THE EFFECTS OF COMPUTER SIMULATION ON REDUCING THE INCIDENCE OF MEDICAL ERRORS ASSOCIATED WITH MASS DISTRIBUTION OF CHEMOPROPHYLAXIS AS A RESULT OF A BIOTERRORISM EVENT

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I dedicate this dissertation to my wife, Jenny who stood by me throughout this entire process.

I love you!

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GLOSSARY

Agent – An individual or collective entity that conducts actions or interactions with other autonomous entities within a simulation model.

Conceptual Model – "A non-software specific description of the simulation model that is to be developed, describing the objectives, inputs, outputs, content, assumptions and simplifications of the model." (Robinson, 2004, p. 65)

Discrete-Event Simulation – "Operation of a system as a discrete sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system. Between consecutive events, no change in the system is assumed to occur; thus the simulation can directly jump in time from one event to the next." (Robinson, 2004, p. 15)

Modeling – "Finding the way from a problem to its solution through a risk-free world where we're allowed to make mistakes, undo things, go back in time, and start over." (Grigoryev, 2015, p. 8)

Point of Distribution (POD) – "Area established in which mass distribution of antibiotics or vaccine is performed and patients are registered, are triaged, have swab samples taken, are medically evaluated, and are provided with antibiotics."(Landesman, 2012, p. 335)

Real System – "The system that which the simulation is to represent." (Robinson, 2004, p. 65)

Simulation – "Experimentation with a simplified imitation (on a computer) of an operations system as it progresses through time, for the purpose of better understanding and/or improving that system." (Robinson, 2004, p. 4)

LIST OF ABBREVIATIONS

Amox – Amoxicillin

ANOVA – Analysis of Variance

Adj R square – Adjusted R Square

CBRNE – Chemical, Biological, Radiological, Nuclear, and Explosives

CDC – Center for Disease Control and Prevention

CIL – Confidence Interval Limit

Cipro – Ciprofloxacin

df – Degrees of Freedom

Disp – Dispenser

Doxy – Doxycycline

DSCA – Defense Support of Civil Authority

EMCAPS – Electronic Mass Casualty Assessment and Planning Scenarios

M – Mean

M S – Mean Square

Med – Medication

N – Number of Observations in Group

NSS – National Strategic Stockpile

OR – Odds Ratio

p – P Value

POD – Point of Distribution

Prob – Probability

RMSE – Root Mean Square Error

RR – Relative Risk

R^2 – Coefficient of Determination

S – Sum of Squares

SD – Standard Deviation

SE – Standard Error

Spring. 15 – Point of Distribution exercise conducted during the Spring semester of 2015

SM – Standard Error of Measurement

ABSTRACT

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The objective of research is to develop a computer simulation model to provide a means to effectively and efficiently reduce medication errors associated with points of distribution sites by identifying and manipulating screeners with a high probability of generating errors. Points of distribution sites are used to rapidly distribute chemoprophylaxis to a large population in response to a pandemic event or a bioterrorism attack. Because of the nature of the rapid response, points of distribution sites require the use of peer-trained helpers who volunteer their services. The implications are that peer-trained helpers could have a variety of experience or education levels. These factors increase the risk of medical errors. Reducing medical errors is accomplished through changing the means in which healthcare providers are trained and focusing on a team approach to healthcare delivery. Computer simulations have been used in the past to identify sources of inefficiency and potential of error. Data for the model were collected over the course of two semesters. Of the 349 data points collected from the first semester, only 137 data points were usable for the purposes of model building. When the experiment was conducted again for the second semester, similar results were found. The control simulation was run 20 times with each screener generating errors with a probability of 0.101 following a Bernoulli distribution. The variable simulation was run 30 times with each screener generating the same probability of errors; however, the researcher identified the screeners generating the errors and immediately stopped them from processing additional agents once they reached five errors. An ANOVA was conducted on the percent errors generated from each simulation run. The results of the ANOVA showed significant difference between individuals within the groups. A simulation model was built to reflect the differences in medical error rates between screeners. By comparing the results of the simulation as the screeners are manipulated in the system, the model can be used to show how medical errors can be reduced in points of distribution sites.

CHAPTER 1. INTRODUCTION

1.1 Statement of Problem

In 1999, the Centers for Disease Control and Prevention (CDC) created the national pharmaceutical stockpile. The goal of this national stockpile was to improve the readiness of the US against potential agents of bioterrorism. The three main diseases of concern were anthrax, smallpox, and tularemia (Centers for Disease Control and Preventions, 2015). The stockpiles contain all of the necessary means and pharmaceuticals to administer oral and intravenous antibiotics, antitoxins, vaccines to patients (Dietz, Black, Aaltonen, Tennessen, & Dietz, 2016). The purpose of maintaining such a large stockpile was to have the capability to distribute medical supplies, inoculations, and chemoprophylaxis to each state within 12 hours of an emergency, or any situation that would warrant their use. The stockpiles are designed to be scalable to a specific response with an assortment of medical threats (Centers for Disease Control and Preventions, 2015).

Within days of the terrorist attacks on New York, The Pentagon and Pennsylvania on September 11, 2001, a perpetrator, the FBI believed to be Bruce Edwards Ivins, used the US Postal Service to distribute letters containing Anthrax spores to members of congress (*FBI Anthrax Report*, 2005). In response to this attempt at a bioterrorism attack on the US Government, the CDC expanded the Strategic National Stockpile, (SNS) for use in catastrophic additional catastrophic emergencies (Dietz et al., 2016). The CDC is responsible for maintaining and distributing the SNS under the guidance of policies established by the US Department of Health and Human Services (Landesman, 2012). State and local health departments are responsible for developing plans to distribute the contents of the SNS to their residents. Federal funding for a bioterrorism response is contingent on the state and local government's ability to

maintain a comprehensive plan for distributing the SNS supplies through the use of distribution hubs (Hupert, Mushlin, & Callahan, 2002).

Despite the planning and preparation made by federal, state and local agencies, major emergencies and disasters can still be intense situations where individuals and teams make critical choices while managing ambiguity and complexity (Power, 2017). In emergency situations, public health and emergency management personnel are asked to make judgement calls and decisions with little background information that could impact the overall health of a population with little background information (Burgess, 2007). Due to this ambiguity and complexity, the probability of errors occurring within a public health emergency increase. Medical errors are typically not the result of a negligent or incompetent provider. They are generally the result of how the health care system is organized and how care is delivered (Crane & Crane, 2008). With the distribution of chemoprophylaxis and therapeutic medication, there is the inherent risk of medication errors made by personnel administering these medications to the public.

1.2 Significance

Medical errors are a major concern in the healthcare field. In a 1999 report, The Institute of Medicine stated medical errors account for as many as 44,000 deaths year. In the same report, The Institute of Medicine also stated that the number of deaths related to medical errors could be as large as 98,000 deaths/ year (Kohn, Corrigan, & Molla, 1999). They define medical errors as "the failure of a planned action to be completed as intended or the use of a wrong plan to achieve an aim" (p.1). James (2013) disagreed with the report published in 1999, and armed with statistical analyses, he suggested that the Institute of Medicine calculations were inaccurate. He estimated the annual number of preventable deaths due to medical error was 175,000 deaths/

year and could be as much as large as 210,000 deaths/ year. This estimate suggests that medicals error are as the third leading cause of death behind heart disease and cancer (Burdwell, Frieden, Thomas, & Rothwell, 2016).

Healthcare delivery is a series of systems that are connected at different points. For example, a patient schedules an appointment with his/her physician. The physician takes notes and records data on an electronic database. That information is then transferred to other physicians, or a pharmacist. The pharmacist will then analyze the information provided by the physician and deliver a medication to the patient. Healthcare delivery is a system where every point where a person interacts with another person or an electronic database is a specific link in the chain. The backbone of the chain is the medical providers.

Errors associated with medicine and medication distribution are more common than society believes, and these errors can have devastating effects on a patient, or a population. A systematic review of literature has found that 1 in 11 patients has suffered at least one adverse event during their hospital stay. As many as one in fourteen of these events are fatal (Edwards & in Siassakos, 2012). An independent research institution at the University of Chicago conducted a cross-sectional survey of 2,500 U.S. adults. Participants were asked their opinion on medical errors, and if they had any experience with medical errors. In that report, 21% of the those who responded stated they had experienced a medical error in their own care, and 31% stated that a patient whom they had been closely involved had experienced an error while being treated (Gandhi, 2007). Accreditation through the Joint Commission requires hospitals to investigate, evaluate and report all sentinel events (Mackles, 2017). Nearly half of the respondents who had experienced a medical error stated it to someone on their care team. However, more than half

did not report because they did not believe it would result in any action, and 40% did were unfamiliar with the reporting procedures (Gandhi, 2007).

According to the Joint Commission, the most frequently identified root causes of medical error include human factors, leadership, communication, and assessment. Human factors include fatigue, confusion and negligence. Leadership factors include failure to maintain appropriate schedules or proper training for healthcare providers. Assessment factors includes a failure to correctly identify the cause of illness or diagnosis. Communication include failure to pass information from one provider to another (Mackles, 2017). The key issues with error rates in meeting medical emergency needs for public health and safety are communication barriers and a fragmented healthcare delivery system. However, the ways and means to improve on medical errors are through improved training and building healthcare teams.

Simulation is a valuable tool for finding faults in the medical delivery process and identifying locations along the process that are unexpectedly fragmented, which increase the risk of error. In a simulated environment, educators allow errors to progress in order to teach the trainee the implications of their errors. This allows the trainees to react to the error, and to rectify any deviations from them (Ziv, Wolpe, Small, & Glick, 2003). A systematic literature review showed that having practicing physicians combine computer simulation modeling with electronic medication prescription can be an effective means to reduce adverse drug effects and risk of medical error to patients (Ammenwerth, Schnell-Inderst, Machan, & Siebert, 2008). The same use of simulation has been used across a variety of industries to reduce the risk of errors and preventing unexpected deaths.

Medical providers are human. They make mistakes throughout their careers. A study conducted in the late 1990s showed that 3.99 errors occurred per every 1000 prescriptions orders

(Lesar, Briceland, & Stein, 1997). These errors can have drastic consequences, such as preventable death. In the context of a man-made or natural disaster, there are concerns with medical errors unique to the situation. Because of the nature of disasters, healthcare providers are limited, and a significant amount of healthcare is delivered via volunteers. Because volunteers' credentials cannot be verified, and the overabundance of patients, patients will typically accept risk by accepting an altered standard of care from these volunteers from an area that is not a standard medical treatment facility.

When disaster strikes, individuals come to a POD site with the intent of receiving care in order to save their lives. They do not foresee receiving the wrong medication due to human error. However, due to the frantic nature of POD sites and the fragmented system in which PODs operate, human error is inevitable. The objective of this research is to develop a computer simulation model to effectively and efficiently provide the most optimal allocation of resources for a POD site that reduces the number of errors to an acceptable rate.

1.3 Cynefin Model

Reducing medical errors associated with PODs is very complex. There are no simple answers. Snowden and Boone (2007) described complexity as a way of examining the world by using simulations and models. They use four categories of context in what Snowden refers to as the Cynefin Model: Simple, Complicated, Complex and Chaotic (Snowden & Boone, 2007; see Figure 1-1).

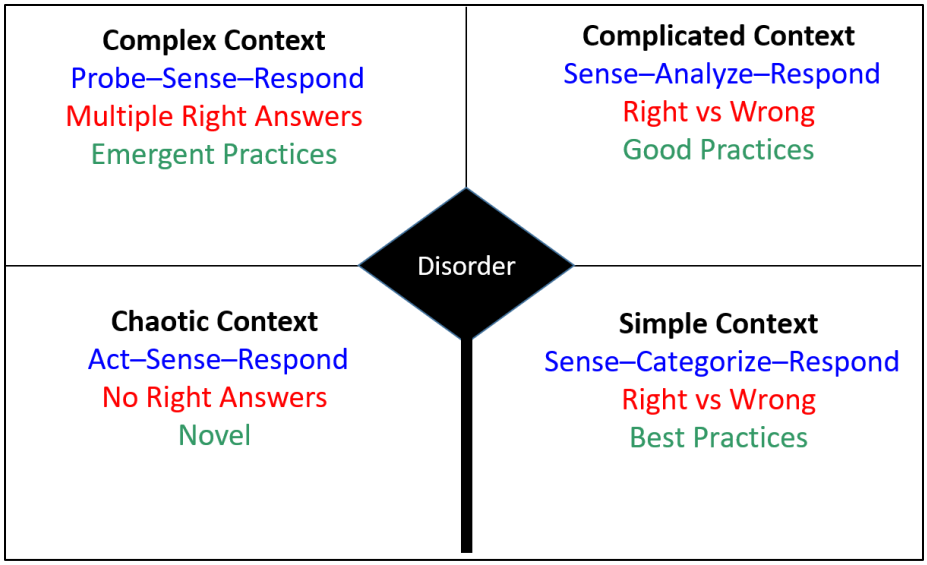

Figure 1-1. Cynefin Model

Simple contexts are clear and understood. They are characterized by stability and cause-effect relationships that are easily discernible. Usually, the correct answer is undisputable and undeniable. Simple contexts are straightforward. In the case of PODS, the individual medical error associated with a patient is usually categorized as a simple context. Leaders assess the facts of the situation, categorize those facts, and then base responses to the situation on the recognized standard practice. Decisions are unquestioned because everyone has a shared understanding of the situation (Snowden & Boone, 2007). In the case of the POD, the medication algorithm is the established practice in which guide the POD volunteers.

Complicated contexts, unlike simple ones, contain multiple correct answers. Like simple contexts, there is a clear relationship between cause and effect; however, it is not necessarily obvious to the observer. "While leaders in a simple context must sense, categorize, and respond to a situation, those in a complicated context must sense, analyze, and respond" (Snowden & Boone, 2007, p. 3). In PODS, the observer must not only recognize the error, but where the error occurred and analyze information to help make decisions to improve the POD.

If there were only one correct answer, or even one answer that would produce better results than the others, then reducing medical errors of a POD would be easy. However, this is not the case, because reducing medical errors of PODs is a complex context. In complex contexts, at least one right answer exists; however, the most appropriate answers may or may not be filtered out. In order to determine the most appropriate solution to the problem, knowledge management is required.

Knowledge management is a systems of thinking as a conceptual framework for problem-solving that considers problems in their entirety (Rubenstein-montano, Liebowitz, Buchwalter, & Mccaw, 2001). Knowledge management begins with retrieving information derived from data from multiple sources and allowing it to be analyzed by the appropriate persons. Knowledge management begins with the retrieval of data.

Snowden, and Boone (2007) defined data as "Any manifestation in the environment, including symbolic representations that in combination may form the basis of information" (p. 3). Data are simply bits of information that are retrieved. In the context of this research, data would be if a patient received the wrong medication or not. Individually, data does not provide the basis for much analysis, if any at all. Data must be processed into information (Rubenstein-montano et al., 2001). However, information is limited in the amount of analysis that can be derived. Information is nothing more than processed data that has a context in which it can be attributed (Snowden & Boone, 2007). Information can be analyzed into knowledge.

Knowledge is "A body of understanding and skills that is constructed by people. Knowledge is increased through interaction with information" (Snowden & Boone, 2007). When multiple people contribute information in a group setting and analyze it, knowledge is obtained (Rubenstein-montano et al., 2001). Reducing errors in PODS is an excellent example

of how knowledge is used. A screener retrieves data from a patient and processes it into information that can be used to determine which medication is correct for that patient. If the medication is incorrect, the dispenser or validator should observe the error, and correct it. If the validator or dispenser observe multiple errors coming from the same screener, they share that information with each other thus creating knowledge. They can use that knowledge to take appropriate steps to adjust the behavior of the screener, which is the basis for the simulation used in this research.

Because there are solutions to reducing medical errors associated with PODs, and there is a cause and effect relationship, a POD context is not defined as a chaotic. In a chaotic context, searching for right answers would be pointless. Because the relationship between cause and effect shift constantly, and no manageable patterns exist, the relationships between cause and effect are impossible to determine (Snowden & Boone, 2007).

1.4 Scope

The scope of this research is to build a computer simulation model for a POD site. The model would be a multimethod simulation consisting of statechart-based agents traversing a discrete-event simulation. The purpose of this simulation model was to replicate the process of participants traversing a POD site. The independent variables for this model included the number of screening and dispensing nodes based on the number of peer-trained helpers to operate the site, and the number of patient-agents traversing the simulation The output of the model was the number of errors observed by an individual within the simulation replicating a validation station at the end of the POD to check for errors. The dependent variable was the total number of medical errors observed in each group.

1.5 Assumptions

- The following assumptions are made about this study:
    - There is enough data to build a computer simulation model to effectively calculate a means to reduce medical error in a POD.
    - The participants used in data collection for the simulation took the exercise seriously, they and executed to their duties and responsibilities to the best of their abilities.
    - The source data collected to build the computer simulation was an accurate portrayal of the real POD system.

1.6 Limitations

- The study is limited to examining the following:
    - The use of multimethod simulation on the outcomes of medical errors associated with POD sites.

1.7 Delimitations

- The following are delimitations for this study:
    - This study examined the application of training during the exercise itself. Synchronous (traditional) training methods verses asynchronous (just-in-time) training methods were not addressed
    - This study did not evaluate patient satisfaction on the outcome of time requirements through the POD site, or on aspects of medical errors associated with POD sites.

1.8 Summary

POD sites are a necessary means to reduce the risk of widespread epidemics either from natural causes, brotherism or terrorist attacks. The CDC and FEMA have a noteworthy task of maintaining and distributing the SNS. The problem is in the event of a disaster, when the number of healthcare providers is low, volunteers are used to fill the voids created by the lack of

trained providers. These volunteers have varying levels or experience and education. This results in potential miscommunication between providers and issuing medication incorrectly or issuing the wrong medications to patients. Viewing healthcare as a system instead of as individual discrete entities can lead medical professionals to build simulations to reduce the risk of errors. In preparation of a disaster situation, computer simulation can be a valuable tool to improve the overall process accuracy and timely staffing for supporting emergency medical response. Unfortunately, there is a dearth of data to support running full scale operations. Also, the resources required to run a full-scale disaster operation would be great, both in time, space and finances. Computer simulation is a means to avoid staging costly full-scale exercises and, instead determine outcomes based on the manipulation of the computer simulation. The purpose of this study is to demonstrate how using a discrete-event computer simulation model could assist in reducing medical errors associated with PODs.

CHAPTER 2. LITERATURE REVIEW

Natural and man-made disasters can generate situations where healthcare services are limited. Given the circumstances of most disasters, trained healthcare professionals would most likely be unavailable for mass medication distribution, which forces emergency services to rely heavily on volunteers with varying levels of experience, and education. These circumstances produce a high risk of medical errors when distributing medications. Ever since humans first began to heal aliments, they have made mistakes in diagnosis and treatment, every mistake from a simple misunderstanding of how the human body functioned to a grave miscalculation of medicine.

The purpose of this literature review is to examine the evidence of medical errors and the historical evidence as to how the healthcare industry has attempted to reduce those errors. This review will discuss how medications interact with the human body, and how those interactions can have devastating effects if administered incorrectly or the wrong medication is administered. This review also will examine the statistical significance of errors in healthcare, the sources of those errors, and the means in which the industry has attempted to reduce these errors. This literature review will examine simulation as being one of these means, and how other industries have used simulation to reduce and mitigate errors. This review will finish by examining the prevalence of medical errors associated with disasters and emergency situations.

2.1 Errors in Medicine Associated with Disasters

Medical errors during a mass distribution site are concerning to professionals; however, there are a dearth of articles published that address this issue. Natural and man-made disasters can generate circumstances where healthcare providers are limited. Given the conditions of most

disasters, a plethora of trained healthcare professionals would most likely be unavailable for mass medication distribution. Therefore, rapidly training volunteers to distribute medication efficiently and effectively is crucial. The rapid training of these volunteers is likely to generate a significant number of associated errors. Because of the nature of disasters, most patients are willing to accept the risk of altering the standard of care (i.e., being seen outside of a healthcare facility). Altering the standard of care could have unforeseen long-term consequences.

Williams, Nocera, and Casteel (2008) found mixed results when they conducted a meta-analysis to examine a relationship between healthcare worker training in disaster preparedness and knowledge in disaster response. They examined 258 studies. Included in those were 19 articles representing in-hospital and out-of-hospital training, occurring inside and outside of the US. They focused on various types of training including computer-based training, lecture based training, and hands-on training. The majority of articles they examined included a re-test/post-test assessment design. Three of the articles included in the meta-analysis tested in-hospital medical personnel, with a focus on emergency department providers, whereas five of the included articles tested pre-hospital medical personnel.

The results of the meta-analysis showed all of the articles describing out-of-hospital participants, emergency medical technicians, firefighters, law enforcement, etc., showed an increase in post-intervention test scores. However, there is a threat of internal validity due to selection bias. The articles described the institutions being allowed to select the participants for the study as opposed to being selected at random. Also, sine the participants were exposed to the post-test questions during the pre-test, the risk of a compromising internal validity exists (Williams et al., 2008). Due to these potential biases and the possibility of confounding factors attributing to the increased post-intervention test scores, conclusions cannot be drawn.

2.2 Mitigating and Reducing the Risk of Medical Error

Despite the prevalence of errors associated with medicine, the healthcare industry is taking efforts to reduce and mitigate those errors. The largest means of reducing errors is through changing ways that healthcare providers are trained. Training now includes everything from focusing on better preparation of the patients to receive medical care just-in-time training.

2.2.1 Identifying Errors

Ever since the beginning of the practice of medicine, it has been established as an ad hoc series of "cottage industries" with no larger organization. Thus, this ad hoc means is the root of the problem associated with errors. The medical industry has grown so vast and complicated that tackling these inefficient systems would be extremely difficult (Giese, 2012). Developing training procedures to reduce the number of errors is contingent upon first identifying sources of error (Fidopiastis, Venta, Baker, & Stanney, 2018).

Typically, healthcare is divided into multiple functions. Nurses are responsible for patient vital signs and statistics, physicians are responsible for ordering medications and therapy. Therapists are responsible for providing therapy. Pharmacists are responsible for delivery of medication. This system of functions can lead to ambiguity and communication breakdowns (Spear, 2005). The ambiguity and communication breakdown are the focus of this paper for sources of errors, because it is the most likely place training procedures will have an effect on reducing errors.

Data mining of medical records has the potential to identify sources of error. The Boolean-rule-based model used electronic health records to examine deviations among physicians. The Boolean-rule-based model compared deviations in standards of care across four disease states: diabetes, cardiovascular disease, asthma and rheumatoid arthritis. The metric

researchers used to examine deviations was the standard of care procedures before and after diagnoses (Fidopiastis et al., 2018). The result of the study demonstrated that diagnosis and treatment should be considered separate processes in the scope of identifying the source of the errors. The results also allowed for a more accurate assessment of provider competency (Fidopiastis et al., 2018).

In an effort to determine individual and professional factors affecting emergency unit medical errors, it was determined that 40.1% of the nurses surveyed previously witnessed medical errors, and 19.4% had made a medical error in the last year. There were, 91.2% of those surveyed who thought medical errors were attributed to excessive workload, 85.1% stated an insufficient number of nurses, and 75.4% attributed the errors to fatigue, or exhaustion (Kiymaz & Koç, 2018).

2.2.2 High-Reliability Organizations

The goal of high-reliability organizations is zero patient injuries due to medical error. John Brumsted, CEO of the Vermont Medical Center, does not think that is possible. He does not think there can be a definition for a High-reliability organization; however, there can be a definition for a high-reliability process, in which the errors can be driven to an absolute minimum, but not zero (Butcher, 2015). Because the probability of removing error from the procedures does not seem realistic, one possibility would be to focus on error identification, and thereafter, mitigating the effects of these errors. Being guided by human cognitive architecture and how the brain processes information, training should be focused on error detection, error reduction and error recovery. It is important to learn how to identify errors, mitigate their effects, and recover from them, not just prevent them (Dror, 2011).

Dror suggested that adjusting training is the key to reducing medical errors. The current training is not effective because it directly focuses on error reduction. Being guided by human cognitive architecture and how the brain processes information, training should be focused on error detection, error reduction and error recovery. Error recovery training requires rapid error detection and what to do to recover from them. The first step is that the learner is required to detect errors through interactive and experimental training. It is easier to detect errors in others than in oneself (2011). The ability to assess the predominance of diagnostic or treatment errors for a given disease state allows for a more accurate assessment of physician competency. This approach provided a means to explore concerns about the system and process-related contributions to patient diagnostic error (Fidopiastis et al., 2018). The persons providing the healthcare can then get a better appreciation for how to prevent errors to begin with once they understand how to identify the errors and learn to mitigate the consequences of the errors. In order to reduce the number of errors in medicine, one must first identify the source of errors, and develop plans to mitigate them. One approach is to adjust training to allow medical providers to make errors, then provide them the opportunity to learn from their mistakes.

Dror stated the training environment should allow trainees to make errors, then identify those errors and to build a cognitive system on how to recover from those errors. Error recovery training requires rapid error detection and what to do to recover from them. The first step is that the learner is required to detect the error through interactive and experimental training. It is easier to see errors in others than in oneself. Focus initially on detecting errors committed by others, then move training to detecting errors in oneself. Once the trainee has learned to identify the error, he/she can then learn methods to minimize the effects of the error. Training to

minimize error involves not only conveying information but must derive from insights and understandings of the causes of the error (Dror, 2011).

2.2.3 Just-in-Time Training

Staffing is a significant issue for medication distribution during a natural or manmade disaster. Given the circumstances of most disasters, trained healthcare professionals would most likely be unavailable for mass medication distribution. Therefore, rapidly training volunteers to distribute medication efficiently and effectively is crucial. Just-in-time training is a type of training used to rapidly train volunteers as they arrive. The intent of just-in-time training is to provide just enough proficiency to the volunteers so they can fill the void created by trained and educated healthcare workers being unavailable. Just-in-time training has been shown to work in past exercises.

Researchers with the University of Pittsburg developed a 5-module educational program. Through a collaborative, multidisciplinary effort with the University of Pittsburg Medical School, they examined if just-in-time training could be used to prepare individuals with little familiarity of dialysis to support staff during a disaster (Stoler, Johnston, Stevenson, & Suyama, 2013). A pilot study testing the program was performed using 20 non-technician dialysis facility employees and 20 clinical-year medical students as subjects. Non-technician dialysis participants included any employee at a standalone dialysis facility who did not have prior detailed knowledge of the dialysis process. These employees included those from administrators to dieticians. The researchers developed a pre-test and a post-test to measure the improvement of both groups. The pre-test and post-test were developed using teaching materials from local dialysis facilities in collaboration with experienced dialysis educators (Stoler et al., 2013).

For the entire study population, there was a mean improvement of 28.9%. There was a mean increase in score of 21.8% for dialysis facility employees, and a 36.4% increase in score for the medical students. The participants who received the intervention using the just-in-time training modules showed a significant improvement to their tests scores (Stoler et al., 2013). The results of this study suggest how knowledge gained by using this program during a staff shortage as a result of a disaster may allow for continuity of care for critical services.

Just-in-time training also has been shown to increase efficiency and effectiveness associated with distribution of medications during a point of distribution (POD) exercise. In 2015 in Tippecanoe County, Indiana, researchers at Purdue University conducted an exercise where volunteers were divided into two groups. Each group was further subdivided into cohorts: synchronous, and asynchronous training. The synchronous subgroup were the ones being trained using the standard practice. The Asynchronous subgroup received the just in time training. The results of the exercise showed the time required to train using asynchronous procedures (just-in-time) was significantly less than the amount of time required to train using the synchronous procedures. The results demonstrated the possible advantages of using just-in-time training to rapidly train volunteers. Asynchronous training has the potential to save money and time, both commodities of importance when responding to disasters. The aspect of just-in-time training that focuses on identifying errors is just as important as the aspect of preventing errors.

2.2.4 Decreasing the incidence of errors through a team approach

One approach to error reduction is using teams for on healthcare delivery. Multidisciplinary teams in acute care provide clinical problem solving and planning, usually at bedside to engage the patients and their loved ones (Rosen et al., 2018). Forming medical cooperative teams are essential for reducing the number of errors seen in medicine.

"Cooperative teams are those whose team members are motivated to work together to pursue collective goals due to shared attitudes and beliefs that drive behavior" (Power, 2017; Rosen et al., 2018, p. 481). There are challenges with teams that prevent them from becoming cooperative teams: lack of trust either in team members benevolence or lack of trust in their abilities; intra-agency competition and inter-team conflict; poor understanding of each team member's role in the emergency; and inefficient or ineffective communication (Power, 2017). In order for a team to work effectively to reduce medical errors, the team members need to possess a combination of both technical skills and non-technical skills. Non-technical skills are social and cognitive skills that support high quality, safe, effective and efficient inter-professional care (Rosen et al., 2018).

Another area that could decrease the number of medical errors within a distribution site is increasing collaboration between healthcare providers. With an increase in communication and collaboration, the healthcare team can focus more effectively on interventions to reduce medical error. Promising interventions include "forcing functions", like checklists, computerized prescriber order entry with decision support, standardization and simulation training to look at how errors will affect patients, and train providers to identify errors before they can cause harm (Woodward et al., 2010). The healthcare community used to view errors as a result of ignorance or negligence. However, healthcare providers are influenced by many different biases including age, gender, class or emotional state (Giese, 2012). These biases can lead providers to take shortcuts. The use of checklists and protocols, which are enforced through communication and collaboration, can help mitigate some of the bias and shortcuts. For example, Michigan Health and Hospital Association began to implement the use of a protocol checklist in 2003 for "central line insertion," a small, soft tube catheter that is placed in a central vein that leads directly to the

patient's heat. As a result, the number of hospital-acquired infections dropped from 2.7/ 1,000 patients to 0 within a matter of months (Giese, 2012).

A study examining medical errors attributed to resident physicians showed lower incidence of medical error were associated with lower levels of independence and higher levels of discussion with the physician on call (Naveh, Katz-Navon, & Stern, 2014). With collaboration and increased communication, the skills and self-efficacy of the providers also increases. When the skills and self-efficacy of providers increased, the result was more patient trust of the healthcare system and compliance with the medical instructions. Sany, et al., conducted a randomized control trial where they enrolled 35 healthcare providers and 240 hypertensive patients. They divided the study participants into two groups, an intervention and a comparison. What they found were following the educational intervention was a substantial improvement in their ability to communicate with patients and self-efficacy. This led to a higher number of patients adhering to medication as directed by their healthcare providers. The hypertension outcomes in the intervention group decreased compared to the control group. The brief training in communication skills targeted at health care providers seemed to be an efficient way to improve patient-provider communication, and also had a positive effect on patient outcome (Tavakoly Sany et al., 2018). Inclusion of teamwork and non-technical skills training is recommended by The latest European and American Guidelines. By highlighting areas of weakness within a team during a resuscitation event, communication tended to enhance constructive feedback and training was more targeted (Edwards & Siassakos, 2012).

Harkanen, Saano, and Vehvilainen-Julkunen (2017) conducted a study to describe ways to prevent errors in medication administration based on reporters' views expressed in incident reports. They used qualitative methods to review free-text descriptions. The results showed the

supporting health professionals by encouraging collaboration among providers providing a reasonable work environment is essential. The reports suggested that healthcare providers prioritize approaches that support the ability of individual professionals to manage daily medications.

2.2.5 Educating Patients

Despite the number of errors associated with medicine, there are ways to improve the delivery of healthcare in emergency settings. The lessons learned from other high-risk industries, such as motor vehicle or airline industry, show that designing a system that focuses on prevention, rather than casting blame, is far more effective (Gostin & Mohr, 2013). The means to decrease errors associated with medical care delivery that this paper will focus on include patient education, training and healthcare delivery teams.

Hiner (2016) stated education should begin with the patient. Educating patients is a key step in reducing medical error. Asking the question, "Why" could result in lower medical mistakes. Hiner also noted there are a plethora of medications on the market. With so many drugs available, most doctors do not have the time or resources to remain current, so they rely on the information given to them by drug manufacture's sales representatives (May, 2016). Therefore, it is the responsibility of the patient to ask his/her provider why the physician is prescribing a particular drug. Is it because he/she has reviewed the research on medication and feels it is the best one to meet the needs of the patient, or is it because that was the most recent drug recommended by the sales representative in his/her office?

2.2.6 Reducing Communication Barriers

Medical processes – diagnosis, procedures, and treatment – is an information management system. There are multiple forms of communication throughout the medical

process, through face-to-face contact, digital and analog medical records, and written communication. Because much of medical care is information management, the communication orally and in writing among team members, the patient, and the patient's family becomes a core component of health care (Schyve, 2007). Effective communication is communication that is comprehended by all participants. This means it is usually bidirectional between participants and enables participants to clarify the message so there is no confusion. Effective communication does not occur when there is an absence of comprehension. The provision of health care is compromised and likely will only result in errors, poor quality services, and risk to patient safety (Schyve, 2007).

Miscommunication is one of the largest causes of medical error. In situations where there was a standardized method for communicating information about a patient between healthcare providers, the result reduced the preventable adverse events caused by medical error by 30% (Digitale, 2014). Better communication between caregivers reduces the chances of medical errors. The screening algorithms used in the Tippecanoe County POD exercises are the way the Tippecanoe County Health Department is attempting to increase communication among healthcare providers. An additional way is that healthcare providers understand how to use the algorithm.

Increased communication among healthcare providers not only can reduce medical errors associated with PODs, it may ameliorate patients' perception of the care they are receiving. Proper communication is an essential to ensuring patient compliance. The Institute for Healthcare Communication (2011) found that 1 in 4 patients believed the instructions from their healthcare provider were too difficult to follow. In the same study, 7% reported they did not understand what they were supposed to do. Patients' perceptions about the quality of care

received is contingent upon the quality of the interactions that they have with their healthcare clinician and team ("Impact of Communication in Healthcare," 2011).

Fear of reprisal due to communication and a lack of communication due to a fragmented healthcare system are leading examples of where and how communication between healthcare providers break down. Healthcare providers do not communicate potential issues to a higher staff member for evaluation because of fear of a negative impact. They are concerned about how the senior staff member will respond to the escalation. In a 2014 study of a tertiary health service in Melborne, Australia in which 51% of the trainees responded to the survey, 42% of the trainees stated they had received an occasional negative response from a senior staff member for escalating a patient concern, and 11% of the trainees stated sometimes or frequently had a negative response to an escalation (Kelly et al., 2014).

Fear of litigation is another potential barrier to communication. Even though physicians' perceptions are that medical malpractice litigation is typically inaccurate, they also perceive it as a barrier to quality improvement. Fear of litigation persuades physicians to practice defensively and maintain secrecy when challenged with a medical error (Gostin & Mohr, 2013). The legal aspects of medical care are thought to reduce errors by ensuring that physicians become less likely to practice negligently after being sued for malpractice; however, there is a dearth of evidence to support this contention (Brasel, Layde, & Hargarten, 2000).

2.3 Simulation Modeling

One effective means to reduce errors in the healthcare industry and outside of it, is simulation. Computer simulations have been used to identify sources of inefficiency and potential errors. Medical training centers also have used simulation as a means to train residents and other healthcare professionals. Simulation is low-cost and allows trainees to make mistakes

without the risk of adverse reactions. Simulation has been used other industries, such as the automotive and aviation industries to identify inefficiencies and reduce the potential of errors occurring.

2.3.1 Computer Simulation Modeling

Computer simulation is a very reasonable means to predict how mass distributing chemoprophylaxis on a large scale will impact resources and time. As pointed out in a previous thesis, there are multiple reasons for using computer modeling for POD planning.

> Models are designed to imitate or replicate a system that already exists or a system that will exist in the future, otherwise known as a *real* system. Robinson (2004) identified four main purposes for experimenting with computer simulation rather than a real system: cost, time, control of the experiment, and the real system may not exist. Experimenting with real systems, planning and executing a POD exercise, can all be very costly. There are not only financial costs (purchasing supplies and equipment), but non-financial costs like time requirements and constraints as well. In order to run a POD for a population of 10,000 within 72 hours, a POD site would require 50-55 persons per shift, running around-the-clock in 12 hour shifts (Landesman, 2012). Each of person would need to volunteer his/her time, take time away from his/her occupation, time from family, etc. When running experiments, there may not be control over all the variables. If there is an interest in comparing outcomes of independent variables, repeating experiments increases confidence in results. Simulations can decrease costs and the time requirements. Robinson (2004) noted that a computer model can run multiple iterations with multiple variables at little to no cost to the user, or the actual system may not exist (Glass, Dietz, Aaltonen, & Black, 2017, p. 14-15).

