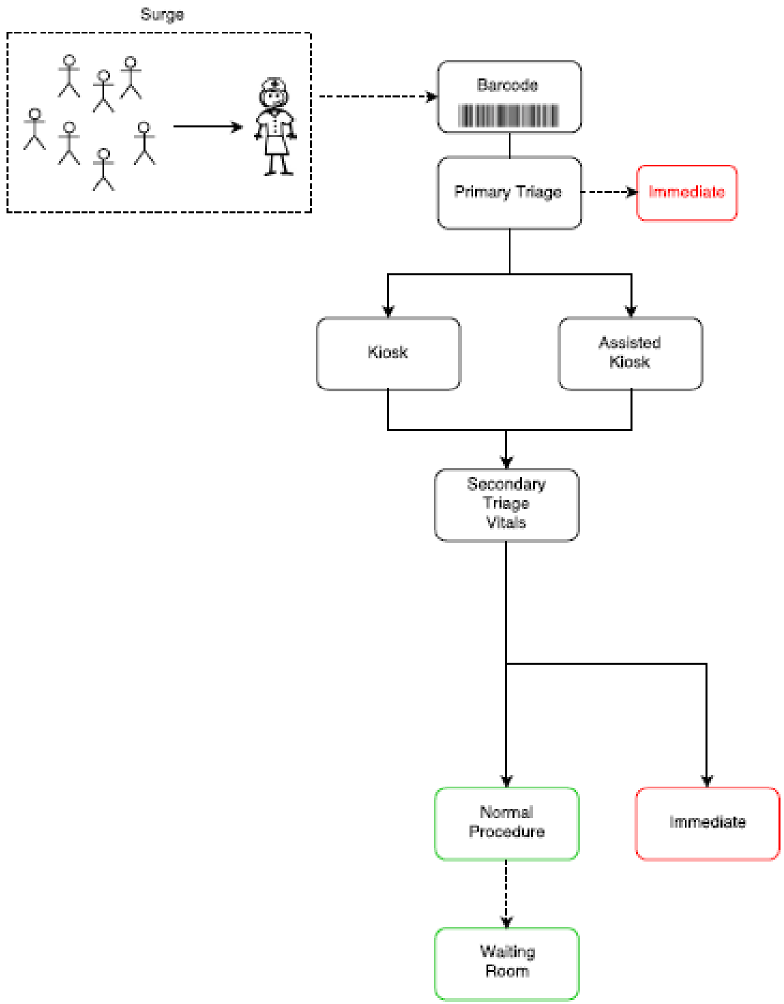


Figure 2.3 Phase 2, Surge Detection. An example of streamlining patients into the hospital triage system

modify their procedures accordingly. For example, depending on the type of chemical exposure a chemical-specific decontamination area can be set up. The patient flow for phase 3, shown in Figure 2.4, is similar to phase 2 where the first step is to continue barcoding the patients in order to identify and track them through the system. Next, the patient gets a primary triage to identify the most critical patients. Again, if the patient meets any of the critical requirements defined in traditional models then the patient is labeled as critical and immediate medical care is given. All other patients proceed to the kiosk data gathering system. However, the information now being collected can be specifically related to the identified MCI. For example, if an airborne culprit is detected, data may be gathered about the patient's pulmonary symptoms. Similarly, vital threshold values can be adjusted to monitor any respiratory distress and existing conditions closely. In addition to MCI specific related signs and symptoms, we have developed artificial intelligence (AI) protocols to assist caregivers in identifying chemically related MCIs. Further details will be given in chapter 3, but in general, we plan to deploy decision logic algorithms such as artificial neural networks and decision trees that will give a suggested culprit chemical. Caregivers can then review patient symptoms and the AI suggestion and either accept or reject the recommendation.

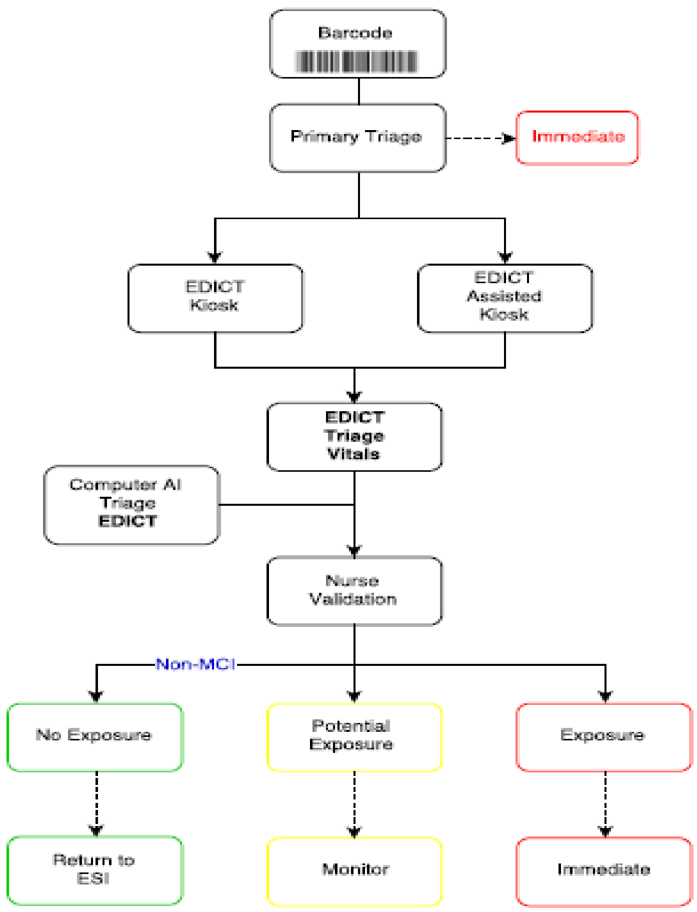


Figure 2.4 Phase 3, MCI Specific Triage. The model is an example of a proposed triage algorithm for detecting irritant gas syndrome (IGSA).

CHAPTER 3

AN AI MODEL FOR RAPID AND ACCURATE IDENTIFICATION OF CHEMICAL AGENTS IN MASS CASUALTY INCIDENTS[1]

[1] Boltin N, Vu D, Janos B, Shofner A, Culley J, Valafar H. 2016. *International Conference in Health Informatics and Medical Systems*, ISBN: 1-60132-437-5, 169-175.

Reprinted here with permission of publisher.

INTRODUCTION & BACKGROUND

Improvement of the healthcare system in the United States is the subject of great interest and debate in the social, political, and economic areas of our society. One obvious approach to improving the overall healthcare system is by eliminating the existing inefficiencies that impede our system[29-31]. Removal of inefficiencies impacts our healthcare network in two basic ways: significant improvement of the patient outcome and a reduction in the cost of healthcare. Although in principle it is clear that removal of inefficiencies is beneficial, in practice there has been little effort to eliminate the existing inefficiencies. This lack of effort is rooted in the complexity of our healthcare system that has manifested itself as a lack of consensus on the method of removing the existing inefficiencies.

Integration of technological advances in our healthcare such as utilization of mobile devices, availability of broadband systems with high throughput, and embedded clinical decision systems[32-34] is cited as some approaches that can reduce overall inefficiencies of our healthcare system. One branch of healthcare that can benefit from better streamlining of patient-care through the integration of clinical decision support is in emergency care during a mass casualty incident (MCI)[35]. The rapid operational tempo of an Emergency Room (ER) serves as an ideal vehicle to study any existing inefficiencies while the resource-limited conditions of an MCI will help in clearly gauging the impact of any proposed improvements. MCI events require rapid treatment of patients with minimum interruption for data collection, while optimal treatment of patients requires the hindering and cumbersome completion of detailed patient information to identify the culprit chemical substance. These two competing objectives have traditionally been a significant impediment to optimizing the MCI treatment process with a natural priority extended to the rapid treatment of patients. Therefore, there has been little advances in improving treatment of chemical MCI events. Research is needed to build a better understanding of the information and technological needs of the healthcare and public health workforce during emergency decision making[36].

A limited set of clinical decision support software has been introduced by the broader community[37]. The National Library of Medicine has created the Wireless Information System for Emergency Responders (WISER)[38], which allows emergency responders to identify a list of possible chemical substances based on the observed patient symptoms. The US Department of Health and Human Services has developed another software tool named the Chemical Hazards Emergency Medical Management-Intelligent Syndromes Tool (CHEMM-IST)[39]. CHEMM-IST is a prototype that guides first-responders through a series of questions related to signs and symptoms that leads to a probabilistic diagnosis of four syndromes rather than a list of chemical hazards. Although such software makes significant strides in assisting the process of emergency care, their efficacy has not been assessed during a chemical-based MCI.

In this report, we examine the effectiveness of WISER as the potential software for early identification of chemical material during an MCI event using simulated patient signs/symptoms (SSx) that we have reverse engineered from WISER. We also report results from Binary Decision Tree and Artificial Neural Network applications to the same set of simulated patient data. We conclude by reporting results of our initial investigation aimed at dimensional reduction of SSx space. Our final objective is to challenge the paradigm that rapid patient treatment is in contrary to data gathering that will assist in early identification of culprit chemical. We contest that careful design of sophisticated clinical decision support tools can satisfy both competing objectives of rapid information gathering and accurate chemical identification processes.

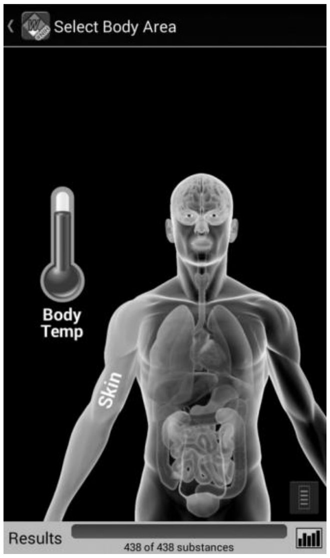
METHODS

Our general approach consists of creating signs and symptoms (SSx) for simulated patients using a reverse-engineered table of SSx from the WISER application. Using the simulated data, we then proceed to evaluate the successful identification of a culprit chemical using WISER, Binary Decision Tree (BDT), and Artificial Neural Network (ANN) machine learning approaches.

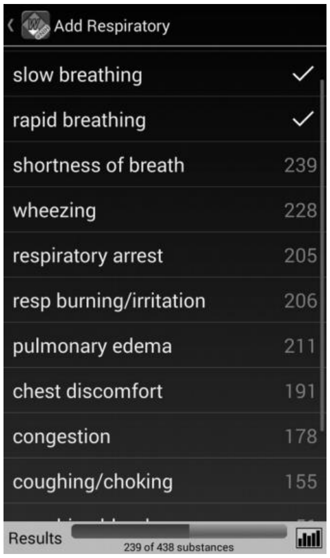
WISER

Wireless Information System for Emergency Responders (WISER)[38] is a free application available for Android and iOS. WISER can also be downloaded as a standalone application on a desktop computer. Developed by the National Library of Medicine (NLM), WISER is a system designed to assist emergency responders in hazardous material incidents. It provides a wide range of information on hazardous substances, including substance identification support, physical characteristics, human health information and containment and suppression advice. Its key features include rapid access to the most critical information about a hazardous substance by an intelligent synopsis engine and display called "Key Info," and access to NLM's Hazardous Substances Data Bank (HSDB), which contains detailed peer-reviewed information on hazardous substances and comprehensive decision support.

The key feature in WISER most relevant to this work is the Substance ID Support (SIDS). It allows an emergency responder to input patient symptoms, from which the SIDS will identify one or more likely hazardous chemicals causing those symptoms. WISER contains a checklist of 79 SSx, which are input for selected systems of the body through an interactive tool as seen in Figure 3.1a. As the signs and symptoms are entered (Figure 3.1b), the pre-populated library of 438 hazardous substances is successively reduced. The user can view the list, select a substance and view toxicology information available in the HSDB, which contains data from the NLM Toxicology Data Network (TOXNET)[40]. The HSDB data file contains information on human exposure, industrial hygiene, emergency handling procedures, environmental fate, regulatory requirements and related area.



(a)



(b)

Figure 3.1 Wireless Information System for Emergency Responders (WISER) for Android operating systems. Panel (a) is the interactive tool and panel (b) is the symptom selection interface. Panel (b) also shows the substance ID support in which an emergency responder can identify an unknown substance based on signs and symptoms of victims.

Reverse Engineering and Compression of the WISER Database

A thorough evaluation of WISER necessitated reverse engineering of all WISER's substances with their associated SSx. This task was performed by manually reviewing NLM's HSDB and parsing the SSx for each substance. An example of the resultant table of SSx is shown in Figure 3.2. Each of the 438 substances found in WISER is represented in the first column in this table, and the following 79 columns represent the corresponding SSx found in WISER for a given chemical. The presence or absence of each SSx is indicated by a 1 or a 0 respectively.

	A	B	C	D	E	F	G	H	I	J
1		abdom_di	abdom_di	agitation	arrhythmi	blistering	bloody_n	bradycard	cardiovas	chest_
2	1,1,1-Trichloroethane	1	0	1	1	1	0	1	1	
3	1,1,2,2-Tetrachloroethane	1	0	1	1	1	0	1	1	
4	1,1-Dichloroethane	1	0	1	1	0	0	1	1	
5	1,1-Dichloroethylene	1	0	1	0	0	0	0	1	
6	1,1-Difluoroethane	0	0	1	1	0	0	1	1	
7	1,1-Difluoroethene	0	0	1	1	0	0	1	1	
8	1,1-Dimethylhydrazine	0	0	1	1	0	0	1	1	
9	1,2,4,5-Tetrachlorobenzene	0	0	1	0	0	0	0	0	
10	1,2-Dibromo-3-chloropropane	1	1	0	1	1	0	1	1	
11	1,2-Dichloroethane	1	0	1	1	0	0	0	1	
12	1,2-Dichloroethylene	1	0	1	1	0	0	1	1	
13	1,2-Dichloropropane	1	0	0	1	0	0	1	1	
14	1,2-Diphenylhydrazine	0	0	1	1	0	1	1	1	

Figure 3.2 WISER's Reconstructed Database. The database was reversed engineered using NLM's toxicology information stored in the Hazardous Substance Data Bank (HSDB)

Examination of the created database revealed several substances with identical SSx profiles. In such instances, a cluster of chemicals was reduced to a single representative. The list of uniquely distinguishable chemicals was then reduced from 438 substances to 311 unique substances, which serves as the reverse-engineered list of individual chemicals.

Creation of Simulated Victims (Test Sets)

Simulated patient-data were generated from the ideal database of 311 unique substances by perturbation of randomly selected SSx. This was done to precisely control the amount of missing data. Signs and symptoms related to a real MCI would be ideal. However, accurate patient records during these scenarios are limited and usually incomplete[41, 42]. Each substance was replicated 100 times to create a reasonably extensive testing set that consisted of 31,100 simulated victims. Three data-sets were created by random toggling of selected SSx at 5%, 10%, and 15% selection rates. Probability density profiles were examined to ensure the proper random selections of perturbed SSx across each of the simulated patient-data. An overview of the perturbed data-sets (shown in Figure 3.3) corroborates the intended rates of perturbation.

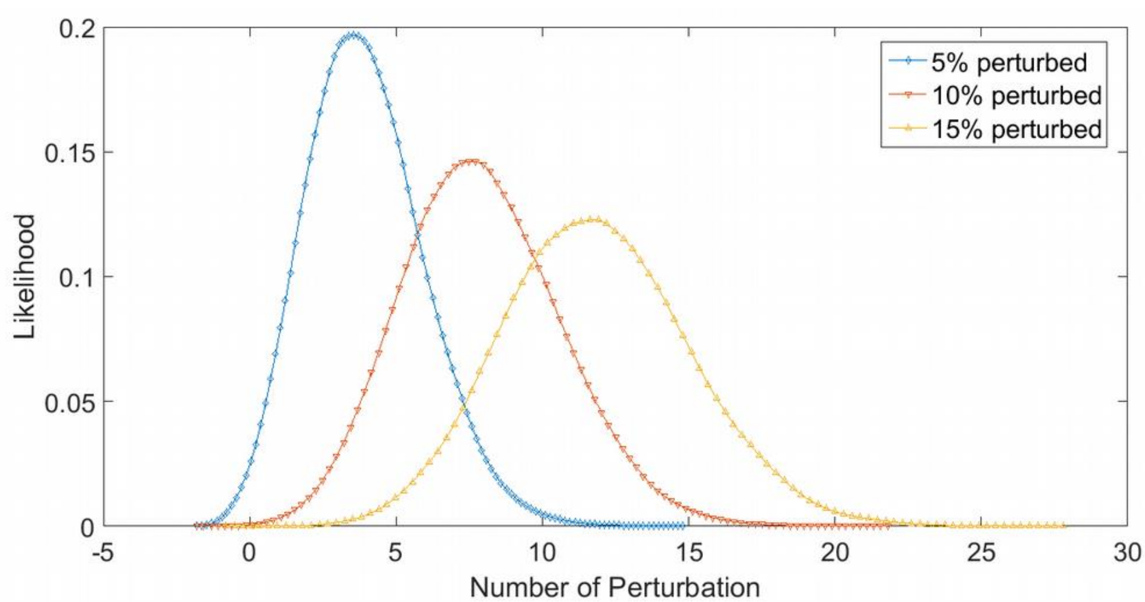


Figure 3.3 Kernel Density Estimations for three test data-sets. Test data were created by starting with the ideal table of symptoms from WISER and changing the symptoms by 5%, 10%, and 15%.

Overview of Machine Learning Approach

Our general work-flow for creating predictive models can be found in Figure 3.4. Supervised machine learning techniques were utilized in the Matlab 2015Rb environment to identify patterns and to develop predictive models. Our process began by importing the reverse-engineered database of 311 unique substances followed by training of two types of classification models: Binary Decision Trees (BDT) and Artificial Neural Networks

(ANN). After successful training of a given model, the known SSx profile for all 311 substances was tested on the trained model to establish proper learning (testing for memorization versus generalization is conducted in a different step). The model with the highest accuracy during the training was chosen as the final model. Evaluation of each trained model was then assessed using the SSx profiles of the 31,100 simulated victims. Prediction accuracy was calculated using Equation 3.1. In this equation A represents the accuracy of the model (expressed in %), N_c indicates the number of correctly identified chemicals, and N_{total} represents the total number of trials (31,100 in this case). The next sections provide a more detailed description of the training and testing for each model.

$$A = \left(\frac{N_c}{N_{Total}}\right) \cdot 100 \qquad \text{Equation 3.1}$$

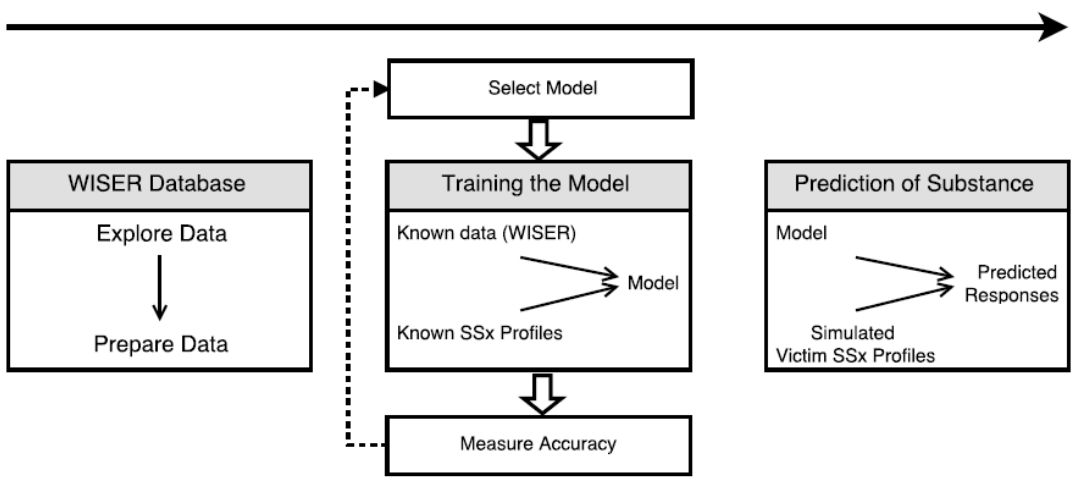


Figure 3.4 Workflow Diagram for data mining, training models and predicting substances using supervised machine learning techniques

Training and Testing of Classification Methods

We evaluated three common classification approaches in our investigation. The classification approaches consisted of: database look-up (as implemented by WISER), Binary Decision Trees, and Artificial Neural Networks. Details for each of the three approaches are described in the following sections.

