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# Predicting the Impact of Mobile Field Hospital Deployment in Reducing Patients Mean Wait Times in Emergency Departments: An Agent-Based Simulation Approach

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## Research Article

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# Abstract

Mean wait time (MWT) in emergency departments refer to the average time patients spend undergoing evaluation, or treatment at each stage, which can be significantly affected by sudden onsets of a disaster. Agent-based modeling (ABM) is a computational technique that simulates the interactions and behaviors of individual agents in a defined environment and enables the study of complex systems by observing the emergent outcomes of agent-agent and agent-environment interactions. This study examines the capability of ABMs in assessing the impact of response operations on hospital emergency departments mean wait time in a post-explosion scenario for an oil and gas industry. The methodology of this study involves the use of an agent-based modelling and simulation tool (NetLogo 6.3.0) to represent the interaction of agents within an emergency response system defined by rules, goals and decision protocols. The response policy includes both a traditional approach and a collaborative intervention through the use of a mobile field hospital (MFH). The dataset was generated, sampled and analyzed using the BehaviorSpace and Pandas tools, respectively. The results of the simulation study show that the strategic use of MFH for a collaborative response resulted in lower MWT, indicating higher effectiveness and efficiency of response efforts. This study highlights the need to generate potential results and test how response strategies might influence emergency department wait times and demonstrates the capability of simulation techniques in modeling complex systems. This could serve as an important tool for training health workers and disaster managers on emergency response and preparedness.

## 1.0 Introduction

Emergency department (ED) mean wait times refer to the average time patients spend being evaluated, treated, and either admitted or discharged. Factors that influence these wait times include inpatient bed occupancy, emergency room visits, patient discharge rates, and length of hospital stay. Studies emphasize the importance of considering patient flow and hospital capacity to reduce wait times and improve patient outcomes (Paling et al., 2020; Vainieri et al., 2020). Longer emergency department wait times can have a significant impact on patient outcomes. Studies have shown that delays in ED throughput can have a variety of negative consequences (Arnold et al., 2023; Tian, Osgood, et al., 2023). For example, the risk of hospitalization has been found to be higher in patients who experience delays in care in emergency departments (Arora et al., 2023). Research has also shown that other variables, such as lower socioeconomic status, are associated with longer emergency room wait times for patients with chest pain. This association can lead to delays in critical diagnosis and treatment of conditions such as acute coronary syndrome (Maynou et al., 2023). Some actions have shown to positively contribute to the reduction of emergency department wait times, such as: simplifying processes and optimizing resource allocation. These are critical to improving patient outcomes and reducing the burden on healthcare systems (Herlitz et al., 2022).

EDs are significantly affected by industrial and other disasters. Emergencies such as chemical, biological, radiological and nuclear accidents; hospital crises and disasters; major disasters such as

hurricanes; and mass accidents such as traffic accidents present emergency doctors with a variety of difficulties (Amakama et al., 2022, 2023, 2024; Barten et al., 2021; Chambers et al., 2020; Mohanty et al., 2022; Ranse et al., 2023). The effects of disasters on EDs include an increase in patient presentations, a wide range of triage needs, resource demands, longer hospital stays, and potential delays in patient care and transfer procedures (Bradley Morrison & Rudolph, 2011). By estimating incomplete data and calibrating simulation models for accuracy, simulation-based optimization approaches that accurately model patient flow in emergency departments ensure reliable evaluation of solutions to address overcrowding (Currie et al., 2023).

By using techniques such as discrete event simulation and agent-based simulation (ABS), simulation models can optimize emergency department workflows (Y. Liu et al., 2023). Strategies such as FIFO + Centralized and Random + Centralized, have proven to provide time-saving benefits during patient stay, these models contribute to effective resource planning (De Santis et al., 2023). In addition, simulation-based optimization and model calibration techniques are often used to achieve reliable simulation results, which are highly dependent on accurate estimation of treatment times and patient flow in emergency departments (Oveysi et al., 2021; Piermarini & Roma, 2023). By considering variables such as service capacity, patient transfers, and wait times, simulation-based optimization of ED networks can also help identify cost-effective alternatives for healthcare systems (De Santis et al., 2023).