The thesis also describes how computer simulation has been used for planning distribution of chemoprophylaxis on a large scale across multiple geographical areas,

Lee (2008) developed a simulation model to assist large metropolitan areas with developing plans for dispensing vaccines and antibiotics to the general public. The intent of the model was to evaluate the effectiveness of the dispensing procedures and identify areas where the cities could improve. The experiment examined four variables: cross-shipping, variable supply quantity for each site, sufficient POD throughput, and the quantity of the safety stock of medical supplies. The experiment began by analyzing a base case where the CDC provided a fixed number of smallpox doses evenly distributed to 50 POD sites. The investigators dispersed the medication across the residents at each site based on population density associated with census data. Once the vaccines were delivered, they would not be redistributed to account for varying population densities across a geographical area. In the event a POD site ran out of resources, the vaccinations would not be redistributed. The results of the base case showed that about half of the POD sites would likely not have sufficient quantities of vaccines, thus resulting in 21.8% of the population being unvaccinated. The base case also showed that there would have a surplus of vaccine at any remaining sites.

Running the experiment multiple times showed the modeling technique provided evidence for the need to cross ship supplies from one POD to another. In addition, not all POD sites would require the same amount of supplies; therefore, a variable supply quantity was required at each site. Each site also required more supplies than what was initially estimated. This additional amount of supply was commonly referred to as a safety stock. Increasing the amount of supply to account for a safety stock would ensure if the number of persons arriving at the POD site were greater than expected, then there would still be enough supplies to account for the overage of people. The experiment provided enough evidence to maximize the throughput at each site (Glass et al., 2017, p. 34-36).

2.3.2 Use of Simulation to Reduce Error in Other Industries

The transfer of safety lessons learned in other high risk industries to the healthcare industry have created new responsibilities for the healthcare field (Ziv et al., 2003). The aviation industry, for example, uses simulation-based modeling to predict transportation of air frames through inclement weather and turbulence. Pilot training programs use simulation modeling to assist trainees in identifying areas where they require additional practice (Gaba, Howard, Fish, Smith, & Sowb, 2001). Using simulation, trainers can find areas where pilots are more likely to make mistakes and identify ways to correct these mistakes while still in training. This is similar to how hospitals and clinics are using simulation to train doctors and pharmacists in the delivery of healthcare to their patients.

Kading (2004) addressed how the automotive industry uses simulation to improve quality BMW engineers wanted to improve the safety of their doors. In order to do that, they needed to build a prototype of the door to test the durability of door and body components. Using testing on physical prototypes delivered reliable results; however, there were drawbacks. The prototypes were expensive and evaluating hundreds of events requires a significant amount of time to conduct. In addition, if testing uncovered an issue, engineers had to change their designs, and modify their prototypes before they could rerun their tests, adding more time and costs to the vehicle development. To reduce costs and improve efficiency in testing, BMW engineers designed their prototype door using computer simulation modeling. The drawback of computer modeling lies with validation. Typically, a large amount of data is required to build a simulation model. BMW engineers used data collected from previous constructions of their doors to build their simulation model. Engineers then validated the model by comparing simulation with the prototype experimental results, which showed an acceptable level of correlation (Kading, 2004).

This same system of using existing data to build computer simulation models can be used as an efficient means to build and test new medical devices and reduce the possibility of medical errors associated with them.

The automotive industry also uses computer simulation modeling to improve road networks and transportation infrastructure. Winkler and Fran (2011) conducted research to determine the effects of lane restrictions, driver behavior parameters, and entrance/exit ramp density on the capacity of freeways containing high heavy vehicle traffic. They used data collected from 30 different states over the course of 20 years to build their simulation model. Their intent was to determine if building traffic lanes specifically for long haul shipping use would be viable or improve transportation. What they found was that the problems are a result of the low maneuverability of large trucks. Whenever a lane change or lane changes are needed to enter or exit the freeway, the freeway would back up as the drivers wait for the necessary lane change.

2.3.3 Simulation in Mass Casualty Exercise

Simulation modeling has been used in mass casualty exercises. Scheulen, et al. (2009) indicated the use of The Electronic Mass Casualty Assessment and Planning Scenarios (EMCAPS).

> EMCAPS is a computer model used to generate casualty estimates in the event of a high-consequence event such as radiological, biological chemical or explosive event. The purpose of EMCAPS is to allow input of certain variables for a specific situation, which provides estimates of requirements based off of the outputs of the model. The intent of EMCAPS is to allow users to model different scenarios then measure the magnitudes of effect applicable to a variety of jurisdictions, regions, types of agencies, and levels of government. The purpose of using the software is to transition a government's all hazard plan to a plan more

tailored to a specific incident. The user can then develop more applicable and detailed response plans (Glass et al., 2017, p. 37-38).

2.4 Adverse and Allergic Drug Reactions

The World Health Organization (WHO, 2015) defined adverse drug reactions as, "all intended pharmacologic effects of a drug except therapeutic failures, intentional or over-dosage, abuse of the drug, or errors in administration" (p. 2). WHO defined adverse drug event as "an injury resulting from medical intervention related to a drug." (p.3) Adverse drug events include medication errors in its definition whereas adverse drug reactions do not. Adverse drug reactions can be classified into two types: predictable and unpredictable. Predictable adverse drug reactions account for 80% of all adverse drug reactions. They are common, dose-dependent and are caused by pharmacologic actions of the drug itself. Unpredictable reactions are uncommon (about 20% of adverse drug reactions), are independent of the dose, and are unrelated to pharmacologic effects of the drug. Allergic drug reactions account for 5-10 percent of adverse drug reactions overall (Abrams & Khan, 2018). Allergic drug reactions are not as common as believed, and a healthcare provider's own misunderstandings about the characteristics of a true drug can play a role in the his/her decision-making process on whether to prescribe a certain antibiotic or not. However, the patients' self-reported history typically has low accuracy for diagnosing an allergy to the medication (Salkind, Cuddy, & Foxworth, 2001).

2.4.1 Identifying Drug Allergy

Diagnosing drug allergies begins with the patient's medical history. Healthcare providers often simply ask the patient if they have any drug allergies without confirming the self-report with a detailed medical record review. The intent is to identify the etiology of the reaction and identify the drug allergy as a possible cause of the symptoms (Abrams & Khan, 2018).

Healthcare providers commonly withhold certain antibiotics based on self-reported clinical history of an adverse reactions (Salkind et al., 2001). Patients will often describe signs and symptoms immediately following the consumption of a drug, but do not have the follow-up testing to confirm if the symptoms were, in fact, caused by an allergic reaction to the medication. Many patients are unsure of specific details about a reaction to penicillin. Nevertheless, clinicians will typically label the patient as having a penicillin allergy simply based on self-report (Salkind et al., 2001).

Following the subjective patient assessment, healthcare providers will call for laboratory tests to confirm the self-diagnosis. Laboratory tests do not confirm the existence of a drug allergy but can support the diagnosis. Abrams and Khan (2018) best described the relationship between adverse drug reactions and allergic drug reactions, "Although adverse drug reactions are common, allergic reactions are uncommon. Cutaneous manifestations are the most common allergic drug reaction diagnosis tool" (p. E537) Apart from skin testing for penicillin, diagnosis almost exclusively relies on medical history (Abrams & Khan, 2018). Salkind, et al (2001), evaluated studies comparing clinical history to the penicillin allergy skin test against patients with and without a self-reported history for penicillin allergy. The results show that only 10-20% of patients who reported a history of penicillin allergy were truly allergic as diagnosed via a skin test. Healthcare providers can mitigate the risk of false reporting by taking a detailed history of a patient's reaction to penicillin allowing these patients to receive penicillin. Skin testing is the most deliberate means of identifying drug allergy; however, penicillin is the only low-molecular weight test available that will generate a IgE-mediated reaction (Abrams & Khan, 2018).

2.4.2 Amoxicillin

Amoxicillin is a derivative of the common antibiotic, Penicillin. Penicillin is a β-lactam antibiotic (Salkind et al., 2001). β-lactam antibiotics such as amoxicillin kill bacteria by inhibiting crosslinking of the bacterial cell wall (Weber, Tolkoff-Rubin, & Rubin, 1984). Its semisynthetic chemical derivatives and other β-lactam antibiotics are the first-line treatments for many infections (Salkind et al., 2001). Despite unconfirmed allergy testing, amoxicillin and other β-lactam antibiotics due to fear of a possible allergy. Healthcare providers often limit the use of drugs containing penicillin because of a patient's unconfirmed, self-identified history of an allergic reaction to penicillin (Salkind et al., 2001).

Abrams and Khan (2018) conducted a meta-analysis of 39 prospective studies and reported an incidence of 6.7% of serious drug reactions, and 0.32% of fatal adverse drug reactions. The number of fatal adverse drug reactions places them between the forth to sixth leading cause of death in the US. What they found was that about 10% of the population in highly developed countries is believed to have an allergy to penicillin, but 90% or more are able to tolerate penicillin after allergy evaluation. In addition, 80-90% of all patients who report a penicillin allergy are negative when assessed by skin testing (Abrams & Khan, 2018).

A 2016 systematic review and meta-analysis of 14 studies reported a prevalence of 2.84% (95CI 1.77-3.91%) IgE-mediated drug allergy to β-lactam antibiotics. The study also reported adults had a higher prevalence (7.78%, 95% CI 6.53%–9.04%) than children. Mill, et., al (2016), conducted a study with the Allergy Clinic of the Montreal Children's Hospital. Between March 1, 2012 and April 1, 2015, they studied children with a suspected allergy to amoxicillin. They examined 818 children. They found that 94.1% of the patients had no reaction to the provocation challenge, 2.1% developed mild reaction within one hour of the challenge, and 3.8% developed nonimmediate reactions which required longer than one hour to show a reaction. All patients

who reacted to the challenge were resolved within a few hours after treatment with second-generation antihistamines (Mill et al., 2016).

Their research continued to examine the amount of time required for the reaction to set in and any correlations that could be derived from the data. After controlling for age, sex, personal and first-degree relatives' comorbidities, their analysis revealed higher odds for a nonimmediate rash that lasted longer than 7 days. In addition, children whose parents had a history of amoxicillin allergy had increased odds of nonimmediate reaction. Children with nonimmediate reactions had a higher prevalence of a rash lasting longer than seven days and parental history of drug allergy. A history of reaction occurring within 5 minutes was more common in children with immediate reactions to the provocation challenge (Mill et al., 2016).

Even if patients had an allergic reaction to an amoxicillin, the adverse effect is generally less severe than the disease which it is combating. At least 98% of patients who have self-reported a history of penicillin allergy and negative skin test can tolerate the proper dose of penicillin (Salkind et al., 2001). If the skin test is negative, patients are able to tolerate oral doses and intravenous penicillin without immediate hypersensitivity reactions (Abrams & Khan, 2018). If patients do report a history of adverse reactions to amoxicillin, they should have a skin test to rule out the possibility of an allergic reaction (Salkind et al., 2001).

2.4.3 Ciprofloxacin

Ciprofloxacin is a fluroquinolone antibiotic, a broad-spectrum antimicrobial drug. Ciprofloxacin's main usage includes treatment of urinary tract infections, respiratory tract infections, sexually transmitted diseases, and skin and soft-tissue infections (Kelesidis, Fleisher, & Tsiodras, 2010). Generally, fluoroquinolones are well-tolerated antibiotics within the general population. Mild and self-limiting gastrointestinal effects, skin rashes, dizziness, and headache

are the most common adverse effects associated with Ciprofloxacin. However, serious and life-threatening adverse events, like anaphylaxis, have been reported with fluoroquinolone use. (Kelesidis et al., 2010).

Ciprofloxacin has been approved for use as a prophylaxis in certain cases. "Although ciprofloxacin 500 mg orally is not licensed as a prophylaxis, it is used because it reduces meningococcal carriage, it can be given as a single dose" (Burke & Burne, 2000, p. 697). The CDC has approved Ciprofloxacin as a post-exposure prophylaxis following inhalational of anthrax. According to the CDC, ciprofloxacin is the preferred antibiotic for pregnant women exposed to *Bacillus anthracis* who show no signs or symptoms of exposure. CDC guidelines include ciprofloxacin for inhalational anthrax treatment (CDC, 2017).

Ciprofloxacin is generally a well-tolerated antibiotic. Anaphylactic reactions in association with ciprofloxacin use are reported in less than 5% of cases (Kelesidis et al., 2010). "According to the manufacturer of ciprofloxacin, pulmonary edema has been described as an adverse event associated with ciprofloxacin in <1% of treated patients" (Kelesidis et al., 2010, p. 524). Family history and genetics are thought to be the main cause of nonallergic angioedema.

Kelesides, et al., (2010) examined the epidemiology of allergic reactions to Ciprofloxacin. "Although ciprofloxacin is a generally well-tolerated fluoroquinolone antibiotic, serious and life-threatening adverse events like anaphylaxis and pulmonary edema have occurred with its use" (Kelesidis et al., 2010, p. 515). A high rate of adverse effects must be weighed against the benefits to a particular target group (Burke & Burne, 2000). The prevalence of serious allergic reactions with fluoroquinolone use is reported to be 0.46 - 1.2/ 100,000 patients treated. "Based on a spontaneous adverse-events report, the frequency of fluoroquinolone-

associated anaphylaxis has been estimated to be 1.8 – 23/ 10 million patient-days of treatment" (Kelesidis et al., 2010, p. 523).

> In a retrospective study based on the database of spontaneous adverse drug reactions in Germany, in 21/ 166 cases (13%), the reactions occurred within the first 3 days of ciprofloxacin administration. In addition, 2 cases (1%) of anaphylaxis occurred after first use or within the first 3 days, suggesting non–immune-mediated mechanisms for the reaction in these 2 cases (Kelesidis et al., 2010, p. 524).

Although not as prevalent, anaphylaxis is a risk worth examining in association with Ciprofloxacin. Kelesidis also conducted a meta-analysis of the prevalence of anaphylaxis associated with Ciprofloxacin.

> One review of 384 case reports of adverse reactions to fluoroquinolones noted anaphylactic reactions occur within 1 hour after fluoroquinolone ingestion. This reaction was reported in 167 individuals, with 39 cases experiencing anaphylactic shock.
> In another retrospective study of 262 cases of adverse reactions, 15 anaphylactoid reactions (5.7%) were reported (p. 516).

A 143 lb, 25-year-old healthy white female with normal renal function presented with an inflamed, bacterial infection of the kidney. Healthcare personnel administered her 500 mg ciprofloxacin and 400 mg ibuprofen for pain control. The following day, she presented with angioedema, specifically edematous lips and face, and pulmonary edema. They discontinued the patient's ciprofloxacin and began supportive care. After 1 week of hospitalization, the patient recovered. The patient experienced an anaphylactoid reaction likely associated with ciprofloxacin use (Kelesidis et al., 2010).

2.4.4 Doxycycline

Doxycycline is a very common antibiotic used as a prophylaxis. Although treatment with doxycycline is usually associated with photosensitivity, and gastrointestinal distress, usually nausea, vomiting, diarrhea and epigastric burning, doxycycline is generally well tolerated. When compared with older tetracyclines and minocycline, doxycycline is less prevalent with respect to adverse reactions (Holmes & Charles, 2009). Nausea, vomiting, diarrhea and epigastric burning are usually mitigated with food consumption in conjunction with the prescriptive does. Doxycycline is a highly lipid soluble tetracycline (TET). It can easily penetrate body tissues and fluids (Pruzanski et al., 1992). "Doxycycline is almost completely absorbed following oral administration in the stomach and proximal small bowel. Food or dairy products do not significantly alter absorption" (Holmes & Charles, 2009, p. 475). Doxycycline has been found to be a powerful inhibitor of the neutral matrix metalloproteinases collagenase and gelatinase (Pruzanski et al., 1992). In addition, it also has been found to reversibly bind to the 30S ribosomal subunit and prevent the association of aminoacyl-tRNA with the bacterial ribosome, thus inhibiting bacterial protein synthesis (Holmes & Charles, 2009).

As a prophylactic, 100mg daily dose of doxycycline is one of the most common chemoprophylactic agents used to prevent malaria. Common practice is for patients to take doxycycline two days prior to entering the exposure area and continue the medication until four weeks after leaving the affected area. This offers protection of over 93% and is equivalent to mefloquine (Holmes & Charles, 2009). Doxycycline has been approved as a preventative drug in the event of an exposure to Anthrax.

> Both naturally occurring anthrax and that due to bioterrorism can be treated with doxycycline. Naturally occurring cutaneous anthrax is treated for 5–7 days while treatment and post-exposure prophylaxis in the event of bioterrorism require 60

days of therapy. Inhalational anthrax is generally more severe and combination therapy is preferred (Holmes & Charles, 2009, p. 479).

There is little data discussing the prevalence of doxycycline hypersensitivity; however, most adverse effects of using doxycycline have not indicated a mortality associated with it.

2.5 Summary

Errors in medicine are prevalent and are not new. Medications interact with the human body differently. They inter the body through different means, they travel through different systems in a variety of ways, and they are metabolized causing secondary and tertiary effects. Errors associated with medicine can have lasting and devastating effects. Identifying the causes of errors is crucial. Once the causes of the errors are identified, then science can use different tools to reduce the risks, especially by using simulation. Emergency situations are particularly vulnerable due to their ad hoc nature, especially with the mass distribution of chemoprophylaxis in response to a bioterrorism event using a POD site. Although literature has been published discussing the incedence of medical errors associated with POD sites, the number of published articles on this topic is sparse. There is a dearth of literature published on the discussion of the effect of simulations and modeling and how it relates to the reduction of the medical errors associated with POD sites. Generally those errors are associated with adverse drug reactions as well as under-reported drug allergies.

Adverse drug reactions are not as common as reported. Healthcare providers will commonly withhold antibiotics based on self-reported clinical history of an adverse reaction without a laboratory test confirming the adverse reaction is due to an allergy to the drug (Salkind et al., 2001). This could have adverse effects on public health as healthcare providers could be

hesitant to administer a drug that is key to mitigating a bioterrorism attack. Such action could put the entire population at risk, despite the patients' self-reported history typically being inaccurate for diagnosing a true allergy.

CHAPTER 3. METHOD

3.1 Research Question

Can a discrete-event simulation model measure the effect of medical errors in a POD site and minimize the amount of medical errors associated with the site?

3.2 Hypotheses

This research investigated three variables. The independent variables are the total population the POD site will serve, and the number of volunteers at the site to include any registered or certified healthcare providers designated for the screening/evaluating portion of the exercise. The dependent variable is the number of medical errors, regardless of type. The most frequent error expected is preventive errors due to failure to diagnosis and evaluate. Each individual simulation run generated a dichotomous outcome: error or no error. Therefore, the results of individual runs were programed to follow a Bernoulli distribution, where the probability of no errors equaled 1-*p*, and the probability of errors equaled *p*, with a variance of *p*(1-*p*). Because the simulation was run for multiple independent iterations, and the results followed a normal distribution, the Central Limit Theorem was applied to test the hypothesis. A 5% error was chosen as the acceptable rate based on the results of previous studies where a validation station at the conclusion of a POD showed to reduce the number of errors in the POD to 5.64% (Glass et al., 2017).

The null hypothesis was that the computer simulation did not decrease the number of medical errors by 5% (H_0: $\hat{p} - p_0 = \Delta_0$). The alternate hypothesis was that the simulation did reduce the number of medical errors by 5% (H_0: $\hat{p} - p_0 > \Delta_0$) where p_0 is the mean percentage of medical errors associated with the control group, $\hat{p}$ is the mean percentage of medical errors

associated with the variable group, and Δ_0 is 5.0% difference that the researcher is expected to generate from the interventions given to the variable group.

3.3 Variables

The independent variable is the number of volunteers for the screening station within the POD site. The dependent variable includes the number of medical errors that occur, regardless of type.

3.4 Apparatus

AnyLogic 7® modeling software was the software used to build the multimethod simulation model. AnyLogic 7® combines the process of an agent-based pedestrian model with a discrete-event simulation. The simulation imitates the POD site used in the exercise. The discrete-event simulation was designed as a flowchart with three nodes: holding area, screening station, and dispensing station. The participants (pedestrian agents) entered the simulation from the left (entrance) and went into an immediate holding area until there was space at the screening station. There were three main stations used in the design of the flowchart: Holding Area, Screening, and Dispensing (see Figure. 3-1).

Data used to build the simulation were collected and analyzed over the course of four years and six different POD exercises. Initial analysis showed an average of 10.1% errors in dispensing correct medications. Once the data were analyzed, the information was used to build a computer simulation model to replicate the POD error percentage. Multiple interactions of the simulation were run to predict when and where the errors will occur, and manipulation of the simulation was used to determine the most efficient means to reduce the errors

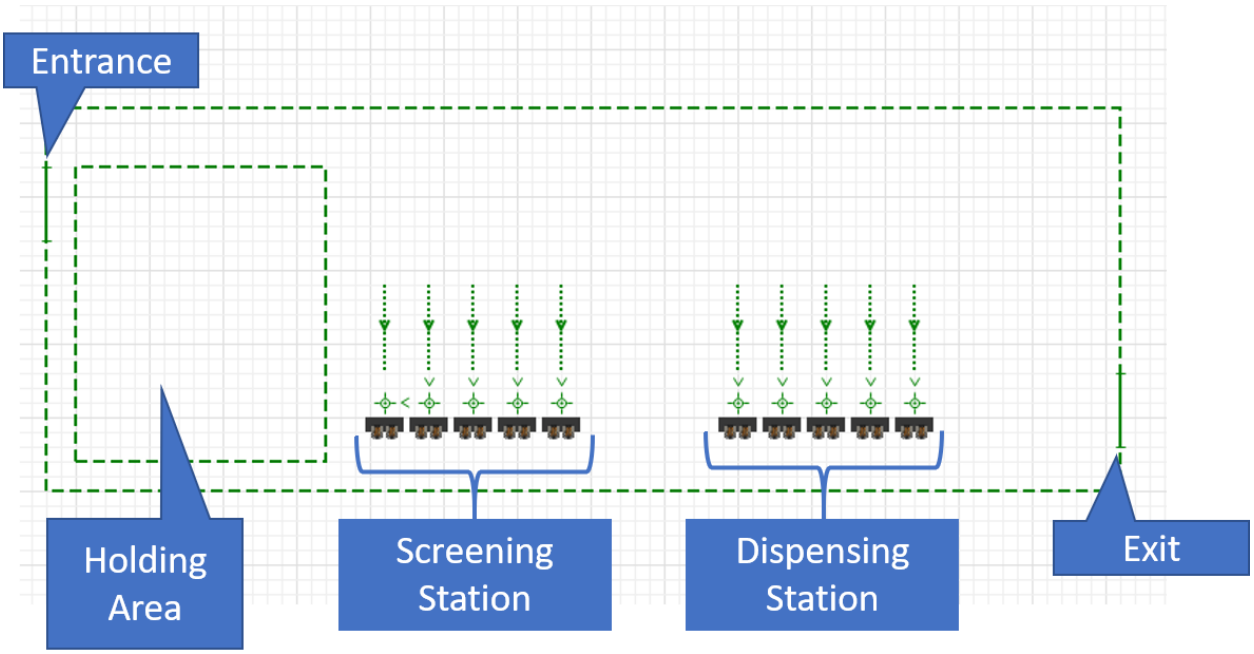

Figure 3-1. Computer Simulation of the POD

The agents populate a two-dimensional, artificial environment designed to replicate a POD site. As the agents pass through the simulation, they travel from each node along random paths. As the agents pass through the screening station node, the simulation followed a Bernoulli distribution and randomly assigned 10.1% of the agents (variance of 0.00898) with an error. The objective of the simulation model was to determine if adjusting the individual screening stations would affect the overall number of errors.

Each agent entered the simulation and begin at the entrance. Once the agents enter the simulation, they are held in the holding area until an open position was available in the screening station. This replicated the patients' registration forms being screened by a healthcare provider in the virtual space. Because not all agents will require the same amount of time to complete screening, the model times were set to simulate the normal distribution of time required for each patient.

Once finished at the screening station, the agents moved to the dispensing station and corresponding que. These replicated patients receiving their required medications. Once complete at the dispensing stations, the agents would proceed along a path to the exit.

3.5 Data Sources

Data used for the data sources for this model was collected as part of a previous graduate thesis. Medical error data were collected over the course of two POD exercises during two semesters of Fall 2017, and Spring 2018 (Glass et al., 2017). Time data were collected from the Fall 2016 POD exercise and Spring 2017 POD exercise. Nursing, Homeland Security, and Pharmacy students from Purdue University participated in the exercise (Glass, Dietz, & Aaltonen, 2018). The nursing students were segregated into two groups to examine the effects of training: synchronous and asynchronous. The risk of confounding due to differences in training was minimized because both groups were running simultaneous. Those who received asynchronous training received a roster number, which they wrote on the data sheets, that had the letter A. Those who received synchronous training received a roster number that had the letter B. The nursing students were then divided equally between two sets: 1 and 2. After a brief instruction from the Tippecanoe Department of Public Health Operations Officer, Group A participants established their stations at 3:15pm, and the experiment began (Glass et al., 2018, 2017).

During the second portion of the experiment, the groups swapped positions. Volunteers who were at the screening and dispensing stations were now the acting patients, and those volunteers who were the acting patients were manned at the screening and dispensing stations. The pharmacy students operated the verification station. Once the participants completed the

POD exercise and exited the experiment, they were instructed to return to the registration table, and move through the POD again (Glass et al., 2017).

On the November 9, 2018 experiment, there were 349 administered medications to the synchronous and asynchronous trained personnel, which were used as data points. However, 55 out of 349 data points were not useable due to missing data, resulting in 294 (84.2%) usable data points. Forty-nine out of 294 (16.6%) are considered medical errors (see Appendix B). However, 24 of the 49 errors did not receive proper "crushing" instructions when they were supposed to. Because crushing instructions were not considered a medical error in previous experiments, they were not represented as an error for the purposes of this study. The medical error for both groups was 25 out of 294 (8.50%). Since research has shown the majority of medical errors occur at the screening or prescribing location (Dean, Schachter, Vincent, & Barber, 2002), all the medical errors recorded were subdivided by screener (see Table 3-1).

Table 3-1. Percent of Errors by Individual for Nov. 9, 2017

Screener ID	# of usable data points	# of medical errors	# of data points	% errors
1S1	10	1	22	10.0
1S2	12	1	13	8.3
1S3	6	3	6	50.0
1S4	10	3	10	30.0
1S7	2	1	4	50.0
1A15	20	1	29	5.0
1A17	8	3	15	37.5
1A21	3	1	3	33.3
2A1	7	1	7	14.3
2A15	16	4	16	25.0
2A17	17	1	17	5.9
2A19	22	1	22	4.5
2A21	4	1	4	25.0

ANOVA of the data shows a 58.6% probability that the percentage of errors are similar to each other (see Table 3-2). The results of the ANOVA show that the percent of errors between the sets of data were not significantly different, and therefore suggest that there is not enough evidence to rule out that the source of errors is equally distributed across all screeners.

Table 3-2. Analysis of Variance for Screening Errors for Nov. 9, 2017.

Source	*df*	Sum of Squares	*M* Square	*F* Ratio	Prob > *F*
Between Groups	11	.305	.028	1.386	.586
Within Groups	1	.020	.020		
Total	12	.325			

When the experiment was conducted again on March 29, 2018, similar results were found (see Appendix C). In this instance, better instruction was given to the participants, which resulted in no unusable data points from the participants (see Table 3-3).

Table 3-3. Percent of Errors by Individual for Mar. 29, 2018

Screener ID	# of usable data points	# of medical errors	# of data points
1A3	2	18	11.11
1A5	1	9	11.11
1A7	1	16	6.25
1S13	3	46	6.52
1S14	1	23	4.35
1S2	2	19	10.53
1S4	2	27	7.41
1S6	2	18	11.11
1S7	1	4	25.00
1S9	1	22	4.55
2A1	3	8	37.50
2A3	1	38	2.63
2A4	1	6	16.67

ANOVA shows there is a 3.8% probability that the percent of errors are similar to each other (see Table 3-4). The results of the ANOVA show that the percent of errors between the sets of data were not significantly different. Again, the results of the ANOVA also suggest there is not enough evidence to rule out the source of errors is equally distributed across all screeners.

Table 3-4. Analysis of Variance for Screening Errors for Mar. 29, 2018.

Source	*df*	Sum of Squares	*M* Square	*F* Ratio	Prob > *F*
Between Groups	10	1917.429	191.743	10.652	.038
Within Groups	3	54.000	18.000		
Total	13	1971.429			

However, when the data are combined into one single dataset and analyzed, the results are different. ANOVA of the combined data shows that there is a 0.9% probability that the percent of errors are similar to each other (see Table 3-5). The results of the ANOVA show that there was a significant difference between the individuals within the groups.

Table 3-5. Analysis of Variance for Screening Errors for the Combined Experiments

Source	*df*	Sum of Squares	*M* Square	*F* Ratio	Prob > *F*
Between Groups	19	2755.630	145.033	6.426	.009
Within Groups	7	158.000	22.671		
Total	26	2913.630			

The volunteers who operate a POD site are human and prone to mistakes. The number of mistakes made by individuals is not identical. At this time, the results of this exercise demonstrate that there is not enough evidence to show a significant difference the percent of errors per individual screeners when the experiments are analyzed individually. However, when the experiments are analyzed as an aggregate, there is sufficient evidence to suggest that there is a significant difference in the percentage of errors per individual screeners. Identifying the source of errors within the system by identifying the screeners with a higher number of errors and correcting the source by removing or retraining these screeners could decrease the overall

error rate within a POD. A computer simulation model could be used to test the effects of different stimuli and identify the procedures for reducing medical errors associated with POD sites very efficiently.

3.6 Calculation of the Number of Simulations

The outcome of each experiment was dichotomous. Either an error was present or not. The results of the simulation followed a binomial distribution with parameters *n*, the number of patients in the simulation, and *p*, the probability that the patient would have an error. Each time the simulation ran, it followed discrete probability distribution of the number of errors in a sequence of *n* independent experiments, each asking a yes–no question, "was there a medical error, Yes or No?" and each with its own boolean-valued outcome: error = 1 (with probability *p* =.101) or no error = 0 (with probability $q = 1 - p$).

The alternate hypothesis is the probability of a medical error occurring in the simulation after the intervention will be less than the probability of a medical error occurring in the population experiments, $H_a: \hat{p} < p_0$. In order to determine the number of simulations, n, to run in order to have statistically significant results, the researcher need to calculate test statistic, Z, based on the significance, α=.05.

$$Z_{\alpha/2} = \frac{\hat{p} - p_0}{\sqrt{p_0(1 - p_0)/n}}$$

A POD exercise conducted on November 16, 2016 where a validation station was established in an attempt to reduce the number of medical errors showed a decrease in the probability of medical errors from 10.1% to 5.76% (Glass et al., 2017). Although the results were not statistically significant, the data were used to calculate the total number of simulations to run.

$$1.96 = \frac{.0576 - .101}{\sqrt{.101(1 - .101)/n}}$$

The number of simulations, *n*, was then calculated to be 18.4.

$$n = \frac{p_0(1 - p_0){Z_{\alpha/2}}^2}{(\hat{p} - p_0)^2} = \frac{.101(1 - .101)1.96^2}{(.0576 - .101)^2} = 18.4$$

3.7 Testing Conditions

The simulation was modeled after the POD exercises established during the Fall 2016, and Spring 2017 semesters. The Fall 2016, and Spring 2017 POD sites were conducted indoors with volunteers acting as patients, and volunteer nursing students, and pharmacy students acting as POD workers (Glass et al., 2017). The simulation was built using data derived from a combination and analysis of these and previous POD exercises. The simulation calculated the estimated number of medical errors likely to occur.

3.8 Testing Procedures

The simulation was conducted over the course of multiple days during the months of August, September and October 2019. An initial simulation optimization was conducted to determine if time requirements for verifying every agent were best as opposed to verifying just a sample portion of the agents. The results of the optimization showed that verifying every agent did not require a significant amount of additional time; therefore, all simulations verified all agents as they completed the POD. A control simulation was run and resulted in an average of 10.1% of the agents having a medical error. Additional simulations were ran with specific interventions to reduce the number of errors.

The experiment was conducted in a virtual environment using AnyLogic 7® computer software. The simulation was used to study the dynamic behavior of agents as replicated in a real system. The simulation was divided into the simulation agents, which represent the patients flowing through the POD, and the simulation flow diagram paths and nodes, which represents the physical infrastructure of the POD. The simulation agents were run as a statecart. The agents enter the statechart simultaneous when it enters the simulation flow diagram. The initial state of the agent is the POD state (see Figure 3-2). The simulation flow chart randomly sent a message "error" to agents with a probability of 0.101 with a variance of 0.089 as they pass through the screening node. Once the agent received an "error" message from the screening node, the agent enterd the Error state, which changed the color of the agent from green to red.

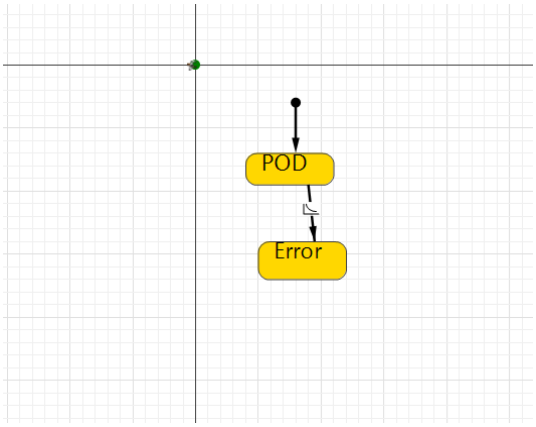

Figure 3-2. Agent Statechart

As agents entered the agent statechart, they simultaneously entered the simulation flowchart (see Figure 3-3). Agents entered the simulation flowchart through a pedestrian source (patEnter), which corelated with the entrance on the model, Figure 3-1. The agents proceeded immediately along a path to a pedestrian wait node, (pedWait), which corelated with the patient holding area. Agents were held in pedWait until there was an opening in the first pedestrian service node (screen). Prior to entering the screen1 node, agents passed through a pedestrian

select output node (screeningSelect), which routed the agents to one of five paths that led to one of five pedestrian service nodes (screen1, screen2, screen3, screen4, screen5). The pedestrian select output node, screeningSelect, equally and randomly distributed the agents to each of the pedestrian service nodes, screen1-5 with an equal probability 0.2 of an agent traveling to each of the screen nodes. Once the agents were at the screen pedestrian service nodes, the simulation randomly assigned an error upon output based on a Bernoulli distribution with a probability of .101 and variance of 0.00898, which is the same probability measured from the POD exercise on November. 9, 2017 and March. 29, 2018.

Data for time requirements at each node was collected from previous POD exercises (Glass et al., 2018). Each screening station has a delay time of 35.5 seconds, with an *SD* of 27.2 seconds (Glass et al., 2018) (see Appendix A). Once the agents pass through the screen pedestrian service node, they moved to the dispensing pedestrian service node. Similar to the screening station, the dispensing station had a required completion time of 36.2 seconds, with an *SD* of 37.8 seconds (Glass et al., 2018) (see Appendix A). Once the agents have completed the dispensing node, they proceeded to the exit, represented by the pedestrian sink (pedSink).