Database Lookup (WISER)

The interactive nature of WISER was the limiting factor in automated and batch evaluation of WISER for 31,100 patients each represented by 79 SSx. This limitation served as one of our primary motivations in establishing a local database of WISER SSx. The first step in replicating a process identical to the WISER application was to understand its selection logic. WISER selects chemicals only based on the presence of a symptom and not its absence. Therefore, WISER will identify the entire library of 438 (or 311 unique) chemicals as the potential list of possible exposed chemicals for a patient exhibiting no apparent SSx. While this logic may appear questionable in our application, we proceeded with our evaluation of WISER in an exact fashion. Our initial evaluation of WISER consisted of a query-based search of our local database of chemicals using MySQL database engine housed on an Ubuntu LTS 14.04 server. This approach required a database lookup for SSx of all 31,100 simulated patients. Since the WISER approach may (and most likely will) return a list of potential chemicals, the database look-up step is followed by a search for the existence of the right chemical in the list of returned chemicals. Although the time requirement of this evaluation mechanism was feasible (in the order of a week) for a list of 31,100 patients, it is an impractical approach for future investigations with larger data-sets to establish a more thorough evaluation of the methods. Our most current strategy consists of an in-house developed program to simulate this table look-up process. Our evolved procedure returns the identical results that WISER would return while reducing the search time from months to seconds. Our testing process consisted of recording the number of times that the correct chemical was present in the list of returned chemicals similar to Equation 2.

Since WISER operates in a deterministic fashion, a statistical model of its performance can be developed. By assuming that every patient will undergo an alteration of exactly *n* SSx, it can be argued that WISER's outcome should closely follow a success rate shown in Equation 3.2. This equation lists all of the possible perturbation of SSx that will result in removal of the correct chemical in WISER’s resultant list. This equation can be simplified using the Binomial theorem as shown in Equation 3.2. Based on binomial distribution modeling of the WISER's outcome, a success rate of 6.25%, 0.4%, and 0.02% can be expected for the cases of 5%, 10% and 15% perturbation of SSx.

$$\mathrm{r} = 1 - \sum_{i=1}^{n} \binom{n}{i} p^i (1-p)^{n-i} = \frac{1}{2^n} \qquad \text{Equation 3.2}$$

Binary Decision Tree

A Binary Decision Tree (BDT) was trained using the reverse-engineered WISER database within the Matlab 2015Rb environment. A maximum deviance reduction was used as the split criterion with 350 maximum splits. Each of the 311 chemicals was replicated 312 times to facilitate the construction of a complete tree and in consideration of Matlab's training algorithm. Under this training conditions, a classification rate of 100% was achieved.

Our adopted testing procedure consisted of observing the chemical identification accuracy of the trained network with the simulated patient-data. It is noteworthy that the trained BDT was based on ideal data while the testing was based on the perturbed data-sets (5%, 10%, and 15% perturbation).

Artificial Neural Network

An Artificial Neural Network (ANN) was trained through the Pattern Recognition toolbox of the Matlab 2015Rb using back-propagation learning algorithm[43-45]. The unique set of 311 ideal chemical SSx was used during the training of the ANNs. The training set consisted of 5 identical replicas for each of the unique 311 chemicals (for a total of 1555 training patterns) to accommodate a random selection of the cross-validation and testing sets. The 1555 training patterns were randomly partitioned into 70% for training, 15% for cross-validation and 15% for testing. Numerous ANNs were trained and tested for selection of the optimal number of hidden neurons. Our investigation concluded 20 neurons as the optimal number of hidden neurons. The final trained ANN model exhibited cross-entropy results of 4.4 for the training set, 12.7 for the cross-validation set, and 12.7 for the testing set. These outcomes correspond to 0% error for the training set, 2.1% error for the validation set and 2.1% for the testing set. 31,100 simulated patient-data were used as unknown data and inputs to test the performance of the trained ANN network.

RESULTS AND DISCUSSION

Database Lookup (WISER)

The results of WISER database look-up approach are shown in Table 3.1 and exhibit a reasonable correlation to the binary distribution model shown in Equation 2. The rapid decay in performance of WISER is easily expected. We use the results of WISER as the basis of comparison since it is the most prominent and existing mechanism.

Table 3.1 Prediction accuracy results from WISER testing using 31,100 simulated patient-data perturbed at 5%, 10%, and 15%

Data-set	Prediction Accuracy	Max	Min
5% Perturbed	1.8%	7%	0%
10% Perturbed	2.3×10^{-2}%	1%	0%
15% Perturbed	0.0%	0%	0%

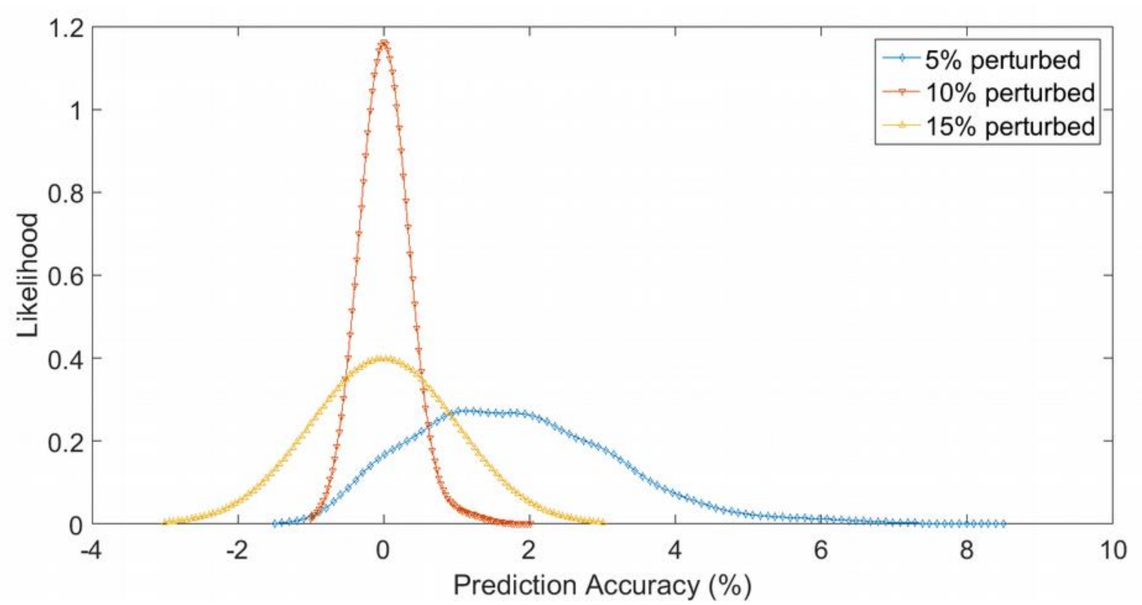


Figure 3.5 The Kernel Density Estimations from testing WISER with 31,100 simulated patient-data perturbed at 5%, 10%, and 15%

Binary Decision Tree

Testing results for BDT are shown in Table 3.2. In this table, the first columns represent the severity of the perturbation and the second column corresponds to the classification accuracy of the BDT. The third and fourth columns of Table 3.2 list the minimum and maximum performance across all of the 311 chemical substances. To better understand the performance of the BDT across the entire ensemble of 311 chemicals, a probability density function was created using the Kernel Density Estimation (KDE) technique[43, 46]. Figure 3.6 illustrates the statistics for BDT classification behavior over the entire 100 representatives of each 311 chemicals. The nearly Gaussian distribution of the statics indicates a very well-behaved system without any particular bias.

Another critical factor to monitor during the construction of a BDT is the topology. Figure 3.7 illustrates the topology of the final tree (in the interest of simplicity the labels are omitted), which indicates a very well-balanced tree of depth 9. This depth is in perfect theoretical agreement with the complexity of the problem, serving as another indication of a successful training session.

Table 3.2 Prediction accuracy results from Binary Decision Tree (BDT) testing using 31,100 simulated patient-data perturbed at 5%, 10%, and 15%

Data-set	**Prediction Accuracy**	**Max**	**Min**
5% Perturbed	64.9%	81%	53%
10% Perturbed	41.8%	54%	27%
15% Perturbed	25.6%	40%	13%

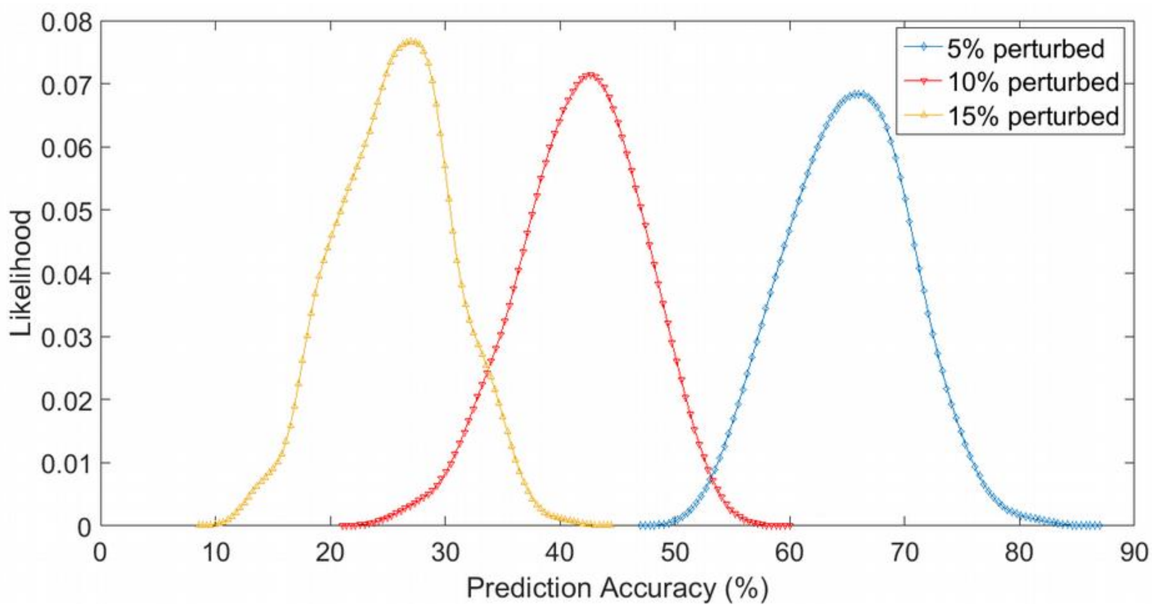


Figure 3.6 The Kernel Density Estimations from testing the BDT with 31,100 simulated patient-data perturbed at 5%, 10%, and 15%

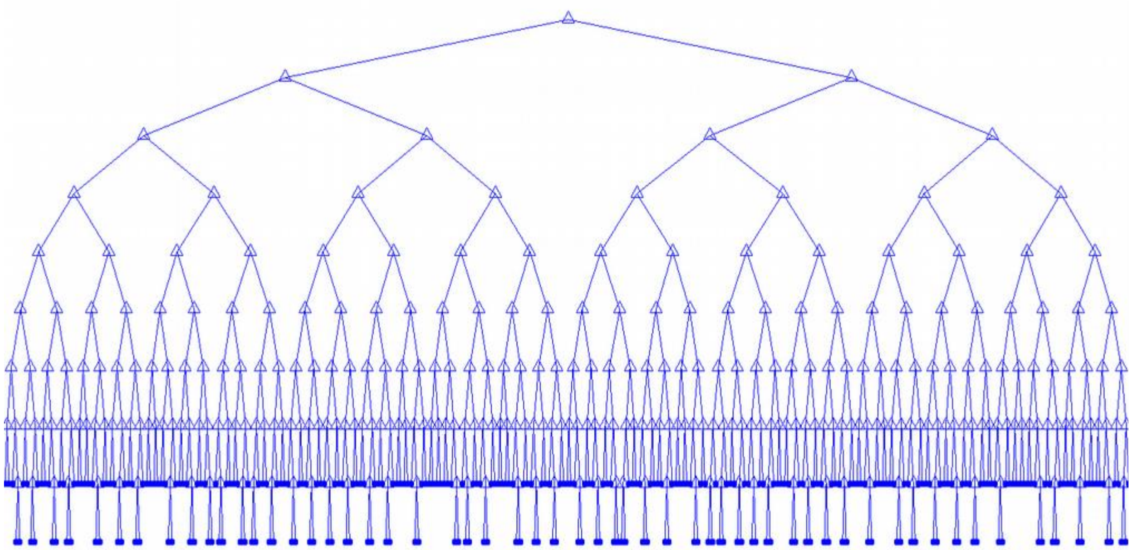


Figure 3.7 Static Binary Decision Tree for 311 unique chemicals found in the National Library of Medicine's Hazardous Substance Data Bank (HSDB)

Artificial Neural Networks

The evaluation results of the ANN are shown in Table 3.3. Similar to the results of BDT, the first two columns of this table indicate the severity of perturbation and outcome accuracy, while columns three and four indicate the range of the outcomes across all 311 chemicals. Remarkably the accuracy of BDT and ANN appear to be similar, while the range of the ANN's performance exhibit a more substantial variation. To better understand the statistics of the ANN's results, probability density profiles were created for each of the experiment using KDE using the exact parameters as the BDT (identical kernels). Similar to BDT, the Gaussian nature of the outcomes indicate a well behaved and un-biased system. Visual inspection of Figure 3.8 confirms the noted differences in variation of outcomes compared to the BDT results.

Table 3.3 Prediction accuracy results for the Artificial Neural Network (ANN) testing using 31,100 simulated patient-data perturbed at 5%, 10%, 15%.

Data-set	Prediction Accuracy	Max	Min
5% Perturbed	67.2%	96%	28%
10% Perturbed	38.4%	73%	10%
15% Perturbed	21.4%	49%	3%

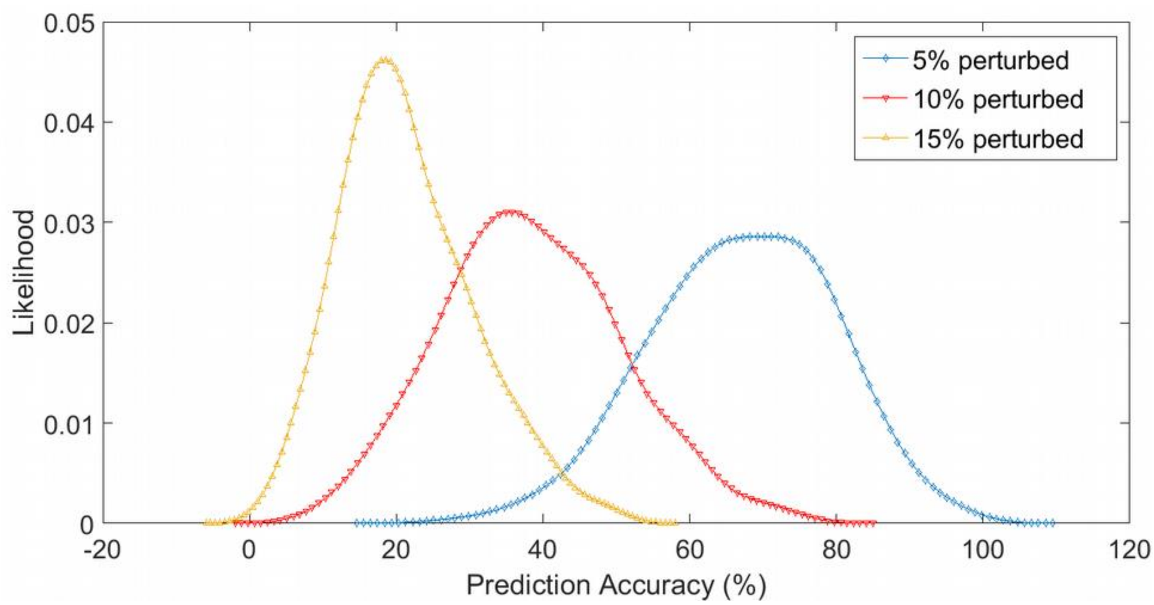


Figure 3.8 The Kernel Density Estimations from testing the ANN model with 31,100 simulated patient-data perturbed at 5%, 10%, and 15%

Dimensional Reduction

To optimize the Artificial Neural Network model, we examined the number of hidden neurons being used during the training phase of the model development. 10 models were trained, each with a different number of hidden neurons starting with 10 hidden neurons, then incrementing by 10 and the final model using 100 hidden neurons. After the model was created, additional testing was performed using the 5% perturbed data-set, and the amount of error from the ANN was recorded. As seen in Figure 3.9, the results show that as we increase the number of hidden neurons, the amount of error from the ANN is reduced with the minimal amount of error being 15.4% at 100 hidden neurons. We then examined training the ANN with only the first 40 SSx instead of the complete database of 79 SSx. Again, 10 models were trained starting with 10 hidden neurons at increments of 10 to 100 hidden neurons. After training the ANN, additional testing was also performed using the 5% perturbed data-set and recording the ANN error. It can be seen in Figure 3.9; the results followed the same pattern as with 79 SSx with the minimal amount of error being 25.8% at 40 hidden neurons. This indicates that using the first 40 SSx can reduce the amount of collected data with an acceptable reduction in the classification rate. This small reduction in classification can potentially be minimized through a more informed selection of SSx and analysis of the MCI over the entire cohort of victims.