This study examines the capability of ABMS to simulate realistic outcomes of the impact of response strategies on average patient wait times in interacting emergency departments. The dataset generated and examined for this study was based on a hypothetical situation. The design, modeling and simulation of the interacting systems enables a comprehensive understanding of complex system interactions and their communication to emergency responders and medical professionals. By conducting a sensitivity analysis of the model results, this study goes beyond evaluating how accurately the simulation model predicts the hypothetical scenario, but also providing a prediction of the possible direction of change in the system.

Therefore, the developed model can serve as a basis for future researchers who, depending on their research goals, can either improve the complexity of the model or modify aspects of it to test equivalent scenarios. The following aspect of this article is structured and follows; Section 2 contains a literature review that provides key themes from previous literature to help readers understand the context of the study. Section 3 presents the methodology for developing the simulation model and the criteria for performing sensitivity analysis. Section 4 presents and discusses the results of the study, while the final section provides the researchers' conclusions based on the study results, including limitations and suggestions for future studies.

## 2.0 Literature Review

In this section, a literature review was conducted to shed light on the strategies used and to provide a framework for evaluating how disaster response strategies impact typical patient wait time between

interacting emergency departments in the aftermath of a disaster. Although there is little evidence to support NetLogo framework being used specifically to compare ED interactions during a disaster in an oil and gas industry, this study uses a statistical boxplot analysis and a Sobol' sensitivity analysis to demonstrate the relevance of the outcomes of the strategies examined.

The study by Tian, Osgood, et al. (2023), used discrete event simulation models to simulate patient flows in emergency departments (EDs) and acute care units of six Canadian hospitals. Their model was critical for assessing the impact of different intervention scenarios on three outcome measures related to emergency department wait times. Administrative data from multiple sources from April 2017 to March 2018 were used to populate the model. To evaluate the impact of the intervention, three outcome measures were assessed, including: the waiting time for the initial assessment, the waiting time for the inpatient bed, and the time the patient spends without being seen. They compared their results to a baseline scenario to assess the effectiveness of the intervention in reducing waiting times. Their results showed that Alternate Level of Care (ALC) resulted in average wait times for inpatient patients in bed of 4.22 to 0.25 hours and saved 30% of inpatient visits. In addition, the expansion of emergency care reduces the waiting time for the initial assessment from 0.46 to 0.16 hours and the introduction of high-quality care reduces the waiting time from 6.85 to 0.34 hours. The study concludes that moderate reductions in the measures examined could reduce emergency room wait times, but the magnitude of the reduction varies by hospital.

In another study by Tian and Basran, et al. (2023), they used DES to identify intervention strategies aimed at reducing emergency department wait times using a four-phase participatory modeling approach. By looking at the system, their simulation helped identify the root causes of long wait times and provide viable solutions. In the context of Canadian healthcare policy, the study aimed to identify intervention strategies to reduce emergency department wait times using discrete event simulations and participatory modeling. The reasons for the long waiting times in the emergency room in the hospitals examined were analyzed and data collected. Part of the data used in the participatory modeling approach was also the opinions and inputs of stakeholders. To evaluate and rank interventions based on reasons for longer emergency department wait times, they used a multi-criteria framework. As part of Canadian health policy, the study identified intervention strategies aimed at reducing waiting times in emergency departments. The study found that a thorough analysis of the reasons and possible remedies for long waiting times in the emergency department from a systems perspective was possible by involving stakeholders at each stage of the modeling process.

Alternative approach in the application of simulation technique have similarly been proposed by Foini et al. (2023), who using the programmable multi-agent modeling environment NetLogo, simulated an emergency in a plaza. The detailed model created with the help of NetLogo enabled the simulation and analysis of mass dynamics during emergency evacuations in crowded areas such as squares, stadiums or halls. The focus was on planning a mass evacuation of crowded areas. The study provided key insights from the simulation experiments conducted in NetLogo and aimed to present recommendations for future research in the areas of evacuation planning and crowd simulation, as well as insights into

crowd behavior during emergencies. The study's conclusions emphasized the usefulness of NetLogo and the importance of using such simulation tools for evacuation planning. Researchers and agencies involved in emergency management and crowd control can benefit significantly from the study's key findings.