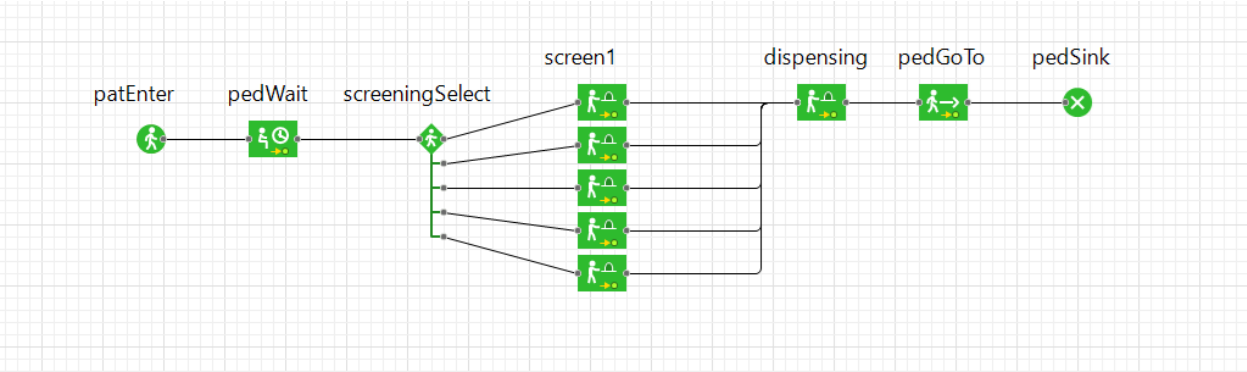

Figure 3-3. Simulation Flow Diagram

3.9 Simulation Optimization

To verify that conducting a check of all screened patients would be efficient, a simulation model was built that measured the time required for each patient to conduct a check at a verification station. The model then tallied the total time required to complete the POD and measured the total number of medical errors not measured based on a sample of patients checked. The only assumption made was that a verifying the proper medications were dispensed would find all medical errors prior to the patients departing the POD site. The researcher conducted a series of optimization experiments using the simulation to determine the percentage of patients that the verification station could observe, and the amount of time required. The results of the optimization can be found in Appendix D. The parameters of the model were fixed to a population of 20,000 and 168 hours to complete. The variable tested during the optimization was number of errors missed given the percent of patients being seen by the verification station. The percentage of patients increased in increments of 5 percent. The intent of the experiments was to find the least number of errors within a fixed population given the restraints on time and the percent of patients being screened for errors at a validation station.

3.10 Specific Measures for Success

The multimethod simulation model is considered a success if the percentage of overall errors falls outside of the margin of error for the POD exercise. This provides evidence for the alternative hypothesis is accepted. This would also suggest that by removing the screeners who generate the errors within a POD and retraining them, instead of the entire screening staff, this procedure would reduce the percentage of errors in a POD without disrupting the overall flow and operation of the POD.

3.11 Threats to Validity

Selection is the main threat to external validity. Because the data were collected over two semesters, there is a possibility there were not enough data to represent a full population of POD exercises. This threat was mitigated, however, by using two independent sets of volunteers and students per experiment. This threat was mitigated by comparing mean times at each station and medical error rates with other POD exercises held during other semesters.

Instrumentation is the main threat to internal validity. Each agent and node within the simulation is built with the same parameters, mean and standard deviation. Because the simulation is replicating a real system of a POD exercise, the parameters where calculated measurements from real POD systems. There is a large enough variance among times and error percentage at each agent and node that the software replicated a real system as close as possible.

CHAPTER 4. RESULTS

The researcher identified the errors in the agents as they departed the screening nodes. Once a screening node generated five errors, that node would be temporarily disabled. The result of the variable simulation showed that an average of 6.39% of the agents would have a medical error. Although the decrease in medical errors was statistically significant, it did not result in the desired 5.0% decrease as stated in the hypothesis.

4.1 Simulation Optimization Results

The simulation showed that a population of 20,000 could be complete with the POD within 53 hours (2.25 days). The results of the simulation optimization concluded that there is a negative linear relationship between the percentage of persons checked and the errors missed ($y = -0.1049x + 2053.4$; $r^2 = 0.9987$; see Figure 4-1).

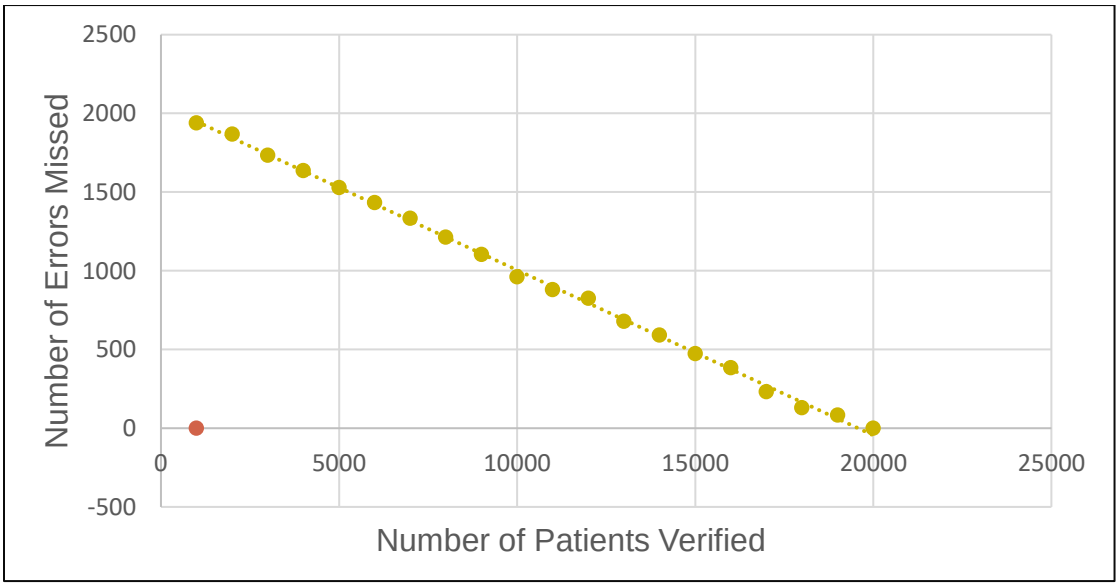

Figure 4-1. Number of Errors Missed as a Function of Number of Persons Verified

The fixed parameters included the number of triage stations to 15, registration stations to 15, screening stations to 9, and dispensing stations to 15. The relationship between the number of errors missed and the number of patients checked by a validation station was measured. The simulation also measured the time required to process the 20,000-person population. The results of the optimization show a logarithmic relationship between the time required to process the number of patients through the POD and the number of persons checked ($y = 0.0178\ln(x) + 53.628$, $r^2 = 0.2078$; see Figure 4-2). There was less than a 10% difference in the amount of time required to check 1,000 patients and the amount of time required to check 20,000 patients.

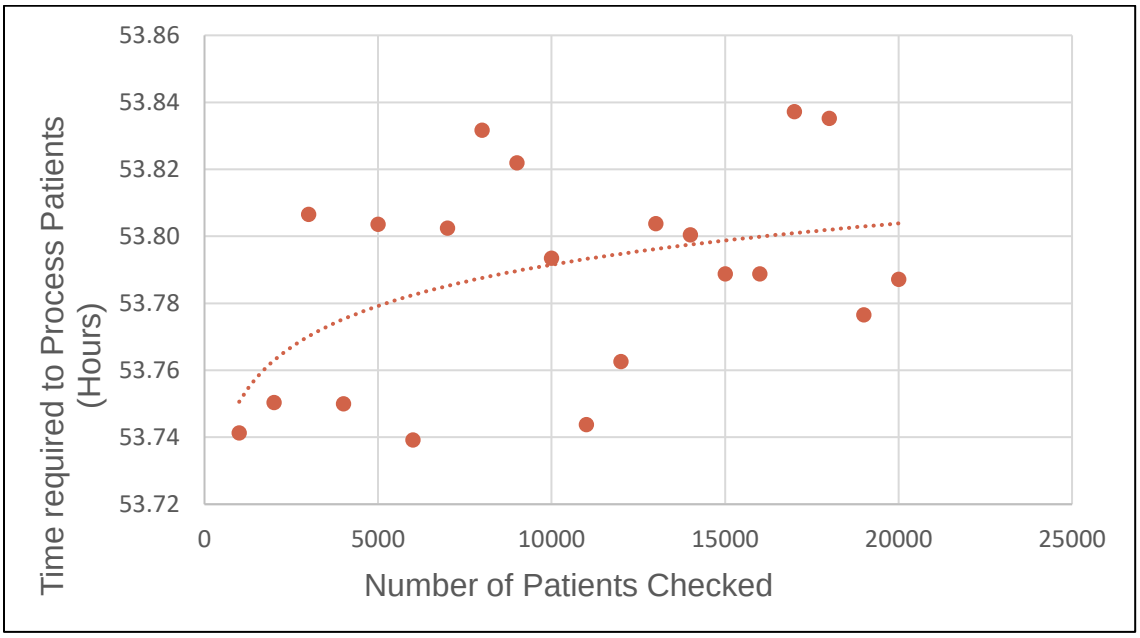

Figure 4-2. POD Completion Time as a Function of the Number of Patients Verified

4.2 Simulation

The control simulation (initial simulation) was ran during the months of August and September, 2019. Differences between synchronous and asynchronous training were not tested. Twenty different simulations were ran as control group. The modeling software, AnyLogic 7®,

tallied the total number of patient-agents that were process through each of the screening nodes. The tallied number was represented at the service exit (see Figure 4-3).

4.2.1 Initial Simulation Results

Each simulation ran for a period of 1 hour with an average of 500 participants in each simulation run. This resulted in a total of 8,431 data points for analysis, with a total of 842 identifiable medical errors generated from the simulation. Each screening agent processed an average of 84.3 patients/ hour and had an average of 8.42 medical errors/ hour. This is represented in an average 10.10% of the patient population with an error with a standard deviation of 0.48%.

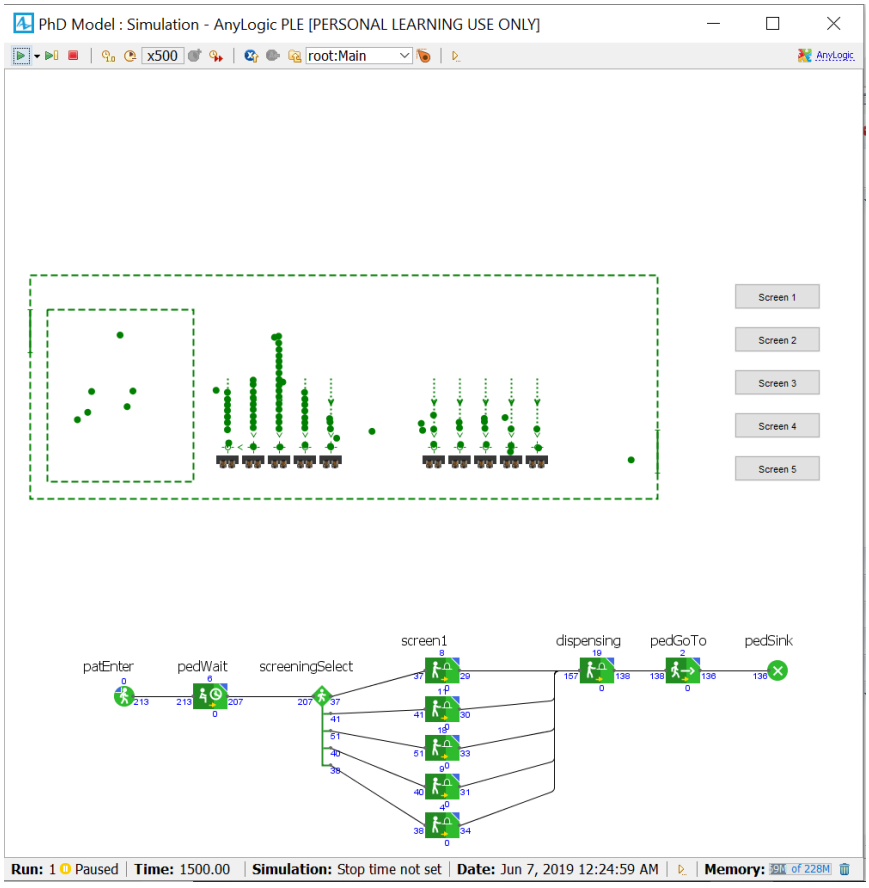

Figure 4-3. Initial POD Simulation

Each run calculated the mean percentage of errors occurring and the standard deviation for each screening node. The results can be seen in Table 4-1. Because each of the simulation runs were random, and independent of each other, the Central Limit Theorem can be used to test the hypothesis.

Table 4-1. Percentage of Medical Errors Occuring for the Control Simulation

	Screen 1	Screen 2	Screen 3	Screen 4	Screen 5	*M*	*SD*
Run 1	10.20	9.68	9.88	10.47	9.76	10.00	0.330
Run 2	9.88	10.11	10.26	10.84	10.34	10.29	0.356
Run 3	9.52	9.64	10.81	9.88	10.00	9.97	0.506
Run 4	10.64	9.64	10.59	10.23	10.53	10.33	0.415
Run 5	9.88	9.89	9.88	10.00	10.84	10.10	0.418
Run 6	9.64	10.11	10.47	10.11	9.89	10.04	0.307
Run 7	10.13	10.00	9.88	10.00	10.39	10.08	0.195
Run 8	10.26	10.26	10.34	9.68	10.13	10.13	0.265
Run 9	9.88	10.42	10.13	10.13	10.13	10.14	0.191
Run 10	8.97	10.00	10.23	10.84	10.34	10.08	0.690
Run 11	9.88	10.11	9.33	10.11	9.64	9.81	0.333
Run 12	10.00	10.84	10.59	10.00	10.26	10.34	0.371
Run 13	11.11	9.52	10.26	9.41	9.46	9.95	0.735
Run 14	10.67	9.41	9.88	9.52	10.71	10.04	0.620
Run 15	9.76	10.26	10.53	10.00	10.00	10.11	0.294
Run 16	10.26	10.64	8.99	12.16	9.76	10.36	1.180
Run 17	10.47	11.11	10.26	10.47	9.59	10.38	0.545
Run 18	10.00	10.13	9.52	10.39	9.64	9.94	0.357
Run 19	10.34	9.88	10.00	10.00	9.47	9.94	0.313
Run 20	10.47	8.97	9.89	10.23	10.13	9.94	0.580

The mean error percentage for all runs was 10.10% with a standard deviation of 0.48%. Because each run was an independent sample, and the averages of each follow a normal

distribution pattern, the central limit theorem was applied to analyze the results and compare the results with the variable groups. ANOVA of the data shows that there is a 94.03% probability that the means are similar. Examination of the ANOVA results indicates no significant difference between the percentage of errors of any of the simulation runs (see Figure 4-4, Tables 4-2, 4-3, & 4-4). A Tukey Ordered Differences Report confirms that the differences between the average times was insignificant (see Appendix F, Table F-1).

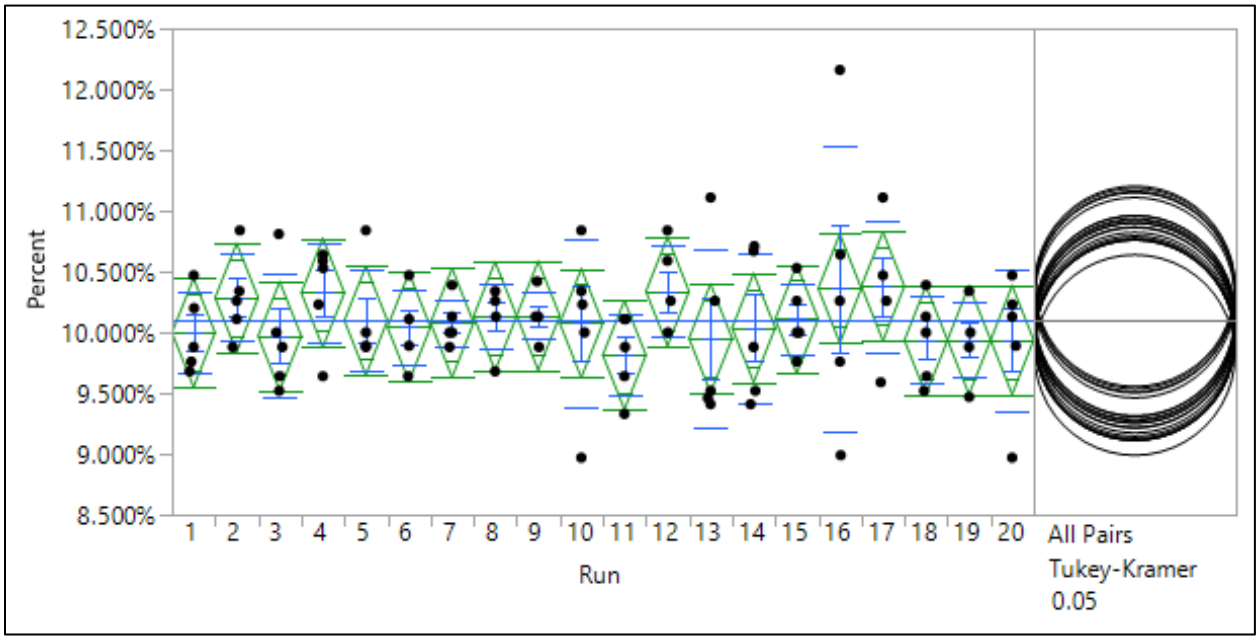

Figure 4-4. One-way ANOVA analysis of the Initial Simulation

Table 4-2. Summary of Fit for the Initial Simulation

Component	Value
R^2	0.111896
Adj R^2	-0.09903
RMSE	0.005031
M Response	0.100978
N	100

Table 4-3. Analysis of Variance for the Initial Simulation

Source	*df*	*S*	*M S*	*F* Ratio	Prob > *F*
Run	19	0.00025516	0.000013	0.5403	0.9403
Error	80	0.00202514	0.000025		
Total	99	0.00228029			

Table 4-4. Means for One-way ANOVA for the Initial Simulation

Run	*N*	*M*	*SD*	*SE*	Lower 95%	Upper 95%
1	5	0.09998	0.0032988	0.0014753	0.095884	0.104076
2	5	0.10286	0.0035578	0.0015911	0.0984424	0.1072776
3	5	0.0997	0.0050646	0.002265	0.0934115	0.1059885
4	5	0.10326	0.0041525	0.001857	0.098104	0.108416
5	5	0.10098	0.0041788	0.0018688	0.0957914	0.1061686
6	5	0.10044	0.0030705	0.0013732	0.0966275	0.1042525
7	5	0.1008	0.0019455	0.0008701	0.0983843	0.1032157
8	5	0.10134	0.0026473	0.0011839	0.098053	0.104627
9	5	0.10138	0.0019123	0.0008552	0.0990055	0.1037545
10	5	0.10076	0.0069031	0.0030872	0.0921887	0.1093313
11	5	0.09814	0.0033321	0.0014902	0.0940026	0.1022774
12	5	0.10338	0.0037084	0.0016584	0.0987755	0.1079845
13	5	0.09952	0.0073455	0.003285	0.0903993	0.1086407
14	5	0.10038	0.0062022	0.0027737	0.092679	0.108081
15	5	0.1011	0.0029394	0.0013145	0.0974503	0.1047497
16	5	0.10362	0.0117954	0.0052751	0.088974	0.118266

Table 4-4. Means for One-way ANOVA for the Initial Simulation continued

Run	*N*	*M*	*SD*	*SE*	Lower 95%	Upper 95%
17	5	0.1038	0.0054489	0.0024368	0.0970344	0.1105656
18	5	0.09936	0.0035655	0.0015946	0.0949328	0.1037872
19	5	0.09938	0.0031292	0.0013994	0.0954946	0.1032654
20	5	0.09938	0.0057976	0.0025928	0.0921813	0.1065787

The results of the initial simulation follow a normal distribution, with an outlier, 12.1%, skewing the results slightly to the right. The mean percentage of medical errors per run based off the average screening errors were arranged in a histogram (see Figure 4.5, and Table 4-5).

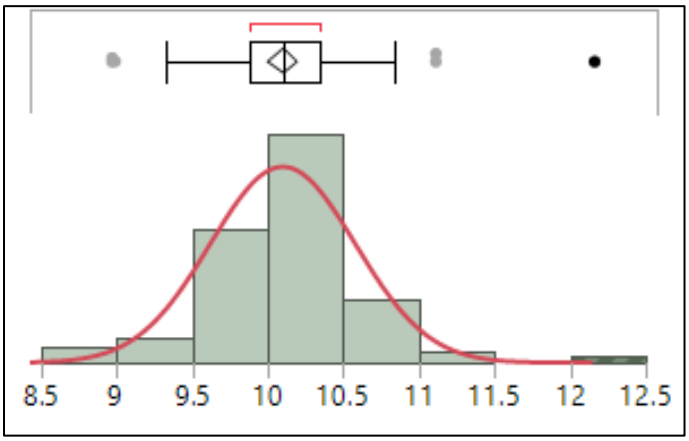

Figure 4-5. Histogram of Medical Error for the Initial Simulations.

Table 4-5. Summary Statistics for Initial Simulations

Component	Value
M	10.0978
SD	0.4799297
SE M	0.047993
Upper 95% Mean	10.193028
Lower 95% Mean	10.002572
N	100

4.2.2 Variable Simulation Results

The variable simulation was run during the months of September, and October 2019. As with the control simulation, there were 20 different simulations ran as the variable groups. The modeling software, AnyLogic, tallied the total number of patient-agents that were process through each of the screening nodes. The researcher counted the number of medical errors from each screening node represented by the agent changing color from green to red, and once any node reached five errors, the researcher would temporarily stop the screening node from seeing additional patients by selecting the control bottom to the right of the graphic editor of the AnyLogic ® model (see Figure 4-6).

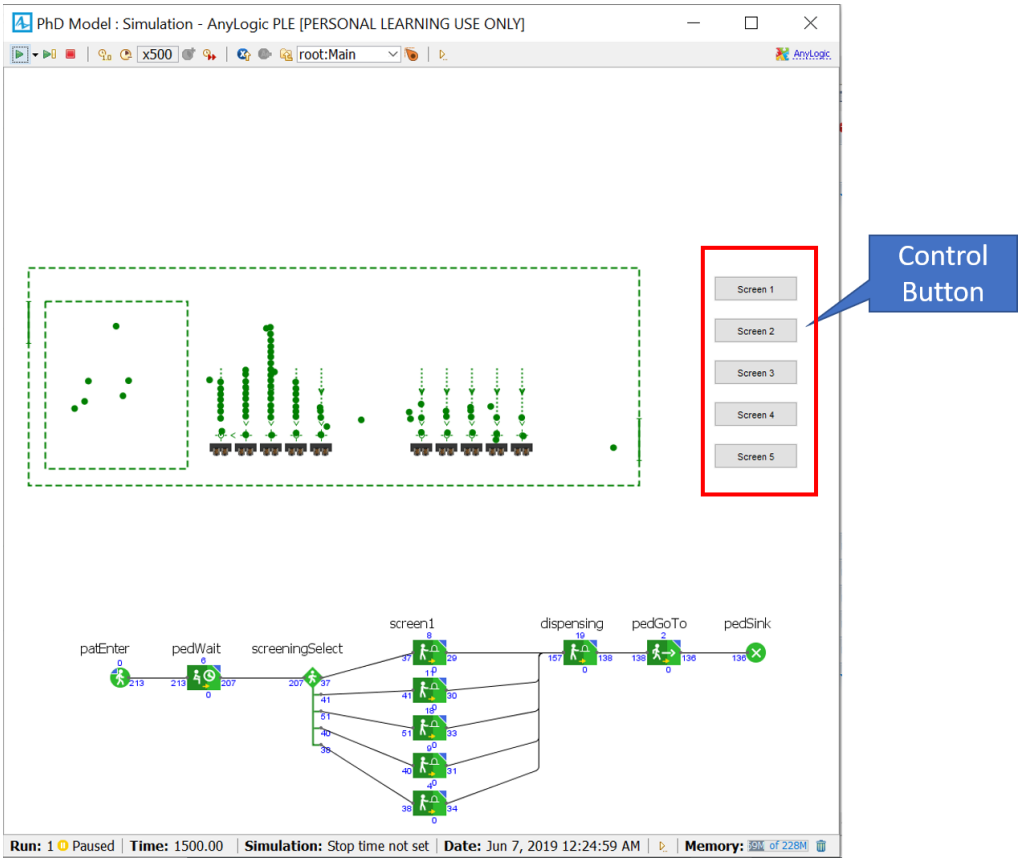

Figure 4-6. Variable Simulation Control Buttons

If all screening nodes reached five, then the researcher would remove the temporary halt and allow the nodes to continue screening patients. Each simulation ran for a period of 1 hour. The variable simulation resulted in a total of 8,214 data points for analysis, with a total of 525 identified medical errors generated from the simulation. Each screening node processed an average of 82.14 agents/ hour and had an average of 5.25 medical errors/ hour. This is represented in an average 6.39% of the patient population with an error with a standard deviation of 0.65%. However, the results of the initial simulation runs did not produce a normal distribution (see Figure 4-7 and Table 4-6).

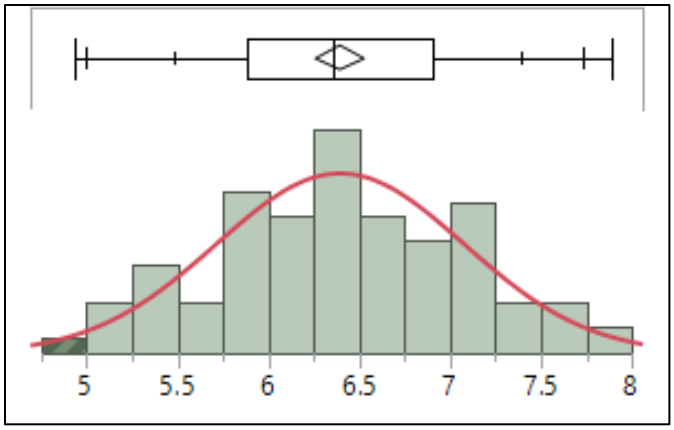

Figure 4-7. Histogram of Medical Error for the first 20 Variable Simulations

Table 4-6. Summary Statistics for first 20 Variable Simulations

Component	Value
M	6.3948
SD	0.6824754
SE M	0.0682475
Upper 95% Mean	6.5302179
Lower 95% Mean	6.2593821
N	100

Therefore, the researcher conducted the simulation an addition ten times for a total of thirty iterations (see Fig 4-8, and Table 4-7). This resulted in a total of 12,375 data points for analysis, with a total of 790 identified medical errors generated from the simulation. Each screening agent processed an average of 82.5 patients per hour and had an average of 5.27 medical errors per hour. This is represented in an average 6.38% of the patient population with an error with a standard deviation of 0.66%.

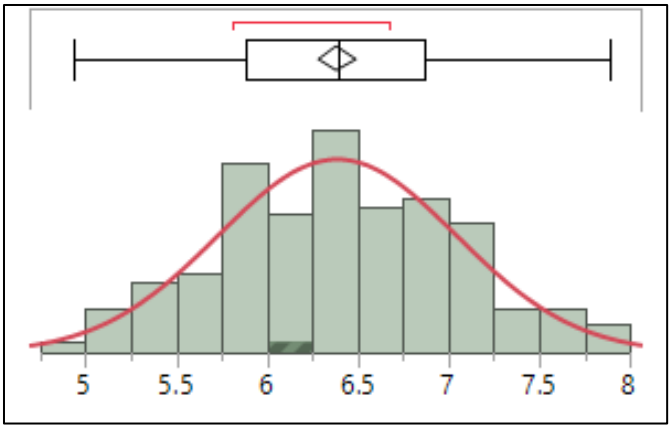

Figure 4-8. Histogram of Medical Error for all Variable Simulations

Table 4-7. Summary Statistics for all Variable Simulations

Component	Value
M	6.387
SD	0.6564791
SE M	0.0536013
Upper 95% Mean	6.4929169
Lower 95% Mean	6.2810831
N	150

The mean percentage of errors occurring and the standard deviation for each screening node for each run was calculated for the variable simulation (see Table 4-8). Just as with the control simulation suns, each of the simulation runs were random, and independent of each other; therefore, the Central Limit Theorem was used to test the hypothesis.

Table 4-8. Percent of Medical Errors Occurring for the Variable Simulations

Run	Screen 1	Screen 2	Screen 3	Screen 4	Screen 5	*M*	*SD*
1	6.17	6.67	5.13	6.32	6.76	6.21	0.65
2	6.67	5.48	6.90	6.10	7.06	6.44	0.65
3	7.06	7.06	6.25	5.48	6.85	6.54	0.68
4	5.41	7.41	5.56	5.88	6.98	6.25	0.89
5	6.49	6.02	5.95	5.81	6.49	6.15	0.32
6	7.06	6.25	6.49	7.41	5.63	6.57	0.70
7	7.61	6.74	7.06	5.95	6.10	6.69	0.69
8	5.68	6.58	6.17	7.06	6.49	6.40	0.51
9	6.67	6.17	6.25	6.74	6.25	6.42	0.27
10	5.26	6.17	7.89	5.88	6.10	6.26	0.98
11	6.25	7.23	5.62	6.85	5.56	6.30	0.74
12	6.45	7.23	5.81	5.00	5.56	6.01	0.86
13	6.33	5.75	6.25	6.82	5.95	6.22	0.41
14	6.10	6.58	6.90	6.82	5.95	6.47	0.43
15	6.33	6.82	5.75	6.82	5.81	6.31	0.52
16	6.82	6.98	5.06	6.74	6.59	6.44	0.78
17	7.06	6.17	6.90	6.49	6.58	6.64	0.35
18	6.58	5.88	7.04	7.06	6.98	6.71	0.50
19	5.88	7.41	5.00	6.94	7.89	6.62	1.17
20	7.23	7.14	5.00	6.41	5.81	6.32	0.94
21	5.88	6.15	5.95	6.25	5.75	6.00	0.20
22	6.9	6.38	7.06	7.06	6.33	6.75	0.36

Table 4-8. Percent of Medical Errors Occurring for the Variable Simulations continued

Run	Screen 1	Screen 2	Screen 3	Screen 4	Screen 5	*M*	*SD*
23	5.43	6.41	6.45	6.1	5.88	6.05	0.42
24	6.67	6.1	4.94	6.67	5.33	5.94	0.78
25	7.53	6.67	5.68	7.69	6.67	6.85	0.81
26	6.25	6.82	6.45	6.49	6.02	6.41	0.30
27	5.48	5.81	7.5	5.68	5.88	6.07	0.81
28	6.02	5.41	6.25	6.58	6.12	6.08	0.43
29	6.49	7.87	7.5	5.56	5.81	6.65	1.02
30	6.58	6.98	7.41	7.41	5.95	6.87	0.62

The mean error percentage from across all runs was 6.38% with a standard deviation of 0.66%. ANOVA of the data shows that there is an 81.69% probability that the means are similar. The results of the ANOVA indicate no significant difference between the percentage of errors of any of the simulation runs (see Figure 4-9, Tables 4-9, 4-10, & 4-11). A Tukey Ordered Differences Report confirms that the differences between the average times was insignificant (see Appendix F, Table F-2). Because each run was an independent sample, and the average of each follow a normal distribution, the central limit theorem applies to analyze the results and compare the results with the control group.

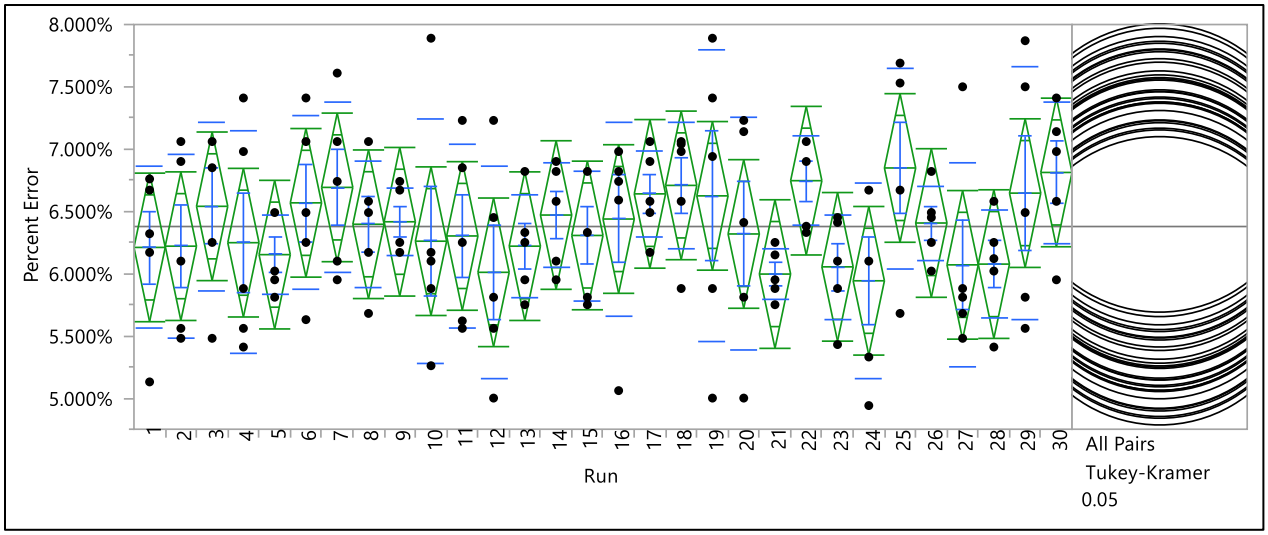

Figure 4-9. Oneway Analysis of the Variable Simulation

Table 4-9. Summary of Fit for the Variable Simulation

Component	Value
R^2	0.152912
Adj R^2	-0.0518
RMSE	0.006739
M Response	0.063778
N	150

Table 4-10. Analysis of Variance for the Variable Simulation

Source	*df*	*S*	*M S*	*F* Ratio	Prob > *F*
Run	29	0.00098361	0.000034	0.7470	0.8169
Error	120	0.00544893	0.000045		
Total	149	0.00643254			

Table 4-11. Means for Oneway ANOVA for the Variable Simulation

Run	*N*	*M*	*SD*	*SE*	Lower 95%	Upper 95%
1	5	0.0621	0.0065081	0.0029105	0.0540192	0.0701808
2	5	0.0622	0.007358	0.0032906	0.0530639	0.0713361
3	5	0.0654	0.0067908	0.0030369	0.0569681	0.0738319
4	5	0.06248	0.0089402	0.0039982	0.0513793	0.0735807
5	5	0.06152	0.0031768	0.0014207	0.0575755	0.0654645
6	5	0.06568	0.0069607	0.0031129	0.0570371	0.0743229
7	5	0.06692	0.0068584	0.0030671	0.0584042	0.0754358
8	5	0.06396	0.0051169	0.0022884	0.0576065	0.0703135
9	5	0.06416	0.0026698	0.001194	0.060845	0.067475
10	5	0.0626	0.0097916	0.0043789	0.0504422	0.0747578
11	5	0.06302	0.0073822	0.0033014	0.0538538	0.0721862
12	5	0.0601	0.0085799	0.0038371	0.0494466	0.0707534
13	5	0.0622	0.0040829	0.0018259	0.0571304	0.0672696
14	5	0.0647	0.0042626	0.0019063	0.0594072	0.0699928
15	5	0.06306	0.0052061	0.0023282	0.0565958	0.0695242
16	5	0.06438	0.0078308	0.0035021	0.0546567	0.0741033
17	5	0.0664	0.0035036	0.0015668	0.0620497	0.0707503
18	5	0.06708	0.0050251	0.0022473	0.0608405	0.0733195
19	5	0.06624	0.0117381	0.0052494	0.0516652	0.0808148
20	5	0.06318	0.0093689	0.0041899	0.0515469	0.0748131
21	5	0.05996	0.0020268	0.0009064	0.0574434	0.0624766
22	5	0.06746	0.0036329	0.0016247	0.0629492	0.0719708

Table 4-11. Means for Oneway ANOVA for the Variable Simulation continued

Run	*N*	*M*	*SD*	*SE*	Lower 95%	Upper 95%
23	5	0.06054	0.0041992	0.0018779	0.055326	0.065754
24	5	0.05942	0.0078477	0.0035096	0.0496757	0.0691643
25	5	0.06848	0.0080649	0.0036067	0.0584662	0.0784938
26	5	0.06406	0.0029737	0.0013299	0.0603676	0.0677524
27	5	0.0607	0.0081376	0.0036392	0.0505959	0.0708041
28	5	0.06076	0.0042805	0.0019143	0.055445	0.066075
29	5	0.06646	0.0101613	0.0045443	0.053843	0.079077
30	5	0.06812	0.0056795	0.00254	0.0610679	0.0751721

4.3 Hypothesis Testing

The mean percentage for the control was 10.978% (95% CI: 9.98, 10.2). The mean percentage for the variable group was 6.38% (95% CI: 6.28, 6.47). A pooled *t*-test and ANOVA of this data showed that the difference in the error percentage is significant ($p<0.001$). This is interpreted as the interventions added to the simulation during the variable runs and resulted in a significantly lower percentage of medical errors in comparison to the control group. (see Figures 4-10, & 4-11, Tables 4-12, 4-13, 4-14 & 4-15).