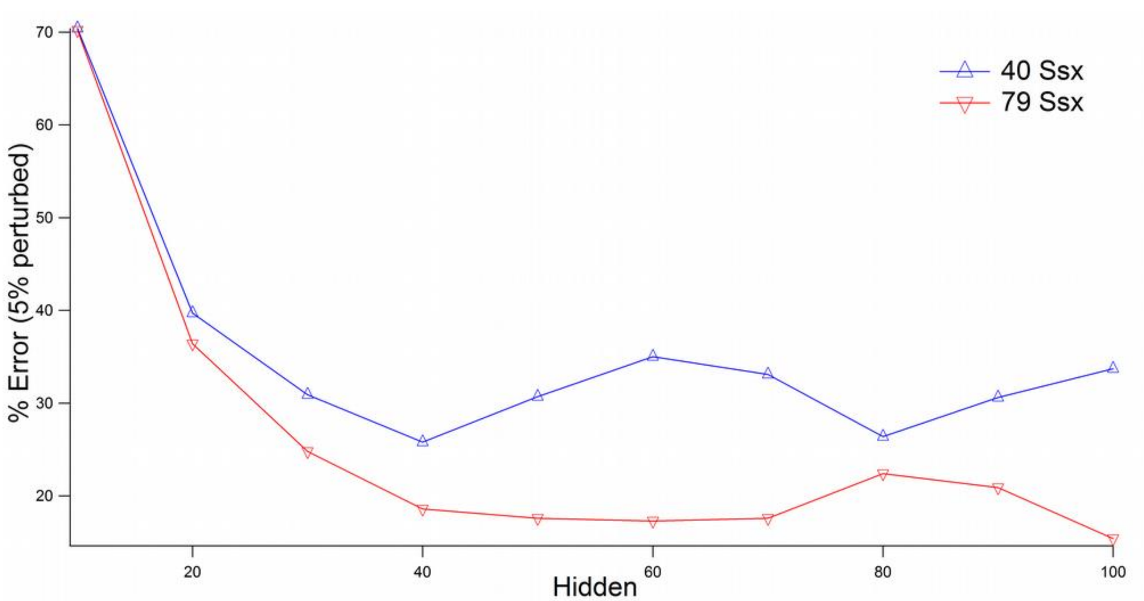


Figure 3.9 Dimension Reduction of ANN. Optimizing the number of hidden neurons used in training the Artificial Neural Network. We used the 5% perturbed simulated patient-data for additional testing on the model.

CONCLUSION

Our overall approach consisted of evaluating WISER in application to MCI under more realistic conditions. We have used the results of WISER as the basis of comparison to highlight the advantages and disadvantages of BDT and ANN; two common classification approaches in machine learning. The summary of results shown in Figure 3.10 illustrates the significantly improved chemical identification performance that can be obtained from BDT or ANN compared to WISER. Results reported in section 3.1 (also summarized in Figure 3.10) reflect the intolerance of WISER to erroneous and imperfect data; a condition that is very likely to occur during the chaos and confusion that occurs during an MCI. Furthermore, WISER operates with a luxury of reporting a potentially long list of unrelated chemicals that share a common list of present SSx. Presenting a long list of unrelated chemicals may provide additional confusion during an MCI. However, creating a list of chemicals affords the benefit of operating with fewer SSx. Therefore, WISER exhibits the advantage of using as many or as little number of SSx as are available while BDT and ANN require a fixed number of SSx in their successful deployment.

Results for BDT and ANN evaluations reported in sections 3.2 and 3.3 highlight the significant robustness of these more sophisticated approaches compared to WISER. In summary, BDT and ANN show promise when compared to WISER for quickly and accurately identifying a culprit chemical during a chemical MCI. This gain in robustness is achieved through the use of these machine-learning techniques' ability to generalize and not simply memorize. Furthermore, BDT provides the clear advantage of arriving at a single chemical requiring only 9 SSx (based on the depth of the tree shown in Figure 3.7). ANN exhibited the same degree of robustness compared to the BDT but with the apparent disadvantage of requiring all 79 SSx during the process of substance identification. However, our exploration of dimensional reduction and results shown in section 3.4 support the possibility of using only 40 of the 79 SSx with little reduction in performance.

Our future investigations will focus on further reduction of data dimensionality by the use of previously established methods such and Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA)[43]. AI tools employed during chemical MCIs could dramatically reduce the amount of information collected from patients resulting in increased accuracy, precision, and efficiency in identifying the chemical.

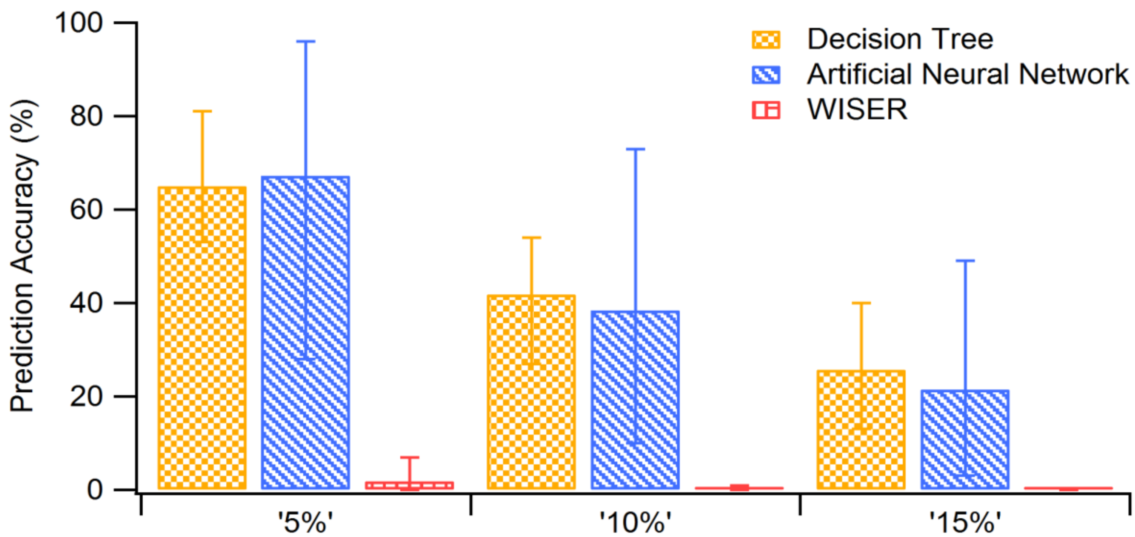


Figure 3.10 Overall prediction accuracy for the BDT model, the ANN model and WISER. Each model was tested with 31,100 simulated patient-data perturbed at 5%, 10%, and 15%.

ACKNOWLEDGMENTS

This study was supported by the National Institutes of Health/The National Library of Medicine grant number 5R01LM011648.

CHAPTER 4

APPLICATION OF DIMENSIONAL REDUCTION IN ARTIFICIAL NEURAL NETWORKS TO IMPROVE EMERGENCY DEPARTMENT TRIAGE DURING CHEMICAL MASS CASUALTY INCIDENTS[2]

[2] Boltin N, Culley J, and Valafar H. To be submitted to the Journal of Medical Internet Research.

INTRODUCTION & BACKGROUND

Improving patient wait times and length of stay in Emergency Departments (ED) has the ability to improve patient quality of care and reduce hospital and emergency response cost. Studies have shown that increasing a patient's length of stay as much as two hours can cost the hospital more than $3 million annually. Likewise, ED crowding is associated with inferior health care and loss of revenue[47-50]. Hospitals have always been faced with the burden of collecting as much information as possible while efficiently triaging all patients with accurate precision. Healthcare providers are now looking to utilize modern technology to assist caregivers with complex decision making.

WISER[38] is a software decision support system developed by the National Library of Medicine (NLM) and is designed to assist emergency responders in hazardous material incidents. It provides a wide range of information on hazardous substances, including substance identification support, physical characteristics, human health information and containment/suppression advice. Its key features include rapid access to the most important information about a hazardous substance via NLM's Hazardous Substance Data Bank (HSDB), which contains detailed peer-reviewed information on hazardous substances and comprehensive decision support.

Previous work done by this lab has demonstrated that chemical identification accuracy could be improved by integrating machine learning algorithms into WISER's substance ID support tool[51]. In this study, we aim to continue improving WISER's support system by reducing the number of signs and symptoms (SSx) needed to identify a hazardous chemical through statistical dimension reduction techniques. By reducing the number of SSx needed, we can reduce the amount of time required to evaluate a patient.

This will increase triage efficiency while maintaining information integrity and reduce the time patients wait to see a caregiver. Ultimately, a more efficient triage will reduce the length of stay and improve patient quality of care.

METHODS

Description of the Training and Testing Data-sets

The data-set used for training artificial neural networks in this study was collected by reviewing the toxicology information in WISER which is derived from NLM's Hazardous Substance Data Bank (HSDB). A listing of 438 chemicals containing 79 associated signs and symptoms was created. An example of the resultant table is shown in Figure 4.1. Each of the 438 substances found in WISER is represented in the first column, where columns 2-80 represent the corresponding 79 SSx found in WISER for a given chemical. The presence of absence of each SSx is indicated by a 1 or 0 respectively.

Examination of the created data-set revealed several substances with identical SSx profiles. In instances where chemicals contained the same profile, this cluster of chemicals was reduced to a single representative. It is understood that two chemicals that produce the same signs and symptoms may not be treated in the exact same way with regard to patient care. However, it is necessary to reduce these sub-groups to a single representation in order to remove bias towards a particular chemical profile. The list of uniquely distinguishable chemicals was then reduced from 438 substances to 311 unique substances, which serves as the reverse-engineered list of unique chemicals.

	A	B	C	D	E	F	G	H	I	J
1		abdom_di	abdom_di	agitation	arrhythmi	blistering	bloody_n	bradycard	cardiovas	chest_
2	1,1,1-Trichloroethane	1	0	1	1	1	0	1	1	
3	1,1,2,2-Tetrachloroethane	1	0	1	1	1	0	1	1	
4	1,1-Dichloroethane	1	0	1	1	0	0	1	1	
5	1,1-Dichloroethylene	1	0	1	0	0	0	0	1	
6	1,1-Difluoroethane	0	0	1	1	0	0	1	1	
7	1,1-Difluoroethene	0	0	1	1	0	0	1	1	
8	1,1-Dimethylhydrazine	0	0	1	1	0	0	1	1	
9	1,2,4,5-Tetrachlorobenzene	0	0	1	0	0	0	0	0	
10	1,2-Dibromo-3-chloropropane	1	1	0	1	1	0	1	1	
11	1,2-Dichloroethane	1	0	1	1	0	0	0	1	
12	1,2-Dichloroethylene	1	0	1	1	0	0	1	1	
13	1,2-Dichloropropane	1	0	0	1	0	0	1	1	
14	1,2-Diphenylhydrazine	0	0	1	1	0	1	1	1	

Figure 4.1 Section of WISER's Reconstructed Database. NLM's toxicology information stored in the Hazardous Substance Data Bank (HSDB) was used to verify and reverse engineer signs and symptoms associated with each chemical.

Three additional test-sets were created to further test the model's performance after training. To precisely control the amount of missing or inaccurate data, simulated patients with SSx profiles were generated from the ideal data-set of 311 unique substances by perturbation of randomly selected SSx. Signs and symptoms related to a real chemical incident would be ideal. However accurate patient records during mass casualty incidents are limited and usually incomplete [41, 42]. Each substance was replicated 100 times to create a reasonably extensive test-set of 31,100 simulated patients. Three test-sets were generated by randomly toggling SSx at a selection rate of 5%, 10%, and 15%. Probability density profiles shown in Figure 4.2 were examined to ensure random selections of perturbed SSx across each of the simulated patient test-sets.

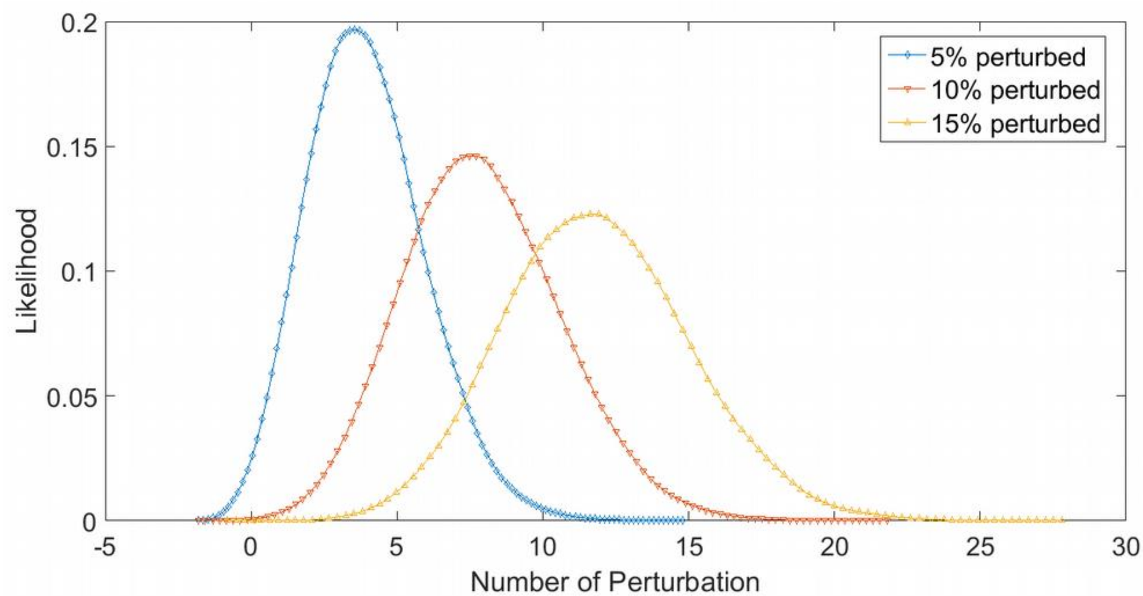


Figure 4.2 The Kernel Density Estimation of the Three Test-sets. Test data-sets were created by starting with the ideal data-set of 311 unique substances from WISER and changing the presence of chemical symptoms by 5%, 10%, and 15%.

Design, Training, and Testing of Artificial Neural Networks

A systematic pipeline was developed to create and optimize Artificial Neural Network (ANN) models. Models were built in the Matlab 2016Ra environment using the pattern recognition toolbox. The type of model used in this study was a scaled conjugate gradient backpropagation Artificial Neural Network[52] and is illustrated in Figure 4.3. Our process began by importing the data-set of 311 unique substances with their 79 SSx profiles. ANN models were created using a standard 70/30 split, where 70% of the data was used to train the ANN, and 30% was used to test the ANN. The output error was then calculated on the ANN's ability to classify chemicals in the 30% test-set. To optimize the ANN model, bootstrap resampling was used to increase the number of observations from 311 to 1,555 with each chemical being replicated 5 times. Figure 4.4 shows that by increasing the data-set by five iterations, the prediction accuracy increases from <1% to

99%. To measure the ANN model's robustness to false or missing information, additional testing was performed on the ANN using the artificially created patient test-sets where SSx were perturbed at rates of 5%, 10%, and 15%.

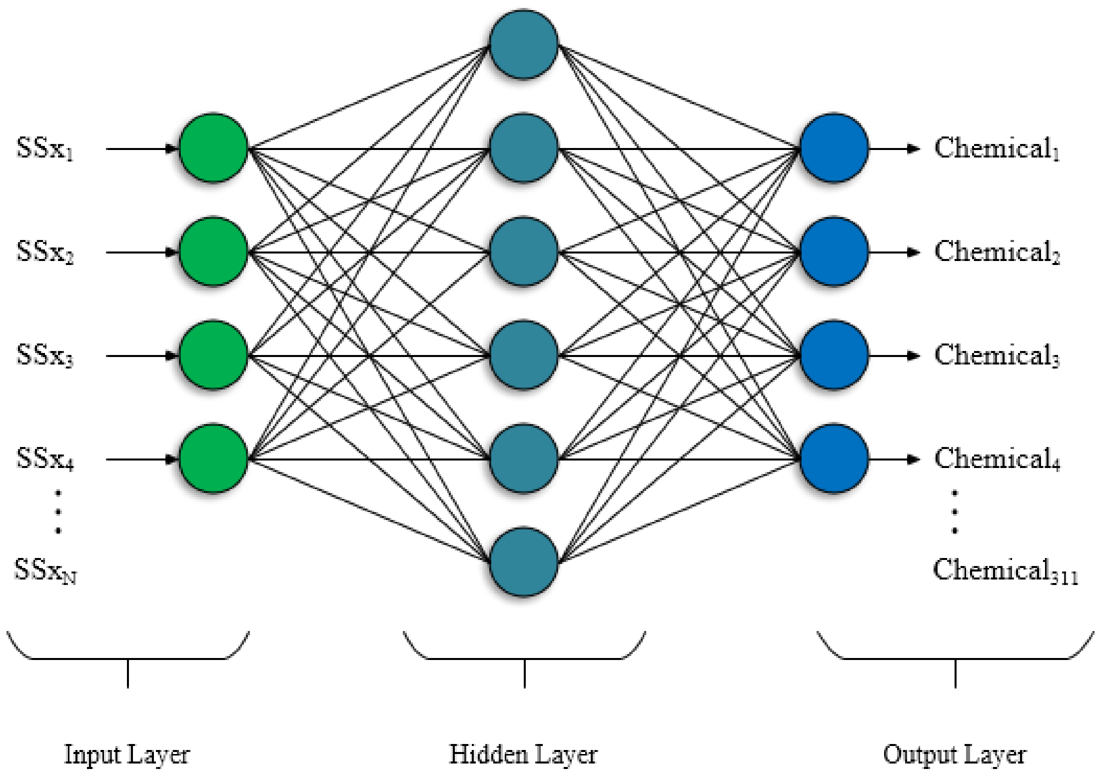


Figure 4.3 Scaled conjugate gradient backpropagation ANN for chemical classification based on signs and symptoms found in the NLM's Hazardous Substance Database.

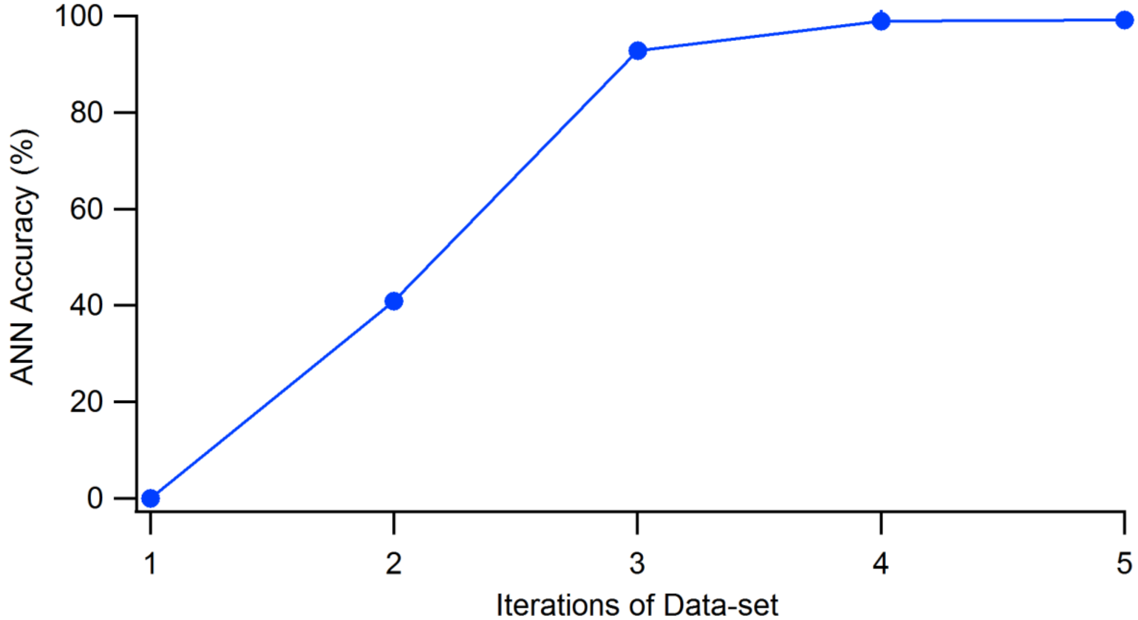


Figure 4.4 Bootstrap Resampling Results. Chemical classification accuracy results from bootstrap resampling of the 311 unique chemicals.