Fava et al. (2022), studied patient flows in a medium-sized emergency department (ED) in central Italy after an earthquake using a DES model. The authors modeled a typical ED situation such as: a sharp increase in patient arrivals due to major events such as natural disasters. Using comprehensive ED procedure data, an accurate DES model was constructed for scenario analysis. The model acted as a decision support system for emergency department managers, assisting them in creating emergency plans tailored to mass casualty events. The aim of the study was to improve service quality, reduce waiting times and correctly assess the problem of overcrowding in the emergency department. The DES model helped streamline resource allocation and improve emergency department emergency response plans through scenario analysis. The study's data set includes details on patient arrivals, treatment procedures, resource utilization, and general emergency room visits. However, no additional statistical analysis of the information was performed. Study results highlight the importance of proactive planning, resource allocation strategies, and operational protocols to improve emergency department efficiency and patient outcomes during unplanned peaks in patient volume. This enables the creation of specialized contingency plans for mass disasters and increases overall preparedness.

Baril et al. (2019), used DES to simulate patient flow in the emergency department and examine how different scenarios would impact patient wait times. Using various factors that influence patient flow, the researchers were able to simulate the dynamic behavior of the system over time. An experimental design was used to observe the effects of systematically varying input parameters such as the number of doctors and nurses on patient waiting times. Using controlled experiments, the Design of Experiment (DOE) facilitated the study of how various factors affected the system's performance. The purpose of their study was to examine outpatient wait times and identify operational changes that could be made in the emergency department to improve efficiency and reduce patient wait times. The study's conclusions underscore the importance of staffing, operational strategies and resource management in improving patient flow and overall performance in emergency departments by highlighting the significant impact that factors such as the number of physicians and nurses have on patient wait times.

The application of simulation techniques to evaluate possible inefficiencies in the emergency department as described in the reviewed literatures, is focus on improving the overall performance of EDs in disaster situations and reducing waiting times for patients. However, despite the compelling results of these studies, the application of ABM (NetLogo) to assess the impact of specific ambulance deployment policies on patient wait times in interacting emergency departments is still lacking. Therefore, previous studies have not extensively examined how interdepartmental dynamics are influenced by external emergency services. The focus of this study builds on previous work and provides useful insight into a way to improve patient outcomes during critical events, which may be helpful in

improving emergency response and training plans for both first responders and healthcare professionals.

## **3.0 Methodology**

The study proposes a hypothetical scenario involving a sudden onset of disaster (SOD) in an oil and gas industry and the response of a regional and a mobile field hospital (depending on response needs) for transport, triage and treatment of victims of the incident. The aim is to provide a framework for predicting and evaluating the potential impact of disaster response strategies on average patient waiting times in interacting emergency departments by leveraging on the capability of agent-based simulation technique. The proposed method also includes processing the generated synthetic dataset using Python to understand and compare the impact of the response policy on the system outcomes. Figure 1 shows the hypothetical scenario of the modeled disaster response problem describing the incident and response protocol.

The scenario examined involves a regional hospital that handles routine triage, treatment, and hospitalization of patients. Additionally, an oil and gas industry working remotely and performing standard tasks such as grinding, welding, and cutting experienced an unexpected explosion that caused various injuries due to the primary incident and its aftermath. such as: exposure to toxic substances. A mobile field hospital is contacted when regional hospital is overwhelmed, to assist in the transportation, triaging and treatment of the victims of the industrial explosion. Other patients also arrive at the emergency department by walk-in. Once patients arrive, they are assessed in the triage area to prioritize treatment and determine the extent of their injuries. Deciding whether the patient's condition has exceeded its "time-to-live" is an important decision point. This allows the agents in the model to determine whether they are immediately suitable for advanced medical procedures or die off. Patients requiring non-surgical procedures or post-operative treatment are transferred to the ward for further care and recovery. However, patients who have fully recovered are sent home after being discharged from the hospital. The goal of the problem is to reduce the average wait time in the emergency departments while efficiently managing hospital resources. It describes an organized and effective disaster response process that ensures patients receive timely and appropriate care depending on the severity of their illness and the decision protocol of the system's agent.

## **3.1 The model development process**

The sequential steps in the agent-based model development process is shown in Fig. 2, which follows the methodology in the design of agent-based models as suggested by Salamon, (2011). The ABMS model was developed, tested and refined to provide reliable and practical simulation results following this systematic process.