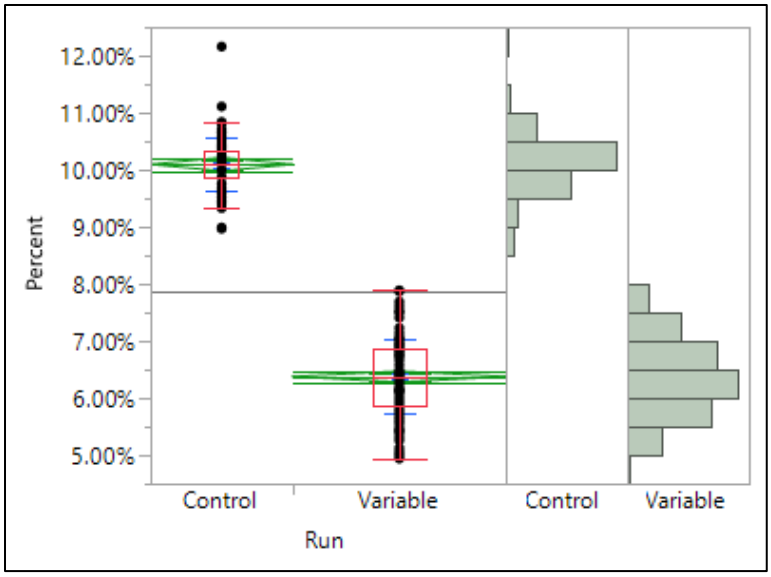

Figure 4-10. Oneway Analysis of Percent Errors By Simulation Run

Table 4-12. Summary of Fit for All Simulation Runs

Component	Value
R square	0.90503
Adj R square	0.904647
Root Mean Square Error	0.005927
Mean of Response	0.078658
Observations	250

Table 4-13. Analysis of Variance for All Simulation Runs

Source	*df*	*S*	*M S*	*F* Ratio	Prob > *F*
Group	1	0.08303040	0.083030	2363.359	<.0001
Error	248	0.00871283	0.000035		
Total	249	0.09174323			

Table 4-14. Means for Oneway ANOVA for All Simulation Runs

Level	*N*	*M*	Std Err	Lower 95%	Upper 95%
Control	100	0.100978	0.00059	0.09981	0.10215
Variable	150	0.063778	0.00048	0.06282	0.06473

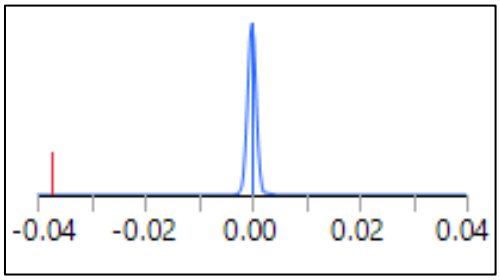

Figure 4-11. Results of the Pooled t-test

Table 4-15. Results of the Pooled t-test

Component	Value
Difference	-0.03720
Std Err Dif	0.00077
Upper CL Dif	-0.03569
Lower CL Dif	-0.03871
Confidence	0.95
t Ratio	-48.6144
df	248
Prob < *t*	<0.0001

However, the hypothesis test was quantitative between the two samples: the null hypothesis that the computer simulation did not decrease the number of medical errors by 5

percent (Δ_0). Given that the two samples have a normal distribution, are independent and random, the following equation was used to determine significance:

$$z = \frac{\bar{x} - \bar{y} - \Delta_0}{\sqrt{\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}}}; or \ z = \frac{.1010 - .0638 - .05}{\sqrt{\frac{.0048^2}{100} + \frac{.0066^2}{150}}} \ or \ z = -17.736$$

The *p*-value for the test is $1 - \Phi(-17.736)$, which equates to $p \cong 1.000$. Even though there is a significant difference between the average values of the control group verse the variable group, the difference is smaller than the 5% difference. Therefore, there is not sufficient evidence to reject the null hypothesis that the computer simulation did not decrease the number of medical errors by 5%. The alternate hypothesis was rejected, and the null hypothesis is accepted.

4.4 Type II Error Analysis

Because the null hypothesis was accepted, it was necessary to conduct a type II error analysis. To begin the type II error analysis, the critical value is found using the following equation where *Z* is the z score corresponding with the α (0.05):

$$Z = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} \ or - 1.96 = \frac{\bar{x} - .101}{.0048/\sqrt{100}}$$

The critical value was calculated from the summary statistics of the control simulation runs. The critical value of $\bar{x}$ is 0.1000592.

The critical value was then inputted into the same equation for the variable simulation runs in order to determine the probability of the type II error:

$$Z = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} \ or \ Z = \frac{.1000592 - .0638}{.0066/\sqrt{150}} = 67.28$$

The probability of a type II error for the test is 1-β, where β is the probability corresponding with $Z > 67.28$. $P_{(Z>67.28)} \cong 1.00$. Therefore, the probability of a type II error 1-1.00 or 0.0. An overlay of the two histograms graphically shows this (see Figure 4-12). Since all of the variable simulation run means fell to the left of the critical value, there is little probability of a type II error.

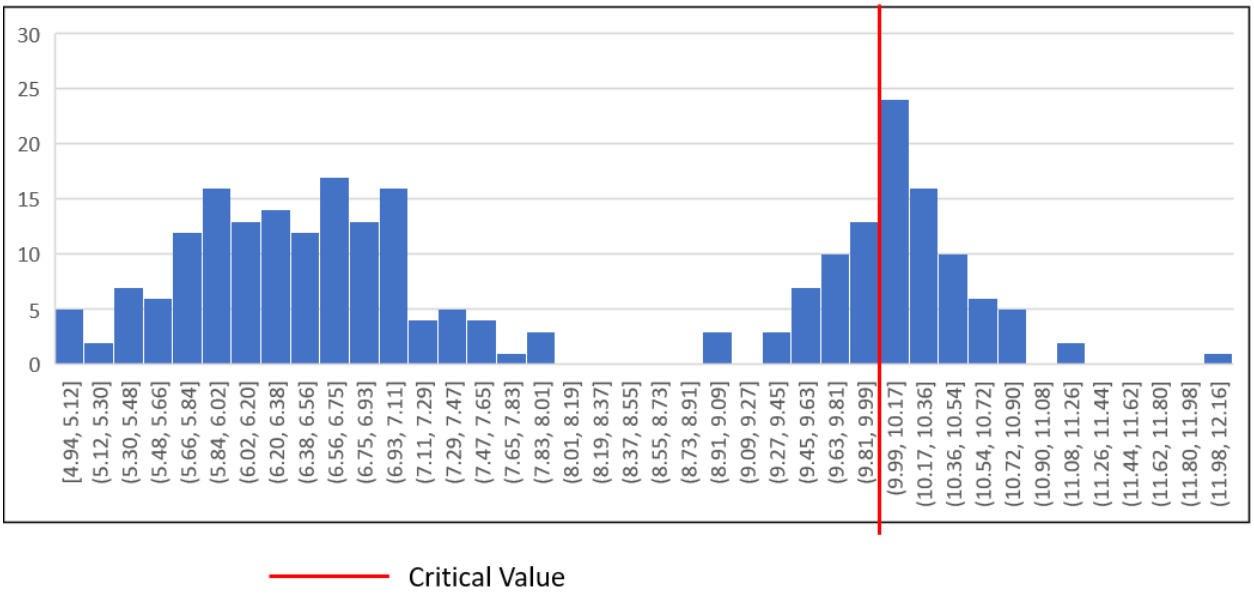

Figure 4-12. Histogram of All Simulation Runs

CHAPTER 5. DISCUSSION

5.1 Medication Dispensing Algorithms

The Tippecanoe County Health Department used two different dispensing algorithms over the course of this study. For the PODs where time data was retrieved, November 16, 2016 POD exercise, they used the Indiana State Department of Health, Public Health Preparedness and Emergency Response Antibiotic Dispensing Algorithm dated May 2, 2011 (see Appendix G). This algorithm had dispensing instructions for three different antibiotics, doxycycline, amoxicillin, and ciprofloxacin, in response to an Anthrax epidemic. This algorithm had instructions for patients who were on a specific asthma medication, Theophylline, and had instructions for any patient who may have severe allergic reaction to any of the three antibiotics being dispensed. This algorithm also had instructions for patients to be referred to a medical professional if the patient was below a specific weight: 90 pounds if dispensing ciprofloxacin, and 45 pounds if dispensing amoxicillin.

In the Spring of 2017, the Indiana Department of Health began to review an updated algorithm that would be easier to comprehend by the general population. In February 2017, Tippecanoe County Health Department began to use the revised algorithm, Antibiotic Dispensing Algorithm (see Appendix H). Changes to the algorithm included no weight restrictions on dispensing any of the medication, and only referring the patient to medical care if the patient was symptomatic. The intent behind the change to algorithm was to make it less confusing for volunteers and peer-trained helpers to understand. Because of the change in algorithm, the medical error data from 2016 could not be combined with medical error data from November 9, 2017, and March 29, 2018. The changes to the algorithm may also have led to confounding factors that influence the outcome of medical errors associated with the POD site.

Since March 29, 2018, the Indiana Department of Public Health has changed the antibiotic dispensing algorithm again and removed amoxicillin from the Anthrax response formulary.

5.2 Simulation Optimization Discussion

The result of the optimization show that the amount of time required to verify all the patients as they depart the POD is marginal compared to the amount of time required to verify even a small sample of the population. However, the number of medical errors that could be missed without verifying the proper medications greatly increases as the number of patients not verified increases. Therefore, the conclusion is that verifying the patients received the proper medications prior to departing the POD site theoretically will reduce the number of medical errors that are associated with that POD. However, the number of additional volunteers required to verify every patients' medication greatly increases, and thus increases the resources required to operate a POD. In order to verify 100% of the patients traversing through the POD have received the proper medication, the same number of volunteers to verify will be required as there are screeners (Glass et al., 2018, 2017). With an finite number of volunteers available to operate the POD, then any persons used as a validation station would be pulled from other aspects of the POD such as registration station, screening station or dispensing station.

There are limitations to this simulation optimization. The first limitation is the assumption verifying 100% of the patients being processed in the POD will identify every medical error. The second limitation is the time required to process the patients will generally fall within the distribution calculated within the simulation. Although over 400 separate data points were analyzed when building the optimization simulation, there still is a probability that some patients might fall outside of the distribution.

5.3 Simulation Results Discussion

The results of this study suggest that removing a screener who is identified as causing a significant number of errors could decrease the overall percentage of medical errors associated with the POD. This study was able to reduce the percent of errors from 10.1% to 6.3%. Although this decrease was not below the 5.0% as predicted by the researcher, it is still a significant decrease in the number of medical errors associated with the POD. The question remains if 6.3% errors is considered an acceptable rate.

Another aspect of the model that remains unaddressed is the disposition of screeners that are found to have identified to incorrect medication. In this model, the screeners were simply prevented from processing any further patients, as if they were pulled out of the screening station. In a real system, these screeners would need to be re-trained in order to maintain the overall efficiency of the POD. Studies from previous POD experiments required one hour, fifteen minutes of training prior to execution of the POD (Craig, 2016; Glass et al., 2017). Essentially, if a screener was to be removed from his/her screening station, then the assumption is that he/she would require an additional one hour, fifteen minutes to be re-trained.

5.4 Incidence of Adverse Drug Reactions as a Result from a POD

Obviously, the goal for any healthcare facility is to reach 0.0% medical errors. However, this goal may be far too obtainable with the amount of resources available. With respect to PODs, 0.0% may be unnecessary. Amoxicillin has a 6.7% incidence of serious drug reactions, and 0.32% of fatal adverse drug reactions associated with it (Abrams & Khan, 2018). Based on these calculations, the probability of a patient traversing the POD having an adverse reaction to amoxicillin due to the POD situation is 0.42% or 42/ 10,000 patients seen. In a population of 20,000, which is the bases for this study, then one would calculate an expected 84 patients to

receive an adverse effect to amoxicillin received from this POD. The incidence of a fatal reaction to amoxicillin would be even less, 2.01/ 10,000 or 40 patients within a population of 20,000.

The incidence of an adverse or allergic reaction to ciprofloxacin as a result of a POD would be even less than that of amoxicillin. The prevalence of serious allergic reactions with a fluoroquinolone based antibiotic such as ciprofloxacin use is reported to be 0.46 - 1.2/ 100,000 patients treated (Kelesidis et al., 2010). Calculate the risk of a serious adverse reaction to ciprofloxacin that is attributed to a POD site is 7.5/ 10,000,000. In a population of 20,000, that would equate to less than one patient having a serious adverse reaction to ciprofloxacin that can be attributed to the POD site.

Of the three medications discussed in this study, doxycycline has the least risk associated with it. Gastrointestinal distress is already associated with doxycycline, and mitigation strategies are usually distributed to patients in the form of handouts and literature (Holmes & Charles, 2009). Currently there is a dearth of published literature on the incidence and prevalence of severe allergic reactions to doxycycline; therefore, at this time there is little means of calculating a risk that can be attributed to POD distribution of doxycycline.

The effects of medical errors associated with POD sites are not as devastating as originally thought. Administering Amoxicillin, Doxycycline or Ciprofloxacin as a chemoprophylaxis in the event of a bioterrorism Anthrax attack does not necessarily increase the risk of adverse reactions to the entire population. The risk of adverse actions within the population that remain can be mitigated using a public affairs marketing strategy stating signs/symptoms of a possible allergic or adverse reaction to the medication. Anyone who

believes that they are exhibiting signs or symptoms of an adverse or allergic reaction should seek medical attention immediately.

5.5 Future Studies and Applications

Distributing medications in the event of emergency situation is a prime example of using commuter simulation modeling to improve efficiency. Researchers use models with the intent to imitate or replicate a real system – system that already exists or a system that will exist in the future (Robinson, 2004). However, there are limitations on using computer simulation modeling as opposed to a real system. Computer simulation is only as good as the data used to build the model. There is a plethora of assumptions made in the building of a computer model that must be addressed. These areas will require additional studies in order to address or count for them.

Computer simulation requires data input from existing systems that can be generalized for the model. Lee (Lee, 2008) built a computer model to assist with developing plans for distributing medications to the general public in large geographical areas. He focused on four areas: cross-shipping, variable supply quantity for each site, enough POD throughput, and the quantity of the safety stock of medical supplies. He gathered data from CDC to build his base model, then manipulated the four variable areas. The result showed he was able to maximize the throughput of each POD and reduce large discrepancies between sites (Lee, 2008). This model has not been verified to determine if the data used to build it replicated an accurate desertion of the real system.

In another study aimed at reducing the number of errors associated with a POD site, past data from high-reliability studies were used. The study at Purdue University focused on the team aspect of reducing medical errors, by having a verification, or "check" station prior to the patients exiting the POD site. The model showed medical errors should decrease to zero (Glass

et al., 2017). When the model was replicated in the form of a real system POD, the results indicated that the addition of the verification station did not reduce the number of errors with any significance.

In addition to the appropriate data required to build, models also rely on assumptions to fill the void from the lack of data in certain areas. In this study, the researcher was quickly able to identify the screening stations making errors because the agents physically changed color from green to red. In a real system, identifying if a patient has the incorrect medication may not be as straight forward. In addition, the researcher for this study was able to immediately stop the screeners identified as causing the most errors. These assumptions can only be addressed when the results of the model are replicated in a real system.

In order to expand on the results of this study, one must consider applying the resources to set up a real system POD with volunteers, medical providers, and the time to do so. Although a plethora of data were used to build the model and build it as accurate as possible, there are still assumptions that need to be addressed, and testing them on a real POD is the only true way to verify the results of this study.

CHAPTER 6. CONCLUSION

6.1 Building a Complex Adaptive System using Simulation Modeling

A Complex Adaptive Systems is a dynamic network of many diverse agents that constantly act and react to what the other agents are doing within the system (Beurden, Kia, Zask, Dietrich, & Rose, 2011). Control tends to be highly discrete and decentralized. Behavior between agents comes from interactions from the agents and each other. The overall behavior of the system results from a large number of decisions made every moment by multiple, different individual agents (Beurden et al., 2011). The agent-based simulation model built for this research is an example of a complex adaptive system. "In agent-based modeling, a system is modeled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set algorithm that reacts to its environment based on a set of rules" (Bonabeau, 2002, p. 7280).

Complex Adaptive Systems theory has been applied within epidemiology, disease and health behavior processes. The potential to utilize Complex Adaptive Systems theory to promote health and improving health systems is considerable (Beurden et al., 2011). This research used Complex Adaptive Systems to find suitable means to design, implement and evaluate changes to the POD regardless of the complexity of the subject at hand.

However, the agent-based model used in this system was a replication of human behavior. By their very nature, human agents in a replicated system have potentially irrational behavior, subjective choices, and complex psychology (Bonabeau, 2002). In other words, soft factors, difficult to quantify, calibrate, and sometimes justify, contribute to the overall outcome of the POD that cannot be replicated in the simulation. Although this may constitute a major source of problems in interpreting the outcomes of simulations, it is fair to say that in the case of

PODs, agent-based modeling is simply the most effective and cost-efficient means of analyzing error reduction.

6.2 Summary

PODs are complex systems. There are no simple solutions to reducing medical errors associated with them. Reducing errors requires managing knowledge from multiple aspects of the POD. Data is received from various sources and processed into information that can be analyzed into knowledge. This knowledge is then managed in order to determine to most effective course of action to reduce errors. With experience, wisdom is gained, and adjustments have been made by the State of Indiana in an effort to reduce confusion and reduce the number of medical errors.

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APPENDIX A. TIME DATA FROM NOV. 16, 2016

Table A-1. Data from POD Exercise on Nov. 16, 2016

Group	Screening	Dispensing
A	63.00	29.00
A	100.00	48.00
A	51.00	54.00
A	28.00	10.00
A	28.00	10.00
A	110.00	17.00
A	16.00	17.00
A	13.00	10.00
A	28.00	9.00
A	16.00	11.00
A	26.00	14.00
A	96.00	30.00
A	46.41	47.08
A	74.4	221.31
A	10.12	14.75
A	20.35	74.6
A	46.53	56.08
A	18.72	31.63
A	24.12	51.34
B	33.95	50.81
B	32.48	24.88
B	28.41	48.38
B	73.35	34.81
B	27.49	55.04
B	6.28	30.25
B	15.72	30.88
B	36.94	21.09
B	13.5	25.25
B	14.72	21.75
B	14.19	23.44
B	14.03	18.81
B	10.56	17.69
Mean	35.53969	36.21469
Standard Deviation	27.93436	37.86655

APPENDIX B. MEDICAL ERROR DATA FROM NOV. 9, 2017

Table B-1. Data from Nov. 9, 2017

Form	Screener	Dispenser	Required Medication	Medication Received	Error
14	1A20	1A26	Doxy	Doxy	no
2	1A16	1A24	Cipro	No Med	yes
34	182	1510	Cipro	Cipro	no
34	182	1510	Doxy	Doxy	no
34	182	1510	Doxy	Doxy	no
92	1A15		Doxy	Doxy	no
92	1A15		Doxy	Doxy	no
92	1A15		Doxy	Doxy	no
92	1A15		Doxy	Doxy	no
92	1A15		Doxy	Doxy	no
85	1S2	159	Doxy	Amox	yes
17	1S2	11	Doxy	Doxy	no
17	1S2	11	Doxy	Doxy	no
30	1A16	1A23	Doxy	Doxy	no
30	1A16	1A23	Doxy	Doxy	no
30	1A16	1A23	Doxy	Doxy	no
30	1A16	1A23	Doxy	Doxy	no
30	1A16	1A23	Doxy	Doxy	no
30	1A16	1A23	Doxy	Doxy	no
41	1S1	1513	Doxy	Doxy	no
41	1S1	1513	Cipro	Cipro	no
46	1S8	159	Doxy	Doxy	no
42	1A17	1A24	Refer to Medical	Amox	yes
42	1A17	1A24	Doxy	Cipro	yes
42	1A17	1A24	Doxy	Doxy	no
55	1S4	1512	Cipro	Amox	yes
48	1S2	159	Doxy	Doxy	no
48	1S2	159	Doxy w/Crushing	Doxy w/Crushing	no
48	1S2	159	Doxy w/Crushing	Doxy w/Crushing	no
62	1A15	A125	Doxy	Doxy	no
73	1A17	1A125	Doxy	Doxy	no
73	1A17	1A125	Doxy	Doxy	no
74	1S3		Doxy	Doxy	no
74	1S3		Doxy	Amox	yes

Table B-1. Data from Nov. 9, 2017 continued

Form	Screener	Dispenser	Required Medication	Medication Received	Error
81	1S4	1512	Doxy	Doxy	no
81	1S4	1513	Doxy	Doxy	no
81	1S4	1512	Doxy w/Crushing	Doxy w/Crushing	no
81	1S4	1512	Doxy w/Crushing	Doxy w/Crushing	no
93		1A23	Cipro	Cipro	no
93		2510	Cipro	Cipro	no
100	2A2	259	Doxy	Doxy	no
100	2A2	259	Doxy	Doxy	no
99	2S6	2510	Doxy	Doxy	no
85	2A15	2A24	Doxy	Doxy	no
62		2A2	Doxy	Amox	yes
62		2A2	Doxy	Doxy	no
77		2A2	Doxy	Doxy	no
70	2S3	2511	Doxy	Doxy	no
70	2S3	2511	Doxy	Doxy	no
69	2S6	2513	Doxy	Doxy	no
69	2S6	2513	Doxy	Doxy	no
69	2S6	2513	Doxy	Doxy	no
63	2S4	2511	Cipro	Cipro	no
47	2S4	259	Doxy	Doxy	no
47	2S4	259	Doxy	Doxy	no
47	2S4	259	Doxy w/Crushing	Doxy w/Crushing	no
56	2S3	2511	Cipro	Cipro	no
34		2A2	Cipro	Cipro	no
34		2A2	Doxy	Doxy	no
34		2A2	Doxy w/Crushing	Doxy w/Crushing	no
31	21A1	2513	Doxy	Doxy	no
31	21A1	2513	Doxy	Doxy	no
31	21A1	2513	Doxy w/Crushing	Doxy w/Crushing	no
30	2S8		Doxy	Doxy	no
30	2S8		Doxy	Doxy	no
30	2S8		Doxy w/Crushing	Doxy	yes

Table B-1. Data from Nov. 9, 2017 continued

Form	Screener	Dispenser	Required Medication	Medication Received	Error
30	2S8		Doxy w/Crushing	Doxy	yes
30	2S8		Doxy w/Crushing	Doxy	yes
20	2A21	2A24	Doxy	Doxy	no
23		2A2	Doxy	Cipro	yes
1		2510	Doxy	Doxy	no
11	2S16	2510	Cipro	Cipro	no
8	1A20	1A26	Doxy	Doxy	no
36	1A19	1A26	Doxy w/Crushing	Doxy w/Crushing	no
9	1S4	1510	Refer to Medical	Doxy Refer to Medical	yes
43		1A19	Doxy	Doxy	no
44	1S5	156	Doxy	Doxy	no
44	1S5	156	Doxy	Doxy	no
44	1S5	156	Doxy	Doxy	no
50	1A24	1A19	Doxy	Doxy	no
57	1A16	1A27	Doxy	Doxy	no
57	1A16	1A27	Doxy	Doxy	no
33	1S4	1510	Doxy	Doxy	no
33	1S4	1510	Refer to Medical	Doxy w/Crushing	yes
60	1S1	11	Cipro	Cipro	no
65	1A23	1A98	Doxy	Doxy	no
65	1A23	1A98	Doxy w/Crushing	Doxy	yes
65	1A23	1A98	Doxy w/Crushing	Doxy	yes
71	1A18	1A24	Doxy	Doxy	no
70	1S5	159	Doxy	Doxy	no
70	1S5	159	Doxy	Doxy	no
69		1514	Doxy	Doxy	no
69		1514	Doxy	Doxy	no
69		1514	Doxy	Doxy	no
66	1S2		Doxy	Doxy	no
66	1S2		Doxy	Doxy	no
82	1A17	A125	Doxy	Doxy	no
89	1A15	1A23	Doxy	Doxy	no

Table B-1. Data from Nov. 9, 2017 continued

Form	Screener	Dispenser	Required Medication	Medication Received	Error
89	1A15	1A23	Doxy	Doxy	no
89	1A15	1A23	Doxy w/Crushing	Doxy	yes
89	1A15	1A23	Doxy w/Crushing	Doxy	yes
86	1S1	156	Doxy	Doxy	no
87	1S1	1513	Amox	Amox	no
94	1S2	1513	Doxy	Doxy	no
99	1S4	1512	Doxy	Doxy	no
100	1A18	A125	Doxy	Doxy	no
100	1A18	A125	Doxy	Doxy	no
97	2A7	2514	Doxy	Doxy	no
97	2A7	2514	Doxy	Doxy	no
97	2A7	2514	Doxy	Doxy	no
97	2A7	2514	Doxy	Doxy	no
88	2A17		Doxy	Doxy	no
88	2A17		Doxy	Doxy	no
88	2A17		Doxy w/Crushing	Doxy	yes
88	2A17		Doxy w/Crushing	Doxy	yes
91	2S4	2513	Amox	Amox	no
81			Doxy	Doxy	no
81			Doxy	Doxy	no
81			Doxy w/Crushing	Doxy w/Crushing	no
81			Doxy w/Crushing	Doxy w/Crushing	no
86	2S6		Doxy	Doxy	no
88	2A1		Doxy	Doxy	no
82	2S3		Doxy	Doxy	no
60	2A19	1A25	Cipro	Cipro	no
84	2A18	2A27	Doxy	Doxy	no
76			Amox	Amox	no
72	2A2	2510	Cipro	Cipro	no
65	2A15	2A24	Doxy	Doxy	no
65	2A15	2A24	Doxy w/Crushing	Doxy w/Crushing	no
65	2A15	2A24	Doxy w/Crushing	Doxy w/Crushing	no

Table B-1. Data from Nov. 9, 2017 continued

Form	Screener	Dispenser	Required Medication	Medication Received	Error
38	2S3	259	Doxy	Doxy	no
92	2A19	2A27	Doxy	Doxy	no
92	2A19	2A27	Doxy	Doxy	no
92	2A19	2A27	Doxy	Doxy	no
92	2A19	2A27	Doxy	Doxy	no
92	2A19	2A27	Doxy	Doxy	no
94	2A22		Doxy	Doxy	no
80	2A17	2A25	Doxy	Doxy	no
78	2A7	2B11	Doxy	Doxy	no
42	2A21	2A27	Refer to Medical	Amox	yes
42	2A21	2A27	Doxy	Doxy	no
42	2A21	2A27	Doxy w/Crushing	Doxy w/Crushing	no
41	2A1		Doxy	Doxy	no
41	2A1		Cipro	Cipro	no
51	2A28	2A16	Cipro	Cipro	no
55	2A19		Cipro	Cipro	no
45	2A19	2A27	Doxy	Doxy	no
45	2A19	2A27	Doxy w/Crushing	Doxy	yes
45	2A19	2A27	Doxy w/Crushing	Doxy	yes
49			Doxy	Doxy	no
43	2A20	2A24	Doxy	Doxy	no
21	2S3		Cipro	Cipro	no
14	2A22	2A23	Doxy	Doxy	no
7		2A24	Doxy	Doxy	no
13	2S6		Doxy	Doxy	no
90		2A16	Doxy	Doxy	no
90		2A16	Doxy	Doxy	no
87	2S8	2514	Amox	Amox	no
74	2A15	2A24	Doxy	Doxy	no
74	2A15	2A24	Doxy	Amox	yes
73	2A16	2A24	Doxy	Doxy	no
73	2A16	2A24	Doxy	Doxy	no
64	2A28	2A16	Cipro	Cipro	no
59	2A15	2A24	Refer to Medical	Amox	yes

Table B-1. Data from Nov. 9, 2017 continued

Form	Screener	Dispenser	Required Medication	Medication Received	Error
59	2A15	2A24	Doxy w/Crushing	Doxy	yes
48	2S5	2514	Doxy	Doxy	no
48	2S5	2514	Doxy w/Crushing	Doxy w/Crushing	no
48	2S5	2514	Doxy w/Crushing	Doxy w/Crushing	no
58	2A17		Doxy	Amox	yes
57		2A24	Doxy	Doxy	no
57		2A24	Doxy	Doxy	no
22	2A28	2A16	Amox	Amox	no
22	2A28	2A16	Cipro	Cipro	no
22	2A28	2A16	Doxy	Doxy	no
44	2A17	2A25	Doxy	Doxy	no
44	2A17	2A25	Doxy	Doxy	no
44	2A17	2A25	Doxy	Doxy	no
37	2A20		Cipro	Cipro	no
32	2A17	2A28	Cipro	Cipro	no
4		2A26	Doxy	Doxy	no
15		2A24	Amox	Amox	no
8	2A19	2A25	Doxy	Doxy	no
19	2A17	2A27	Doxy	Doxy	no
98	2A15	2A25	Cipro	Amox	yes
98	2A15	2A25	Doxy w/Crushing	Doxy	yes
96	2S8	259	Doxy	Doxy	no
96	2S8	259	Doxy	Doxy	no
67	2A19	2A26	Doxy	Doxy	no
67	2A19	2A26	Doxy	Doxy	no
67	2A19	2A26	Doxy	Doxy	no
67	2A19	2A26	Doxy w/Crushing	Doxy w/Crushing	no
67	2A19	2A26	Doxy w/Crushing	Doxy w/Crushing	no
83		2A16	Doxy	Doxy	no
79	2A19		Doxy	Doxy	no
75	2A17		Doxy	Doxy	no
68	2A18	2A26	Doxy	Doxy	no
66	2A17		Doxy	Doxy	no
66	2A17		Doxy	Doxy	no

Table B-1. Data from Nov. 9, 2017 continued

Form	Screener	Dispenser	Required Medication	Medication Received	Error
39	2A19		Doxy	Doxy	no
39	2A19		Doxy	Doxy w/Crushing	yes
54	2S6	2513	Doxy	Doxy	no
54	2S6	2513	Doxy w/Crushing	Doxy	yes
54	2S6	2513	Doxy w/Crushing	Doxy	yes
54	2S6	2513	Doxy w/Crushing	Doxy	yes
54	2S6	2513	Doxy	Doxy	no
40	2A15	2A25	Doxy	Doxy	no
40	2A15	2A25	Doxy w/Crushing	Doxy	yes
40	2A15	2A25	Doxy w/Crushing	Doxy	yes
50	2A17	2A24	Doxy	Doxy	no
25	2A15	2A23	Refer to Medical	Amox	yes
25	2A15	2A23	Doxy	Doxy	no
25	2A15	2A23	Doxy	Doxy	no
18	2A20	2A23	Doxy	Doxy	no
12	2A20	2A28	Doxy	Doxy	no
12	2A20	2A28	Doxy	Doxy	no
16	2A19	2A27	Doxy w/Crushing	Doxy w/Crushing	no
24	2S5		Doxy	Doxy	no
26	2S6		Doxy	Doxy	no
26	2S6		Doxy	Doxy	no
5	2A17	2A23	Doxy	Doxy	no
27	2A27	2A18	Doxy	Doxy	no
27	2A27	2A18	Refer to Medical	Refer to Medical	no
33		2A26	Doxy	Doxy	no
33		2A26	Amox	Amox	no
46	2S6	2S11	Doxy	Doxy	no
53			Cipro	Cipro	no
52		2A2	Doxy	Doxy	no
52		2A2	Doxy	Doxy	no
61	2A1	289	Doxy	Amox	yes

Table B-1. Data from Nov. 9, 2017 continued

Form	Screener	Dispenser	Required Medication	Medication Received	Error
71	2A1		Doxy	Doxy	no
36	2A17	2A24	Doxy w/Crushing	Doxy	yes
29	2A19	2A25	Doxy	Doxy	no
29	2A19	2A25	Doxy	Doxy	no
17	2S8	2514	Doxy	Doxy	no
17	2S8	2514	Doxy w/Crushing	Doxy	yes
3	2A1	2520	Doxy	Doxy	no
3	2A1	2520	Doxy w/Crushing	Doxy w/Crushing	no
10	2S7		Doxy w/Crushing	Doxy w/Crushing	no
15	1A22	1A23	Amox	Amox	no
22		1A28	Amox	Amox	no
22		1A28	Cipro	Cipro	no
22		1A28	Doxy	Doxy	no
56	1A15	A125	Cipro	Cipro	no
75		1A24	Doxy	Doxy	no
67	1A15	1A27	Doxy	Doxy	no
67	1A15	1A27	Cipro	Doxy	yes
67	1A15	1A27	Doxy w/Crushing	Doxy	yes
67	1A15	1A27	Doxy	Doxy	no
97	1S1		Doxy	Doxy	no
97	1S1		Doxy w/Crushing	Doxy	yes
97	1S1		Doxy	Amox	yes
97	1S1		Doxy	Doxy	no
64	1A17	1A28	Cipro	Amox	yes
11			Doxy	Doxy	no
28	1A16	1A25	Doxy	Doxy	no
16	1S5	1514	Doxy	Doxy	no
18	1S3	1512	Doxy	Doxy	no
32	1S3	1514	Cipro	Amox	yes
40	1A15	1A24	Doxy	Doxy	no
40	1A15	1A24	Doxy w/Crushing	Doxy w/Crushing	no
49	1A15		Doxy	Doxy	no
27	1S7	1510	Doxy	Amox	yes
27	1S7	1510	Doxy	Doxy	no

Table B-1. Data from Nov. 9, 2017 continued

Form	Screener	Dispenser	Required Medication	Medication Received	Error
45	1A23	A22	Doxy	Doxy	no
45	1A23	1A22	Doxy w/Crushing	Doxy w/Crushing	no
45	1A23	1A22	Doxy w/Crushing	Doxy w/Crushing	no
58	1A20	1A24	Doxy	Doxy	no
31	1S2	11	Doxy	Doxy	no
31	1S2	11	Doxy	Doxy	no
31	1S2	11	Doxy w/Crushing	Doxy	yes
52		1A26	Doxy	Doxy	no
52		1A26	Doxy	Doxy	no
59	1A21	1A24	Refer to Medical	Amox	yes
59	1A21	1A24	Doxy w/Crushing	Doxy w/Crushing	no
72	1A16	1A26	Cipro	Cipro	no
78	1S8		Doxy	Doxy	no
79	1A15	1A23	Doxy	Doxy	no
76	1S5		Amox	Amox	no
80	1S1	159	Doxy	Doxy	no
84	1A16	1A26	Doxy	Doxy	no
90		1A20	Doxy	Doxy	no
90		1A20	Doxy	Doxy	no
91	1A17	1A27	Amox	Amox	no
88	1S3	1510	Doxy	Doxy	no
96	1S5	159	Doxy	Doxy	no
96	1S5	159	Doxy	Doxy	no
6	1A21	1A218	Doxy	Doxy	no
4	1S3		Doxy	Refer to Medical	yes
5	1A18	1A25	Doxy	Doxy	no
2			Cipro	Amox	yes
6	2S5	2513	Doxy	Doxy	no
28	A54		Doxy	Doxy	no
9			Refer to Medical	Amox	yes
35	2S6	2511	Doxy	Doxy	no