Dimension Reduction

Creating an ANN model that has been trained to classify 311 chemicals allowed us to measure the accuracy of deploying such models when caregivers are able to collect all 79 SSx. We recognized that in some scenarios, such as mass casualty incidents (MCIs), it might not be feasible to obtain and develop a complete patient profile. In the case that all 79 SSx cannot be collected, it may be practical to use dimension reduction techniques to reduce the amount of SSx necessary to classify a chemical and still maintain a degree of accuracy in the ANN model. To explore reducing the number of SSx, we have utilized the following popular statistical methods for dimension reduction, random feature selection, variance/covariance, correlation coefficients, and principal component analysis. To measure the performance of these methods, each dimension reduction technique was used to determine 40 SSx. These 40 SSx were then used to create ANN models just like the 79

SSx model in the previous section. In addition, because an ANN model's accuracy is dependent on the number of hidden layers used during training we tested models at increments of 10 hidden layers, starting at 10 and ending at 100 hidden layers. The average performance accuracy was measured at each increment of hidden layers.

All 79 SSx

One hundred ANN models were created using all original 79 SSx found in the chemical data-set. This was done to set a standard for which future models would be compared. Ten models were trained starting at 10 hidden neurons in order to obtain an average accuracy and then sequentially increased by steps of 10 hidden networks. This allowed us to not only calculate the overall performance accuracy of the model but also determine the number of hidden networks to use that would maximize the model's efficiency. Additional testing was also performed on the model using the test-sets perturbated at 5%, 10%, and 15%.

First 40 SSx (Alphabetically)

The first method used to reduce the number of SSx needed to predict a chemical from 79 to 40 SSx was to choose symptoms at random. For simplicity, SSx were ordered alphabetically, and the first 40 SSx were chosen which significantly reduce the data-set to nearly half the original size. To compare the results, 100 ANN models were created, and average performance accuracy was calculated using the same method described for the 79 SSx.

40 SSx based on Covariance/Variance

ANN models were then created by reducing the original data-set from 79 SSx to 40 SSx based on the variation between SSx. For any two random SSx vectors A and B, the covariance between A and B can be described using Equation 4.1, where N is the number of observations, μ_A is the mean of A, μ_B is the mean of B, and * denotes the complex conjugate. A 79x79 covariance matrix was created by a pairwise covariance calculation between each SSx column observations in the original data-set. The diagonal vector of the covariance matrix describes the variation of the 79 SSx and can be defined by equation 4.2, where μ is the mean of A and defined by equation 4.3. The binary distribution of the data made it unnecessary to normalize the data-set. The workflow pipeline was then followed to create 100 ANN models and calculate their prediction accuracy.

$$\frac{1}{N-1}\sum_{i=1}^{N}(A_i - \mu_A) * (B_i - \mu_B) \qquad \text{Equation 4.1}$$

$$V = \frac{1}{N-1}\sum_{i=1}^{N}|A_i - \mu\,|^2 \qquad \text{Equation 4.2}$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N}A_i \qquad \text{Equation 4.3}$$

40 SSx based on Correlation Coefficient

Pearson's linear correlation coefficients were calculated for each of the 79 SSx in the original chemical data-set and can be defined by equation 4.4, where X_a is one of the columns in the original data matrix X, and *n* is the length of each column. Correlation coefficients range between -1 and 1 where a value of -1 indicates a perfect anti-correlation between the SSx, while a value of +1 indicates a perfect positive correlation between the SSx. An example of the correlation vector for Arrhythmia can be seen in Figure 4.5. The figure shows that Tachycardia, Bradycardia and Hypotension Shock are positively correlated indicating that when the symptom Arrhythmia is present, there is a strong likelihood that Tachycardia, Bradycardia or Hypotension Shock will be present as well.

$$\bar{X}_a = \sum_{i=1}^{n} X_{a,j}/n \qquad \text{Equation 4.4}$$

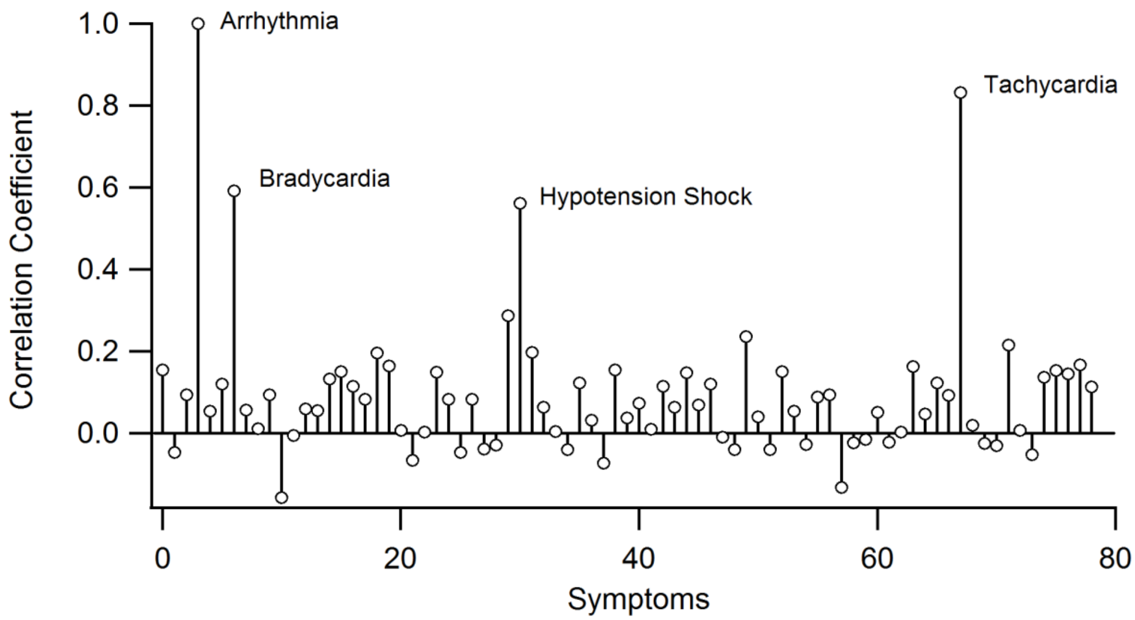


Figure 4.5 The Correlation Coefficient Vector for Arrhythmia. The plot shows that bradycardia, hypotension shock, and tachycardia have a strong positive correlation with Arrhythmia.

40 PCs based on Principal Component Analysis

The original 311x79 data-set was analyzed using principal component analysis. Single value decomposition was used to evaluate the 79 SSx and can be defined by equation

4.5, where U is the orthonormal matrix with the eigenvectors of XX^T, S is the diagonal matrix with the singular values, and V^T is the orthonormal matrix with the eigenvectors of X^TX. 40 principal components were selected by selecting the first 40 columns of X. The proportion of variance explained in each principal component was calculated by squaring the standard deviation of each Principle Component (PC) and then dividing by the trace or total sum of variance. The first 40 PCs were used to create 100 ANN models using the same protocol as used for previous techniques described and prediction accuracies were calculated.

$$X_{mn} = U_{mm}S_{mn}V_{nn}^T \qquad \text{Equation 4.5}$$

RESULTS

The average performance accuracy was calculated for each of the dimension reduction techniques described in the previous section. Table 4.1 describes the overall average performance for each of the dimension reduction techniques when training the ANN models and performing additional testing using the 5%, 10% and 15% perturbated data-sets. Table 4.2 describes the number of hidden networks used where the model's prediction accuracy experienced the best performance. Figure 4.8 shows the model prediction accuracy for each of the techniques used and is discussed further in the following sections.

All 79 SSx

ANN models were created using all 79 SSx associated with the chemical data-set. Figure 4.8A shows the model prediction accuracy when training the ANN and for all additional test-sets. When training the ANN models using all 79 SSx, the average performance accuracy was 99.5% across all hidden networks. When testing the ANN models with the 5%, 10%, and 15% data-sets, the performance accuracy was 73.3%, 43.5%, and 23.9% respectively. The model performed best at 100 hidden networks with 99.9% accuracy, and when additional testing was done on the model using the 5%, 10%, and 15% perturbated data-sets, the model performed with 83%, 51%, and 27% accuracy respectively.

First 40 SSx (Alphabetically)

ANN models were created using the first 40 SSx chosen alphabetically as inputs. Figure 4.8B shows the model prediction accuracy when training with only the first 40 SSx and for testing with all additional test-sets. The average performance for training ANN models with 40 alphabetic SSx was 97.1%. Additional testing with 5%, 10% and 15% data-sets demonstrated an overall accuracy of 65.2%, 38.1% and 21.2% respectively. The model's best training performance was at 80 hidden networks with 2.7% error and an accuracy of 97.2%. When tested with the 5%, 10% and 15% perturbated data-sets the model performed with 71%, 42%, and 23% accuracy respectively.

40 SSx based on Covariance/Variance

Figure 4.6 shows the distribution of variance for the 79 SSx in the chemical data-set. The 40 SSx were selected by examining the highest values in the variance vector. ANN models were created using the 40 SSx with the largest variation in their data as inputs. Figure 4.8C shows the model prediction accuracy when training with 40 SSx based on variance and for testing with all additional test-sets. When training the ANN models, the average accuracy for all hidden networks was 98.1% for identifying chemicals in the original test-set. For chemicals in the 5%, 10%, and 15% perturbated test-sets, the ANN model's performance accuracy was 72.6%, 46.2%, and 27.2% respectively. The ANN model performance was best at 40 hidden networks with 98.5% accuracy and when doing additional testing using the 5%, 10% and 15% perturbated data-sets the model performed with 79%, 52%, and 32% accuracy respectively.

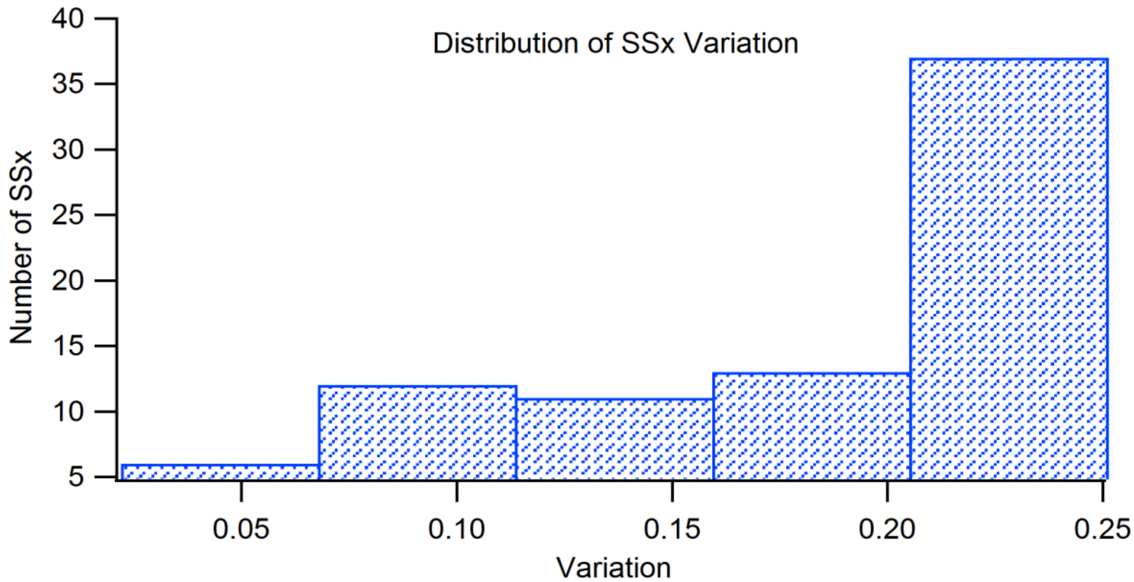


Figure 4.6 Variance Distribution. The distribution of variance for the 79 signs/symptoms in the chemical data-set.

40 SSx based on Correlation Coefficient

A correlation coefficient threshold of 0.4555 was found to reduce the original data-set from 79 SSx to 40 SSx with the least similarity. These 40 uncorrelated SSx were used to create one hundred ANN models using the designed workflow discussed in the methods section and test the model's accuracy to predict harmful chemicals. ANN models were created using the 40 SSx with the least amount of correlation in the chemical data-set. Figure 4.8D shows the ANN model prediction accuracy when training with 40 SSx based on correlation and for testing with all additional test-sets while optimizing the hidden networks from ten nodes to one hundred nodes. The overall performance accuracy for training ANN models based on the 40 uncorrelated SSx was 98.8%. The overall performance of ANN models tested with the 5%, 10%, and 15% test-sets was 65.6%, 38.9%, and 21% respectively. The best-trained model saw a performance error of 1.07% and an accuracy of 98.9% at 70 hidden networks. When additional testing was done using the 5%, 10%, and 15% perturbated test-sets, the ANN model performed with 73%, 44%, and 25% accuracy respectively.

40 PCs based on Principal Component Analysis

The scree plot seen in Figure 4.7A shows that the first principal component (PC), which accounts for the most variability in the data-set, explains 8.8% of the variability in the original data-set or variance. The second PC explains 6.9% of the total variance. Figure 4.7B shows the cumulative variance for the original data-set of all 79 SSx. It was determined that the first 40 PCs cumulatively explains 89% of the variability in the original data. The top 40 principal components were used to create one hundred ANN models. Figure 4.8E shows the ANN model prediction accuracy when training with 40 PCs and for testing with all additional test-sets while optimizing the hidden networks from ten nodes to one hundred nodes. Training ANN models with 40 principal components produced an overall prediction accuracy of 99.8%. With additional testing using the 5%, 10% and 15% perturbated test-set the overall prediction accuracy was 74.1%, 46.1% and 25.7% respectively. The ANN model performance was best at 60 hidden networks with 99.9% accuracy and when doing additional testing using the 5%, 10% and 15% perturbated test-sets the ANN model performed with 81%, 52%, and 29% accuracy respectively.

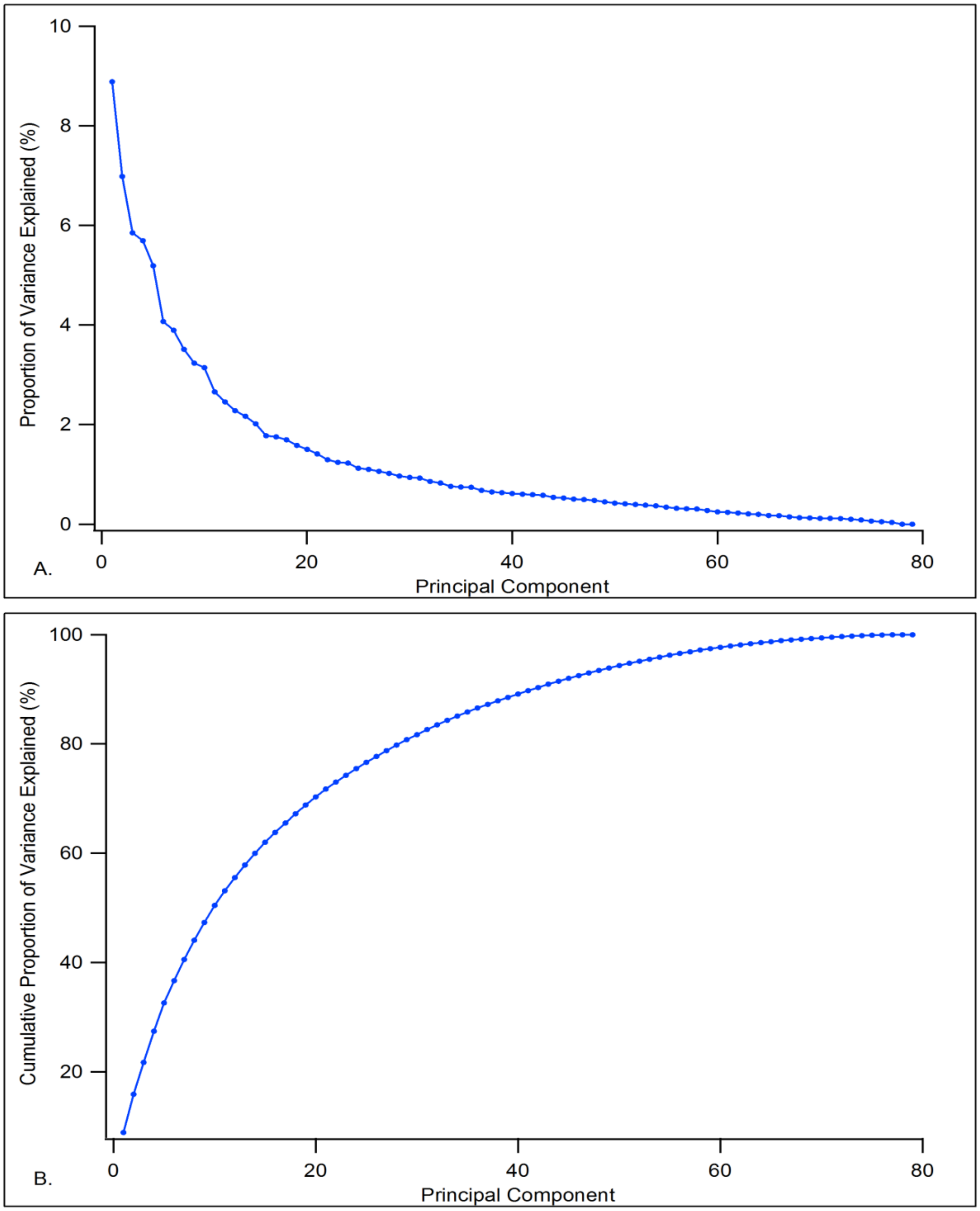


Figure 4.7 PCA Variation. (A) The figure describes the proportion of variance that each principal component explains. (B) The figure describes the cumulative summation of each principal component. The first 40 principal components explain ~89% of the variability in the original data-set

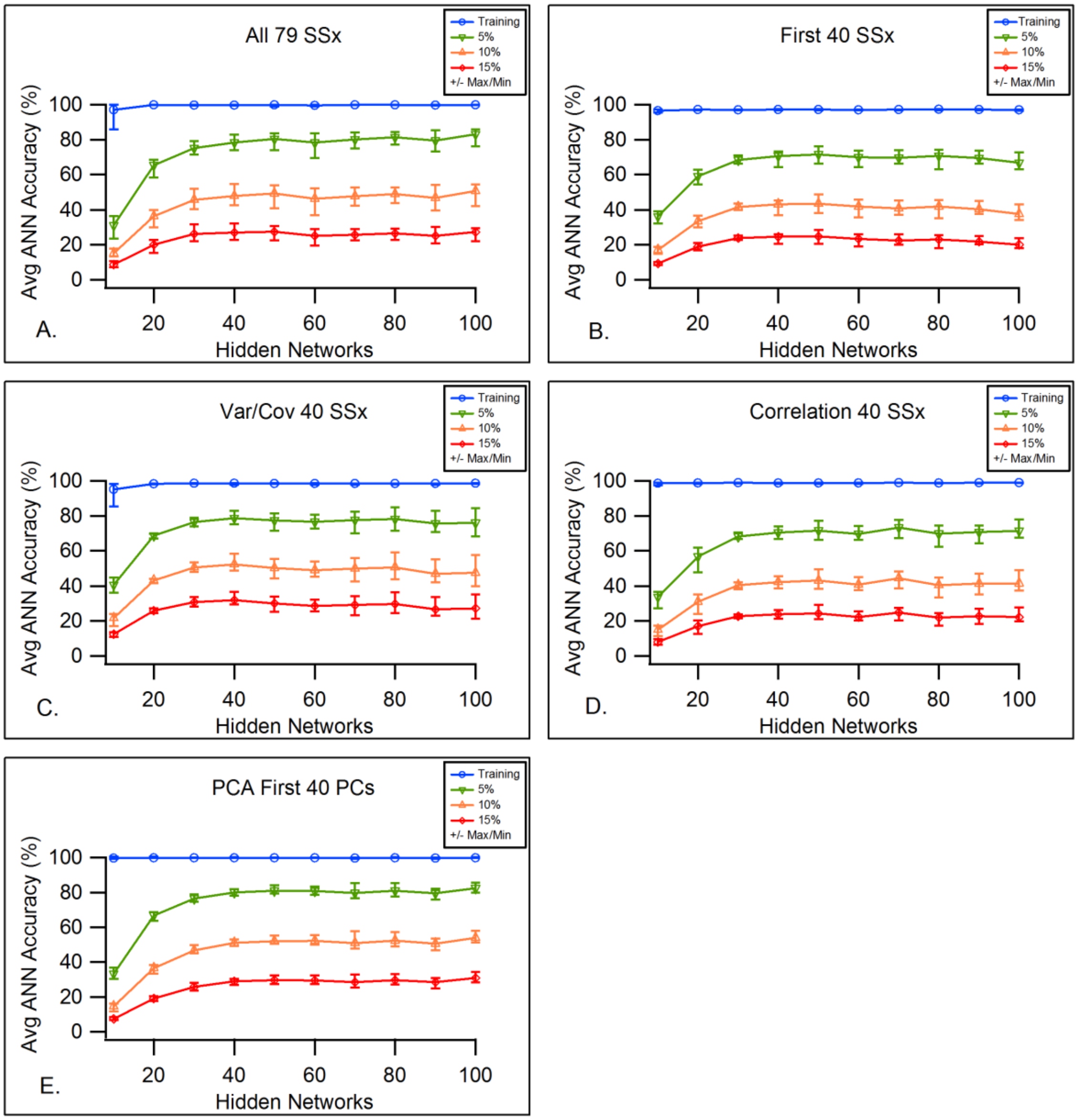


Figure 4.8 Prediction accuracy for ANN models using (A) All 79 SSx, (B) Frist 40 random SSx, (C) 40 SSx based on highest variation, (D) 40 SSx based on least correlation, (E) First 40 principal components. The average prediction accuracy was calculated for models with the training data-set and the 5%, 10% and 15% perturbated data-sets.