## **3.2 Materials, sampling, data generation, and analysis**

Typically, the generation, collection, analysis and visualization of data sets are crucial elements of any successful scientific investigation. Sampling, data generation, analysis and presentation in this study were enabled by NetLogo 6.3.0 (BehaviorSpace) and Pandas Python libraries for data cleaning, filtering and aggregation - including sensitivity analysis - using the Isigami function. The graphical user interface of the impact of the ambulance policy on mean waiting times is presented in the Results section.

## 4.0 Results

Figure 3 shows the graphical user interface of the designed and implemented agent-based model used in assessing the impact of a disaster response policy based on ambulance dispatching policy on mean waiting times within the interacting emergency department, which is a function of the efficiency of the systems and can reflect efficient patient flow, quality of care and staffing needs.

The model implemented examined two response strategies: “Always go to RH,” which describes a policy that the regional hospital will use to respond to the disaster, and “Alternate,” which describes the deployment of the mobile field hospital in conjunction with the regional hospital to support emergency operations. The following sections present the results of the impact of emergency medical service policy on mean waiting times in the interacting emergency departments in the disaster scenario, including a sensitivity analysis of the model results.

## 4.2 Effects of ambulance policy on patient’s mean wait times

By considering the various demands for emergency services and the use of ambulances, the simulations seek to replicate a possible operational environment for both effective response strategies and resource allocation. The large number of simulations runs ensures a comprehensive data set that covers a broad spectrum of results, boosting the validity of the comparative analysis.

The quantified mean wait times for the two ambulance policies are compared in two boxplots shown in Fig. 4 (“Always go to RH” and “Alternate”). These charts are valuable for showing the distribution of data within each examines ambulance policy. The codes used to analyze and visualize mean wait times are available on our GitHub page at: [https://github.com/Nimisingha/Ambulance\\_Policy\\_RPG](https://github.com/Nimisingha/Ambulance_Policy_RPG).

ABMs are collections of parameters that control the actions and interactions of agents. Sensitivity analysis is a crucial step in understanding the behavior of the output variables from the interactions of the input variables because it systematically examines the effects of model parameters on the output. The following section presents the methodology used to perform the sensitivity analysis on the model outputs and results.

## 4.3 Sensitivity analysis on the effects of response strategy on EDs MWT



Sensitivity analysis helps understand how variables behave in the data set of an agent-based model. The results of the Sobol' sensitivity analysis for the model is shown in Fig. 5. By highlighting input parameters that have a significant impact on the model's output, this analysis improves the understanding of the model's dependencies and sensitivities.

The influence of different model input uncertainties on the output uncertainty can be evaluated using the Sobol' sensitivity analysis method. This method is particularly suitable for simulating complex mathematical or computational systems with low input variables. By examining the primary effects of the components as well as their interactions, the overall Sobol' index (ST) evaluates the contribution of each input to the variance of the output. The first-order Sobol' index (S1), indicates the independent influence of an input variable on the output variance. Furthermore, the second-order sensitivity index (S2), illustrates how the joint variation of two input variables affects output variance in addition to their individual contributions. The following section presents a discussion and implication of these results.

## 5.0 Discussion

### 5.1 Effects of ambulance response policy on EDs mean wait times

The boxplot in Fig. 4 shows that the "Always go to RH" policy results in longer mean wait times (12.34 vs. 10.20) and a higher standard deviation (2.23 vs. 1.59) compared to the "Alternate" based on descriptive statistics. The "Always go to RH" guideline also has a larger interquartile range, reflecting greater variability in MWT results. While the minimum waiting times are similar for both policies, the maximum MWT for the "Always go to RH" (17.48) is higher than that of the "Alternate" policy (13.81). Implementing the "Alternate" policy will reduce average wait times by 17.34%. This means that in similar disaster response situations, the "Alternate" policy, which involves deploying a mobile field hospital to work with the regional hospital, could reduce waiting times and improve quality of care and patient outcomes. The improved MWT results for the "Alternative" policy suggest that it could be more versatile for different disaster scenarios. However, a comprehensive analysis should rely on the distribution of the data sets. The results confirm the utility of a collaborative disaster response approach for optimal outcomes.