APPENDIX C. MEDICAL ERROR DATA FROM MAR. 29, 2018

Table C-1. Data from Mar. 29, 2018

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
91	2A1		2A6	2A7	Refer to Medical	Amox	yes
90	1S4				Doxy	Doxy	no
90	1S4				Doxy	Doxy	no
88	1S9		2S7		Doxy	Doxy	no
84	2A9		2A14	2A12	Doxy	Doxy	no
83	2A3	2A4	1A12	1A14	Doxy	Doxy	no
72	2A3	2A4	2A14	2A12	Cipro	Cipro	no
78	1S4		2S7		Doxy	Doxy	no
75	1S8		1S5	1S7	Doxy	Doxy	no
63	1S14	1S3	1S11	1S16	Cipro	Cipro	no
42	2A3	2A4	1A13	1A14	Refer to Medical	Cipro	yes
42	2A3	2A4	1A13	1A14	Doxy	Doxy	no
42	2A3	2A4	1A13	1A14	Doxy	Doxy	no
56	1S4		1S8		Cipro	Cipro	no
38	1S2		2S7		Doxy	Doxy	no
43	2A1		2A14	2A12	Doxy	Doxy	no
44	1S9		1S10	1S11	Doxy	Doxy	no
44	1S9		1S10	1S11	Doxy	Doxy	no
44	1S9		1S10	1S11	Doxy	Doxy	no
45	1S13		2S7		Doxy	Doxy	no
45	1S13		2S7		Doxy w/ Crushing	Doxy w/ Crushing	no
45	1S13		2S7		Doxy w/ Crushing	Doxy w/ Crushing	no
25	1S13		1S11	1S10	Refer to Medical	Cipro	yes
25	1S13		1S11	1S10	Doxy	Doxy	no
25	1S13		1S11	1S10	Doxy	Doxy	no
35	2A13		1A12	1A14	Doxy	Doxy	no
27	1S14	1S3	2S7		Doxy	Doxy	no
27	1S14	1S3	2S7		Doxy	Doxy	no
24	2A3		1A12	1A14	Doxy	Doxy	no
21	1S4		2S7		Cipro	Cipro	no
16	2A11		1A13	1A14	Doxy	Doxy	no

Table C-1. Data from Mar. 29, 2018 continued

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
14	1S13		2S7		Doxy	Doxy	no
2	1S4		1S5	1S7	Cipro	Cipro	no
5	1S14	1S3	2S7		Doxy	Doxy	no
96	1A3		1A8	1A6	Doxy	Doxy	no
96	1A3		1A8	1A6	Doxy	Doxy	no
96	1A3		1A8	1A6	Doxy	Doxy	no
96	1A3		1A8	1A6	Doxy	Doxy	no
95	1A7		1A13	1A14	Doxy	Doxy	no
95	1A7		1A13	1A14	Doxy	Doxy	no
88	1S13		2S8		Doxy	Doxy	no
88	1S13		2S8		Doxy	Doxy	no
88	1S13		2S8		Doxy w/ Crushing	Doxy w/ Crushing	no
88	1S13		2S8		Doxy w/ Crushing	Doxy w/ Crushing	no
85	2S14		2S7		Doxy	Doxy	no
83	2A8		1A12	1A9	Doxy	Doxy	no
69	2A8		1A1	1A11	Doxy	Doxy	no
69	2A8		1A1	1A11	Doxy	Doxy	no
69	2A8		1A1	1A11	Doxy	Doxy	no
75	1A5		1A8	1A6	Doxy	Doxy	no
70	2S14		2S8		Doxy	Doxy	no
70	2S14		2S8		Doxy	Doxy	no
54	1S6		2S7		Doxy	Doxy	no
54	1S6		2S7		Doxy w/ Crushing	Doxy w/ Crushing	no
54	1S6		2S7		Doxy w/ Crushing	Doxy w/ Crushing	no
54	1S6		2S7		Doxy w/ Crushing	Doxy w/ Crushing	no
54	1S6		2S7		Doxy w/ Crushing	Doxy w/ Crushing	no
59	1A7		1A1	1A11	Refer to Medical	Doxy	yes
59	1A7		1A1	1A11	Doxy	Doxy	no
60			1A8	1A6	Cipro	Cipro	no
57	1S13		2S8		Doxy	Doxy	no
58	1S13		2S8		Doxy	Doxy	no
55	1A7		1A8	1A6	Cipro	Cipro	no

Table C-1. Data from Mar. 29, 2018 continued

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
49	2S15		1S5	1S7	Doxy	Doxy	no
50	1S2		1S5	1S7	Doxy	Doxy	no
43	1S13		2S8		Doxy	Doxy	no
30	1S6		2S6		Doxy	Doxy	no
30	1S6		2S6		Doxy	Doxy	no
30	1S6		2S6		Doxy w/ Crushing	Doxy	yes
30	1S6		2S6		Doxy w/ Crushing	Doxy	yes
30	1S6		2S6		Doxy w/ Crushing	Doxy	yes
31	1A4		1A12	1A9	Doxy	Doxy	no
31	1A4		1A12	1A9	Doxy	Doxy	no
31	1A4		1A12	1A9	Doxy w/ Crushing	Doxy	yes
35	1A2		1A8	1A6	Doxy	Doxy	no
28	1S14		2S8		Doxy	Doxy	no
23	2A8				Doxy	Doxy	no
24	1S13		1S8		Doxy	Doxy	no
20	1S13		2S6		Doxy	Doxy	no
13	1S2		1S8		Doxy	Doxy	no
5	1A3				Doxy	Doxy	no
87	1S2		2S7		Refer to Medical	Amox	yes
80	1S2				Doxy	Doxy	no
3	1S4		2S7		Doxy	Doxy	no
3	1S4		2S7		Doxy	Cipro	yes
52	2A1		2A6	2A7	Doxy	Doxy	no
52	2A1		2A6	2A7	Doxy	Doxy	no
40	2A7		2A14	2A12	Doxy	Doxy	no
40	2A7		2A14	2A12	Doxy	Doxy	no
40	2A7		2A14	2A12	Doxy w/ Crushing	Doxy	yes
36	1S13		1S5	1S7	Doxy	Doxy	no
10	2A4		2A6	2A7	Doxy	Doxy	no
98	2A3	2A4			Doxy	Doxy	no
97	1S9		1S5	1S7	Cipro	Cipro	no
97	1S9		1S5	1S7	Doxy w/ Crushing	Doxy	yes

Table C-1. Data from Mar. 29, 2018 continued

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
87	2A1		2A5		Cipro	Amox	yes
76	2A1		2A13	2A14	Refer to Medical	Cipro	yes
80	1S14	1S3	1S5	1S7	Doxy	Doxy	no
74	2A13				Doxy	Doxy	no
74	2A13				Doxy	Doxy	no
77	1S7		1S5	1S7	Doxy	Doxy	no
68	2A3	2A4	1A12	1A14	Doxy	Doxy	no
65			1A12	1A14	Doxy	Doxy	no
65			1A12	1A14	Doxy w/ Crushing	Doxy	yes
65			1A12	1A14	Doxy w/ Crushing	Doxy	yes
60	2A3	2A4	1A13	1A14	Cipro	Cipro	no
54	2A3	2A4	2A14	2A12	Doxy	Doxy	no
54	2A3	2A4	2A14	2A12	Doxy w/ Crushing	Doxy	yes
54	2A3	2A4	2A14	2A12	Doxy w/ Crushing	Doxy	yes
54	2A3	2A4	2A14	2A12	Doxy w/ Crushing	Doxy	yes
54	2A3	2A4	2A14	2A12	Doxy	Doxy	no
38	2A3	2A4	2A6	2A7	Doxy	Doxy	no
38	2A3	2A4	2A6	2A7	Cipro	Cipro	no
38	2A3	2A4	2A6	2A7	Doxy w/ Crushing	Doxy	yes
38	2A3	2A4	2A6	2A7	Doxy w/ Crushing	Doxy	yes
38	2A3	2A4	2A6	2A7	Doxy w/ Crushing	Doxy	yes
46	2A13		2A5		Doxy	Doxy	no
49	1S2		2S7		Doxy	Doxy	no
33	2A9		2A5		Doxy	Doxy	no
37	1S14	1S3	2S7		Cipro	Cipro	no
31			2A1		Doxy	Doxy	no
31			2A1		Doxy	Doxy	no
31			2A1		Doxy w/ Crushing	Doxy	yes
29	2A13		1A13	1A14	Doxy	Doxy	no

Table C-1. Data from Mar. 29, 2018 continued

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
29	2A13		1A13	1A14	Doxy	Doxy	no
17	2A9		1A13	1A14	Doxy	Doxy	no
17	2A9		1A13	1A14	Doxy	Doxy	no
12	1S9		1S12		Doxy	Doxy	no
12	1S9		1S12		Doxy	Doxy	no
9	2A4		2A5		Refer to Medical	Doxy	yes
6	2A13		1A13	1A14	Doxy	Doxy	no
3	2A4	2A5	2A6	2A7	Doxy	Doxy	no
3	2A4	2A5	2A6	2A7	Doxy	Doxy	no
7.a					Doxy	Doxy	no
8	1A11		1A1		Doxy	Doxy	no
1.a					Doxy	Doxy	no
14	1A3				Doxy	Doxy	no
19	1A3				Doxy	Doxy	no
15	1S13		2S7		Cipro	Cipro	no
17	1S14		1S5	1S7	Doxy	Doxy	no
17	1S14		1S5	1S7	Doxy w/ Crushing	Doxy w/ Crushing	no
6	1S9		2S6		Doxy	Doxy	no
16	1A3				Doxy	Doxy	no
18.a					Doxy	Doxy	no
9.a					Refer to Medical	Doxy	yes
2	1S14		1S12		Cipro	Cipro	no
11.a					Cipro	Cipro	no
12	1S13		1S5	1S7	Doxy	Doxy	no
12	1S13		1S5	1S7	Doxy	Doxy	no
4	1S6		2S8		Doxy	Amox	yes
10	1A2				Doxy	Doxy	no
21	1S6		2S7		Cipro	Cipro	no
26.a					Doxy	Doxy	no
26.a					Doxy	Doxy	no
25	1S9		2S7		Refer to Medical	Cipro	yes
25	1S9		2S7		Doxy	Doxy	no
25	1S9		2S7		Doxy	Doxy	no
37	1A4				Cipro	Cipro	no
36	1A7		1A9	1A12	Doxy w/ Crushing	Blank	yes

Table C-1. Data from Mar. 29, 2018 continued

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
46	1A5		1A8	1A6	Doxy	Doxy	no
47	1A3		1A9	1A12	Doxy	Doxy	no
47	1A3		1A9	1A12	Doxy	Doxy	no
47	1A3		1A9	1A12	Doxy w/ Crushing	Doxy	yes
38			1A8	1A6	Doxy	Doxy	no
38			1A8	1A6	Cipro	Cipro	no
38			1A8	1A6	Doxy w/ Crushing	Doxy	yes
38			1A8	1A6	Doxy w/ Crushing	Doxy	yes
38			1A8	1A6	Doxy w/ Crushing	Doxy	yes
61	1A5				Doxy	Doxy	no
63	1S4		1S8		Cipro	Cipro	no
62	1S2		1S5	1S7	Doxy	Doxy	no
62	1S2		1S5	1S7	Doxy	Doxy	no
77	1A2		1A12	1A9	Doxy	Doxy	no
33	1S13		1S5	1S7	Doxy	Doxy	no
33	1S13		1S5	1S7	Doxy	Doxy	no
86	1A5				Doxy	Doxy	no
88	1A7		1A12	1A9	Doxy	Doxy	no
93	1S4		2S7		Cipro	Cipro	no
92	2A8		1A1	1A11	Doxy	Doxy	no
92	2A8		1A1	1A11	Doxy	Doxy	no
92	2A8		1A1	1A11	Doxy	Doxy	no
92	2A8		1A1	1A11	Doxy	Doxy	no
92	2A8		1A1	1A11	Doxy	Doxy	no
97	2S14		2S7		Cipro	Cipro	no
97	2S14		2S7		Doxy w/ Crushing	Blank	yes
99	1A4		1A9	1A12	Doxy	Doxy	no
99	1A4		1A9	1A12	Doxy	Doxy	no
100	1S9		2S8		Doxy	Doxy	no
81			1S8		Doxy	Doxy	no
81			1S8		Doxy	Doxy	no
81			1S8		Doxy w/ Crushing	Doxy w/ Crushing	no
81			1S8		Doxy w/ Crushing	Doxy w/ Crushing	no

Table C-1. Data from Mar. 29, 2018 continued

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
88	1S13		1S5	1S7	Doxy	Doxy	no
94	1A4		1A12	1A9	Doxy	Doxy	no
90	1S6		1S5	1S7	Doxy	Doxy	no
90	1S6		1S5	1S7	Doxy	Doxy	no
91	1A3		1A8	1A6	Refer to Medical	Amox	yes
76	2S14		2S6		Refer to Medical	Amox	yes
84	1S9		1S5	1S7	Doxy	Doxy	no
67	1S13		1S8		Doxy	Doxy	no
67	1S13		1S8		Doxy	Doxy	no
67	1S13		1S8		Doxy	Doxy	no
67	1S13		1S8		Doxy	Doxy	no
67	1S13		1S8		Doxy	Doxy	no
82	1A4		1A8	1A6	Doxy	Doxy	no
74	1A7				Doxy	Doxy	no
74	1A7				Doxy	Doxy	no
78	1S6		2S9		Doxy	Amox	yes
79	1A4		1A5	1A6	Doxy	Doxy	no
73	1S8		1S7		Doxy	Doxy	no
73	1S8		1S7		Doxy	Doxy	no
65	1A7		1A9	1A12	Doxy	Doxy	no
65	1A7		1A9	1A12	Doxy w/ Crushing	Doxy	yes
65	1A7		1A9	1A12	Doxy w/ Crushing	Doxy	yes
72	1A5		1A8	1A6	Cipro	Cipro	no
66	1A7				Doxy	Doxy	no
66	1A7				Doxy	Doxy	no
71	1A7		1A8	1A6	Doxy	Doxy	no
68	1A5		1A1	1A11	Doxy	Doxy	no
64	2A8		1A8	1A6	Cipro	Cipro	no
38	1S9		2S6		Doxy	Doxy	no
52	1S13		1S12		Doxy	Doxy	no
52	1S13		1S12		Doxy	Doxy	no
56	1A4		1A12	1A9	Cipro	Cipro	no
42	1A5				Refer to Medical	Cipro	yes
42	1A5				Doxy	Doxy	no

Table C-1. Data from Mar. 29, 2018 continued

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
42	1A5				Doxy w/ Crushing	Doxy	yes
51	1A7		1A1	1A11	Cipro	Cipro	no
53	1A4		1A9	1A12	Cipro	Cipro	no
45	1S6		2S7		Doxy	Doxy	no
45	1S6		2S7		Doxy w/ Crushing	Doxy w/ Crushing	no
45	1S6		2S7		Doxy w/ Crushing	Doxy w/ Crushing	no
44	1S9		1S12		Doxy	Doxy	no
44	1S9		1S12		Doxy	Doxy	no
44	1S9		1S12		Doxy	Doxy	no
48	1S13				Doxy	Doxy	no
48	1S13				Doxy w/ Crushing	Doxy w/ Crushing	no
48	1S13				Doxy w/ Crushing	Doxy w/ Crushing	no
40	1S2		1S5	1S7	Doxy	Doxy	no
40	1S2		1S5	1S7	Doxy w/ Crushing	Doxy w/ Crushing	no
40	1S2		1S5	1S7	Doxy w/ Crushing	Doxy w/ Crushing	no
22	1A3		1A11	1A1	Refer to Medical	Amox	yes
22	1A3		1A11	1A1	Cipro	Cipro	no
22	1A3		1A11	1A1	Doxy w/ Crushing	Doxy	yes
41	1S14		2S7		Doxy	Amox	yes
41	1S14		2S7		Cipro	Cipro	no
39	1S4		1S8		Doxy	Doxy	no
39	1S4		1S8		Doxy	Doxy w/ Crushing	yes
34	1A3		1A8	1A6	Cipro	Cipro	no
34	1A3		1A8	1A6	Doxy	Doxy	no
34	1A3		1A8	1A6	Doxy w/ Crushing	Doxy	yes
27			1S12		Doxy	Doxy	no
27			1S12		Doxy	Refer to Medical	yes
32	1A2				Cipro	Cipro	no
29	2A8				Doxy	Doxy	no

Table C-1. Data from Mar. 29, 2018 continued

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
29	2A8				Doxy	Doxy	no
95	2A11		1A12	1A14	Doxy	Doxy	no
95	2A11		1A12	1A14	Doxy	Doxy	no
100	2A11		2A6	2A7	Doxy	Doxy	no
96	1S4				Doxy	Doxy	no
96	1S4				Doxy	Doxy	no
96	1S4				Doxy	Doxy	no
96	1S4				Doxy	Doxy	no
96	1S4				Doxy	Doxy	no
99	1S4		1S10	1S11	Doxy	Doxy	no
99	1S4		1S10	1S11	Doxy	Doxy	no
88	1S14	1S3	2S7		Doxy	Doxy	no
88	1S14	1S3	2S7		Doxy	Doxy	no
88	1S14	1S3	2S7		Doxy w/ Crushing	Doxy	yes
88	1S14	1S3	2S7		Doxy w/ Crushing	Doxy	yes
93	1S13		1S5	1S7	Cipro	Cipro	no
92	2A3	2A4	2A14	2A12	Doxy	Doxy	no
92	2A3	2A4	2A14	2A12	Doxy	Doxy	no
92	2A3	2A4	2A14	2A12	Doxy	Doxy	no
92	2A3	2A4	2A14	2A12	Doxy	Doxy	no
92	2A3	2A4	2A14	2A12	Doxy	Doxy	no
94	1S2		1S10	1S11	Doxy	Doxy	no
86	2A3	2A4	2A6	2A7	Doxy	Doxy	no
85	1S13		1S8		Doxy	Doxy	no
81	1S4		2S7		Doxy	Doxy	no
81	1S4		2S7		Doxy	Doxy	no
81	1S4		2S7		Doxy	Doxy	no
81	1S4		2S7		Doxy	Doxy	no
79	2A3	2A4	2A6	2A7	Doxy	Doxy	no
82	1S2		1S10	1S11	Doxy	Doxy	no
67	1S13				Doxy	Doxy	no
67	1S13				Doxy	Doxy	no
67	1S13				Doxy	Doxy w/ Crushing	yes
67	1S13				Doxy	Doxy	no
67	1S13				Doxy	Doxy	no
62	2A4		2A6	2A7	Doxy	Doxy	no
62	2A4		2A6	2A7	Doxy	Doxy	no

Table C-1. Data from Mar. 29, 2018 continued

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
69	1S14	1S3	1S11	1S10	Doxy	Doxy	no
69	1S14	1S3	1S11	1S10	Doxy	Doxy	no
69	1S14	1S3	1S11	1S10	Doxy	Doxy	no
70	2A11		1A13	1A14	Doxy	Doxy	no
71	2A1		2A5		Doxy	Doxy	no
73	1S2		2S7		Doxy	Doxy	no
73	1S2		2S7		Doxy	Doxy	no
48	2A9		2A5		Doxy	Doxy	no
48	2A9		2A5		Doxy	Doxy	no
48	2A9		2A5		Doxy	Doxy	no
64	2A11				Cipro	Cipro	no
66	1S9		2S7		Doxy	Doxy	no
66	1S9		2S7		Doxy	Doxy	no
59	1S13		1S8		Refer to Medical	Doxy	yes
59	1S13		1S8		Doxy w/ Crushing	Doxy w/ Crushing	no
57	2A3	2A4	2A14	1A12	Doxy	Doxy	no
57	2A3	2A4	2A14	1A12	Doxy	Doxy	no
61	1S9		2S7		Doxy	Doxy	no
55	1S14	1S3	1S10	1S11	Cipro	Cipro	no
51	2A3	2A4	2A4		Cipro	Cipro	no
47	1S4		1S8		Doxy	Doxy	no
47	1S4		1S8		Doxy	Doxy	no
47	1S4		1S8		Doxy w/ Crushing	Doxy	yes
53	1S13		1S5	1S7	Cipro	Cipro	no
50	1S14	1S3	2S7		Doxy	Doxy	no
30	2A3	2A4	1A13	1A14	Doxy	Doxy	no
30	2A3	2A4	1A13	1A14	Doxy	Doxy	no
30	2A3	2A4	1A13	1A14	Doxy w/ Crushing	Doxy	yes
30	2A3	2A4	1A13	1A14	Doxy w/ Crushing	Doxy	yes
30	2A3	2A4	1A13	1A14	Doxy w/ Crushing	Doxy	yes
41	1S13		1S5	1S7	Doxy	Doxy	no
41	1S13		1S5	1S7	Cipro	Cipro	no
22	1S7		1S8		Refer to Medical	Amox	yes

Table C-1. Data from Mar. 29, 2018 continued

Form	Screen 1	Screen 2	Disp 1	Disp 2	Required Med	Med Received	Error
22	1S7		1S8		Cipro	Cipro	no
22	1S7		1S8		Doxy	Doxy	no
39	2A11		2A6	2A7	Doxy	Doxy	no
39	2A11		2A6	2A7	Doxy	Doxy	no
32	2A11		2A6	2A7	Cipro	Cipro	no
34	1S2		2S7		Cipro	Cipro	no
34	1S2		2S7		Doxy	Doxy	no
34	1S2		2S7		Doxy	Doxy w/ Crushing	yes
28	2A1		2A5		Doxy	Doxy	no
26	2A3		2A6	2A7	Doxy	Doxy	no
26	2A3		2A6	2A7	Doxy	Doxy	no
23			2A9		Doxy	Doxy	no
20	1S9		1S5	1S7	Doxy	Doxy	no
15	1S14	1S3	1S11	1S10	Cipro	Cipro	no
11	2A3		2A14	1A12	Cipro	Cipro	no
19	1S12		1S5	1S7	Doxy	Doxy	no
18	1S4		2S7		Doxy	Doxy	no
4			2A1		Doxy	Doxy	no
7	1S2				Doxy	Doxy	no
13	1S14	1S3	1S5	1S7	Doxy	Doxy	no
1	1S13		1S8		Doxy	Doxy	no
8	2A3		1A12	1A14	Doxy	Doxy	no

APPENDIX D. SIMULATION OPTIMIZATION RESULTS

Table D-1. Data from Optimization Simulation

Number of Patients Verified	Number of Errors Missed	Time Required to Process Patients (Hours)
1000	1,939	53.74
2000	1,868	53.75
3000	1,735	53.81
4000	1,637	53.75
5000	1,529	53.80
6000	1,433	53.74
7000	1,335	53.80
8000	1,214	53.83
9000	1,104	53.82
10000	963	53.79
11000	880	53.74
12000	825	53.76
13000	679	53.80
14000	592	53.80
15000	474	53.79
16000	384	53.79
17000	232	53.84
18000	130	53.84
19000	84	53.78
20000	0	53.79

APPENDIX E. DATA FROM NOV 16, 2016

Table E-1. Synchronous Training Data

Reference Number	Error Y/N	Reference Number	Error Y/N	Reference Number	Error Y/N	Reference Number	Error Y/N
3.1	No	34.1	No	54.5	No	81.4	No
3.2	No	34.2	No	55	No	82	No
4	No	34.3	No	56	No	83	No
5	No	35	No	57.1	No	84	Yes
6	No	36	No	57.2	No	85	No
7	No	37	No	58	No	86	No
8	No	38.1	No	59.1	Yes	87	No
9	Yes	38.2	No	59.2	No	88	No
10	No	38.3	No	60	Yes	89.1	No
11	No	38.4	No	61	No	89.2	No
12.1	No	38.5	No	62.1	No	89.3	No
12.2	No	39.1	No	62.2	No	89.4	No
13	No	39.2	No	63	No	90.1	No
14	No	40.1	No	64	No	90.2	No
15	No	40.2	No	65.1	No	91	No
16	No	40.3	No	65.2	No	92.1	No
17.1	No	41.1	No	65.3	No	92.2	No
17.2	No	41.2	No	66.1	No	92.3	No
18	No	42.1	Yes	66.2	No	92.4	No
19	No	42.2	No	67.1	No	92.5	No
20	No	42.3	No	67.2	No	93	No
21	No	43	No	67.3	No	94	No
22.1	No	44.1	No	67.4	No	95.1	No
22.2	No	44.2	No	67.5	No	95.2	No
22.3	Yes	44.3	No	68	No	96.1	No
23	No	45.1	No	69.1	No	96.2	No
24	No	45.2	No	69.2	No	96.3	No
25.1	Yes	45.3	No	69.3	No	96.4	No
25.2	No	46	No	70.1	No	97.1	No
25.3	No	47.1	No	70.2	No	97.2	No
26.1	No	47.2	No	71	No	98	No
26.2	No	47.3	No	72	Yes	99.1	No
27.1	No	48.1	No	73.1	No	99.2	No

Table E-1.. Synchronous Training Data continued

Reference Number	Error Y/N	Reference Number	Error Y/N	Reference Number	Error Y/N	Reference Number	Error Y/N
27.2	No	48.2	No	73.2	No	100	No
30.1	No	48.3	No	74.1	No	101.1	No
30.2	No	49	No	74.2	No	101.2	No
30.3	No	50	No	75	No	101.3	No
30.4	No	51	Yes	76	No	101.4	No
30.5	No	52.1	No	77	No	101.5	No
31.1	No	52.2	No	78	No	102.1	No
31.2	No	53	No	79	No	102.2	No
31.3	No	54.1	No	80	No	102.3	No
32	No	54.2	No	81.1	No	102.4	No
33.1	No	54.3	No	81.2	No	102.5	No
33.2	No	54.4	No	81.3	No	103	Yes
						104	No

Table E-2. Asynchronous Training Data

Reference Number	Error Y/N	Reference Number	Error Y/N	Reference Number	Error Y/N	Reference Number	Error Y/N
1	No	34.2	Yes	62.1	No	92.2	No
2	No	34.3	Yes	62.2	No	92.3	No
4	No	35	No	63	No	92.4	No
5	No	36	No	64	No	92.5	No
6	No	37	No	65.1	No	93	No
7	No	38.1	No	65.2	No	94	No
8	No	38.2	No	65.3	No	95.1	No
9	No	38.3	No	66.1	No	95.2	No
10	No	38.4	No	66.2	No	96.1	No
11	No	38.5	No	67.1	No	96.2	No
12.1	No	39.1	No	67.2	No	96.3	No
12.2	No	39.2	No	67.3	No	96.4	No
13	No	40.1	No	67.4	No	97.1	No
13.1	No	40.2	No	67.5	No	97.2	No
13.2	No	40.3	No	68	No	98	No
14	No	41.1	No	69.1	No	99.1	No
15	No	41.2	No	69.2	No	99.2	No
16	No	42.1	Yes	69.3	No	100	No
17.1	No	42.2	No	70.1	No	101.1	No

Table E-2. Asynchronous Training Data continued

Reference Number	Error Y/N	Reference Number	Error Y/N	Reference Number	Error Y/N	Reference Number	Error Y/N
17.2	No	42.3	No	70.2	No	101.2	No
18	No	43	No	71	No	101.3	Yes
19	No	44.1	No	72	No	101.4	No
20	No	44.2	No	73.1	No	101.5	No
21	No	44.3	No	73.2	No	102.1	No
22.1	No	45.1	No	74.1	No	102.2	No
22.2	No	45.2	No	74.2	No	102.3	No
22.3	Yes	45.3	No	75	No	102.4	No
23	No	46	No	76	No	102.5	No
24	No	47.1	No	77	No	103	Yes
25.1	No	47.2	No	78	No	104	No
25.2	Yes	47.3	No	79	No	105	No
25.3	No	48	No	80	No	106	No
26.1	No	49	No	81.1	No	107	Yes
26.2	No	51	No	81.2	No	108	No
27.1	No	52.1	No	81.3	No	109.1	No
27.2	No	52.2	No	81.4	No	109.2	No
28	No	53	No	82	No	110	No
29.1	No	54.1	No	83	No	111	No
29.2	No	54.2	No	84	No	112	No
30.1	No	54.3	No	85	No	113	Yes
30.2	No	54.4	No	86	Yes	114	No
30.3	No	54.5	No	87	No	115.1	No
30.4	No	55	No	88	No	115.2	No
30.5	No	56	No	89.1	No	116	No
31.1	No	57.1	No	89.2	No	117	No
31.2	No	57.2	No	89.3	No	118	No
31.3	No	58	No	89.4	No	119	No
32	No	59.1	No	90.1	No	120	No
33.1	No	59.2	No	90.2	No	N/A.1	No
33.2	No	60	No	91	No	N/A.2	No
34.1	Yes	61	No	92.1	No	N/A.3	No

APPENDIX F. TUKEY ORDERED DIFFERENCES REPORTS

Table F-1. Tukey Ordered Differences Report for Control Simulations

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value	
17	11	0.0056600	0.0031821	-0.006003	0.0173232	0.9604	
16	11	0.0054800	0.0031821	-0.006183	0.0171432	0.9709	
12	11	0.0052400	0.0031821	-0.006423	0.0169032	0.9814	
4	11	0.0051200	0.0031821	-0.006543	0.0167832	0.9854	
2	11	0.0047200	0.0031821	-0.006943	0.0163832	0.9941	
17	18	0.0044400	0.0031821	-0.007223	0.0161032	0.9972	
17	19	0.0044200	0.0031821	-0.007243	0.0160832	0.9973	
17	20	0.0044200	0.0031821	-0.007243	0.0160832	0.9973	
17	13	0.0042800	0.0031821	-0.007383	0.0159432	0.9982	
16	18	0.0042600	0.0031821	-0.007403	0.0159232	0.9983	
16	19	0.0042400	0.0031821	-0.007423	0.0159032	0.9984	
16	20	0.0042400	0.0031821	-0.007423	0.0159032	0.9984	
17	3	0.0041000	0.0031821	-0.007563	0.0157632	0.9990	
16	13	0.0041000	0.0031821	-0.007563	0.0157632	0.9990	
12	18	0.0040200	0.0031821	-0.007643	0.0156832	0.9992	
12	19	0.0040000	0.0031821	-0.007663	0.0156632	0.9993	
12	20	0.0040000	0.0031821	-0.007663	0.0156632	0.9993	
16	3	0.0039200	0.0031821	-0.007743	0.0155832	0.9994	
4	18	0.0039000	0.0031821	-0.007763	0.0155632	0.9995	
4	19	0.0038800	0.0031821	-0.007783	0.0155432	0.9995	
4	20	0.0038800	0.0031821	-0.007783	0.0155432	0.9995	
12	13	0.0038600	0.0031821	-0.007803	0.0155232	0.9995	
17	1	0.0038200	0.0031821	-0.007843	0.0154832	0.9996	
4	13	0.0037400	0.0031821	-0.007923	0.0154032	0.9997	
12	3	0.0036800	0.0031821	-0.007983	0.0153432	0.9998	
16	1	0.0036400	0.0031821	-0.008023	0.0153032	0.9998	
4	3	0.0035600	0.0031821	-0.008103	0.0152232	0.9999	
2	18	0.0035000	0.0031821	-0.008163	0.0151632	0.9999	
2	19	0.0034800	0.0031821	-0.008183	0.0151432	0.9999	
2	20	0.0034800	0.0031821	-0.008183	0.0151432	0.9999	
17	14	0.0034200	0.0031821	-0.008243	0.0150832	0.9999	
12	1	0.0034000	0.0031821	-0.008263	0.0150632	0.9999	
17	6	0.0033600	0.0031821	-0.008303	0.0150232	0.9999	
2	13	0.0033400	0.0031821	-0.008323	0.0150032	0.9999	
4	1	0.0032800	0.0031821	-0.008383	0.0149432	1.0000	
16	14	0.0032400	0.0031821	-0.008423	0.0149032	1.0000	
9	11	0.0032400	0.0031821	-0.008423	0.0149032	1.0000	

Table F-1. Tukey Ordered Differences Report for Control Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
8	11	0.0032000	0.0031821	-0.008463	0.0148632	1.0000
16	6	0.0031800	0.0031821	-0.008483	0.0148432	1.0000
2	3	0.0031600	0.0031821	-0.008503	0.0148232	1.0000
17	10	0.0030400	0.0031821	-0.008623	0.0147032	1.0000
17	7	0.0030000	0.0031821	-0.008663	0.0146632	1.0000
12	14	0.0030000	0.0031821	-0.008663	0.0146632	1.0000
15	11	0.0029600	0.0031821	-0.008703	0.0146232	1.0000
12	6	0.0029400	0.0031821	-0.008723	0.0146032	1.0000
4	14	0.0028800	0.0031821	-0.008783	0.0145432	1.0000
2	1	0.0028800	0.0031821	-0.008783	0.0145432	1.0000
16	10	0.0028600	0.0031821	-0.008803	0.0145232	1.0000
5	11	0.0028400	0.0031821	-0.008823	0.0145032	1.0000
16	7	0.0028200	0.0031821	-0.008843	0.0144832	1.0000
4	6	0.0028200	0.0031821	-0.008843	0.0144832	1.0000
17	5	0.0028200	0.0031821	-0.008843	0.0144832	1.0000
17	15	0.0027000	0.0031821	-0.008963	0.0143632	1.0000
7	11	0.0026600	0.0031821	-0.009003	0.0143232	1.0000
16	5	0.0026400	0.0031821	-0.009023	0.0143032	1.0000
10	11	0.0026200	0.0031821	-0.009043	0.0142832	1.0000
12	10	0.0026200	0.0031821	-0.009043	0.0142832	1.0000
12	7	0.0025800	0.0031821	-0.009083	0.0142432	1.0000
16	15	0.0025200	0.0031821	-0.009143	0.0141832	1.0000
4	10	0.0025000	0.0031821	-0.009163	0.0141632	1.0000
2	14	0.0024800	0.0031821	-0.009183	0.0141432	1.0000
17	8	0.0024600	0.0031821	-0.009203	0.0141232	1.0000
4	7	0.0024600	0.0031821	-0.009203	0.0141232	1.0000
17	9	0.0024200	0.0031821	-0.009243	0.0140832	1.0000
2	6	0.0024200	0.0031821	-0.009243	0.0140832	1.0000
12	5	0.0024000	0.0031821	-0.009263	0.0140632	1.0000
6	11	0.0023000	0.0031821	-0.009363	0.0139632	1.0000
16	8	0.0022800	0.0031821	-0.009383	0.0139432	1.0000
12	15	0.0022800	0.0031821	-0.009383	0.0139432	1.0000
4	5	0.0022800	0.0031821	-0.009383	0.0139432	1.0000
16	9	0.0022400	0.0031821	-0.009423	0.0139032	1.0000
14	11	0.0022400	0.0031821	-0.009423	0.0139032	1.0000
4	15	0.0021600	0.0031821	-0.009503	0.0138232	1.0000
2	10	0.0021000	0.0031821	-0.009563	0.0137632	1.0000
2	7	0.0020600	0.0031821	-0.009603	0.0137232	1.0000
12	8	0.0020400	0.0031821	-0.009623	0.0137032	1.0000
9	18	0.0020200	0.0031821	-0.009643	0.0136832	1.0000
12	9	0.0020000	0.0031821	-0.009663	0.0136632	1.0000

Table F-1. Tukey Ordered Differences Report for Control Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value	
9	19	0.0020000	0.0031821	-0.009663	0.0136632	1.0000	
9	20	0.0020000	0.0031821	-0.009663	0.0136632	1.0000	
8	18	0.0019800	0.0031821	-0.009683	0.0136432	1.0000	
8	19	0.0019600	0.0031821	-0.009703	0.0136232	1.0000	
8	20	0.0019600	0.0031821	-0.009703	0.0136232	1.0000	
4	8	0.0019200	0.0031821	-0.009743	0.0135832	1.0000	
4	9	0.0018800	0.0031821	-0.009783	0.0135432	1.0000	
2	5	0.0018800	0.0031821	-0.009783	0.0135432	1.0000	
9	13	0.0018600	0.0031821	-0.009803	0.0135232	1.0000	
1	11	0.0018400	0.0031821	-0.009823	0.0135032	1.0000	
8	13	0.0018200	0.0031821	-0.009843	0.0134832	1.0000	
2	15	0.0017600	0.0031821	-0.009903	0.0134232	1.0000	
15	18	0.0017400	0.0031821	-0.009923	0.0134032	1.0000	
15	19	0.0017200	0.0031821	-0.009943	0.0133832	1.0000	
15	20	0.0017200	0.0031821	-0.009943	0.0133832	1.0000	
9	3	0.0016800	0.0031821	-0.009983	0.0133432	1.0000	
8	3	0.0016400	0.0031821	-0.010023	0.0133032	1.0000	
5	18	0.0016200	0.0031821	-0.010043	0.0132832	1.0000	
5	19	0.0016000	0.0031821	-0.010063	0.0132632	1.0000	
5	20	0.0016000	0.0031821	-0.010063	0.0132632	1.0000	
15	13	0.0015800	0.0031821	-0.010083	0.0132432	1.0000	
3	11	0.0015600	0.0031821	-0.010103	0.0132232	1.0000	
2	8	0.0015200	0.0031821	-0.010143	0.0131832	1.0000	
2	9	0.0014800	0.0031821	-0.010183	0.0131432	1.0000	
5	13	0.0014600	0.0031821	-0.010203	0.0131232	1.0000	
7	18	0.0014400	0.0031821	-0.010223	0.0131032	1.0000	
7	19	0.0014200	0.0031821	-0.010243	0.0130832	1.0000	
7	20	0.0014200	0.0031821	-0.010243	0.0130832	1.0000	
15	3	0.0014000	0.0031821	-0.010263	0.0130632	1.0000	
10	18	0.0014000	0.0031821	-0.010263	0.0130632	1.0000	
9	1	0.0014000	0.0031821	-0.010263	0.0130632	1.0000	
10	19	0.0013800	0.0031821	-0.010283	0.0130432	1.0000	
10	20	0.0013800	0.0031821	-0.010283	0.0130432	1.0000	
13	11	0.0013800	0.0031821	-0.010283	0.0130432	1.0000	
8	1	0.0013600	0.0031821	-0.010303	0.0130232	1.0000	
5	3	0.0012800	0.0031821	-0.010383	0.0129432	1.0000	
7	13	0.0012800	0.0031821	-0.010383	0.0129432	1.0000	
10	13	0.0012400	0.0031821	-0.010423	0.0129032	1.0000	
19	11	0.0012400	0.0031821	-0.010423	0.0129032	1.0000	
20	11	0.0012400	0.0031821	-0.010423	0.0129032	1.0000	
18	11	0.0012200	0.0031821	-0.010443	0.0128832	1.0000	