Table 4.1 The Overall Average Performance Accuracy for ANN models created using all 79 signs/symptoms and for each of the dimension reduction techniques.

	Average ANN Performance Accuracy (%)			
Model	Training	5%	10%	15%
All 79 SSx	99.5	73.3	43.5	23.9
First 40 SSx	97.1	65.2	38.1	21.2
40 SSx Var/Cov	98.1	72.6	46.2	27.2
40 SSx Corr	98.8	65.6	38.9	21.0
PCA (First 40 PCs)	99.8	74.1	46.1	25.7

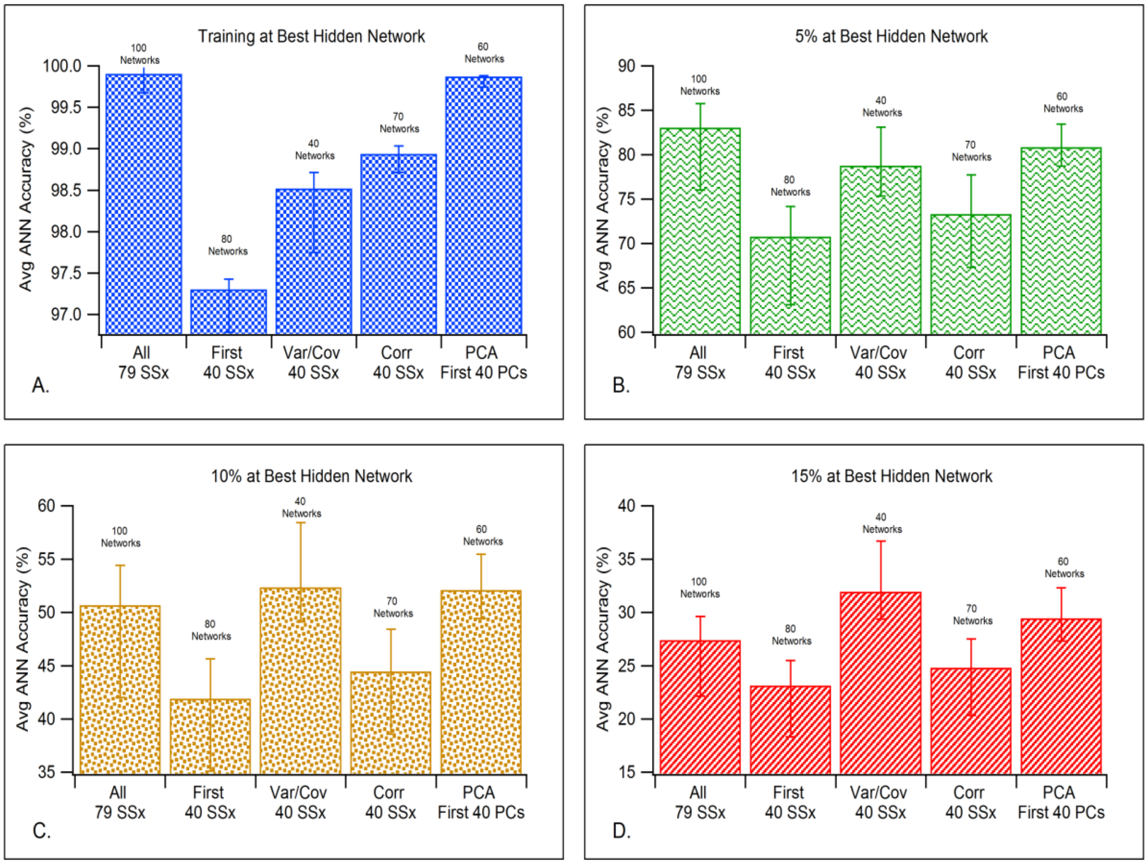


Figure 4.9 Comparing ANN Model Prediction Accuracy. (A) Comparison of ANN model performance during training. (B) Comparison of ANN model performance when tested with the 5% perturbated test-set. (C) Comparison of ANN model performance when tested with the 10% perturbated test-set. (D) Comparison of ANN model performance when tested with the 15% perturbated test-set.

Table 4.2 Best Number of Hidden Networks. Average prediction accuracy of ANN models created with dimension reduction techniques at the hidden networks that had the best performance.

Model	Best# of Hidden Networks	**Average ANN Performance Accuracy (%)** Training	5%	10%	15%
All 79 SSx	100	99.9	83.0	50.7	27.4
First 40 SSx	80	97.3	70.8	41.9	23.1
Cov/Var 40 SSx	40	98.5	78.7	52.4	31.9
Corr 40 SSx	70	98.9	73.3	44.4	24.8
PCA 40 PCs	60	99.9	80.8	52.1	29.4

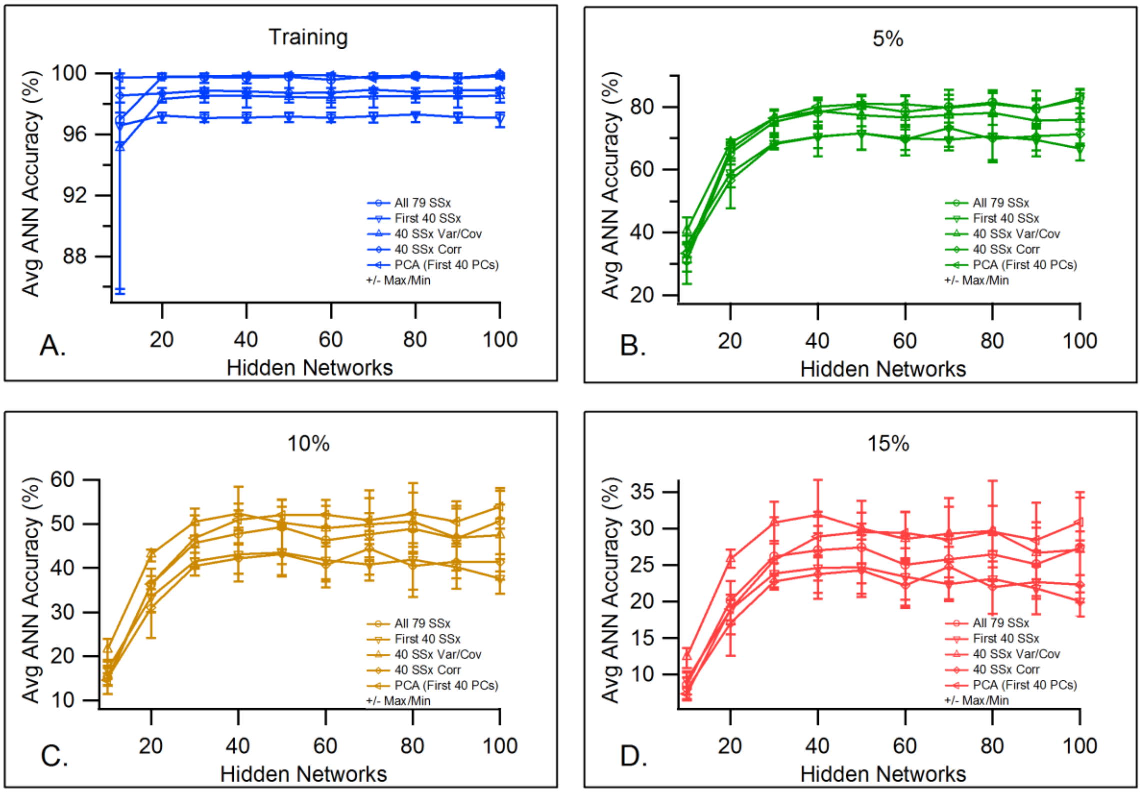


Figure 4.10 Comparing ANN Models with Different Test-set. (A) Average ANN model prediction accuracy for all dimensional reduction techniques during training. (B) Average ANN model prediction accuracy for all dimensional reduction techniques when tested with the 5% perturbated test-set. (C) Average ANN model prediction accuracy for all dimensional reduction techniques when tested with the 10% perturbated test-set. (D) Average ANN model prediction accuracy for all dimensional reduction techniques when tested with the 15% perturbated test-set.

Discussion

Table 4.1 describes the overall performance accuracy of each of the dimension reduction techniques. When training the ANN models, all DRTs were able to classify chemicals with a high degree of accuracy with PCA performing the best overall at 99.8% and the first 40 alphabetical SSx performing the worst at 97.1%. This would make sense, seeing as the first 40 alphabetical SSx were not chosen based on any correlation or variation what-so-ever. For this reason, there could be SSx in the selected dataset with high correlation which would provide little additional information to the model or SSx with a high degree of variation that is missing from the data-set which could have provided the model with valuable decision-making information. Table 4.1 also shows that when we start to introduce inaccuracies in the data the ANN model's overall performance will diminish. When SSx were perturbated by 5%, which is the equivalent of changing approximately four SSx from their correct value to an incorrect value, each of the DRT's accuracy was reduced by an average of 28%. This is most notably seen in ANN models create using the first 40 alphabetic SSx and models created based on a correlation threshold where performance accuracy dropped to 65.2% and 65.6% respectively.

If we assume that ANN models trained with all 79 SSx to be the standard, meaning that we would not expect any models created using a reduction technique to perform better, we can then compare DRT models to the 79 SSx ANN performance. Examining the best performance accuracy, seen in Figure 4.9 for each model allows us to compare ANN models trained with DRT and the 79 SSx ANN standard. In Table 4.2 we see that models trained with 40 principal components performed the same as the standard while all others performed at least a degree less. When we performed additional testing using the 10% and 15% perturbated data-sets we see that models create with PCA and models created using variance performed better than the 79 SSx standard. This may suggest that selecting precise SSx based on their variation and information gain may be more robust than just adding SSx that would provide little additional information and will even reduce the accuracy in predicting chemicals.

CONCLUSIONS

In general, this work has demonstrated that utilizing dimension reduction techniques can be an effective way of determining the sign and symptoms necessary to make a chemical classification. When we compare the ANN models created with DRTs to the standard model which used all 79 SSx, we see that each of the models performed similarly during training and with the additional testing. With an optimized number of hidden networks, ANN models trained with 40 SSx can outperform 79 SSx and show greater robustness to inaccurate data. This work demonstrates that artificial neural networks can be used to improve decision support tools used to give guidance to chemical exposures such as WISER and that collecting 40 SSx can be just as effective as collecting 79 SSx.

ACKNOWLEDGMENTS

Research reported in this publication was supported by a grant from the National Institutes of Health (5R01LM011648 and P20 RR-01646100)

CHAPTER 5

MOBILE DECISION SUPPORT TOOL FOR EMERGENCY DEPARTMENTS AND MASS CASUALTY INCIDENTS (EDICT): INITIAL STUDY[3]

[3] Boltin N, Valdes D, Culley J and Valafar H. 2018. JMIR Mhealth Uhealth, 6(6):e10727, PMID: 29934288, doi: 10.2196/10727.

Reprinted here with permission of publisher.

INTRODUCTION & BACKGROUND

Biomedical informatics is an interdisciplinary field that deals with the storage, retrieval, sharing, and optimal use of biomedical information, data and knowledge for problem-solving and decision-making. The broad area of Biomedical informatics touches on all basic and applied fields in biomedical science and is closely tied to modern information technologies, such as computing and communication. Historically, Health Information Systems (HIS) and the medical community, in general, have been slow in the adaptation of new technologies [53]. While in the last 30 years there have been significant advances in electronic health records (EHR), healthcare institutions are now seeking to develop integrated computer-based information management environments with the support of NIH, NLM, and NSF [54]. Adoption of various informatics tools to aid in decision-making can be of paramount importance in some specific areas of healthcare.

One area that could benefit from the advancement of technology is the hospital emergency department (ED). The ED typically operates under a set of conflicting main objectives. On the one hand, the ED system aims to process patients promptly, and on the other hand, the most optimal treatment of patients relies on a collection of detailed information from patients, which is time-consuming. The net effect of these competing objectives results in a compromise in one of the two main objectives. Under extreme circumstances such as Mass Casualty Incidents (MCIs) where the ED is inundated with a large number of patients, additional constraints are imposed by overwhelmed hospital resources. Adaptation of modern technology can assist in diminishing the degree of compromise during the normal ED operations, and ED operations under MCI conditions.

Over the past few years, a limited set of software products have been presented spanning mobile devices, desktop computers, and web-based services. Relevant to this study, the National Library of Medicine has created the Wireless Information System for Emergency Responders (WISER)[3], which allows emergency personnel to identify a list of possible chemical substances based on observed patient signs/symptoms. The US Department of Health and Human Services has developed another software tool, the Chemical Hazards Emergency Medical Management-Intelligent Syndromes Tool (CHEMM-IST)[4], which aims to identify a possible syndrome based on observed patient symptoms. Although such software makes significant strides in assisting the process of emergency care, they are not designed for a hospital ED. Therefore, the software efficiency, especially during MCI events, has not been well established[51].

The Emergency Department Informatics Computational Tool (EDICT), is a comprehensive tool for processing, management, and triage of patients during an MCI. EDICT is designed to assist with the process of seamless data collection, aggregation, and dissemination using mobile technology to facilitate a client-server transaction model. EDICT has also been designed to include a recommendation decision support system, which we have utilized its potential for Chlorine exposure. In this report, we present the EDICT software package and demonstrate its efficiency and agreement among nurses in application to a simulated reenactment of a 2005 Chlorine spill that took place in Graniteville SC.

METHODS

Background on Triage Systems

Triage is used to define how patients are categorized in the ED based on the severity of their condition. A triage nurse typically assigns a triage level with little information and in a short amount of time. Therefore, an effective triage requires a complex clinical decision based on a small amount of data with a very limited margin for error. Given the complexity of the pragmatic cost of mistakes in patient assessment, triage-nurses typically favor over-triaging patients to guarantee patient care. Triage bias may be tolerable during normal ED operations, but over-triaging patients during an MCI event can place an unnecessary burden on already taxed hospital resources and reduce patient outcome[55, 56].

Over the years, many models have been developed for triaging patients at the scene of the incident (field-triage) and in the hospital system (hospital-triage). Most of these models either use a 3-tiered color system such as Sort, Assess, Lifesaving Interventions, Treatment/Transport (SALT)[57] or a 5-tiered numeric system such as the Emergency Severity Index (ESI)[15]. The ESI algorithm is one of the most commonly used triage systems and found in over 70% of large hospitals across the United States[58]. Triage algorithms are simplistic to train ED personnel quickly and simplify the decision-making process. However, the simplistic nature of these triage systems is not a reflection of their ability to optimize patient outcome. In fact, the effectiveness of these triage models to accurately triage patients in an MCI is widely unproven[8, 25, 26].

A modern triage system should incorporate existing mobile technology to reduce the cost of data collection and improve efficiency by providing rapid and accurate decision support. In the following sections, we outline a prototype for a patient management triage system that is capable of providing decision support for ED personnel during a chemical MCI. This innovative tool utilizes mobile technology, giving staff the freedom to move about the ED, provides secure data collection with redundant features, and deploys artificial intelligent algorithms to provide clinical decision support.

EDICT: Emergency Department Informatics Computational Tool

EDICT has been designed to improve patient outcomes during a chemical MCI through the utilization of mobile technology and incorporation of Artificial Intelligence. To achieve its objectives, the EDICT software package integrates three main components: fast and accurate data collection through aggregation and dissemination of information; re-engineering of the patient processing protocol; and a clinical recommendation system. Each of these components is described in the following sections.

Component 1: EDICT Data collection, aggregation and dissemination platform

The EDICT software package has been engineered to seamlessly facilitate data collection, aggregation, and dissemination during an MCI event. EDICT employs a Client-Server model that allows safe and fast bi-directional communication of data between mobile devices and a data storage server. The data-storage and AI servers can be located offsite to ensure additional data security. In addition to the centralized server, each client device creates and maintains its local database. This concurrent model of distributed and centralized data storage provides data redundancy that ensures data integrity against hardware failure. Recovery from a server-crash can be accomplished through aggregation of all the local data distributed across the clients. In return, local data can be reconstituted from the central server in the case of accidental damage to a client device.

Another critical feature of EDICT is providing situational awareness to all of the pertinent members of the ED personnel. The current implementation distributes relevant information to all mobile devices such as the number of patients admitted, number of critical and non-critical patients, and geographical distribution of admitted patients. It is easy to envision future expansions of this feature to include a list of available ED resources and occupied resources as part of the global situational awareness report.

The current version of the application allows the proper function of each device to be selected through a login and setup process (Figure 5.1). A super-user can select between two distinct modes of operation: Patient-Mode and Nurse-Mode (Figure 5.2). The ability to switch between the two modes provides a dynamically adaptive system that can mitigate the effects of a surge at any point in the patient processing pipeline. Each of the two modes of operation will be described in the sections below.

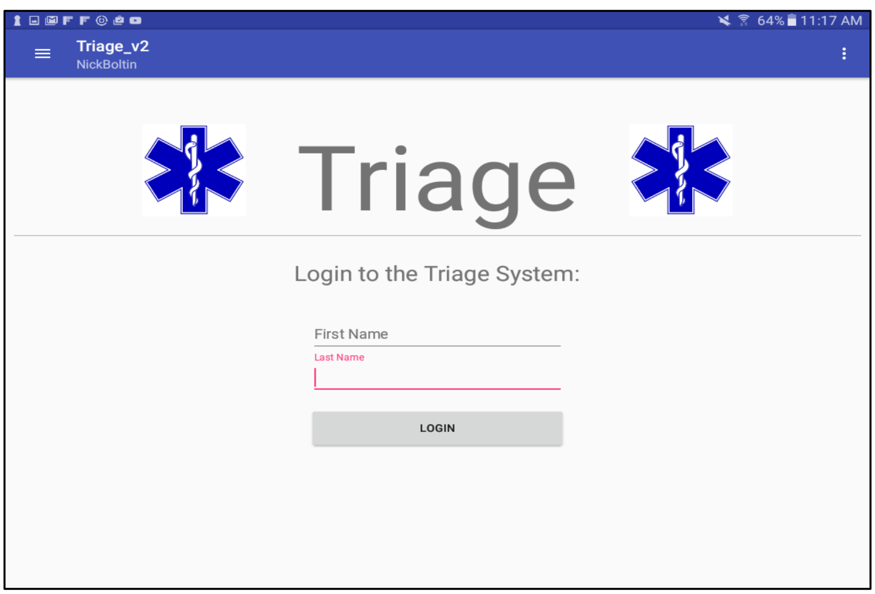


Figure 5.1 Triage App Home Screen

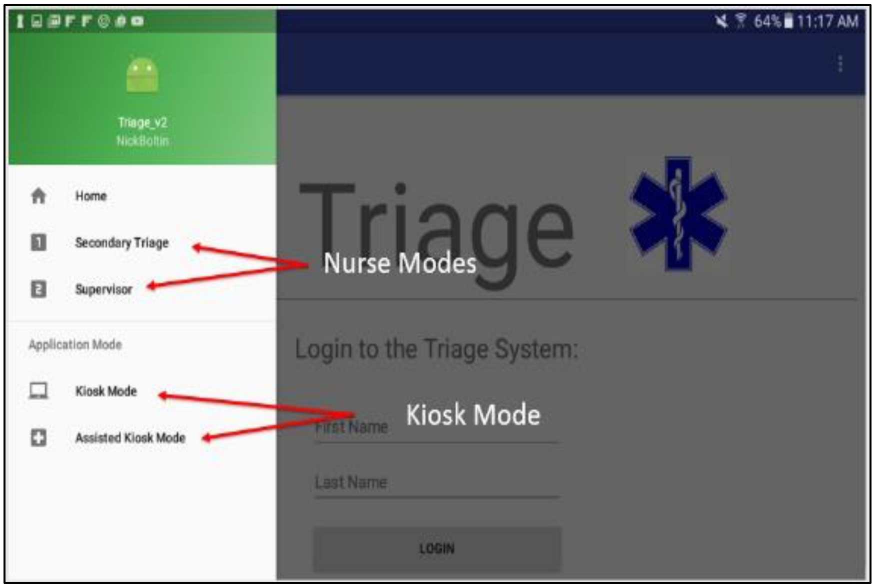


Figure 5.2 App Navigation & Set-up

EDICT's mobile application – Patient Mode

The Patient-Mode enables a Kiosk system that facilitates the process of collecting data from patients and divides into two operational sub-modes: Assisted and non-Assisted. The non-Assisted mode will initiate the Kiosk data collection module and operated by a patient. The Assisted mode is identical, with the exception that the login identification of the assistant ED personnel is recorded.

When patients interact with the kiosk system, they are greeted with a welcome screen and asked to scan their barcode (Figure 5.3). Instructions are given on how to align the barcode inside the scanner window correctly. Under some abnormal conditions, the barcode scanning may fail or take too long. To mitigate such instances, patients and nurses have the option of entering the numeric value of their barcode to bypass the scanning process.

On the patient's initial entry into the system, the central server creates an instance of a new record based on barcode values. Patients then proceed linearly through a series of screens that collect information on their demographics including name, and date of birth (Figure 5.4). Information related to their symptoms and chief complaint (Figure 5.5) are also collected. Additional features of the kiosk system include collecting pulse rate and oxygen saturation values using a pulse oximeter. The geographic location where a patient first experienced their signs/symptoms (Figure 5.7) is also collected. Google maps API[43] facilitates the location and can accept a street address, a manually placed marker, or a longitude/latitude.

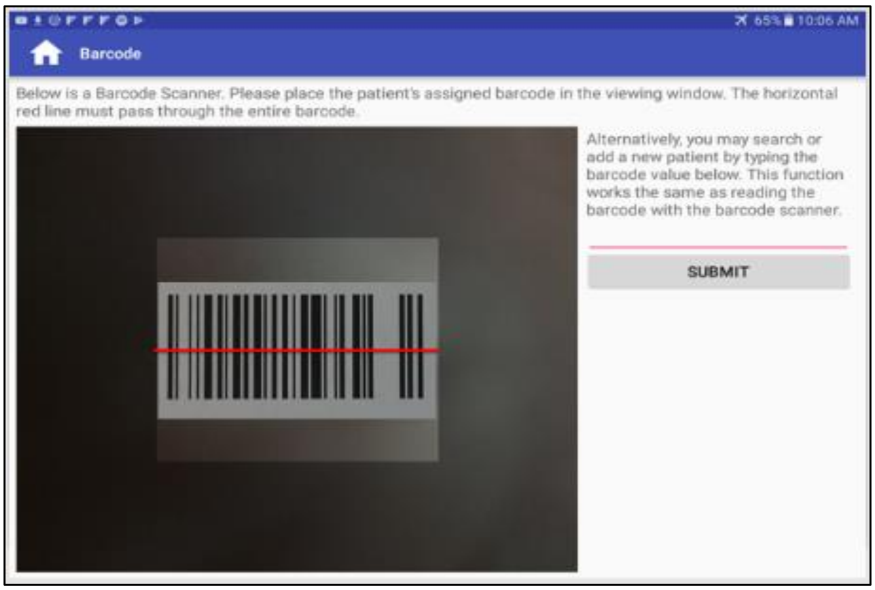


Figure 5.3 Kiosk Barcode Scanner

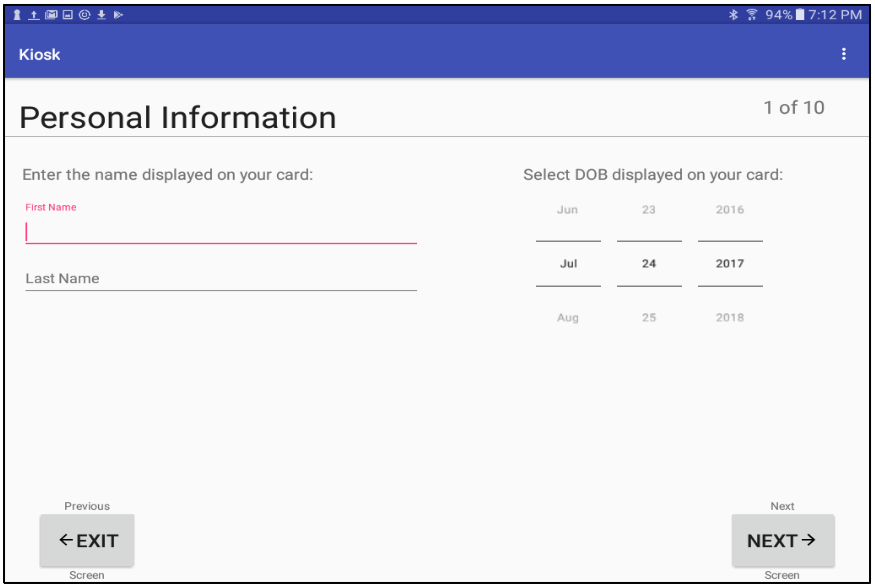


Figure 5.4 Kiosk Demographic Screen

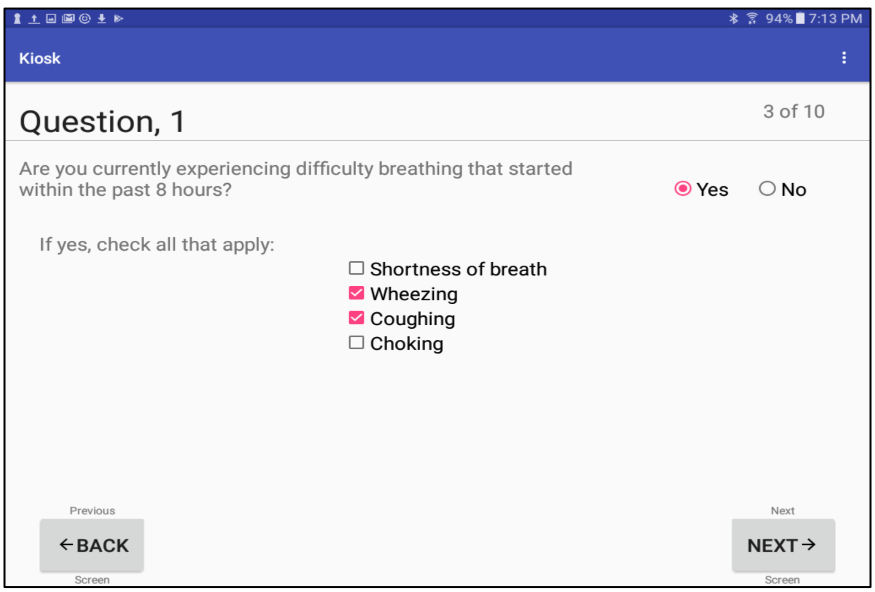


Figure 5.5 Signs/Symptoms

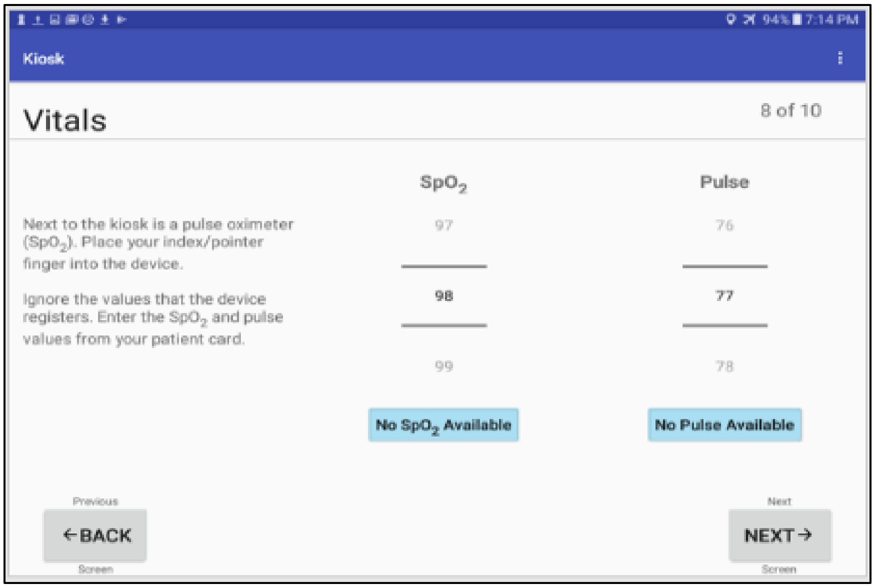


Figure 5.6 Kiosk Vital Screen

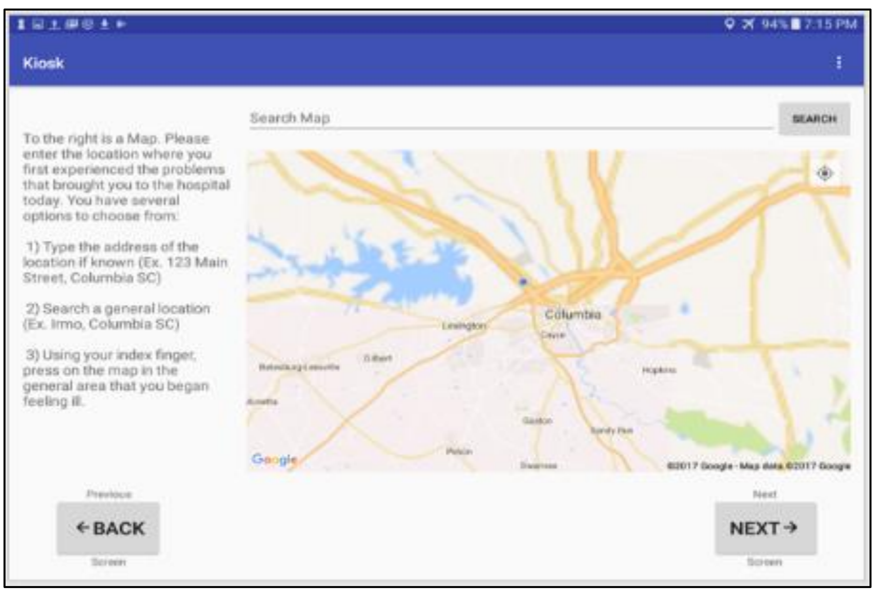


Figure 5.7 Kiosk Google Map

EDICT's mobile application – Nurse Mode

The Nurse-Mode provides more diverse sub-functions when compared to Patient-Mode. One example is the information related to global awareness of the MCI event. The situational awareness view (right panel, Figure 5.8) gives an overview of the event by displaying the number of patients in the system and a breakdown of triage levels currently assigned. The spatial view (Figure 5.9) helps establish the geographical scattering of patients within the event which is critical when determining if incoming patients have been exposed to the MCI event.

The Nurse-mode can also be used to view a comprehensive list of patients currently in the system and a summary of collected information (left panel, Figure 5.8). Detailed information can be displayed by selecting an individual patient in one of three ways: manually navigating the list of patients, using the search dialogue, or scanning a patient's barcode. Figure 5.10 illustrates an example of the detailed patient information screen. Additional functions are available through different functional tabs at the top of the screen and include: review/update patient data such as geographical location, signs/symptoms or initial triage category. Tabs are also available for reviewing AI recommendations for each patient (subject to availability of sufficient data), and the evaluation screen, where nurses assign the final triage classification. EDICT's system menu (top left corner Figure 5.8) allows easy navigation to other modes or screens.

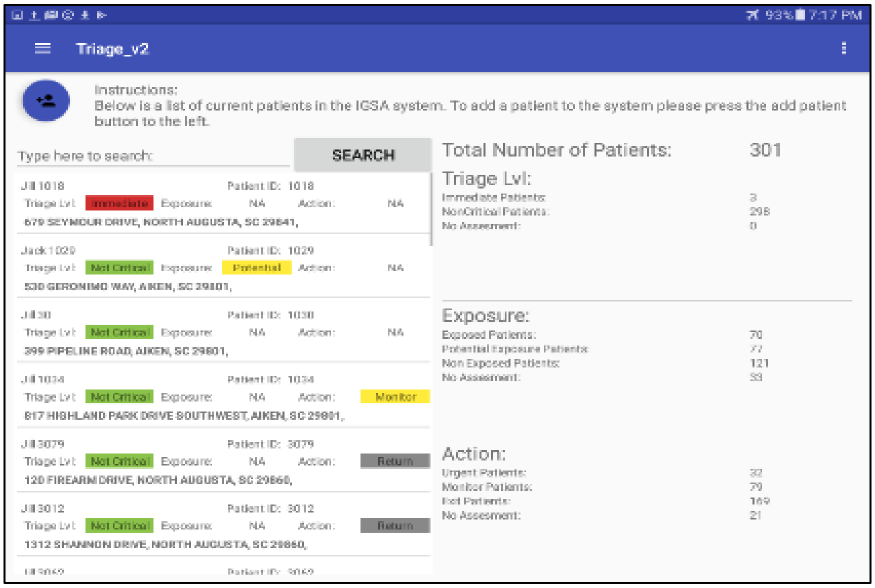


Figure 5.8 Global View Screen

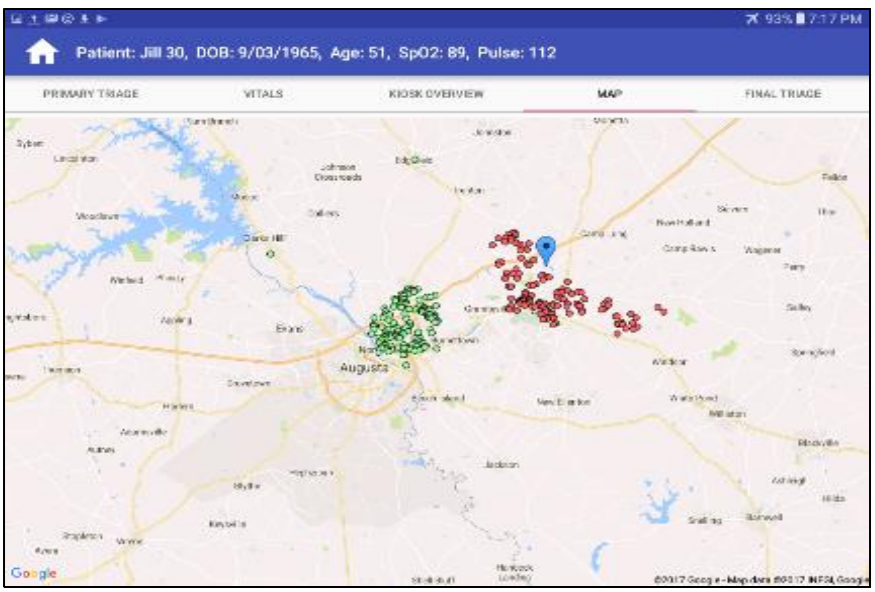


Figure 5.9 Nurse Google Map

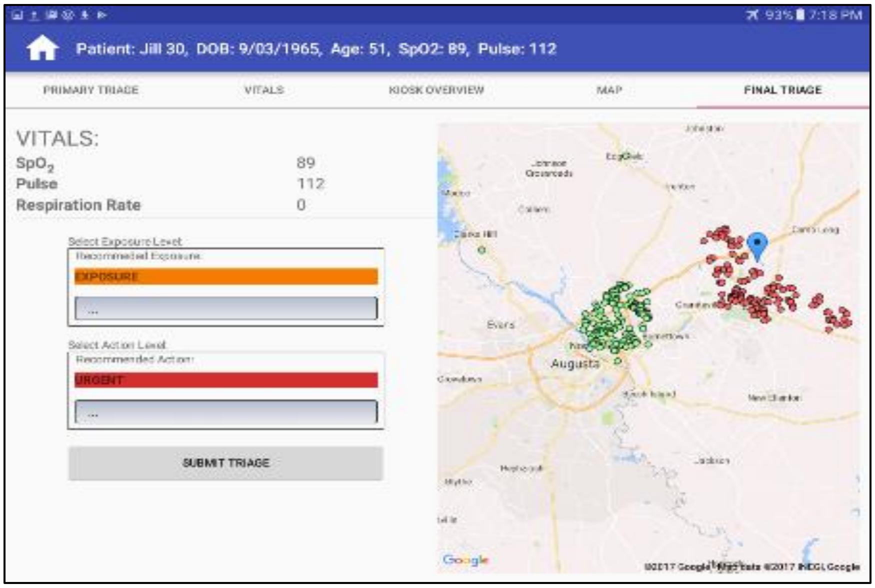


Figure 5.10 Patient Information

Component 2: Re-engineered patient processing pipeline

An improved patient management system can benefit from establishing order during the chaos that takes place during an MCI. Here we propose a patient processing pipeline that helps improve patient management while facilitating a faster mechanism for collecting data and tracking patients. The patient tracking system will consist of three main stages shown in Figure 5.11. The three stages are denoted as the “Primary Triage” “Kiosk System” and the “Secondary Triage” phases, which are described in the following sections.