Table F-1. Tukey Ordered Differences Report for Control Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
15	1	0.0011200	0.0031821	-0.010543	0.0127832	1.0000
7	3	0.0011000	0.0031821	-0.010563	0.0127632	1.0000
6	18	0.0010800	0.0031821	-0.010583	0.0127432	1.0000
10	3	0.0010600	0.0031821	-0.010603	0.0127232	1.0000
6	19	0.0010600	0.0031821	-0.010603	0.0127232	1.0000
6	20	0.0010600	0.0031821	-0.010603	0.0127232	1.0000
14	18	0.0010200	0.0031821	-0.010643	0.0126832	1.0000
5	1	0.0010000	0.0031821	-0.010663	0.0126632	1.0000
9	14	0.0010000	0.0031821	-0.010663	0.0126632	1.0000
14	19	0.0010000	0.0031821	-0.010663	0.0126632	1.0000
14	20	0.0010000	0.0031821	-0.010663	0.0126632	1.0000
8	14	0.0009600	0.0031821	-0.010703	0.0126232	1.0000
17	2	0.0009400	0.0031821	-0.010723	0.0126032	1.0000
9	6	0.0009400	0.0031821	-0.010723	0.0126032	1.0000
6	13	0.0009200	0.0031821	-0.010743	0.0125832	1.0000
8	6	0.0009000	0.0031821	-0.010763	0.0125632	1.0000
14	13	0.0008600	0.0031821	-0.010803	0.0125232	1.0000
7	1	0.0008200	0.0031821	-0.010843	0.0124832	1.0000
10	1	0.0007800	0.0031821	-0.010883	0.0124432	1.0000
16	2	0.0007600	0.0031821	-0.010903	0.0124232	1.0000
6	3	0.0007400	0.0031821	-0.010923	0.0124032	1.0000
15	14	0.0007200	0.0031821	-0.010943	0.0123832	1.0000
14	3	0.0006800	0.0031821	-0.010983	0.0123432	1.0000
15	6	0.0006600	0.0031821	-0.011003	0.0123232	1.0000
1	18	0.0006200	0.0031821	-0.011043	0.0122832	1.0000
9	10	0.0006200	0.0031821	-0.011043	0.0122832	1.0000
5	14	0.0006000	0.0031821	-0.011063	0.0122632	1.0000
1	19	0.0006000	0.0031821	-0.011063	0.0122632	1.0000
1	20	0.0006000	0.0031821	-0.011063	0.0122632	1.0000
9	7	0.0005800	0.0031821	-0.011083	0.0122432	1.0000
8	10	0.0005800	0.0031821	-0.011083	0.0122432	1.0000
5	6	0.0005400	0.0031821	-0.011123	0.0122032	1.0000
17	4	0.0005400	0.0031821	-0.011123	0.0122032	1.0000
8	7	0.0005400	0.0031821	-0.011123	0.0122032	1.0000
12	2	0.0005200	0.0031821	-0.011143	0.0121832	1.0000
6	1	0.0004600	0.0031821	-0.011203	0.0121232	1.0000
1	13	0.0004600	0.0031821	-0.011203	0.0121232	1.0000
17	12	0.0004200	0.0031821	-0.011243	0.0120832	1.0000
7	14	0.0004200	0.0031821	-0.011243	0.0120832	1.0000
4	2	0.0004000	0.0031821	-0.011263	0.0120632	1.0000
14	1	0.0004000	0.0031821	-0.011263	0.0120632	1.0000

Table F-1. Tukey Ordered Differences Report for Control Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
9	5	0.0004000	0.0031821	-0.011263	0.0120632	1.0000
10	14	0.0003800	0.0031821	-0.011283	0.0120432	1.0000
16	4	0.0003600	0.0031821	-0.011303	0.0120232	1.0000
7	6	0.0003600	0.0031821	-0.011303	0.0120232	1.0000
8	5	0.0003600	0.0031821	-0.011303	0.0120232	1.0000
15	10	0.0003400	0.0031821	-0.011323	0.0120032	1.0000
3	18	0.0003400	0.0031821	-0.011323	0.0120032	1.0000
10	6	0.0003200	0.0031821	-0.011343	0.0119832	1.0000
3	19	0.0003200	0.0031821	-0.011343	0.0119832	1.0000
3	20	0.0003200	0.0031821	-0.011343	0.0119832	1.0000
15	7	0.0003000	0.0031821	-0.011363	0.0119632	1.0000
1	3	0.0002800	0.0031821	-0.011383	0.0119432	1.0000
9	15	0.0002800	0.0031821	-0.011383	0.0119432	1.0000
16	12	0.0002400	0.0031821	-0.011423	0.0119032	1.0000
8	15	0.0002400	0.0031821	-0.011423	0.0119032	1.0000
5	10	0.0002200	0.0031821	-0.011443	0.0118832	1.0000
5	7	0.0001800	0.0031821	-0.011483	0.0118432	1.0000
17	16	0.0001800	0.0031821	-0.011483	0.0118432	1.0000
3	13	0.0001800	0.0031821	-0.011483	0.0118432	1.0000
13	18	0.0001600	0.0031821	-0.011503	0.0118232	1.0000
13	19	0.0001400	0.0031821	-0.011523	0.0118032	1.0000
13	20	0.0001400	0.0031821	-0.011523	0.0118032	1.0000
12	4	0.0001200	0.0031821	-0.011543	0.0117832	1.0000
15	5	0.0001200	0.0031821	-0.011543	0.0117832	1.0000
6	14	0.0000600	0.0031821	-0.011603	0.0117232	1.0000
9	8	0.0000400	0.0031821	-0.011623	0.0117032	1.0000
7	10	0.0000400	0.0031821	-0.011623	0.0117032	1.0000
19	18	0.0000200	0.0031821	-0.011643	0.0116832	1.0000
20	18	0.0000200	0.0031821	-0.011643	0.0116832	1.0000
20	19	0.0000000	0.0031821	-0.011663	0.0116632	1.0000

Table F-2. Tukey Ordered Differences Report for Variable Simulations

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
25	24	0.0090600	0.0042618	-0.007315	0.0254347	0.9470
30	24	0.0087000	0.0042618	-0.007675	0.0250747	0.9664
25	21	0.0085200	0.0042618	-0.007855	0.0248947	0.9738
25	12	0.0083800	0.0042618	-0.007995	0.0247547	0.9786
30	21	0.0081600	0.0042618	-0.008215	0.0245347	0.9848
22	24	0.0080400	0.0042618	-0.008335	0.0244147	0.9875
30	12	0.0080200	0.0042618	-0.008355	0.0243947	0.9879
25	23	0.0079400	0.0042618	-0.008435	0.0243147	0.9894
25	27	0.0077800	0.0042618	-0.008595	0.0241547	0.9920
25	28	0.0077200	0.0042618	-0.008655	0.0240947	0.9928
18	24	0.0076600	0.0042618	-0.008715	0.0240347	0.9936
30	23	0.0075800	0.0042618	-0.008795	0.0239547	0.9945
7	24	0.0075000	0.0042618	-0.008875	0.0238747	0.9953
22	21	0.0075000	0.0042618	-0.008875	0.0238747	0.9953
30	27	0.0074200	0.0042618	-0.008955	0.0237947	0.9960
22	12	0.0073600	0.0042618	-0.009015	0.0237347	0.9965
30	28	0.0073600	0.0042618	-0.009015	0.0237347	0.9965
18	21	0.0071200	0.0042618	-0.009255	0.0234947	0.9979
29	24	0.0070400	0.0042618	-0.009335	0.0234147	0.9982
18	12	0.0069800	0.0042618	-0.009395	0.0233547	0.9985
17	24	0.0069800	0.0042618	-0.009395	0.0233547	0.9985
7	21	0.0069600	0.0042618	-0.009415	0.0233347	0.9985
25	5	0.0069600	0.0042618	-0.009415	0.0233347	0.9985
22	23	0.0069200	0.0042618	-0.009455	0.0232947	0.9987
19	24	0.0068200	0.0042618	-0.009555	0.0231947	0.9989
7	12	0.0068200	0.0042618	-0.009555	0.0231947	0.9989
22	27	0.0067600	0.0042618	-0.009615	0.0231347	0.9991
22	28	0.0067000	0.0042618	-0.009675	0.0230747	0.9992
30	5	0.0066000	0.0042618	-0.009775	0.0229747	0.9994
18	23	0.0065400	0.0042618	-0.009835	0.0229147	0.9995
29	21	0.0065000	0.0042618	-0.009875	0.0228747	0.9995
17	21	0.0064400	0.0042618	-0.009935	0.0228147	0.9996
18	27	0.0063800	0.0042618	-0.009995	0.0227547	0.9997
7	23	0.0063800	0.0042618	-0.009995	0.0227547	0.9997
25	1	0.0063800	0.0042618	-0.009995	0.0227547	0.9997
29	12	0.0063600	0.0042618	-0.010015	0.0227347	0.9997
18	28	0.0063200	0.0042618	-0.010055	0.0226947	0.9997
17	12	0.0063000	0.0042618	-0.010075	0.0226747	0.9997
19	21	0.0062800	0.0042618	-0.010095	0.0226547	0.9997

Table F-2. Tukey Ordered Differences Report for Variable Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
25	2	0.0062800	0.0042618	-0.010095	0.0226547	0.9997
25	13	0.0062800	0.0042618	-0.010095	0.0226547	0.9997
6	24	0.0062600	0.0042618	-0.010115	0.0226347	0.9998
7	27	0.0062200	0.0042618	-0.010155	0.0225947	0.9998
7	28	0.0061600	0.0042618	-0.010215	0.0225347	0.9998
19	12	0.0061400	0.0042618	-0.010235	0.0225147	0.9998
30	1	0.0060200	0.0042618	-0.010355	0.0223947	0.9999
25	4	0.0060000	0.0042618	-0.010375	0.0223747	0.9999
3	24	0.0059800	0.0042618	-0.010395	0.0223547	0.9999
22	5	0.0059400	0.0042618	-0.010435	0.0223147	0.9999
30	2	0.0059200	0.0042618	-0.010455	0.0222947	0.9999
30	13	0.0059200	0.0042618	-0.010455	0.0222947	0.9999
29	23	0.0059200	0.0042618	-0.010455	0.0222947	0.9999
25	10	0.0058800	0.0042618	-0.010495	0.0222547	0.9999
17	23	0.0058600	0.0042618	-0.010515	0.0222347	0.9999
29	27	0.0057600	0.0042618	-0.010615	0.0221347	1.0000
6	21	0.0057200	0.0042618	-0.010655	0.0220947	1.0000
19	23	0.0057000	0.0042618	-0.010675	0.0220747	1.0000
29	28	0.0057000	0.0042618	-0.010675	0.0220747	1.0000
17	27	0.0057000	0.0042618	-0.010675	0.0220747	1.0000
30	4	0.0056400	0.0042618	-0.010735	0.0220147	1.0000
17	28	0.0056400	0.0042618	-0.010735	0.0220147	1.0000
6	12	0.0055800	0.0042618	-0.010795	0.0219547	1.0000
18	5	0.0055600	0.0042618	-0.010815	0.0219347	1.0000
19	27	0.0055400	0.0042618	-0.010835	0.0219147	1.0000
30	10	0.0055200	0.0042618	-0.010855	0.0218947	1.0000
19	28	0.0054800	0.0042618	-0.010895	0.0218547	1.0000
25	11	0.0054600	0.0042618	-0.010915	0.0218347	1.0000
3	21	0.0054400	0.0042618	-0.010935	0.0218147	1.0000
25	15	0.0054200	0.0042618	-0.010955	0.0217947	1.0000
7	5	0.0054000	0.0042618	-0.010975	0.0217747	1.0000
22	1	0.0053600	0.0042618	-0.011015	0.0217347	1.0000
25	20	0.0053000	0.0042618	-0.011075	0.0216747	1.0000
3	12	0.0053000	0.0042618	-0.011075	0.0216747	1.0000
14	24	0.0052800	0.0042618	-0.011095	0.0216547	1.0000
22	2	0.0052600	0.0042618	-0.011115	0.0216347	1.0000
22	13	0.0052600	0.0042618	-0.011115	0.0216347	1.0000
6	23	0.0051400	0.0042618	-0.011235	0.0215147	1.0000

Table F-2. Tukey Ordered Differences Report for Variable Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
30	11	0.0051000	0.0042618	-0.011275	0.0214747	1.0000
30	15	0.0050600	0.0042618	-0.011315	0.0214347	1.0000
22	4	0.0049800	0.0042618	-0.011395	0.0213547	1.0000
6	27	0.0049800	0.0042618	-0.011395	0.0213547	1.0000
18	1	0.0049800	0.0042618	-0.011395	0.0213547	1.0000
16	24	0.0049600	0.0042618	-0.011415	0.0213347	1.0000
30	20	0.0049400	0.0042618	-0.011435	0.0213147	1.0000
29	5	0.0049400	0.0042618	-0.011435	0.0213147	1.0000
6	28	0.0049200	0.0042618	-0.011455	0.0212947	1.0000
18	2	0.0048800	0.0042618	-0.011495	0.0212547	1.0000
18	13	0.0048800	0.0042618	-0.011495	0.0212547	1.0000
17	5	0.0048800	0.0042618	-0.011495	0.0212547	1.0000
22	10	0.0048600	0.0042618	-0.011515	0.0212347	1.0000
3	23	0.0048600	0.0042618	-0.011515	0.0212347	1.0000
7	1	0.0048200	0.0042618	-0.011555	0.0211947	1.0000
14	21	0.0047400	0.0042618	-0.011635	0.0211147	1.0000
9	24	0.0047400	0.0042618	-0.011635	0.0211147	1.0000
7	2	0.0047200	0.0042618	-0.011655	0.0210947	1.0000
7	13	0.0047200	0.0042618	-0.011655	0.0210947	1.0000
19	5	0.0047200	0.0042618	-0.011655	0.0210947	1.0000
3	27	0.0047000	0.0042618	-0.011675	0.0210747	1.0000
3	28	0.0046400	0.0042618	-0.011735	0.0210147	1.0000
26	24	0.0046400	0.0042618	-0.011735	0.0210147	1.0000
14	12	0.0046000	0.0042618	-0.011775	0.0209747	1.0000
18	4	0.0046000	0.0042618	-0.011775	0.0209747	1.0000
8	24	0.0045400	0.0042618	-0.011835	0.0209147	1.0000
25	8	0.0045200	0.0042618	-0.011855	0.0208947	1.0000
18	10	0.0044800	0.0042618	-0.011895	0.0208547	1.0000
22	11	0.0044400	0.0042618	-0.011935	0.0208147	1.0000
7	4	0.0044400	0.0042618	-0.011935	0.0208147	1.0000
25	26	0.0044200	0.0042618	-0.011955	0.0207947	1.0000
16	21	0.0044200	0.0042618	-0.011955	0.0207947	1.0000
22	15	0.0044000	0.0042618	-0.011975	0.0207747	1.0000
29	1	0.0043600	0.0042618	-0.012015	0.0207347	1.0000
25	9	0.0043200	0.0042618	-0.012055	0.0206947	1.0000
7	10	0.0043200	0.0042618	-0.012055	0.0206947	1.0000
17	1	0.0043000	0.0042618	-0.012075	0.0206747	1.0000
22	20	0.0042800	0.0042618	-0.012095	0.0206547	1.0000
16	12	0.0042800	0.0042618	-0.012095	0.0206547	1.0000
29	2	0.0042600	0.0042618	-0.012115	0.0206347	1.0000
29	13	0.0042600	0.0042618	-0.012115	0.0206347	1.0000

Table F-2. Tukey Ordered Differences Report for Variable Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
9	21	0.0042000	0.0042618	-0.012175	0.0205747	1.0000
17	2	0.0042000	0.0042618	-0.012175	0.0205747	1.0000
17	13	0.0042000	0.0042618	-0.012175	0.0205747	1.0000
6	5	0.0041600	0.0042618	-0.012215	0.0205347	1.0000
14	23	0.0041600	0.0042618	-0.012215	0.0205347	1.0000
30	8	0.0041600	0.0042618	-0.012215	0.0205347	1.0000
19	1	0.0041400	0.0042618	-0.012235	0.0205147	1.0000
25	16	0.0041000	0.0042618	-0.012275	0.0204747	1.0000
26	21	0.0041000	0.0042618	-0.012275	0.0204747	1.0000
30	26	0.0040600	0.0042618	-0.012315	0.0204347	1.0000
18	11	0.0040600	0.0042618	-0.012315	0.0204347	1.0000
9	12	0.0040600	0.0042618	-0.012315	0.0204347	1.0000
19	2	0.0040400	0.0042618	-0.012335	0.0204147	1.0000
19	13	0.0040400	0.0042618	-0.012335	0.0204147	1.0000
18	15	0.0040200	0.0042618	-0.012355	0.0203947	1.0000
14	27	0.0040000	0.0042618	-0.012375	0.0203747	1.0000
8	21	0.0040000	0.0042618	-0.012375	0.0203747	1.0000
29	4	0.0039800	0.0042618	-0.012395	0.0203547	1.0000
30	9	0.0039600	0.0042618	-0.012415	0.0203347	1.0000
26	12	0.0039600	0.0042618	-0.012415	0.0203347	1.0000
14	28	0.0039400	0.0042618	-0.012435	0.0203147	1.0000
17	4	0.0039200	0.0042618	-0.012455	0.0202947	1.0000
18	20	0.0039000	0.0042618	-0.012475	0.0202747	1.0000
7	11	0.0039000	0.0042618	-0.012475	0.0202747	1.0000
3	5	0.0038800	0.0042618	-0.012495	0.0202547	1.0000
7	15	0.0038600	0.0042618	-0.012515	0.0202347	1.0000
8	12	0.0038600	0.0042618	-0.012515	0.0202347	1.0000
29	10	0.0038600	0.0042618	-0.012515	0.0202347	1.0000
16	23	0.0038400	0.0042618	-0.012535	0.0202147	1.0000
17	10	0.0038000	0.0042618	-0.012575	0.0201747	1.0000
25	14	0.0037800	0.0042618	-0.012595	0.0201547	1.0000
19	4	0.0037600	0.0042618	-0.012615	0.0201347	1.0000
20	24	0.0037600	0.0042618	-0.012615	0.0201347	1.0000
7	20	0.0037400	0.0042618	-0.012635	0.0201147	1.0000
30	16	0.0037400	0.0042618	-0.012635	0.0201147	1.0000
16	27	0.0036800	0.0042618	-0.012695	0.0200547	1.0000
19	10	0.0036400	0.0042618	-0.012735	0.0200147	1.0000
15	24	0.0036400	0.0042618	-0.012735	0.0200147	1.0000
16	28	0.0036200	0.0042618	-0.012755	0.0199947	1.0000
9	23	0.0036200	0.0042618	-0.012755	0.0199947	1.0000
11	24	0.0036000	0.0042618	-0.012775	0.0199747	1.0000

Table F-2. Tukey Ordered Differences Report for Variable Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
6	1	0.0035800	0.0042618	-0.012795	0.0199547	1.0000
26	23	0.0035200	0.0042618	-0.012855	0.0198947	1.0000
22	8	0.0035000	0.0042618	-0.012875	0.0198747	1.0000
6	2	0.0034800	0.0042618	-0.012895	0.0198547	1.0000
6	13	0.0034800	0.0042618	-0.012895	0.0198547	1.0000
9	27	0.0034600	0.0042618	-0.012915	0.0198347	1.0000
29	11	0.0034400	0.0042618	-0.012935	0.0198147	1.0000
8	23	0.0034200	0.0042618	-0.012955	0.0197947	1.0000
30	14	0.0034200	0.0042618	-0.012955	0.0197947	1.0000
22	26	0.0034000	0.0042618	-0.012975	0.0197747	1.0000
29	15	0.0034000	0.0042618	-0.012975	0.0197747	1.0000
9	28	0.0034000	0.0042618	-0.012975	0.0197747	1.0000
17	11	0.0033800	0.0042618	-0.012995	0.0197547	1.0000
26	27	0.0033600	0.0042618	-0.013015	0.0197347	1.0000
17	15	0.0033400	0.0042618	-0.013035	0.0197147	1.0000
22	9	0.0033000	0.0042618	-0.013075	0.0196747	1.0000
3	1	0.0033000	0.0042618	-0.013075	0.0196747	1.0000
26	28	0.0033000	0.0042618	-0.013075	0.0196747	1.0000
29	20	0.0032800	0.0042618	-0.013095	0.0196547	1.0000
8	27	0.0032600	0.0042618	-0.013115	0.0196347	1.0000
19	11	0.0032200	0.0042618	-0.013155	0.0195947	1.0000
17	20	0.0032200	0.0042618	-0.013155	0.0195947	1.0000
20	21	0.0032200	0.0042618	-0.013155	0.0195947	1.0000
6	4	0.0032000	0.0042618	-0.013175	0.0195747	1.0000
3	2	0.0032000	0.0042618	-0.013175	0.0195747	1.0000
3	13	0.0032000	0.0042618	-0.013175	0.0195747	1.0000
8	28	0.0032000	0.0042618	-0.013175	0.0195747	1.0000
19	15	0.0031800	0.0042618	-0.013195	0.0195547	1.0000
14	5	0.0031800	0.0042618	-0.013195	0.0195547	1.0000
10	24	0.0031800	0.0042618	-0.013195	0.0195547	1.0000
18	8	0.0031200	0.0042618	-0.013255	0.0194947	1.0000
15	21	0.0031000	0.0042618	-0.013275	0.0194747	1.0000
25	3	0.0030800	0.0042618	-0.013295	0.0194547	1.0000
22	16	0.0030800	0.0042618	-0.013295	0.0194547	1.0000
6	10	0.0030800	0.0042618	-0.013295	0.0194547	1.0000
20	12	0.0030800	0.0042618	-0.013295	0.0194547	1.0000
19	20	0.0030600	0.0042618	-0.013315	0.0194347	1.0000
4	24	0.0030600	0.0042618	-0.013315	0.0194347	1.0000
11	21	0.0030600	0.0042618	-0.013315	0.0194347	1.0000
18	26	0.0030200	0.0042618	-0.013355	0.0193947	1.0000
7	8	0.0029600	0.0042618	-0.013415	0.0193347	1.0000

Table F-2. Tukey Ordered Differences Report for Variable Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
15	12	0.0029600	0.0042618	-0.013415	0.0193347	1.0000
18	9	0.0029200	0.0042618	-0.013455	0.0192947	1.0000
3	4	0.0029200	0.0042618	-0.013455	0.0192947	1.0000
11	12	0.0029200	0.0042618	-0.013455	0.0192947	1.0000
7	26	0.0028600	0.0042618	-0.013515	0.0192347	1.0000
16	5	0.0028600	0.0042618	-0.013515	0.0192347	1.0000
25	6	0.0028000	0.0042618	-0.013575	0.0191747	1.0000
3	10	0.0028000	0.0042618	-0.013575	0.0191747	1.0000
2	24	0.0027800	0.0042618	-0.013595	0.0191547	1.0000
13	24	0.0027800	0.0042618	-0.013595	0.0191547	1.0000
7	9	0.0027600	0.0042618	-0.013615	0.0191347	1.0000
22	14	0.0027600	0.0042618	-0.013615	0.0191347	1.0000
30	3	0.0027200	0.0042618	-0.013655	0.0190947	1.0000
18	16	0.0027000	0.0042618	-0.013675	0.0190747	1.0000
1	24	0.0026800	0.0042618	-0.013695	0.0190547	1.0000
6	11	0.0026600	0.0042618	-0.013715	0.0190347	1.0000
10	21	0.0026400	0.0042618	-0.013735	0.0190147	1.0000
9	5	0.0026400	0.0042618	-0.013735	0.0190147	1.0000
20	23	0.0026400	0.0042618	-0.013735	0.0190147	1.0000
6	15	0.0026200	0.0042618	-0.013755	0.0189947	1.0000
14	1	0.0026000	0.0042618	-0.013775	0.0189747	1.0000
7	16	0.0025400	0.0042618	-0.013835	0.0189147	1.0000
26	5	0.0025400	0.0042618	-0.013835	0.0189147	1.0000
4	21	0.0025200	0.0042618	-0.013855	0.0188947	1.0000
15	23	0.0025200	0.0042618	-0.013855	0.0188947	1.0000
6	20	0.0025000	0.0042618	-0.013875	0.0188747	1.0000
14	2	0.0025000	0.0042618	-0.013875	0.0188747	1.0000
14	13	0.0025000	0.0042618	-0.013875	0.0188747	1.0000
10	12	0.0025000	0.0042618	-0.013875	0.0188747	1.0000
29	8	0.0025000	0.0042618	-0.013875	0.0188747	1.0000
20	27	0.0024800	0.0042618	-0.013895	0.0188547	1.0000
11	23	0.0024800	0.0042618	-0.013895	0.0188547	1.0000
8	5	0.0024400	0.0042618	-0.013935	0.0188147	1.0000
30	6	0.0024400	0.0042618	-0.013935	0.0188147	1.0000
17	8	0.0024400	0.0042618	-0.013935	0.0188147	1.0000
20	28	0.0024200	0.0042618	-0.013955	0.0187947	1.0000
29	26	0.0024000	0.0042618	-0.013975	0.0187747	1.0000
3	11	0.0023800	0.0042618	-0.013995	0.0187547	1.0000
4	12	0.0023800	0.0042618	-0.013995	0.0187547	1.0000
18	14	0.0023800	0.0042618	-0.013995	0.0187547	1.0000
15	27	0.0023600	0.0042618	-0.014015	0.0187347	1.0000

Table F-2. Tukey Ordered Differences Report for Variable Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
3	15	0.0023400	0.0042618	-0.014035	0.0187147	1.0000
17	26	0.0023400	0.0042618	-0.014035	0.0187147	1.0000
11	27	0.0023200	0.0042618	-0.014055	0.0186947	1.0000
29	9	0.0023000	0.0042618	-0.014075	0.0186747	1.0000
15	28	0.0023000	0.0042618	-0.014075	0.0186747	1.0000
19	8	0.0022800	0.0042618	-0.014095	0.0186547	1.0000
16	1	0.0022800	0.0042618	-0.014095	0.0186547	1.0000
11	28	0.0022600	0.0042618	-0.014115	0.0186347	1.0000
2	21	0.0022400	0.0042618	-0.014135	0.0186147	1.0000
13	21	0.0022400	0.0042618	-0.014135	0.0186147	1.0000
25	19	0.0022400	0.0042618	-0.014135	0.0186147	1.0000
17	9	0.0022400	0.0042618	-0.014135	0.0186147	1.0000
3	20	0.0022200	0.0042618	-0.014155	0.0185947	1.0000
14	4	0.0022200	0.0042618	-0.014155	0.0185947	1.0000
7	14	0.0022200	0.0042618	-0.014155	0.0185947	1.0000
19	26	0.0021800	0.0042618	-0.014195	0.0185547	1.0000
16	2	0.0021800	0.0042618	-0.014195	0.0185547	1.0000
16	13	0.0021800	0.0042618	-0.014195	0.0185547	1.0000
1	21	0.0021400	0.0042618	-0.014235	0.0185147	1.0000
14	10	0.0021000	0.0042618	-0.014275	0.0184747	1.0000
5	24	0.0021000	0.0042618	-0.014275	0.0184747	1.0000
2	12	0.0021000	0.0042618	-0.014275	0.0184747	1.0000
13	12	0.0021000	0.0042618	-0.014275	0.0184747	1.0000
25	17	0.0020800	0.0042618	-0.014295	0.0184547	1.0000
19	9	0.0020800	0.0042618	-0.014295	0.0184547	1.0000
29	16	0.0020800	0.0042618	-0.014295	0.0184547	1.0000
22	3	0.0020600	0.0042618	-0.014315	0.0184347	1.0000
10	23	0.0020600	0.0042618	-0.014315	0.0184347	1.0000
9	1	0.0020600	0.0042618	-0.014315	0.0184347	1.0000
25	29	0.0020200	0.0042618	-0.014355	0.0183947	1.0000
17	16	0.0020200	0.0042618	-0.014355	0.0183947	1.0000
1	12	0.0020000	0.0042618	-0.014375	0.0183747	1.0000
9	2	0.0019600	0.0042618	-0.014415	0.0183347	1.0000
9	13	0.0019600	0.0042618	-0.014415	0.0183347	1.0000
26	1	0.0019600	0.0042618	-0.014415	0.0183347	1.0000
4	23	0.0019400	0.0042618	-0.014435	0.0183147	1.0000
16	4	0.0019000	0.0042618	-0.014475	0.0182747	1.0000
10	27	0.0019000	0.0042618	-0.014475	0.0182747	1.0000
30	19	0.0018800	0.0042618	-0.014495	0.0182547	1.0000
19	16	0.0018600	0.0042618	-0.014515	0.0182347	1.0000
8	1	0.0018600	0.0042618	-0.014515	0.0182347	1.0000

Table F-2. Tukey Ordered Differences Report for Variable Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
26	2	0.0018600	0.0042618	-0.014515	0.0182347	1.0000
26	13	0.0018600	0.0042618	-0.014515	0.0182347	1.0000
10	28	0.0018400	0.0042618	-0.014535	0.0182147	1.0000
22	6	0.0017800	0.0042618	-0.014595	0.0181547	1.0000
16	10	0.0017800	0.0042618	-0.014595	0.0181547	1.0000
4	27	0.0017800	0.0042618	-0.014595	0.0181547	1.0000
8	2	0.0017600	0.0042618	-0.014615	0.0181347	1.0000
8	13	0.0017600	0.0042618	-0.014615	0.0181347	1.0000
29	14	0.0017600	0.0042618	-0.014615	0.0181347	1.0000
30	17	0.0017200	0.0042618	-0.014655	0.0180947	1.0000
6	8	0.0017200	0.0042618	-0.014655	0.0180947	1.0000
4	28	0.0017200	0.0042618	-0.014655	0.0180947	1.0000
17	14	0.0017000	0.0042618	-0.014675	0.0180747	1.0000
14	11	0.0016800	0.0042618	-0.014695	0.0180547	1.0000
18	3	0.0016800	0.0042618	-0.014695	0.0180547	1.0000
9	4	0.0016800	0.0042618	-0.014695	0.0180547	1.0000
30	29	0.0016600	0.0042618	-0.014715	0.0180347	1.0000
2	23	0.0016600	0.0042618	-0.014715	0.0180347	1.0000
13	23	0.0016600	0.0042618	-0.014715	0.0180347	1.0000
20	5	0.0016600	0.0042618	-0.014715	0.0180347	1.0000
14	15	0.0016400	0.0042618	-0.014735	0.0180147	1.0000
6	26	0.0016200	0.0042618	-0.014755	0.0179947	1.0000
26	4	0.0015800	0.0042618	-0.014795	0.0179547	1.0000
1	23	0.0015600	0.0042618	-0.014815	0.0179347	1.0000
5	21	0.0015600	0.0042618	-0.014815	0.0179347	1.0000
25	7	0.0015600	0.0042618	-0.014815	0.0179347	1.0000
9	10	0.0015600	0.0042618	-0.014815	0.0179347	1.0000
19	14	0.0015400	0.0042618	-0.014835	0.0179147	1.0000
15	5	0.0015400	0.0042618	-0.014835	0.0179147	1.0000
14	20	0.0015200	0.0042618	-0.014855	0.0178947	1.0000
7	3	0.0015200	0.0042618	-0.014855	0.0178947	1.0000
6	9	0.0015200	0.0042618	-0.014855	0.0178947	1.0000
2	27	0.0015000	0.0042618	-0.014875	0.0178747	1.0000
13	27	0.0015000	0.0042618	-0.014875	0.0178747	1.0000
11	5	0.0015000	0.0042618	-0.014875	0.0178747	1.0000
8	4	0.0014800	0.0042618	-0.014895	0.0178547	1.0000
26	10	0.0014600	0.0042618	-0.014915	0.0178347	1.0000
3	8	0.0014400	0.0042618	-0.014935	0.0178147	1.0000
2	28	0.0014400	0.0042618	-0.014935	0.0178147	1.0000
13	28	0.0014400	0.0042618	-0.014935	0.0178147	1.0000
5	12	0.0014200	0.0042618	-0.014955	0.0177947	1.0000

Table F-2. Tukey Ordered Differences Report for Variable Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
1	27	0.0014000	0.0042618	-0.014975	0.0177747	1.0000
25	18	0.0014000	0.0042618	-0.014975	0.0177747	1.0000
18	6	0.0014000	0.0042618	-0.014975	0.0177747	1.0000
16	11	0.0013600	0.0042618	-0.015015	0.0177347	1.0000
8	10	0.0013600	0.0042618	-0.015015	0.0177347	1.0000
3	26	0.0013400	0.0042618	-0.015035	0.0177147	1.0000
28	24	0.0013400	0.0042618	-0.015035	0.0177147	1.0000
1	28	0.0013400	0.0042618	-0.015035	0.0177147	1.0000
16	15	0.0013200	0.0042618	-0.015055	0.0176947	1.0000
6	16	0.0013000	0.0042618	-0.015075	0.0176747	1.0000
27	24	0.0012800	0.0042618	-0.015095	0.0176547	1.0000
7	6	0.0012400	0.0042618	-0.015135	0.0176147	1.0000
3	9	0.0012400	0.0042618	-0.015135	0.0176147	1.0000
22	19	0.0012200	0.0042618	-0.015155	0.0175947	1.0000
16	20	0.0012000	0.0042618	-0.015175	0.0175747	1.0000
30	7	0.0012000	0.0042618	-0.015175	0.0175747	1.0000
9	11	0.0011400	0.0042618	-0.015235	0.0175147	1.0000
23	24	0.0011200	0.0042618	-0.015255	0.0174947	1.0000
9	15	0.0011000	0.0042618	-0.015275	0.0174747	1.0000
10	5	0.0010800	0.0042618	-0.015295	0.0174547	1.0000
20	1	0.0010800	0.0042618	-0.015295	0.0174547	1.0000
22	17	0.0010600	0.0042618	-0.015315	0.0174347	1.0000
29	3	0.0010600	0.0042618	-0.015315	0.0174347	1.0000
30	18	0.0010400	0.0042618	-0.015335	0.0174147	1.0000
26	11	0.0010400	0.0042618	-0.015335	0.0174147	1.0000
25	22	0.0010200	0.0042618	-0.015355	0.0173947	1.0000
3	16	0.0010200	0.0042618	-0.015355	0.0173947	1.0000
22	29	0.0010000	0.0042618	-0.015375	0.0173747	1.0000
26	15	0.0010000	0.0042618	-0.015375	0.0173747	1.0000
17	3	0.0010000	0.0042618	-0.015375	0.0173747	1.0000
9	20	0.0009800	0.0042618	-0.015395	0.0173547	1.0000
6	14	0.0009800	0.0042618	-0.015395	0.0173547	1.0000
5	23	0.0009800	0.0042618	-0.015395	0.0173547	1.0000
20	2	0.0009800	0.0042618	-0.015395	0.0173547	1.0000
20	13	0.0009800	0.0042618	-0.015395	0.0173547	1.0000
4	5	0.0009600	0.0042618	-0.015415	0.0173347	1.0000
15	1	0.0009600	0.0042618	-0.015415	0.0173347	1.0000
8	11	0.0009400	0.0042618	-0.015435	0.0173147	1.0000
11	1	0.0009200	0.0042618	-0.015455	0.0172947	1.0000
8	15	0.0009000	0.0042618	-0.015475	0.0172747	1.0000
26	20	0.0008800	0.0042618	-0.015495	0.0172547	1.0000

Table F-2. Tukey Ordered Differences Report for Variable Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
15	2	0.0008600	0.0042618	-0.015515	0.0172347	1.0000
15	13	0.0008600	0.0042618	-0.015515	0.0172347	1.0000
19	3	0.0008400	0.0042618	-0.015535	0.0172147	1.0000
18	19	0.0008400	0.0042618	-0.015535	0.0172147	1.0000
5	27	0.0008200	0.0042618	-0.015555	0.0171947	1.0000
11	2	0.0008200	0.0042618	-0.015555	0.0171947	1.0000
11	13	0.0008200	0.0042618	-0.015555	0.0171947	1.0000
28	21	0.0008000	0.0042618	-0.015575	0.0171747	1.0000
8	20	0.0007800	0.0042618	-0.015595	0.0171547	1.0000
29	6	0.0007800	0.0042618	-0.015595	0.0171547	1.0000
5	28	0.0007600	0.0042618	-0.015615	0.0171347	1.0000
14	8	0.0007400	0.0042618	-0.015635	0.0171147	1.0000
27	21	0.0007400	0.0042618	-0.015635	0.0171147	1.0000
17	6	0.0007200	0.0042618	-0.015655	0.0170947	1.0000
3	14	0.0007000	0.0042618	-0.015675	0.0170747	1.0000
20	4	0.0007000	0.0042618	-0.015675	0.0170747	1.0000
18	17	0.0006800	0.0042618	-0.015695	0.0170547	1.0000
12	24	0.0006800	0.0042618	-0.015695	0.0170547	1.0000
7	19	0.0006800	0.0042618	-0.015695	0.0170547	1.0000
2	5	0.0006800	0.0042618	-0.015695	0.0170547	1.0000
13	5	0.0006800	0.0042618	-0.015695	0.0170547	1.0000
28	12	0.0006600	0.0042618	-0.015715	0.0170347	1.0000
30	22	0.0006600	0.0042618	-0.015715	0.0170347	1.0000
14	26	0.0006400	0.0042618	-0.015735	0.0170147	1.0000
18	29	0.0006200	0.0042618	-0.015755	0.0169947	1.0000
27	12	0.0006000	0.0042618	-0.015775	0.0169747	1.0000
1	5	0.0005800	0.0042618	-0.015795	0.0169547	1.0000
23	21	0.0005800	0.0042618	-0.015795	0.0169547	1.0000
15	4	0.0005800	0.0042618	-0.015795	0.0169547	1.0000
20	10	0.0005800	0.0042618	-0.015795	0.0169547	1.0000
19	6	0.0005600	0.0042618	-0.015815	0.0169347	1.0000
14	9	0.0005400	0.0042618	-0.015835	0.0169147	1.0000
21	24	0.0005400	0.0042618	-0.015835	0.0169147	1.0000
22	7	0.0005400	0.0042618	-0.015835	0.0169147	1.0000
11	4	0.0005400	0.0042618	-0.015835	0.0169147	1.0000
7	17	0.0005200	0.0042618	-0.015855	0.0168947	1.0000
10	1	0.0005000	0.0042618	-0.015875	0.0168747	1.0000
7	29	0.0004600	0.0042618	-0.015915	0.0168347	1.0000
15	10	0.0004600	0.0042618	-0.015915	0.0168347	1.0000
23	12	0.0004400	0.0042618	-0.015935	0.0168147	1.0000
16	8	0.0004200	0.0042618	-0.015955	0.0167947	1.0000

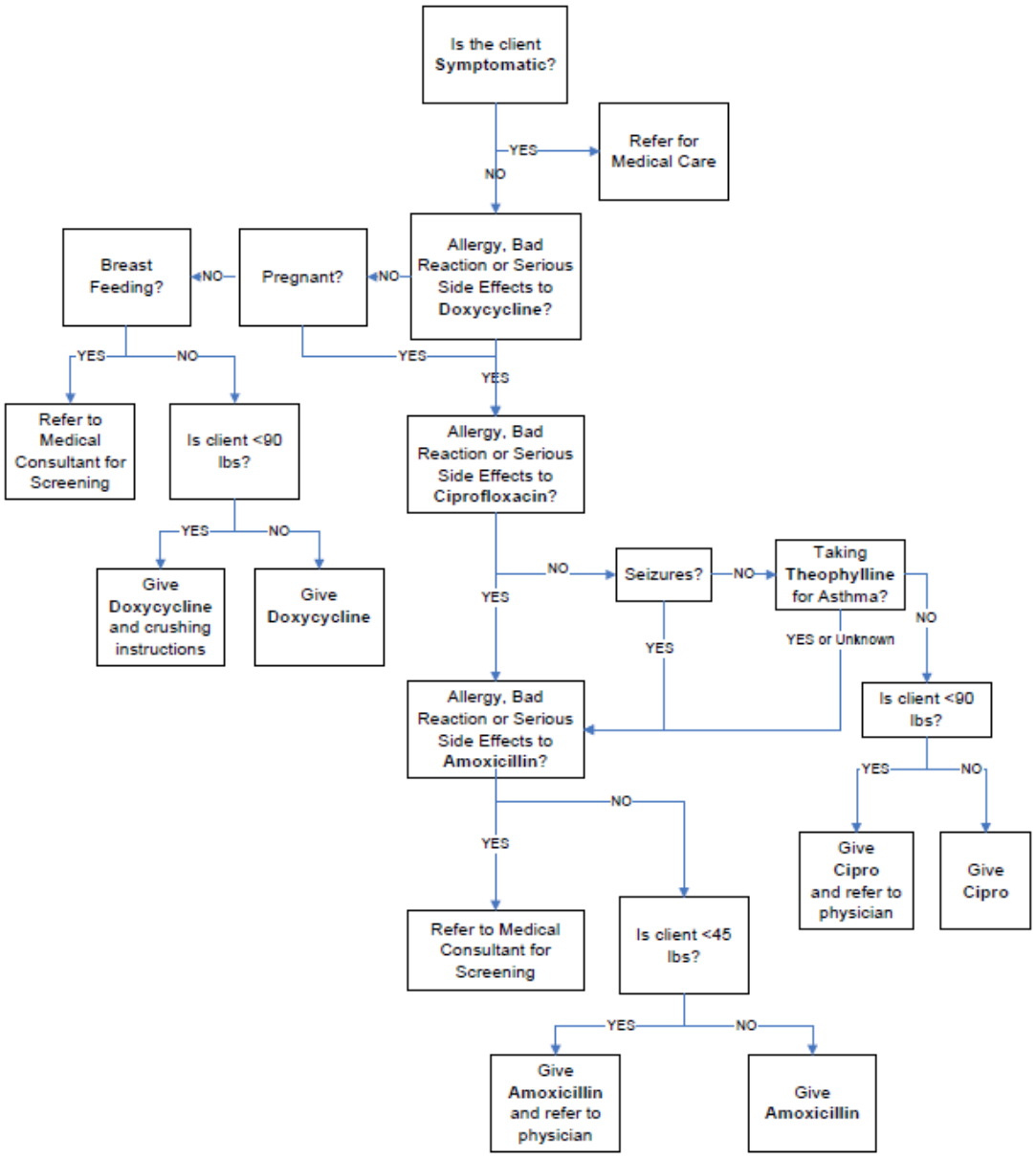
Table F-2. Tukey Ordered Differences Report for Variable Simulations continued

Level	Level	Difference	*SE* Difference	Lower CL	Upper CL	*p*-Value
11	10	0.0004200	0.0042618	-0.015955	0.0167947	1.0000
10	2	0.0004000	0.0042618	-0.015975	0.0167747	1.0000
10	13	0.0004000	0.0042618	-0.015975	0.0167747	1.0000
22	18	0.0003800	0.0042618	-0.015995	0.0167547	1.0000
4	1	0.0003800	0.0042618	-0.015995	0.0167547	1.0000
25	30	0.0003600	0.0042618	-0.016015	0.0167347	1.0000
16	26	0.0003200	0.0042618	-0.016055	0.0166947	1.0000
14	16	0.0003200	0.0042618	-0.016055	0.0166947	1.0000
6	3	0.0002800	0.0042618	-0.016095	0.0166547	1.0000
4	2	0.0002800	0.0042618	-0.016095	0.0166547	1.0000
4	13	0.0002800	0.0042618	-0.016095	0.0166547	1.0000
16	9	0.0002200	0.0042618	-0.016155	0.0165947	1.0000
28	23	0.0002200	0.0042618	-0.016155	0.0165947	1.0000
29	19	0.0002200	0.0042618	-0.016155	0.0165947	1.0000
9	8	0.0002000	0.0042618	-0.016175	0.0165747	1.0000
18	7	0.0001600	0.0042618	-0.016215	0.0165347	1.0000
20	11	0.0001600	0.0042618	-0.016215	0.0165347	1.0000
27	23	0.0001600	0.0042618	-0.016215	0.0165347	1.0000
17	19	0.0001600	0.0042618	-0.016215	0.0165347	1.0000
12	21	0.0001400	0.0042618	-0.016235	0.0165147	1.0000
10	4	0.0001200	0.0042618	-0.016255	0.0164947	1.0000
20	15	0.0001200	0.0042618	-0.016255	0.0164947	1.0000
9	26	0.0001000	0.0042618	-0.016275	0.0164747	1.0000
2	1	0.0001000	0.0042618	-0.016275	0.0164747	1.0000
13	1	0.0001000	0.0042618	-0.016275	0.0164747	1.0000
26	8	0.0001000	0.0042618	-0.016275	0.0164747	1.0000
29	17	0.0000600	0.0042618	-0.016315	0.0164347	1.0000
28	27	0.0000600	0.0042618	-0.016315	0.0164347	1.0000
15	11	0.0000400	0.0042618	-0.016335	0.0164147	1.0000
13	2	0.0000000	0.0042618	-0.016375	0.0163747	1.0000

APPENDIX G. ANTIBIOTIC DISPENSING ALGORITHM

INDIANA STATE DEPARTMENT OF HEALTH
Public Health Preparedness and Emergency Response

Antibiotic Dispensing Algorithm



Current as of May 2, 2011

Instructions for Using Algorithm

1) First determine if the client is symptomatic for anthrax exposure. If they are, direct them to seek off site medical attention immediately.

2) Doxycycline is the first drug of choice. If the client is **NOT** allergic, pregnant, or breastfeeding, they may receive Doxycycline. If the client is less than 90 lbs or cannot swallow pills you will need to provide crushing instructions with their medication.

3) If the client **IS** breastfeeding send them to your on-site medical consultant for further screening.

4) If the client **IS** allergic to Doxycycline or pregnant the next drug of choice is Ciprofloxacin. If a client is **NOT** allergic to Ciprofloxacin, does **NOT** have seizures, and does **NOT** take Theophylline for asthma, then the client should receive Ciprofloxacin. If the client is less than 90 lbs then they should be referred to their family or other primary care physician with their medication to determine the best dosing procedure.

5) If a client **IS** allergic to Ciprofloxacin, **DOES** have seizures, or **IS** either taking Theophylline for asthma or is taking medication for asthma but **DOES NOT KNOW** what it is, the client should receive Amoxicillin.

6) If a client **IS** allergic to Amoxicillin refer them to your on-site medical consultant for further screening. If a client is **NOT** allergic to Amoxicillin then they should receive it. If the client is less than 45 lbs then they should be referred to their family or other primary care physician with their medication to determine the best dosing procedure.

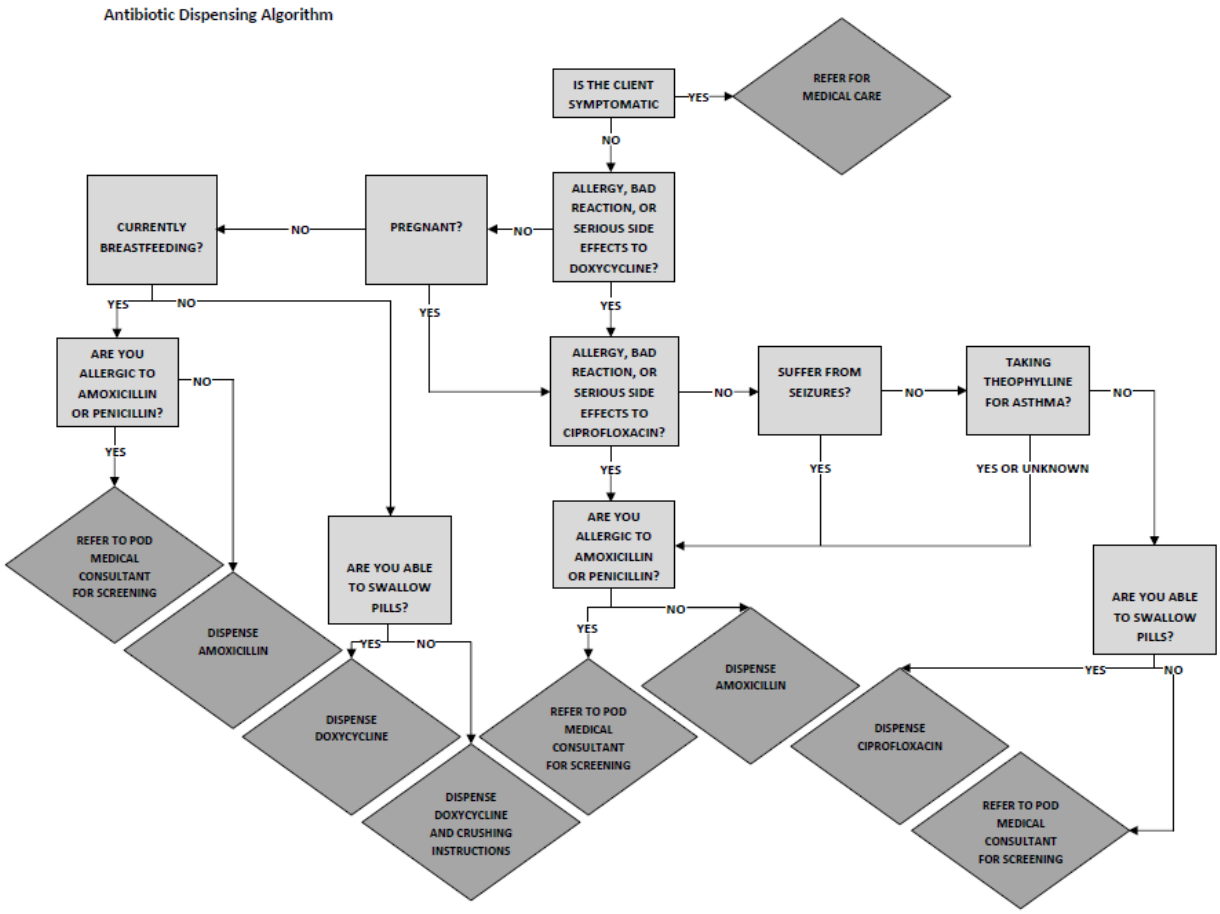
Notes:

Ciprofloxacin and Amoxicillin are currently not approved for crushing by the Food and Drug Administration (FDA). If clients are to receive Ciprofloxacin or Amoxicillin, and are either under 90 lbs. or cannot swallow pills, direct them to their family or other primary care physician for dosing instructions.

An algorithm cannot account for every potential condition or adverse reaction that may be caused by medication. If a client has concerns regarding an adverse reaction due to a medical condition or medications they are taking that are not covered in this algorithm, have them speak with the on-site medical consultant or their personal physician.

The information provided in this document is current as of May 2, 2011, and is based on the best information available. The information provided herein is subject to change based on new or revised guidance from the Centers for Disease Control & Prevention (CDC) and/or changes in best practices suggested by the medical or pharmaceutical community. Updates to this information will be provided as needed.

APPENDIX H. REVISED ANTIBIOTIC DISPENSING ALGORITHM



VITA

MAJ Patrick Glass

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Publications

Glass, P., Dietz, E., & Aaltenon, P. (2018). Using discrete-event simulation to increase the efficiency of point of distribution sites. *Journal of emergency management (Weston, Mass.)*, *16*(5), 279-287.

Glass, P., & Karas, A., (Unpublished). Using Computer Simulation Modeling To Accurately Describe Allocation Of Resources For A Point Of Distribution Site. In J. E. Dietz., D. R. Black (ed)

Glass, P. (2017). Evaluation of Cornerstone Autism Center for active shooter incidents. In *Technologies for Homeland Security (HST), 2017 IEEE International Symposium*. 1-6.

Glass, P. (2017). Solutions Through Computer Simulation. *70H Newsletter, Army Medical Department April 2017*, 18-19.

Civilian Education

Public Health Practicum — May 2017 to June 2017
Knox County Health Department
Vincennes, Indiana 47591

- Developed a summer immunization program including three radio broadcast interviews, one television interview, and a poster campaign
- Developed a residential well water testing campaign including an algorithm for when residents on well water should comply with a boil order to prevent the ingestion of nitrates
- Developed an emergency community action plan for a chlorine gas leak

Masters of Public Health, College of Health and Human Sciences — December 2017
Purdue University
West Lafayette, Indiana

- Implemented a nutritional education campaign that decreased students' use of misinformation when making decisions about their diet
- Developed a behavior model to reduce the incidence of gun violence among adolescent within an urban setting
- Researched and studied the effects of positive youth development and physical activity on behaviors related to alcohol and tobacco use among young adolescents.

Masters of Science, Purdue Polytechnic Institute — May 2017
Purdue University
West Lafayette, Indiana

- Concentration in Public Health Support to Homeland Security
- Represented Purdue University at the annual AnyLogic Conference in Nashville, November 2016
- Coached, taught and mentored two Law and Society undergraduate interns as part of the Homeland Security Institute

Bachelors of Science, General Health Science — May 2004
Purdue University
West Lafayette, Indiana

- Graduated with honors: 3.74 GPA out of 4.0
- Distinguished Military Graduate from the Reserve Officer Training Corps
- Minors in Biology and Organizational Leadership and Supervision
- Teaching Assistant for Undergraduate Genetics course, Biology 241

MAJ Patrick Glass

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Military Experience

Operations Officer — April 2019 to Present
Headquarters and Headquarters Battalion
82nd Airborne Division
Fort Bragg, North Carolina

- The Officer in Charge of the forward operating base in Ramstein, Germany for 1,400 Soldiers from nine different countries in support of OPERATION SWIFT RESPONSE 19

Deputy Division Surgeon — July 2018 to April 2019
82nd Airborne Division
Fort Bragg, North Carolina

- Conducted the first Expert Field Medical Badge training and testing under the updated AMEDD standards and maintained comparable results with the previous standard.
- Planned, and coordinated medical plans and evacuations for 18,000 paratroopers for two warfighting exercises

Small Group Instructor — May 2013 to July 2015
Army Medical Department Captains Career Course
Fort Sam Houston, Texas

- Provided graduate level education to medical officers of the US Army
- Curriculum discusses both operational and institutional processes, as well as company level operations through brigade level staff.
- Serves as mentor, academic counselor, and role model for students.
- Coached, mentored, developed new instructors as the Faculty Development Co-Leader

Company Commander — February 2011 to February 2013
C Company (Medical), 526th Brigade Support Battalion
Fort Campbell, Kentucky

- Responsible for the combat readiness, technical proficiency, and deployability of a diverse staff of health care personnel capable of a world-wide deployment in direct support of full spectrum brigade combat operations
- Provided Combat Health Support to a 3,400 Soldier Brigade Combat Team
- Responsible for over $23 million in combat and organizational equipment

Medical Plans and Operations Officer — November 2009 to February 2011
2nd Brigade Combat Team, 101st Airborne Division (Air Assault)
Fort Campbell, Kentucky

- Developed Health Service Support plans and brigade-level operation orders in support of an area of operations the size of Connecticut
- Briefed the brigade commander on the medical concepts of support for all brigade and echelon-above-brigade exercises.
- Mentored Medical Service Corps lieutenants within the Brigade Combat Team

Medical Operations Officer — April 2007 to April 2009
Headquarters, 1st Battalion, 75th Ranger Regiment
Hunter Army Airfield, GA

- Planned, Coordinated and Executed medical support for 850 Special Operations Forces
- Coordinated with units both internal and external to the organization to provide medical coverage, logistical support and casualty evacuations
- Accounted for all DEA scheduled drugs and controlled substances valued at $500,000

MAJ Patrick Glass

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Medical Platoon Leader — April 2005 to April 2007
2nd Battalion, 4th Infantry, 4th Brigade Combat Team, 10th Division (Mountain)
Fort Polk, LA

- Maintained the medical readiness of 653 Soldiers including maintaining their vaccination records, dental status, physical status, vision and hearing readiness
- Oversaw successful treatment and evacuation of 167 trauma, and 250 disease, non-battle injury patients during combat operations.
- Organized and led six village medical outreach missions, where we distributed medications, and medical treatment to the Afghan population
- Led 36 Soldier-Medics in a Light Infantry Battalion
- Maintained accountability and responsibility of equipment valued at over $600,000.

Military Education

Intermediate Level Education
U.S. Army Command and General Staff College — August 2017 to June 2018
Fort Leavenworth, Kansas

Combined Logistics Captains Career Course — May 2009 to October 2009
Army Logistics University
Fort Lee, Virginia

- Graduated 2 out of 177 students, Honor Graduate and Commandant's List
- Selected over 22 officers for the Combined Arms Support Command's Leadership award, and as the superior logistician for the team
- Distinguished Logistician Professional

AMEDD Officers Basic Course — January 2005 to April 2005
Army Medical Department Center & School
Fort Sam Houston, Texas

- Commandant's List: overall average of 93% of total scores available, and top 20% of the class
- Certificate of Achievement for superior Physical Fitness
- Finished within the top five of the Modern Army Combatives competition

Military Awards & Decorations

Bronze Star Medal with Oak Leaf Cluster
Meritorious Service Medal with Oak Leaf Cluster
Army Commendation Medal with four Oak Leaf Clusters
Army Achievement Medal with two Oak Leaf Clusters
Presidential Unit Citation
Valorous Unit Award
Meritorious Unit Citation
Army Good Conduct Medal
Combat Medical Badge
Expert Field Medical Badge
Expert Infantryman's Badge

Military Certifications

Ranger Course, March 1999
Pathfinder Course, March 2013
Basic Airborne Course, December 1995
Jumpmaster Course, October 2019
Air Assault Course, August 2011
Faculty Development Phase 1, March 2015
Faculty Development Phase 2, September 2014
Small Group Leader Instructor Course, July 2013
Basic Healthcare Administration Course, February 2014
Modern Army Combatives Program Level II, November 2013
Modern Army Combatives Program Level I, August 2009
Combat Lifesavers Course, February 2005

PUBLICATIONS

Using Discrete-Event Simulation to Increase the Efficiency of Point of Distribution Sites

Using discrete-event simulation to increase the efficiency of point of distribution sites

Patrick Glass, MS, MPH
Eric Dietz, PhD
Pamela Aaltenon, PhD, RN

ABSTRACT

Objective: *The objective of this research was to develop a computer simulation model that will provide the most optimal allocation of resources for a point of distribution (POD) site.*

Design: *A baseline assessment was conducted by participants establishing POD sections with no guidance from the investigator. A computer model was built with four stations: triage, registration, screening, and dispensing. The information from the computer simulation was used to design the allocation of volunteers for the experimental group. Once the data were collected, a two-sample t test was used to determine the significance of the difference between the average times of the two groups to complete the POD.*

Setting: *The POD site was conducted indoors with volunteers acting as patients, and volunteer nursing students, and pharmacy students acting as POD workers. Volunteers were divided into two groups, group B, experimental and group A, control. Time was recorded using a digital time-stamp at the beginning and at the end of the POD.*

Interventions: *The researcher inputted the total number of volunteers into the model, and the model generated the most applicable ratio for distribution of human capital: a one-to-one ratio of screeners to dispensers.*

Main outcome measures: *The mean time for Group A was 4.55 minutes (95% CI: 4.27, 4.83). The mean time for group B was 3.05 minutes (95% CI: 2.79, 3.31). A two-sample t test and Analysis of Variance of these data show that the difference is meaningful ($p < 0.001$).*

Results: *The results show that a discrete-event computer simulation can be used to identify the most efficient use of resources in order to decrease the amount of time that patients are required to participate.*

Conclusions: *The discrete-event computer simulation model was found to be effective at identifying ways to increase efficiency and reduce the overall time required by patients to complete the POD.*

Key words: point of distribution site, computer simulation modeling, discrete-event simulation

INTRODUCTION

A point of distribution (POD) site is a location where chemoprophylaxis, antibiotics, or other medical supplies can be rapidly distributed to a large population who may or may not have been exposed to a biological hazard.[1,2] The idea is that if ever there is an immediate threat to the health of a population from a biological hazard or other, the local, state, and federal public health agencies can activate protocols that will distribute stockpile items in a timely manner. A POD site is one of the most expeditious means to do so. The issue is that although a POD site is very expeditious, it is also very taxing on the community and its resources. Landesman (2012) pointed out that in order to provide prophylaxis and antibiotics to a population of 10,000 within 72 hours, a POD site would require 50-55 persons per shift, running round-the-clock in 12-hour shifts. The POD site also would require at least 2,500 square feet of real estate in order to meet the demands of the population.

The scope of this research was to build a discrete-event computer simulation model for a POD site. The purpose of this model was to simulate the process of a given number of patients moving through a POD site.

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The independent variables for this model included the number of volunteers to operate the site. The output of the model was the ratio of volunteers per station of the POD site: triage, registration, screening, and dispensing. The dependent variable for the research was the total amount of time for the POD site to process the given number of patients.

POD sites are very necessary to reduce and mitigate the risk of widespread epidemics from natural causes, brotherism, or terrorist attacks. The Centers for Disease Control and Prevention and Federal Emergency Management Agency both do a remarkable job maintaining and distributing the Strategic National Stockpile. The problem is that in order to make the POD sites effective, volunteers with varying levels or experience and education are required. This leads to potential miscommunication between providers, and issuing medication incorrectly or issuing the wrong medications to patients. The purpose of this study was to demonstrate how using a discrete-event computer simulation model could assist in reducing time required for patients to complete PODs and receive their required medications.

METHODS

The research question addressed is can a computer simulation model precisely optimize human capital in a way to reduce the amount of time required for each patient to flow through a POD. A baseline assessment was conducted by participants establishing POD sections with no guidance from the investigator. Once the baseline assessment was complete, a model was run to determine the most efficient means of using volunteer resources. The simulation is a computer model using AnyLogic 7 modeling software. The software combines the process of an agent-based pedestrian model with a discrete-event simulation. The discrete-event simulation was designed as a flowchart with four stations. The participants (pedestrian agents) then passed through the flowchart as independent agents. There were four main stations used in the design of the flowchart: triage, registration, screening, and dispensing (see Figure 1).

The agents populated an artificial environment designed to reflect a POD site. The objective of the simulation model was to optimize the required number of patients being seen at each station, given a set

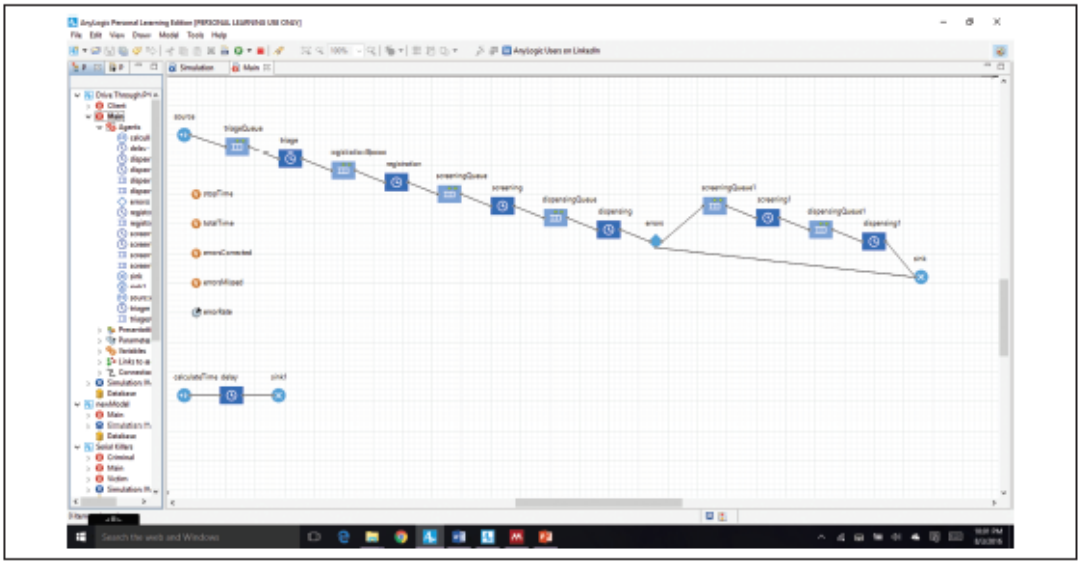

Figure 1. POD simulation model.

population, and maximum required competition time. Optimization can be customized to identify capacity needed, time required, or population size that can be served based on the fixed parameters. The population was fixed to 20,000. This was an estimate of a proportion of a population that would likely be seen in a POD ran by Tippecanoe County Health Department. Each agent entered the flow and begins at the triage station que. The triage station que, just like all the station ques, had an unlimited capacity. As the agents finished the previous station, they were inserted into the next corresponding que. The times used to build the model were derived from observations of three separate POD events: a POD exercise in spring of 2015 and two Mumps PODs on Purdue University campus on April 12 and 18, 2016. The flow of the model was linear and has one branch. The purpose of this branch was to simulate the errors that occur within the POD site, which were studied in another paper.

MODEL VALIDATION

The computer simulation model used for this experiment was validated using data from previous PODs conducted under similar conditions. Validation can be found in a master's thesis.[3] The times used to build the model were derived from observations of three separate POD events: a POD exercise in spring of 2015 and two Mumps PODs on Purdue University campus on April 12 and 18, 2016. The triage station itself has a completion time of 30 seconds. The triage station simulated the agents entering the POD and being directed to the location that is best for them. Once the agents completed the triage station, the model sent them to the registration que and registration station. At this juncture, the registration station had a completion time of 145 seconds. This simulated the patients taking the time to complete required questionnaires in preparation for screening. The screening station, and corresponding que, had a delay time of 38 seconds, with a minimum of 9 seconds and maximum of 117 seconds. This simulated the patients' registration forms being screened by a healthcare provider. Because not all agents will require the same amount of time to complete screening, the minima and maxima times set to simulate the normal distribution of time required for each patient. Once complete at the screening station, the agents were then moved to the dispensing station and corresponding que. This simulated the patients receiving their required medications, vaccinations, or treatments. Similarly, to the screening station, the dispensing station had a required completion time of 145 seconds with a minimum of 90 seconds and maximum of 176 seconds.

TESTING CONDITIONS AND PROCEDURES

The POD site was conducted indoors with volunteers acting as patients, and volunteer nursing students, and pharmacy students acting as POD workers. The number of volunteers available for each role was entered into the simulation model. Then, the computer simulation model was ran to calculate the optimal number of workers for each station. The simulation then calculated the estimated number of medical errors that should occur and the best locations for medical personnel to correct those errors.

On the day of the exercise, volunteers served as patients, and healthcare personnel in training, nursing, and pharmacy students served as POD workers. The participants were divided into two groups: group B was an experimental group and group A was a comparison group. Group A conducted the POD exercise with no guidance as to how many students should be placed at each station (see Figure 2). Whereas the group B received instructions from the researcher as to how many students should be at each station based on the calculations generated from the AnyLogic optimization model.

Once the total number of participants available for group B was inputted, the model calculated the optimal placement of volunteers and generated the number of volunteers required for each station. Group B also had a validation station staffed by pharmacy students where the participants reported to ensure that they received the proper medication in an attempt to identify the medical errors (see Figure 3).

All participants received a patient data card, independent of the experimental condition. In order to save time, the data cards were previously completed with all pertinent information by the Tippecanoe Public Health Department staff. The participants then proceeded

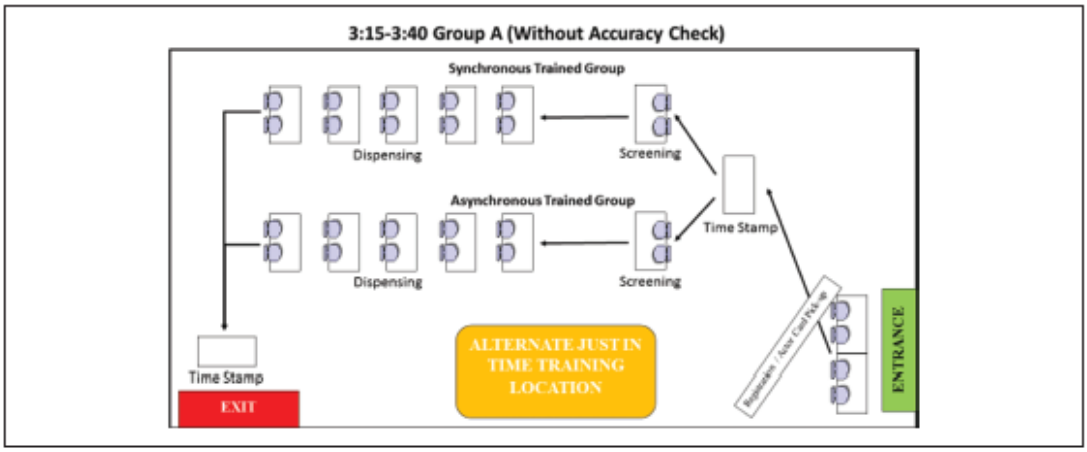

Figure 2. Group A diagram.

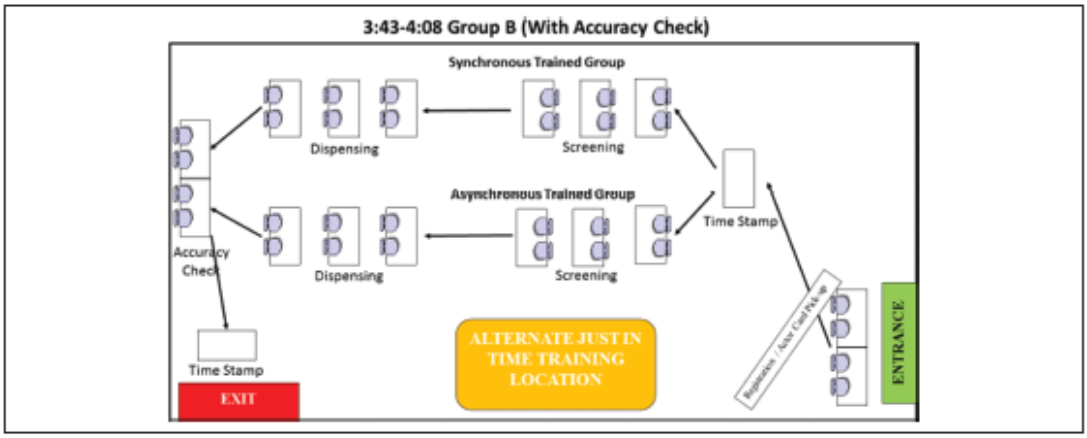

Figure 3. Group B diagram.

through the POD. Once the POD exercise was complete, the researcher collected the data and compared the observed results with the expected results from the computer simulation. The researcher conducted a two sample *t* test in order to determine if the null hypothesis of the computer simulation will not reduce the overall time that patients are required to navigate the POD.