Figure 5.11 EDICT, an MCI Specific Triage tool used to map data gathered by the mobile application to the IGSA algorithm. Information gathered in the primary triage, the kiosk system and secondary triage is used to determine a specific exposure level and action

Primary Triage

The main objective of Primary Triage is to identify the patients who are in need of immediate care. Functionally, ED personnel can engage the arriving patients in a variety of ways. For our research, we assume patients will be given a wristband with a barcode that will serve as the patient's unique identification for the remainder of their virtual existence within the EDICT system. In addition to receiving a wristband, patients will be evaluated by a primary-triage nurse if necessary and receive a triage category of "Immediate" if assessed to have a life-threatening problem and sent directly for treatment. All remaining patients are initially categorized by default as "Not-Critical" and directed to the Kiosk area for further acquisition of information.

Kiosk System

The Kiosk System is designed to interactively collect individual information such as name, date of birth and other demographics from patients initially categorized as "Not-Critical." Additional information is obtained to help define the location of the incident using an applet similar to Google maps. Data is also collected on signs/symptoms of the presenting condition, and chief complaint. The Kiosk stage is partitioned into assisted and non-assisted sections, where patients can complete the registration process independently or with the help of designated ED personnel. The patient information is gathered concurrently by multiple mobile devices and can, therefore, contribute to rapid data collection and patient processing.

Information collected from patients are aggregated into a central database and analyzed by the AI system to understand the nature of the incident better and provide decision support for triage recommendations. The aggregated information is also disseminated throughout the system to all registered ED personnel as a means of providing a global view of the event. After patients have completed the data collection process, they are given instructions to proceed to the final stage of the patient management system, secondary triage.

Secondary Triage

At Secondary Triage, nurses are tasked with providing the most appropriate triage category to optimize patient outcomes. EDICT assists secondary triage nurses by providing decision support specific to each patient. EDICT offers a complete information profile and a system triage recommendation based on the AI analysis of each patient. The secondary-nurse can scan the patient's barcode to retrieve information collected, which eliminates errors related to miss-identification of patients. The nurse can view recommendations from the central server on a patient's possible chemical exposure, and the appropriate course of action for each patient. The nurse provides the final triage category by agreeing or disagreeing with the decision support system recommendation and providing a rationale when they disagree. The AI recommendation system is described in the following section.

Component 3: Triage decision support system for IGSA exposure

EDICT is designed to provide clinical decision support for each patient based on available information. EDICT offers a summary of all data acquired for each patient as they proceed through the patient processing pipeline. When sufficient information is gathered for a given patient, the central AI engine in EDICT provides inferred recommendations regarding a patient's exposure level and the most effective course of action for each patient. The patient exposure feature is designed to separate patients who visit the ED uninvolved in the MCI event and therefore do not need to be subjected to the chemical triage process.

The current recommendation system of EDICT is optimized for exposure to an Irritant Gas Syndrome Agent (IGSA) (Figure A.1)[59]. In principle, however, EDICT could house a comprehensive collection of possible triage mechanisms from which the optimal procedure could be selected for each MCI. Table 5.1 describes the categories for exposure and the recommended actions that are provided by the central AI engine in EDICT based on the IGSA mechanism.

Table 5.1 EDICT Decision Logic Summary for the triage recommendation system. Nurses are given recommendations by the decision support system based on information provided by patients in the kiosk system.

Category	Outcome
Exposure	
Exposed	Patient has been exposed to an IGSA
Potentially Exposed	Patient has potentially been exposed to an IGSA
Not Exposed	Patient has not been exposed to an IGSA
Action	
Exit	Re-triage using a non-chemical related algorithm
Monitor	Monitor the patient for up to 8 hours for latent symptoms
Urgent	Seek immediate medical treatment

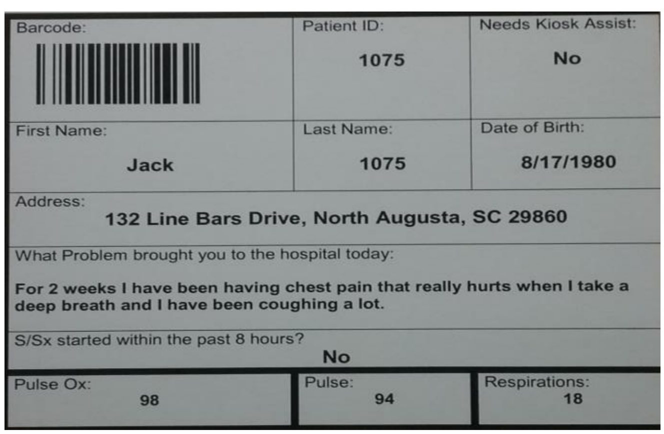
Test and Evaluation Process

In April of 2017, a large-scale exercise was conducted utilizing over 500 emergency responders and nursing students. For this exercise, a chemical MCI event was simulated to replicate a derailed train accident that took place in 2005, releasing chlorine gas into the town of Graniteville, South Carolina. Participants were separated into four groups: patients, assisted kiosk helpers, primary triage nurses and secondary triage nurses. EDICT was used for patient management, data collection, and decision support.

During the exercise, 15 tablets were used to study the effectiveness of the patient management system. The tablets were partitioned into three functional groups based on the app's operational mode: assisted-kiosk mode, non-assisted-kiosk mode, and nurse mode. EDICT was evaluated on its efficiency in triaging patients and the agreement with the decision support system. Information related to each of the participant groups and EDICT users is found in the following sections

ED Patients

Two hundred ninety-six students from USC's nursing program participated as ED patients. 95% were female, and 90% were 18-24 years old. ED patients were split randomly into two patient populations. The first group consisted of 198 patients that were part of the Chlorine exposure event. Data used for this group was gleaned from de-identified medical records of patients from the 2005 train derailment. The second group consisted of 100 patients suffering from ailments unrelated to the MCI event. The data for this group was acquired from de-identified medical records of patients with flu-like symptoms who visited the same hospital in 2016. As part of the exercise, students randomly received a patient card (Figure 5.12), about either a victim of the first group or a flu patient from the second group. The cards outlined specific information related to their visit to the ED, vitals and a location where they first felt sick. Students used the information displayed on their card to interact with the kiosk system and proceed through the patient processing pipeline. Students had no pre-exercise access to their patient data or the EDICT software until they entered the simulated ED.



Barcode:	Patient ID: 1075	Needs Kiosk Assist: No
First Name: Jack	Last Name: 1075	Date of Birth: 8/17/1980
Address: 132 Line Bars Drive, North Augusta, SC 29860		
What Problem brought you to the hospital today: For 2 weeks I have been having chest pain that really hurts when I take a deep breath and I have been coughing a lot.		
S/Sx started within the past 8 hours? No		
Pulse Ox: 98	Pulse: 94	Respirations: 18

Figure 5.12 Example of a patient card given to participates in the chemical MCI exercise. Participates were asked to enter information and answer question in the kiosk system based on the cards they received.

Kiosk Helpers

Five assisted kiosk stations were set up for the April 2017 exercise. Each station was assigned a kiosk helper tasked with helping patients enter information into the kiosk system. The helpers were all female between the ages of 29-59. They received 1 hour of individual training before the exercise with a member of the app development team who guided them in navigating through the kiosk system and entering patient information.

Triage Nurses

Thirteen registered nurses and emergency responders were assigned to evaluate patients in the secondary triage stage. There was one male nurse, and 12 female nurses between the ages of 30-69. Each received 1 hour of training before the exercise with a member of the app development team on how to use the nurse-interface. They also received instruction on how to review patient information using the app and how to assign triage categories based on the IGSA algorithm. In addition, secondary-nurses were given an information packet describing the IGSA algorithm and the MCI scenario.

Data Exclusion

Two categories of data were excluded from our analysis of EDICT's performance. The first consisted of records that contained No-Available (NA) information. Some NAs were identified as "Immediate" patients who required instant attention and were removed from the patient pipeline or patients who were able to bypass a section of the registration process. The latter cause is currently under investigation by the development team and will be resolved in a future iteration of the app. In total, an insignificant number of NA instances were observed (4%, 214/5096 of database transactions) and therefore have little impact on our outcomes.

The second criterion for data exclusion was based on the implausibility of data values (outliers). Outliers were identified using the Tukey's method described in Equation 5.1 were q is a tabulated score[60], w is the range of the normal distribution and s is the standard error of the sum of the means. The Tukey's test uses the interquartile range (IQR) defined in Equation 5.2 to identify outliers and removing points +/-1.5*IQR. Outliers were identified for each of the questions in the kiosk, the time spent at the kiosk, the time patients spent waiting to enter secondary triage and the time spent in secondary triage. The exclusion of this category of data is justified by students who may have received a phone call or engaged in a chat discussion on their cell phone during the exercise. Other more relevant exclusions are based on patients who may have needed to pause the registration process for personal reasons (bathroom break, etc.).

$$q_{r,v} = \frac{w}{s} \qquad \text{Equation 5.1}$$

$$IQR = Q3 - Q1 \qquad \text{Equation 5.2}$$

RESULTS

Component 1: EDICT Data collection, aggregation and dissemination platform

During the April 2017 exercise, every item of submitted data and its corresponding timestamp was captured in EDICT's central database. The information included: patient demographics, answers to all the Kiosk questions, vitals, illness onset location, the central server's recommended triage, and triage levels assigned by nurses, to name a few. In summary, the EDICT software package captured 5471 data transactions for the April 2017 exercise.

The patient management utility of EDICT processed 296 patients within a window of fewer than 3 hours. This results in an average of 36 seconds per patient to complete the initial triage, information collection, waiting to be seen by a secondary-triage nurse, and the final triage assessment. The information acquired by the data aggregation mechanism of EDICT can provide a global view of the event as illustrated in Figure 5.13. In this figure, each block represents the interval of time required to process each patient. The blue, yellow and red cells in Figure 5.13 correspond to patients categorized by EDICT as not-exposed, potentially exposed, and exposed respectively.

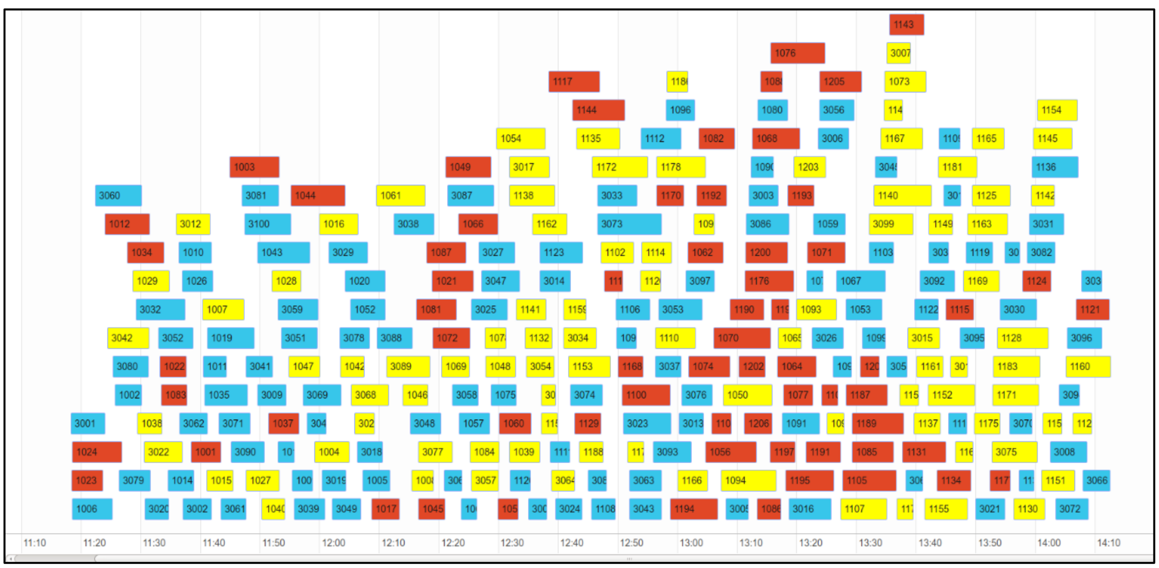


Figure 5.13 Overall triage results from the April 2017 drill. Blue cells indicate patients EDICT recommended as not exposed. Yellow cells indicate patients EDICT recommended as potentially exposed and red cells indicate patients EDICT recommended as exposed. The length of the cells describes the amount of time the patient spent in the patient management system.

Component 2: Re-engineered pipeline of patient processing

The second component of EDICT aims to improve individual patient's processing time and patient management. Timestamps captured by EDICT have been used to assess the efficiency of each step and identify outliers. By analyzing the outliers found at each of the data points we could identify areas of concern and investigate technical or usability issues. The following sections provide results related to each of the three components of the patient processing pipeline.

Kiosk System

The efficiency of the Kiosk system and its discrete question components were measured using timestamps from patients as they progressed through the questionnaire screens. Table 5.2 summarizes the results of our analysis with and without outliers. In this table, the first column corresponds to the different questions asked in the kiosk system. The second column indicates the number of excluded patients from the 296 created patient IDs. Figure 5.14 shows the average time spent by patients answering each question in the kiosk system. Of the 296 created patient IDs, 288 completed the kiosk. On average, patients required 3 minutes, 22 seconds to complete the patient kiosk system. The longest and shortest completion times consisted of 7 minutes, 12 seconds and 1 minute, 8 seconds respectively. Question 1 required the longest time to complete with an average of 92.9 seconds closely followed by the google map with an average of 46.9 seconds. Questions with only checkboxes (Questions 2-6) required the least amount of time to complete with question 6 being the shortest average of 3.7 seconds.

Secondary Triage

Efficiency in the secondary triage was measured by examining two factors: the wait time separating the Kiosk and the Secondary Triage stages, and the duration of the Secondary Triage stage. Table 5.3 below summarizes the average, maximum, and minimum time required by patients to complete various portions of the triage process. The Triage Completion time in Table 5.3 corresponds to the time it took patients to complete the entire process, starting from the first entry into the system until the exit from the secondary-triage stage.

Table 5.2 Summary of data outliers. Strict rules were developed by identifying outliers at each step of the triage process. These outliers were then investigated further to see if a user or technical error could be determined.

Step	Outliers, n (%)	Mean of Outliers (sec)	Mean with Outliers (sec)	Mean w/o Outliers (sec)
Q1	2 (1)	240.50	94.04	92.95
Q2	19 (7)	30.89	10.31	8.76
Q3	20 (8)	26.45	7.05	5.63
Q4	14 (5)	16.57	5.71	5.17
Q5	6 (2)	15.83	4.42	4.18
Q6	11 (4)	13.18	4.03	3.67
Vitals	19 (7)	65.26	21.86	18.82
Map	10 (4)	166.90	51.07	46.93
Waiting	25 (12)	1095.84	156.84	45.58
Time in kiosk	1 (1)	593.00	203.76	202.41
Time in secondary	14 (7)	202.50	77.79	69.56

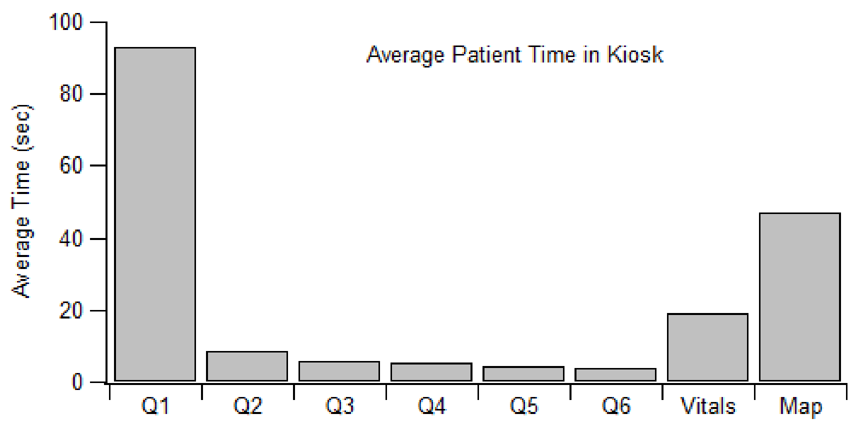


Figure 5.14 Time comparison of questions asked in the patient kiosk system

Component 3: Triage decision support system for IGSA exposure

While patient processing speed is an essential aspect of a patient management system, it should be at no cost to improving patient outcome. Therefore, it is as equally important to review the performance of the AI recommendation system. The app's decision support system was quantified by examining the agreement and disagreement between secondary nurses and the decision support system regarding patient exposure and triage action (Table 5.4 & Table 5.5). The data shows that 286 of the starting 296 patients (96.6%) completed the triage process and received recommendations from EDICT. In summary, EDICT's exposure and action recommendation exhibited 91.6% (262/286) and 84.3% (241/286) agreement with nurses' assessments respectively. It is worth noting that in the critical subcategory of patients requiring Urgent care, there was 100% (11/11) agreement between EDICT's recommendation and nurses' assessment.

Table 5.3 Time summary for Waiting, Secondary Triage, and Triage Completion. The mean, maximum and minimum amount of time a patient spent waiting to be seen by a nurse, in secondary triage and the overall time to be triaged using EDICT.

	Mean (sec)	Min (sec)	Max (sec)
Wait Time	45	0	117
Secondary Triage Time	69	19	168
Triage Complete Time	334	152	646

Table 5.4 Exposure agreement among secondary triage nurses and the decision support system for the IGSA triage.

Nurse Input	Computer Recommendation		
	Exposed (n)	Potential (n)	Not Exposed (n)
Exposed (n)	65	8	1
Potential (n)	1	80	0
Not Exposed (n)	2	12	117

Table 5.5 Action agreement among secondary triage nurses and the decision support system for the IGSA triage

Nurse Input	Computer Recommendation		
	Urgent (n)	Monitor (n)	Exit (n)
Urgent (n)	11	10	11
Monitor (n)	0	57	23
Exit (n)	0	1	173

DISCUSSION

The utility of EDICT being evaluated during a large-scale mock exercise has demonstrated many successful aspects of the system. The efficiency of such an approach has the potential to substantially improve patient management during chaotic situations, improve patient outcome, and provided a research platform for data collection, data-mining, and modeling during an MCI related triage. In Table 5.2 we have presented information related to outliers in each stage of the patient triage process. While in this work we have used these temporal anomalies to further investigate the functionality of the app, during an actual deployment of this app, this feature can be used to monitor patient progress. For example, a patient who may exhibit a long waiting time, or does not have an exit timestamp, may be traced and any problems rectified. The fast analysis of complex data by computers allows for the incorporation of sophisticated triage processes, which will inevitably lead to improved patient outcomes.

Two components of EDICT have contributed substantially to accelerating patient processing. The first component harnesses the organization and improved efficiency of a pipeline mechanism during an MCI event. The utility of a pipeline to improve productivity has been exploited significantly in designing current computer hardware[61] and predates to as far back as Henry Ford's Model T production[62]. The second contributing factor takes advantage of the concurrency in gathering data and processing patients which demonstrates dynamically adaptive nature of EDICT. This was accomplished by using several mobile devices (as many as eight at times) to gather patient data in the Kiosk system and triage patients in the Secondary-Triage stage. Since a given mobile device can function in either Kiosk or Nurse mode, the utility of the devices can be altered to accelerate the slowest segment of the patient processing pipeline. For instance, during our exercise, between 12:30 pm and 2:00 pm (Figure 5.13), a rush of patients inundated the Kiosk stage of the pipeline. In response, two additional tablets were switched into Kiosk mode and added to the patient processing pipeline to resolve a potential bottleneck. This feature of the app allows for real-time modification of the system to satisfy the most demanding portion of the triage process.