RESULTS

The experiment was conducted on November 16, 2016. Students from Purdue University Nursing 415, Public Health Nursing Course and Computer and Information Technology 511, Fundamentals of Homeland Security Course participated in the exercise as well as students from the Purdue Pharmacy program. There were a total of 77 participants in the experiment, 50 from the Nursing 415 course, 15 from the Pharmacy program, and 11 from CNIT 511. Although this researcher did not test the differences between synchronous and asynchronous training, the nursing students were segregated into two groups for the purposes of examining the effects of training

for another research project. The risk of confounding due to synchronous versus asynchronous training was minimized because both groups of participants were running simultaneous. The nursing students were then divided equally between group A and group B. After a brief block of instruction from the Tippecanoe Department of Public Health Operations Officer, group A participants established their stations at 3:15 PM and the experiment began. Two persons from the CNIT 511 course were observers and measured the amount of time required to complete each station. Two additional persons from the CNIT 511 course were observers and received the documents and equipment from the participants prior to them leaving the experiment. During the second portion of the experiment, group B, the nursing students switched places: those who were at the screening and dispensing stations were now the participants, and those who were the participants were now stationed at the screening and dispensing stations. The pharmacy students operated the verification station. Once the participants completed the POD exercise and exited the experiment, they were instructed to return to the registration table and move through the POD again. This resulted in a total of 385 data points (n = 385) for analysis: 181 data points for group A and 204 data points for group B.

The times required for persons from group A to complete the exercise were distributed normally with a mean time of 4.55 minutes (SD: 2.29 minutes). There was one event, reference number 7, where the participant failed to mark either the time he/she began the POD exercise or the time he/she completed it. This mistake on the part of the participant was not calculated in the overall average or standard deviation. The times required for persons from group B to complete the exercise were distributed normally with a mean time of 3.05 minutes (SD: 1.38 minutes). There were four events, reference numbers 39.1, 39.2, 52.1, and 52.2, where the participants failed to mark either the time they began the POD exercise, or the time they completed the POD exercise. There were two events, reference numbers 106 and 110, where they marked both the time they began the POD exercise and the time they completed the POD exercise, but the marks were illegible.

The mean time for group A was 4.55 minutes (95% CI: 4.27, 4.83). The mean time for group B was 3.05 minutes (95% CI: 2.79, 3.31). A two-sample *t* test and ANOVA of these data show that the difference is meaningful ($p < 0.001$). This is interpreted as the time required for group A to complete the POD exercise was significantly higher than the time required for group B to complete the POD exercise. Therefore, the null hypothesis that the computer simulation will not reduce the overall time that patients are required to navigate the POD exercise is rejected and the alternate hypothesis that the simulation will reduce the overall time that patients are required to navigate the POD exercise is accepted (Figure 4 and Tables 1-3).

When looking at the screening times individually, the average time for group A was 42.98 seconds (95% CI: 31.49, 54.36), group B was 24.74 seconds (95% CI: 10.91, 38.56). ANOVA of the data shows that there is a 12.36 percent probability that the means are similar to the screening times from the Spring 2015 POD

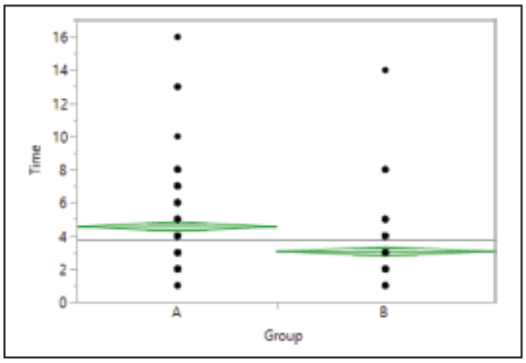

Figure 4. Oneway analysis of time by group.

Table 1. Summary of fit for overall times

Component	Value
R square	0.137489
Adjusted R square	0.135195
Root mean square error	1.881343
Mean of response	3.769841
Observations	378

Table 2. Analysis of variance for overall times					
Source	df	Sum of squares	M square	F ratio	Prob > F
Group	1	212.1429	212.143	59.9367	<0.0001
Error	376	1,330.8333	3.539		
Total	377	1,542.9762			

Table 3. Two sample t test for overall groups	
Component	Value
Difference	–1.5
Standard error of difference	0.1938
Upper CL difference	–1.119
Lower CL difference	–1.881
Confidence	0.95

exercise of 38.33 (95% CI: 30.35, 46.31). The results of the ANOVA represent that there was not a significant difference between the screening times of either group or the Spring 2015 POD exercises (see Figure 5 and Table 4).

A Tukey Ordered Differences Report confirms that the differences between the average times were insignificant ($p > 0.05$) (see Table 5).

Analysis of dispensing times shows a different story. The average time for group A was 39.77 seconds (95% CI: 24.05, 55.49) and group B was 31.00 seconds (95% CI: 12.00, 50.01). ANOVA of the data shows that there is a 1.97 percent probability that the means are similar to the screening times from the Spring 2015 POD exercise of 59.12 (95% CI: 48.15, 70.10). The results of the ANOVA show that the averages of the three sets of data were significantly different (see Figure 6 and Table 6).

A Tukey Ordered Differences Report shows that a significant difference between the average times of group B and the Spring of 2015 POD exercise ($p = 0.0338$), but not between group B and group A ($p = 0.7586$), or between group A and Spring of 2015 POD exercise ($p = 0.1165$) (see Table 7). The difference between group A and Spring of 2015 POD exercise averages is much more significant that the difference between group A and group B.

DISCUSSION

The purpose of this research was to test the hypothesis that a computer simulation will reduce the overall time that patients are required to navigate a POD. The results show that a discrete-event computer simulation can, in fact, be used to identify the most efficient use of resources in order to decrease the amount of time that patients are required to participate.

The discrete-event computer simulation model was found to be effective at identifying ways to increase efficiency and reduce the overall time required by

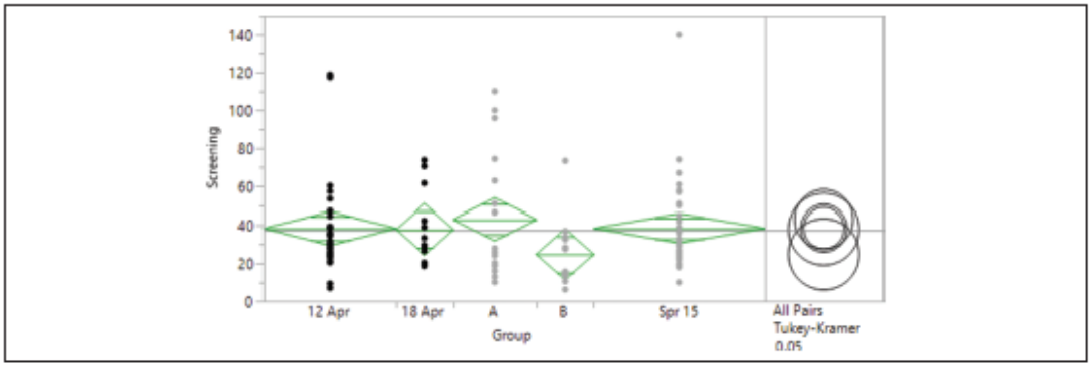

Figure 5. Oneway analysis of screening by group.

patients to complete the POD. As Robinson described, computer simulation is useful in order to reduce costs and time.[4] The computer simulation model used in this research could reduce the average time required for each patient to navigate the POD by one and a half minutes. This is similar to the results from previous research on using computer models to improve the efficiency of PODs. Hupert et al.[5] developed a model very similar to the one used in this experiment. However, that model was designed for a larger population using multiple PODs. This research demonstrates that a discrete-event simulation can be scaled down to a smaller population.

The average time for group A was 39.77 seconds and group B was 31.00 seconds. The results of the analysis show that the averages of the three sets of data are significantly different. This investigator's

Table 4. Analysis of variance for screening groups

Source	df	Sum of squares	M square	F ratio	Prob > F
Group	4	2,722.934	680.733	1.1474	0.3383
Error	109	64,669.808	593.301		
C. total	113	67,392.741			

Abbreviation: C. total = total (corrected).

Table 5. Tukey ordered differences report for screening groups

Level	Level	Difference	Standard error of difference	Lower CL	Upper CL	p Value
A	B	18.18895	8.767263	−6.1312	42.50908	0.2386
Spring 15	B	13.59333	7.80073	−8.0457	35.23233	0.4126
April 12, 2018	B	13.549	8.087969	−8.8868	35.98479	0.4535
April 18, 2018	B	12.98615	9.553904	−13.5161	39.4884	0.6548
A	April 18, 2018	5.20279	8.767263	−19.1173	29.52292	0.9758
A	April 12, 2018	4.63995	7.141643	−15.1708	24.45066	0.9664
A	Spring 15	4.59561	6.814632	−14.308	23.4992	0.9615
Spring 15	April 18, 2018	0.60718	7.80073	−21.0318	22.24617	1
April 12, 2018	April 18, 2018	0.56285	8.087969	−21.8729	22.99863	1
Spring 15	April 12, 2018	0.04433	5.915196	−16.3642	16.45291	1

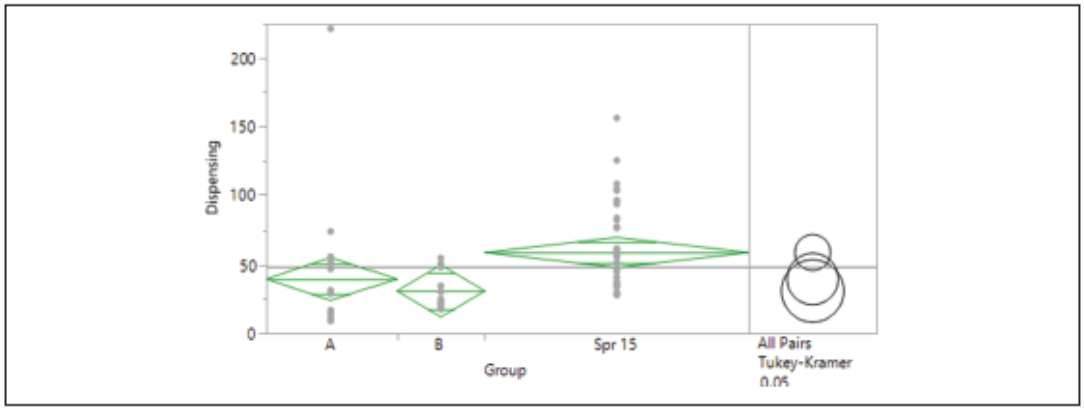

Figure 6. Oneway analysis of dispensing by group.

Table 6. Analysis of variance for dispensing groups					
Source	df	Sum of squares	M square	F ratio	Prob > F
Group	2	9,822.662	4,911.33	4.1649	0.0197
Error	68	80,186.518	1,179.21		
Total	70	90,009.18			

hypothesis is that this is a reflection of variances in dispensing medication based on possible bias of the time recorders or circumstances that the experiment was held. This investigator does not believe that the difference in variances between the POD exercise on November 16, 2016 and the POD exercise in the Spring of 2015 are a result of the computer simulation, or verification station.

LIMITATIONS

PODs are generally established to distribute mass quantities of prophylaxis in a short period of time with as much efficiency as possible. Hupert et al. developed a model very similar to the one used in this experiment. However, that model was designed for a larger population using multiple PODs.[5] This research demonstrates that a discrete-event simulation can be scaled down to a smaller population and for a specific infectious agent. Depending on the type of agent used, there may be a shortage of medical resources available including volunteers participating in the POD. A POD is a type of nontraditional treatment center that is established on short notice and may require the assistance of nonmedical volunteers. One of the limitations of this experiment is the source of both the subjects and the participants. The source of both the subjects and the participants came from university students. Using enrolled university students presents the potential of selection bias because the students already have a relationship with each other through coursework. In addition, the students were selected from nursing pharmacy and homeland security courses. These students already have a higher level of understanding that a typical POD volunteer may not have. The effects of the bias were mitigated by using the same volunteers for both the POD participants and the POD volunteers. The effects were also mitigated by having the registration paperwork prefilled out prior to the patients entering the POD.

Williams, Nocera, and Casteel conducted a meta-analysis on whether training in disaster preparedness improved knowledge and skills necessary for disaster response. Because study participants were hand-selected by their supervisors, there is the possibility of selection bias presence because the supervisors could have picked the participants who they believed would show the most success.[6] The results of the Williams et al. analysis is that there is an increase in knowledge and skills following either computer- or lecture-based training; however, since the results are statistically insignificant, the evidence is mixed.

There is a possible source of bias involved with the results of the experiment. During the time that group A was conducting the experiment, the participants began to congregate between the time that the participants completed the dispensing station and the time that they stamped the ending time to the patient record. Whenever this was observed, the investigator and other members of the observation

Table 7. Tukey ordered differences report for dispensing groups						
Level	Level	Difference	Standard error of difference	Lower CL	Upper CL	p Value
Spring 15	B	28.12205	10.9975	1.771	54.473	0.0338
Spring 15	A	19.34978	9.60729	–3.6702	42.3697	0.1165
A	B	8.77227	12.36012	–20.843	38.3882	0.7586

group would immediately attempt to rectify the situation. The exact number of participants who did not immediately stamp the ending time on their card is not known, but it is not believed to be very significant.

FUTURE CONSIDERATIONS

The purpose of this model was to use computer simulation modeling to improve the efficiency of PODs and the rapid delivery of prophylaxis in the event of a bioterrorism attack. This model proves that staffing done strategically can have a significant improvement on efficiency. The greatest potential value of this research thus far is to establish a set of core abstract rules for how to assign staff that could be calculated ad hoc, on the ground, or other high-level observations that could be immediately and/or broadly applied to future and ongoing POD sites. Future experiments will conduct a pre-test of volunteers to determine the level of understanding of each individual pertaining to the specific POD. Those volunteers with a higher understanding of the antibiotics used will be placed with the screening group in an effort to increase the efficiency of the POD.

Similarly in the Williams et al. meta-analysis, Williams et al. reviewed nine articles on experiments where subjects were administered a pre-test for knowledge of disaster response skills, given some type of training, and then administered a post-test to see if there is a difference in knowledge and skills. Five articles contained subjects from out-of-hospital healthcare providers, such as fire-fighters, emergency medical technicians, and public health nurses. Three of the studies included subjects that were only hospital-based healthcare providers, specifically emergency department physicians, and medical students. Three of the studies (two out-of-hospital studies and one in-hospital study) had the participants conduct computer-based intervention and three of the out-of-hospital-based studies had the participants conduct lecture-based interventions.[6]

CONCLUSION

The POD site is a resourceful way to distribute medications and vaccinations to populated area. The main objective of a POD is to help reduce the risk that a pathogen will infect a population. The methods explored in this study show a means for the distribution to be even more effective and reduce the total time required to complete a POD. The simulation model showed the amount of stations that would be the most efficient at each area; however, it does not account for number of persons required to run each station, or the area of land required for each station. In conclusion, the goal of this research was to optimize the time required to triage and screen patients, then distribute proper medications through the use of a POD. The computer simulation model was able to provide this information.

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Evaluation of Cornerstone Autism Center for Active Shooter Incidents

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Abstract— **With an increased perceived threat of an active shooter incident, Cornerstone Autism Center approached Purdue University requesting assistance developing an active shooter risk mitigation evaluation. The researcher evaluated the overall risk of an active shooter incident to Cornerstone Autism Center by identifying ways to reduce threats, vulnerabilities, and consequences. With the incidents of active shooter events increasing over time in the U.S., the means to reduce the threat is to identify a possible active shooter before he/she begins the act. Once a perpetrator begins shooting, the facility must reduce vulnerabilities, and consequences. Relying on law enforcement response may not be viable due to the response time of law enforcement. The most effective means of reducing vulnerability is to place barriers between the shooter and his/her victims. The two recommended barriers are locks on the classroom doors, and impact resistant glass windows. Reducing consequences involves developing a plan and rehearsing the plan periodically. Lockdown drills and practicing the Run-Hide-Fight method of reacting to active shooter are the recommended plans to rehears.**

Index Terms— **Active Shooter, Risk Mitigation.**

I. Introduction

Cornerstone Autism Center is a medical treatment facility located in West Lafayette, Indiana that provides specialized therapy to 50 children and adolescents who were diagnosed with autism spectrum disorder. The clients receive applied behavior analysis therapy from 8:30 am to 3:30 pm five days per week. Therefore, Cornerstone Autism Center's daily functions more closely resemble a school than a medical treatment facility. Due to a perceived increased threat of an active shooter incident occurring within their facility, Cornerstone Autism Center approached Purdue Homeland Security Institute for assistance with evaluating the risk of an active shooter incident. Cornerstone Autism Center's goal was to improve the safety of their clients from what they believed to be a perceived threat of an active shooter incident due to increased media exposure of school shootings within the U.S. In order to fully evaluate the threat of an active shooter to Cornerstone Autism Center, the researcher defined what an active shooter is, defined how to measure the risk of an active shooter, and assessed means of reducing those risks.

The U.S. Federal Bureau of Investigation and Federal Emergency Management Agency define an active shooter as, "an individual actively engaged in killing or attempting to kill people in a confined and populated area."[1]. The purpose of this paper is to assist Cornerstone Autism Center in West Lafayette, Indiana with finding ways to reduce the risk of active shooter incidents within the property of their establishment. In order to find ways to reducing risk, one must first define risk. The Department of Homeland Security uses one of the most common definitions of risk: "the potential for an unwanted outcome resulting from an incident, or occurrence, as determined by its likelihood and the associated consequences" [2]. For the purposes of this paper, one can restrict the definition of incident or occurrence to an active shooter incident. The Department of Homeland Security further expands the definition of risk as the potential for an adverse outcome assessed as a function of threats (T), vulnerabilities (V), and consequences (C) associated with the incident, event or occurrence [2].

$$\text{Risk} = \text{T} \times \text{V} \times \text{C}$$

Therefore, if one can reduce the threat, decrease the vulnerabilities, or decrease the consequences of an active shooter event, then one can effectively reduce the overall risk of an active shooter incident. Even though Cornerstone Autism Center is the focus for this article, these practices can be applied to any organization desiring to reduce the risk of active shooter events.

II. Reducing Threat

The first portion of the equation that this paper will address is threat. The definition of threat is an occurrence, individual entity or action that has the potential to harm life, information, operations, environment, or property [2]. Threat is the probability that an incident will occur.

$$\text{T} = P(A)$$

Probability is calculated as a function of the number of incidents per a given time, per a given population. Therefore, one must first explore the total number of active shooter

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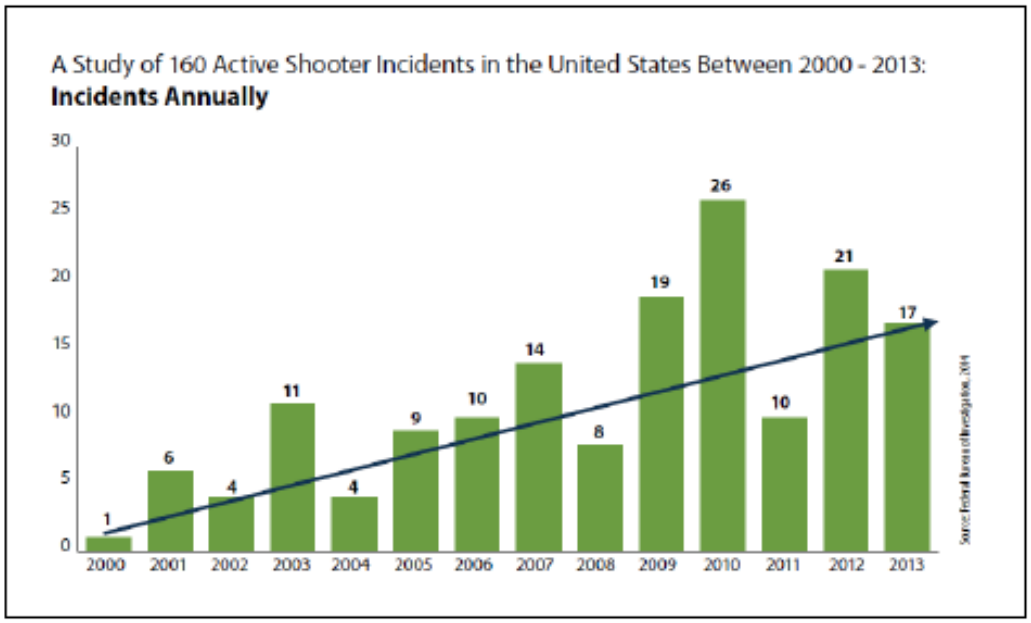

Figure 1, FBI study of active shooter incidents from 2000-2013 [1]

incidents within a given time within the U.S. A recent FBI report identified 160 active shooter incidents that occurred in the United States between the years 2000 and 2013 [1]. The same report also shows that the amount of active shooter incidents is increasing with time, an average of 6.4 incidents per year during the first seven years studied, and an average of 16.4 incidents per year during the last seven years [1]. Therefore, the FBI report shows an increasing trend in the overall probability of an active shooter event occurring within the U.S (see fig 1). With 24.4% of the incidents occurring in educational facilities and 2.5% occurring in healthcare facilities, that puts 26.9% of active shooter incidents occurring within a facility that closely resembles Cornerstone Autism Center [1]. The goal of reducing the risk of active shooter incidents is to prevent them from happening to begin with.

A. Stages of an Active Shooter Incident

The main effort to reduce the threat of an active shooter incident at Cornerstone Autism Center is to prevent an incident from occurring. Marcou [3] explains that there are five stages of an active shooter incident: 1. Fantasy stage, 2. Planning stage, 3. Preparation stage, 4. Approach stage, and 5. Implementation stage. The fantasy stage begins when the active shooter creates a picture in his/her mind what the incident will look like. During the fantasy phase, the potential active shooter may fantasize about the media coverage, draw pictures, make web postings about the event, or may even discuss these feelings and ideas with friends, family, or potential victims [3]. The second stage is the planning stage. Here the potential shooter begins to logistically support his/her plan. The potential shooter will plan targets [3]. The FBI estimates that 15% of active shooters targeted family members, and 10.0% targeted current, estranged, or former wives or girlfriends. The same report also noted that 22 of the 23 incidents that occurred in businesses close to pedestrian traffic involved a shooter who was either employed or previously employed at said business [1]. The third stage is preparation stage. Here the potential shooter will begin to acquire the necessary weapons. The potential shooter may also do a practice run or walkthrough of the operation, gearing up for the assault. Potential shooters have been known to call friends and tell them not to go to school or work on a certain day, in order to keep them out of the line-of-fire [3].

Any intervention during the first three stages of an active shooter incident will generally lead to little or no casualties. An example of appropriate interventions could be addressing issues with a dissatisfied parent whose child was recently involuntarily released from Cornerstone Autism Center, or a disgruntled employee.

The fourth stage is the approach stage. At this point, the suspect has made plans and has committed himself/herself to perform the act. During this stage, the shooter is carrying the necessary tools required to perform the task. The closer the potential shooter gets to his/her target, the more dangerous he/she is [3]. In at least nine incidents from 2000 to 2013, the shooters first shot and killed family members in a residence before moving toward their intended target [1]. The fifth and final stage is the implementation stage. Here the shooter opens fire on his/her targets. Immediate action must be taken in order to prevent additional loss of life [3]. In 64 of the 160 active shooter incidents where the duration of time could be

ascertained, 69.0% of the 64 ended within 5 minutes, and 23 ended within 2 minutes [1].

B. Law Enforcement Proximity

The nearest law enforcement agency to Cornerstone Autism Center is the West Lafayette Police Station on Navajo St, 1.8 miles via driving. Judging by the distance that law enforcement would have to travel, this would be approximately a 6 minute response time given an active shooter incident [4], well over the 5 minute duration of most active shooter incidents (see fig 2). The FBI report also noted that 60.0% of the active shooter incidents between 2000 and 2013 ended before police arrived and could engage the shooter. Relying on law enforcement to reduce the threat of an active shooter incident may not be the most viable option. Even times when law enforcement was present, civilians often had to make life or death decisions about how to react. The FBI study identified 13.1% of the active shooter incidents where unarmed civilians made selfless and deeply personal choices to face danger and successfully disrupted the shootings [1].

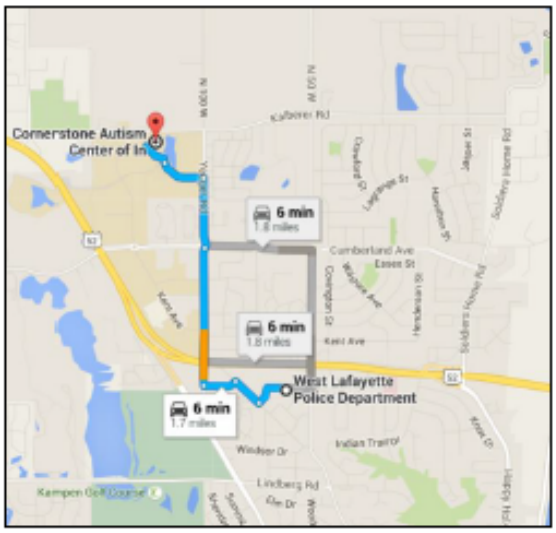

Figure 2, Map view of the closest law enforcement station to Cornerstone Autism Center [4]

III. Reducing Vulnerability

Once an active shooter begins the act of violence, reducing the threat is void, and one must look at ways to reduce vulnerability. Vulnerability is defined as a "physical feature or operational attribute that renders an entity, asset, system, network or geographic area open to exploitation or susceptible to a given hazard" [2]. In other words, vulnerability is the probability of a successful attack, given once the attack occurs.

$$V = P(S \mid A)$$

The most efficient way to reduce the vulnerability of Cornerstone Autism Center is to increase the physical security of the building. Cornerstone Autism Center already restricts entry to the clinical areas of the building via limited access doors activated with a magnetic card system. This system requires anyone without magnetic card access to be escorted into the clinical areas. The researcher assessed other areas which Cornerstone Autism Center could reduce the vulnerability, such as the child pick up and drop off times, and physical barriers within the building, such as door locks on the classroom and clinical areas, and exterior windows.

A. Child Pick up and Drop off

The two most vulnerable times of any school building are pick-up and drop-off. The researcher conducted an assessment of Cornerstone Autism Center's process for picking up and dropping off the children. During these times, Cornerstone Autism Center also limits access to the building by restricting the pedestrian traffic into and out of the building. The staff at Cornerstone Autism Center wait for the child's parents to drive up in their vehicle. Once the vehicle is in front of the entrance, the staff members walk out to the vehicle, four at a time, and retrieve the child. A simple random sample (8 out of 50, 16%) was taken of the amount of time necessary for staff members to pick up each child from his/her parents, and a simple random sample (10 out of 50, 20%) was taken of the amount of time necessary to return each child to his/her parents. The average amount of time for a staff member to retrieve the child from the parents was 1.47 minutes (95% CI: 1.30, 1.65), and the average amount of time for the staff to return the child to the parents was 1.68 minutes (95% CI: 1.11, 2.25) (see fig 3).

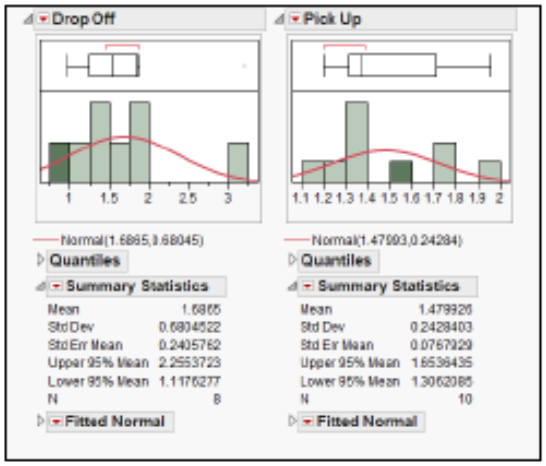

Figure 3, Statistical data of the time required for parents to drop off children with Cornerstone Autism Center and pick up children from Cornerstone Autism Center

Because the sample sizes where relatively small, they did not follow a normal distribution pattern. Although the recorded times did not follow a normal distribution, this paper

will still use them for analysis. According to the data observed for pick up and drop off of the children, parents dropping off their children at the center require about 12 more seconds per child than picking them up (see fig 4). Because there are fifty children for pick up and drop off, and four staff members retrieve and return the children at a time, the estimated time required to pick up all fifty children is 18.375 minutes, and the estimated time to return the children to the parents is 21.08 minutes. This system tends to minimize the amount of vulnerable time that Cornerstone Autism Center is exposed to a threat. The assessment of Cornerstone Autism Center's pick up and drop off procedures found that this was a viable option for reducing the vulnerability of the children and staff; therefore, this procedure reduced the overall risk of an incident occurring during these times.

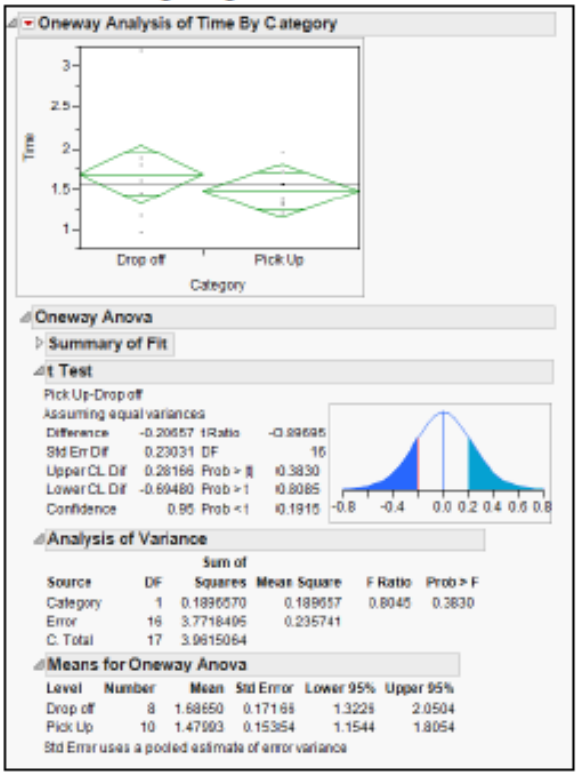

Figure 4, ANOVA of the time required to drop off children at Cornerstone Autism Center versus picking up children

B. Physical Barriers

The two areas that this paper will address for potential improvement are impact-resistant windows, and interior door locks. Originally designed to increase protection from high velocity winds from hurricanes and tornados, impact-resistant glass is also beginning to show potential in the active shooter field. The Sandy Hook Shooting incident in 2012 can attest to this: "Many schools rushed to fortify their front entrance doors, failing to recognize that the Sandy Hook shooter shot out the glass next to the doorway, not in the actual doorway" [5]. Tests conducted by the Department of Homeland Security and U.S. General Services Administration demonstrate that installing impact-resistant security glass, either in the form of laminated glass, or window films, can increase the time required to penetrate the window or door via forced entry by adding resistance [6]. The researcher's assessment of the building found that Cornerstone Autism Center did not have locks on any of the classroom doors, or doors within the clinical areas. The researcher also found that all of the exterior window had standard window glass with little or no impact resistance.

The most effective way to reduce the probability of injury or death from an active shooter is to place a barrier between the shooter and his/her potential victim. The most likely candidate for a barrier is a locked door to an isolated room. The department of Homeland Security and the Indiana State Police both strongly advocate for securing doors in the event of an active shooter [7], [8]. The Indiana State Police goes further stating, "The administration should provide the hardware to rapidly secure classroom doors. All staff members must be able to easily and rapidly secure the doors" [7]. The International Association for Healthcare Security & Safety recommend if locking doors is unavailable, then one should barricade the doors with whatever means necessary, i.e., furniture [9]. Providing the ability for staff to enter a room and lock the door may be one of the key elements of saving lives during an active shooter incident. During the Sandy Hook active shooter incident, two rooms where the children and educators were killed had unlocked doors and showed no signs of forced entry [5].

IV. Reducing Consequences

Even if every room has a lock, and every glass window is impact resistant, none of this will be beneficial if the clients and staff are not familiar with the policies and procedures during an active shooter incident. Once the active shoot has begun shooting, the only possible remaining option is to reduce the consequences of the event. There are many different ways to determine the consequences of an active shooter event: lives lost versus lives saved, amount of property damaged, amount of capitol lost during the event, etc. Consequences depend on what the administrators and stakeholders find valuable. Because consequences are the most subjective item within this equation, it cannot be calculated in the form of a mathematics or statistics equation.

One of the easiest means of reducing consequences of an active shooter incident is to have a policy in place that details the requirements of staff and clients in the event of an active shooter, then rehearse those requirements routinely. An assessment of Cornerstone Autism Center's emergency preparedness plans revealed that they did not have any such plans. The researcher recommends having a plan in place for both soft and hard lockdown drills, which will be defined in the following paragraph. In addition to rehearsing the lockdown drills, Cornerstone Autism Center should also rehearse the Department of Homeland Security's Run-Hide-

Fight model for reacting specifically to an unexpected active shooter event.

A. Rehearsals and Drills

The State of Indiana does not require businesses to conduct drills of any kind; however, the Federal Occupational Safety and Health Act (OSH Act) requires companies with 10 or more employees to have written fire prevention and emergency exit plans in place [10]. The Department of Education does require schools to conduct a monthly fire drill; two of those drills can be substituted with a tornado drill, or a man-made emergency drill, such as an active shooter drill [10]. An after-action review of the Sandy Hook active shooter incident released by the Connecticut State's Attorney's Office recommends rehearsing lockdown drills as one of the other man-made emergency drills. "Lockdowns work and are still one of the most effective tools available to get students and staff out of harm's way" [5]. A lockdown drill is simply a drill that prevents anyone or anything from either entering or escaping the building or room [5]. One of the most commonly used lockdown procedures is the layered approach: a "soft" lockdown and a "hard" lockdown as used by the Granite School District, Salt Lake City, Utah [11]. A soft lockdown is called when there is suspicious activity in the area. In a soft lockdown, Cornerstone Autism Center's staff will lock all doors, cancel all outdoor activities, and require anyone outside to return indoors. All personnel will move to a room, and ensure the door is secured and locked. Lessons and educational plans continue as usual, but within a securable room [11]. A hard lockdown is called when there is an immediate threat in the area. During a hard lockdown, all doors are locked, all activities are canceled, anyone in an open area room, such as a cafeteria or gymnasium, will immediately move to a lockable room. Once Cornerstone Autism Center's clients and staff are in a lockable room, they will lock and blockade the door. The staff and clients do not open the door for anyone; police and emergency responders will have a key to open the door. All electronic devices are silenced, and leadership in the room will attempt to contact the administration emergency responders or law enforcement (dial 911). Clients and staff should be trained on when it is acceptable and how to fight back, if necessary, to save lives [11]. Both examples of lockdown are initiated with either a public address system, an intercom system, mass telephone system, or internal message alert system.

B. Run-Hide-Fight

The most widely accepted reaction for active shooter incidents is the "Run-Hide-Fight" methodology. The Department of Homeland Security developed this methodology and the Federal Bureau of Investigation endorses it. The idea behind Run-Hide-Fight is that as soon as there is an imminent threat and as long as there is an accessible escape path, the first thing that clients and staff should do is attempt to evacuate the premises [8]. If evacuation is not possible, then clients and staff should find a place to hide where the active shooter is not likely to find them. Hiding places should be outside of the shooter's line of sight, provide protection if the shooter begins to fire, and should not hinder options for movement [8]. Lockdown drills mentioned earlier in this paper will aid staff in identifying locations that meet this description. While hiding, staff and clients should do everything possible to refrain from alerting the shooter to their location: silencing cell phones, turning off all sources of noise, and remaining quiet [8]. If evacuating and hiding are outside the realm of possibility, then the last effort should be to fight. As a last resort, and only when one's life is in pending and immediate danger, staff should attempt to disrupt or incapacitate the active shooter [8]. Once one has made the decision to fight, one should commit completely to incapacitating the aggressor.

V. Summary

An active shooter incident can be a very confusing event, riddled with chaos, insecurity, and unpredictability. However, once one understands the concepts of risk and means to mitigate risk, one can decrease a lot of the confusion. Risk is a simple function of threat, vulnerabilities, and consequences. By decreasing these, one can reduce risk. Reducing threat requires an understanding of how likely a location is to be attacked, then finding ways to reduce the probability of actually sustaining an attack. Reducing vulnerabilities requires an increase in physical security of the structure, such as placing locks on classroom doors and installing impact resistant glass in the windows. Reducing the consequences of an attack requires the clients and staff to better understand the standard procedures of an active shooter incident. This requires training, rehearsals and routine drills. If these recommendations are followed, then Cornerstone Autism Center will have a higher probability of reducing the risk of an active shooter incident, and potentially save lives in the process. If this advice is distributed to a larger audience and a greater number of organizations, then hopefully the next FBI report can begin to show a decrease in the number of lives lost due to an active shooter incident versus an increase in number of lives lost.

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