LIMITATIONS

Future iterations of EDICT will look to resolve important obstacles identified during our analysis. First, despite a 97.1% (5174/5328 transactions) data completeness, some patients were able to bypass sections of the software by using the app in unintended ways (e.g., exiting the app and reopening it). Second, during the exercise, we identified some instances where the final submission button was not clicked by the user (nurse or patient). These instances were the primary contributors to anomalous times. To resolve these issues, future developments of the app may include automatic time-out features.

A key aspect of developing a triage system is the identification of bottlenecks or areas in which the patient processing might be slowed down. By quantifying the time patients spent at different sections, we were able to identify and remedy these bottlenecks for future iterations of EDICT. For example, patients spent more time on question 1 in the kiosk system than any other question. The expertise of a human-computer interaction researcher can help design better approaches to the limitations imposed by the cumbersome use of the on-screen keyboard. Advances in the area of Natural Language Processing can also be of immense help in this category.

During the April 2017 exercise, we anticipated two additional limitations: battery life, and internet availability. Although both issues are current limitations for any mobile development, they can be resolved in numerous ways. During the exercise, we provided redundancy in our system by having power-packs ready to be used if necessary. We also prepared a backup laptop server with 10 hours of battery life and a battery operated mobile Wi-Fi system to handle any possible power failure. Theoretically, with the use of solar panels, one could deploy our independent integrated system to any remote location.

CONCLUSIONS

Analysis of the data from the 2017 drill allowed us to quantify user behavior and measure the performance of the decision support system. The data shows that the kiosk system design performed well during the exercise regarding patient management related to a chemical MCI. Of 296 patient users 97.3% (288/296) were able to complete the kiosk system either on their own or with an assistant, which suggest very few usability issues. This is substantial considering that participants using the kiosk without an assistant had no training or prior experience using the app.

The data also showed strong agreement among nurses regarding EDICT’s decision support system. Overall, nurses agreed with EDICT 91.6% (262/286) of the time when it came to choosing an exposure level and 84.3% (241/286) of the time when selecting an action. EDICT reliably demonstrated the ability to collect patient data through a self-service kiosk system, thus reducing the burden on hospital resources. Also, the mobile technology allowed nurses the freedom to triage patients on the go while staying connected to a decision support system which they felt would give reliable recommendations. This work has set a precedent for the way patients will be triaged in the future and is a testimony that mobile technology can be a viable resource, even in an environment as chaotic as a hospital ED during a chemical MCI.

REFERENCES

1. Iserson KV, Moskop JC: **Triage in medicine, part I: Concept, history, and types**. *Ann Emerg Med* 2007, **49**(3):275-281.
2. Hogan DE, Burstein JL: **Disaster medicine**, 2nd edn. Philadelphia: Lippincott Williams & Wilkins; 2007.
3. Bollet AJ: **Civil War medicine : challenges and triumphs**. Tucson, Ariz.: Galen Press; 2002.
4. Keen WW: **The treatment of war wounds**, 2d edn. Philadelphia and London,: W. B. Saunders company; 1918.
5. United States. Department of Defense.: **Emergency war surgery. U.S. Armed Forces issue of NATO handbook prepared for use by the medical services of NATO nations**. Washington,: U.S. Govt. Print. Off.; 1958.
6. Weinerman ER, Ratner RS, Robbins A, Lavenhar MA: **Yale studies in ambulatory medical care. V. Determinants of use of hospital emergency services**. *Am J Public Health Nations Health* 1966, **56**(7):1037-1056.
7. Super G: **START: a triage training module**. *Newport Beach, CA: Hoag Memorial Hospital Presbyterian* 1984.
8. Kahn CA, Schultz CH, Miller KT, Anderson CL: **Does START Triage Work? An Outcomes Assessment After a Disaster**. *Annals of Emergency Medicine* 2009, **54**(3):424-430.
9. Wallis L, Carley S, Hodgetts CT: **A procedure based alternative to the injury severity score for major incident triage of children: results of a Delphi consensus process**. *Emerg Med J* 2006, **23**(4):291-295.
10. Kollek D, Welsford M, Wanger K: **Chemical, biological, radiological and nuclear preparedness training for emergency medical services providers**. *Can J Emerg Med* 2009, **11**(4):337-342.
11. Cone DC, Koenig KL: **Mass casualty triage in the chemical, biological, radiological, or nuclear environment**. *Eur J Emerg Med* 2005, **12**(6):287-302.
12. Ramesh AC, Kumar S: **Triage, monitoring, and treatment of mass casualty events involving chemical, biological, radiological, or nuclear agents**. *J Pharm Bioallied Sci* 2010, **2**(3):239-247.
13. Lerner EB, Schwartz RB, Coule PL, Weinstein ES, Cone DC, Hunt RC, Sasser SM, Liu JM, Nudell NG, Wedmore IS *et al*: **Mass casualty triage: an evaluation of the data and development of a proposed national guideline**. *Disaster Med Public Health Prep* 2008, **2 Suppl 1**:S25-34.
14. Lerner EB, Cone DC, Weinstein ES, Schwartz RB, Coule PL, Cronin M, Wedmore IS, Bulger EM, Mulligan DA, Swienton RE *et al*: **Mass casualty triage: an**

evaluation of the science and refinement of a national guideline. *Disaster Med Public Health Prep* 2011, **5**(2):129-137.

15. Wuerz RC, Travers D, Gilboy N, Eitel DR, Rosenau A, Yazhari R: **Implementation and refinement of the emergency severity index**. *Acad Emerg Med* 2001, **8**(2):170-176.
16. Travers DA, Waller AE, Katznelson J, Agans R: **Reliability and validity of the emergency severity index for pediatric triage**. *Acad Emerg Med* 2009, **16**(9):843-849.
17. Platts-Mills TF, Travers D, Biese K, McCall B, Kizer S, LaMantia M, Busby-Whitehead J, Cairns CB: **Accuracy of the Emergency Severity Index triage instrument for identifying elder emergency department patients receiving an immediate life-saving intervention**. *Acad Emerg Med* 2010, **17**(3):238-243.
18. Elshove-Bolk J, Mencl F, van Rijswijck BT, Simons MP, van Vugt AB: **Validation of the Emergency Severity Index (ESI) in self-referred patients in a European emergency department**. *Emerg Med J* 2007, **24**(3):170-174.
19. Casarett LJ, Doull J, Klaassen CD: **Casarett and Doull's toxicology : the basic science of poisons**, 7th edn. New York: McGraw-Hill; 2008.
20. Williams PL, James RC, Roberts SM: **Principles of toxicology : environmental and industrial applications**, Third edition. edn. Hoboken, New Jersey: Wiley; 2015.
21. **US Department of Transportation Pipeline and Hazardous Materials Safety Administration Incident Report** [http://www.phmsa.dot.gov/hazmat/library/data-stats/incidents]
22. Workgroup P: **Biological and chemical terrorism: strategic plan for preparedness and response**. *MMWR* 2000(49):1-14.
23. **Centers for Disease Control and Prevention** [https://www.cdc.gov]
24. **Hospital Preparedness Program** [https://www.phe.gov]
25. Culley JM, Svendsen E: **A review of the literature on the validity of mass casualty triage systems with a focus on chemical exposures**. *Am J Disaster Med* 2014, **9**(2):137-150.
26. Culley JM, Svendsen E, Craig J, Tavakoli A: **A Validation Study of 5 Triage Systems Using Data from the 2005 Graniteville, South Carolina, Chlorine Spill**. *J Emerg Nurs* 2014, **40**(5):453-460.
27. Einav S, Aharonson-Daniel L, Weissman C, Freund HR, Peleg K, Israel Trauma G: **In-hospital resource utilization during multiple casualty incidents**. *Ann Surg* 2006, **243**(4):533-540.
28. Hirshberg A, Holcomb JB, Mattox KL: **Hospital trauma care in multiple-casualty incidents: a critical view**. *Ann Emerg Med* 2001, **37**(6):647-652.
29. Greene W: **Distinguishing between heterogeneity and inefficiency: stochastic frontier analysis of the World Health Organization's panel data on national health care systems**. *Health Econ* 2004, **13**(10):959-980.
30. Berwick DM, Hackbarth AD: **Eliminating Waste in US Health Care**. *Jama-J Am Med Assoc* 2012, **307**(14):1513-1516.
31. Garber AA, Skinner J: **Is American Health Care Uniquely Inefficient?** *J Econ Perspect* 2008, **22**(4):27-50.

32. Hunt DL, Haynes RB, Hanna SE, Smith K: **Effects of computer-based clinical decision support systems on physician performance and patient outcomes - A systematic review**. *Jama-J Am Med Assoc* 1998, **280**(15):1339-1346.
33. Garg AX, Adhikari NKJ, McDonald H, Rosas-Arellano MP, Devereaux PJ, Beyene J, Sam J, Haynes RB: **Effects of computerized clinical decision support systems on practitioner performance and patient outcomes - A systematic review**. *Jama-J Am Med Assoc* 2005, **293**(10):1223-1238.
34. Kawamoto K, Houlihan CA, Balas EA, Lobach DF: **Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success**. *Brit Med J* 2005, **330**(7494):765-768e.
35. Aylwin CJ, Konig TC, Brennan NW, Shirley PJ, Davies G, Walsh MS, Brohi K: **Reduction in critical mortality in urban mass casualty incidents: analysis of triage, surge, and resource use after the London bombings on July 7, 2005**. *Lancet* 2006, **368**(9554):2219-2225.
36. Culley J: **Mass casualty information decision support**. *OJNI* 2011, **15**(3).
37. Swain C: **WISER and REMM: resources for disaster response**. *Journal of Electronic Resources in Medical Libraries* 2009, **6**(3):253-259.
38. **Wireless Information System for Emergency Responders (WISER)** [http://www.webcitation.org/6ySY4t6v0 https://wiser.nlm.nih.gov/]
39. **Chemical Hazards Emergency Medical Management-Intelligent Syndromes Tool (CHEMM-IST)** [https://webwiser.nlm.nih.gov/tools/Chemmist.do]
40. **Google Maps APIs** [http://www.webcitation.org/6ySjiBYvu, https://developers.google.com/maps/]
41. Haynes BE, Freeman C, Rubin JL, Koehler GA, Enriquez SM, Smiley DR: **Medical response to catastrophic events: California's planning and the Loma Prieta earthquake**. *Annals of emergency medicine* 1992, **21**(4):368-374.
42. Nie H, Tang SY, Lau WB, Zhang JC, Jiang YW, Lopez BL, Ma XL, Cao Y, Christopher TA: **Triage during the week of the Sichuan earthquake: a review of utilized patient triage, care, and disposition procedures**. *Injury* 2011, **42**(5):515-520.
43. Gershenfeld NA: **The nature of mathematical modeling**: Cambridge university press; 1999.
44. McClelland JL, Rumelhart DE, Group PR: **Parallel distributed processing**, vol. 2: MIT press Cambridge, MA:; 1987.
45. Rumelhart DE, McClelland JL: **The PDP Research Group 1986. Parallel Distributed Processing: Explorations in the Microstructure of Cognition, vol. 1: Foundations**. In.: Cambridge, Mass.: Bradford Books (MIT Press).
46. Fukunaga K: **Introduction to statistical pattern recognition**: Academic press; 2013.
47. Falvo T, Grove L, Stachura R, Vega D, Stike R, Schlenker M, Zirkin W: **The opportunity loss of boarding admitted patients in the emergency department**. *Acad Emerg Med* 2007, **14**(4):332-337.
48. Huang Q, Thind A, Dreyer JF, Zaric GS: **The impact of delays to admission from the emergency department on inpatient outcomes**. *BMC Emerg Med* 2010, **10**:16.

49. Krochmal P, Riley TA: **Increased Health-Care Costs Associated with Ed Overcrowding**. *Am J Emerg Med* 1994, **12**(3):265-266.
50. Rabin E, Kocher K, McClelland M, Pines J, Hwang U, Rathlev N, Asplin B, Trueger NS, Weber E: **Solutions To Emergency Department 'Boarding' And Crowding Are Underused And May Need To Be Legislated**. *Health Affair* 2012, **31**(8):1757-1766.
51. Boltin N, Vu D, Janos B, Shofner A, Culley J, Valafar H: **An AI model for Rapid and Accurate Identification of Chemical Agents in Mass Casualty Incidents**. In: *Int'l Conf Health Informatics and Medical Systems: 2016; Las Vegas, NV*. CSREA: 169-175.
52. Moller MF: **A Scaled Conjugate-Gradient Algorithm for Fast Supervised Learning**. *Neural Networks* 1993, **6**(4):525-533.
53. J Ball M: **The history of medical informatics in the United States**. New York, NY: Springer Berlin Heidelberg; 2015.
54. Shortliffe EH, Cimino JJ: **Biomedical informatics: computer applications in health care and biomedicine**: Springer Science & Business Media; 2013.
55. Lerner EB, Cushman JT, Drendel AL, Badawy M, Shah MN, Guse CE, Cooper A: **Effect of the 2011 Revisions to the Field Triage Guidelines on Under- and Over-Triage Rates for Pediatric Trauma Patients**. *Prehosp Emerg Care* 2017, **21**(4):456-460.
56. Aydelotte JD, Lammie JJ, Kotora JG, Riesberg JC, Beekley AC: **Combat Triage and Mass Casualty Management**. In: *Front Line Surgery*. Springer; 2017: 17-37.
57. **SALT mass casualty triage: concept endorsed by the American College of Emergency Physicians, American College of Surgeons Committee on Trauma, American Trauma Society, National Association of EMS Physicians, National Disaster Life Support Education Consortium, and State and Territorial Injury Prevention Directors Association**. *Disaster Med Public Health Prep* 2008, **2**(4):245-246.
58. McHugh M, Tanabe P, McClelland M, Khare RK: **More Patients Are Triaged Using the Emergency Severity Index Than Any Other Triage Acuity System in the United States**. *Academic Emergency Medicine* 2012, **19**(1):106-109.
59. Culley JM, Richter J, Donevant S, Tavakoli A, Craig J, DiNardi S: **Validating Signs and Symptoms From An Actual Mass Casualty Incident to Characterize An Irritant Gas Syndrome Agent (IGSA) Exposure: A First Step in The Development of a Novel IGSA Triage Algorithm**. *J Emerg Nurs* 2017, **43**(4):333-338.
60. Hampton RE, Havel JE: **Introductory biological statistics**: Waveland Press; 2006.
61. Rojas R: **Konrad Zuse's legacy: The architecture of the Z1 and Z3**. *Ieee Ann Hist Comput* 1997, **19**(2):5-16.
62. Alizon F, Shooter SB, Simpson TW: **Henry Ford and the Model T: Lessons for Product Platforming and Mass Customization**. *Dect2008: Proceedings of the Asme International Design Engineering Technical Conference and Computers and Information in Engineering Conference, Vol 5* 2009:59-66.

APPENDIX A

SUPPLEMENTAL MATERIAL

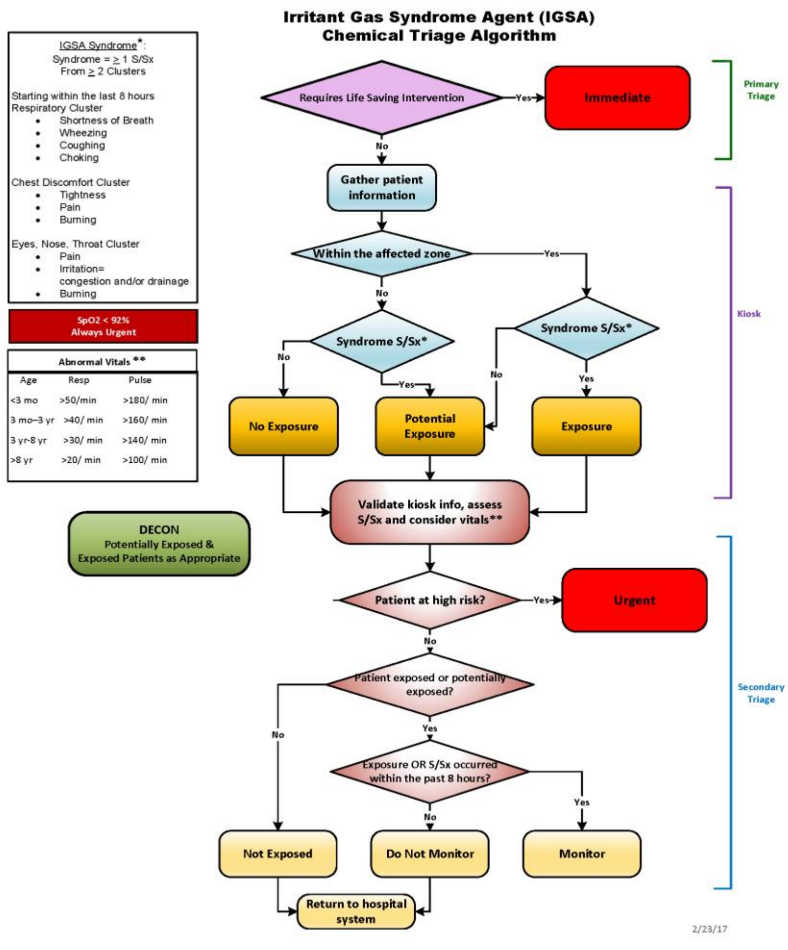


Figure A.1 Irritant Gas Syndrome Agent Chemical Triage Algorithm. A chemical triage algorithm for detecting an irritant gas syndrome agent. The algorithm requires that decisions be made regarding a patient’s exposure level and action to correctly assign a triage category.

APPENDIX B

PERMISSIONS TO REPRINT

A **Creative Commons** (**CC**) **license** is one of several public copyright licenses that enable the free distribution of an otherwise copyrighted work. A CC license is used when an author wants to give people the right to share, use, and build upon a work that they have created.

A CC license (other than CC0, see below) is not a transfer of copyright. The license only governs the terms of use - under which conditions and how the material can be used. The copyright holder remains the holder of the copyright and can grant rights that exceed what is allowed under the license.

There are several types of CC licenses. In the context of JMIR Publications, the most important licenses are cc-by (attribution license) and CC0 (public domain: material can be used freely). All articles in JMIR are published under cc-by, which is the most liberal cc-license other than CC0. The only condition for use is attribution (cite the origin/copyright holder) and stating that it is published under cc-by.

When editorial staff or authors pick a TOC image for an article, they typically look for an image licensed under CC-BY or CC0, unless it is created by the authors themselves (Copyright, Licensing, Attribution of TOC images).

Figure B.1 JMIR Permission. Documentation showing permission to reprint from the Journal of Medical Internet Research (JMIR)

Copyright and Reprint Permission

Copying without a fee is permitted provided that the copies are not made or distributed for direct commercial advantage, and credit to source is given. Abstracting is permitted with credit to the source. Please contact the publisher for other copying, reprint, or republication permission.

Copyright © 2016 CSREA Press
ISBN: 1-60132-437-5
Printed in the United States of America

Figure B.2 HIMS Permission. Documentation showing permission to reprint from the proceedings of the 2016 International Conference on Health Informatics and Medical Systems.