Based on these results, it is safe to assume that the collaborative "alternative" response strategy for an equivalent scenario will improve triage and treatment protocols, responsiveness and resource allocation effectiveness, and reduce overall MWT. Against this background, the decision to deploy a mobile field hospital in addition to the existing regional hospital can be crucial in the event of an explosion disaster. The study illustrates the complexity and diversity of disaster scenarios by developing an agent-based model. This suggests that while both approaches are used regularly, there are significant differences in the effectiveness with which they reduce waiting times. Since civil protection frameworks serve as the basis for disaster response measures, their flexibility and adaptability are important features. To evaluate and improve these tactics for different disaster scenarios, future simulation studies should conduct a more thorough analysis of similar response strategies.

## 5.2 Sensitivity analysis: effect of ambulance strategy on mean waits times

The use of global sensitivity analyzes in this study, particularly Sobol', improves our understanding of the results by illuminating the characteristics, behavior, and impact of system agents on the overall results. This sensitivity analysis also identifies important variables that could influence how effectively future disaster response models are developed. The results of the overall index (ST), the first-order sensitivity index (S1) and the second-order sensitivity index (S2) are briefly explained below.

- **Total sensitivity index (ST):** With an ST value of 0.64, the “Ambulance Policy” stands out as the most important influencing factor on the input performance indicators of the MWT. Furthermore, “N Ambulances” has a significant ST value of 0.45, suggesting that it also plays an important role in determining the results of the model.
- **First-order sensitivity index (S1):** With an S1 value of 0.54, this index shows that ambulance policy has the greatest impact on performance on mean wait time metrics. In terms of correlation with service performance, the variable “N ambulances” ranks second with an S1 value of 0.35. The amount that each input variable individually contributes to the output variance is represented in detail by the S1 values.
- **Second-order sensitivity index (S2):** For the pair “N Ambulances” and “Ambulance Policy,” the S2 value of 0.11 indicates a strong combined influence on the output variable. However, other combinations have negative to almost zero S2 values, indicating small interaction effects on the model results. Examples of these combinations are “ambulance insurance” with “injured person” and “injured person” with “N ambulance”.

The results show that mean waiting times (MWTs) in the emergency department (ED) are significantly influenced by the “ambulance strategy” chosen for the disaster response intervention. High ST and S1 values also suggest that the number of ambulances deployed in such scenarios is another crucial element that impacts the best possible operation of emergency departments. From a practical perspective, to influence positive outcomes, decision makers must prioritize optimizing the rescue strategy, while also giving careful consideration of the number of ambulances needed to respond to disaster situations. Taking these two factors into account can guarantee a more effective response to improve the MWT of patients. These results highlight the need for strategic planning in responding to emergencies and emphasize a coordinated strategy that combines resource allocation and policies to increase the effectiveness of emergency medical services in the event of a disaster.

## 6.0 Conclusion

In this article, we conceptualized, developed and implemented a NetLogo 6.3.0 model of a hypothetical disaster response scenario to determine the potential and predictive ability of computational technology in simulating a realistic scenario to test the possible impact of two disaster response management

strategies on patient wait times. The simulation model was able to fairly but accurately reproduce the conceptualized scenario in terms of reducing mean waiting times through a more collaborative response policy, which was our main focus for the study. The experiments conducted with the BehaviorSpace feature of the NetLogo model showed that the shorter mean waiting times when using the alternate policy are a function of both the effective use of the number of ambulances and the entities' decision protocol. The implemented model and the analysed results proved to be a double-edged sword: on the one hand (in an equivalent scenario), it led to a reduction in the mean waiting times within the interacting emergency departments, on the other hand, it provided insights that could predict the direction of change in the system, which can assist in informed decision-making. The conclusion of this study is that in such a scenario, policymakers should prioritize ambulance policy to achieve positive results in mean wait times, while also putting into consideration the number of ambulances deployed. If the results of this study are calibrated against a real-world scenario, they may be particularly valuable to disaster managers and disaster management organizations in improving their standards and policies, including for training and education. Future work could focus on using this model in examining different or similar scenarios to understand the effects of different combinations of factors and introduce a model capable of regulating the interaction of entities in the simulation. In summary, this work has demonstrated the potential of using safe, cost-effective and effective agent-based simulation techniques to improve understanding of the complex interaction of healthcare systems interaction in disaster situations.

## Declarations

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## Unsectioned Paragraphs

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# Figures

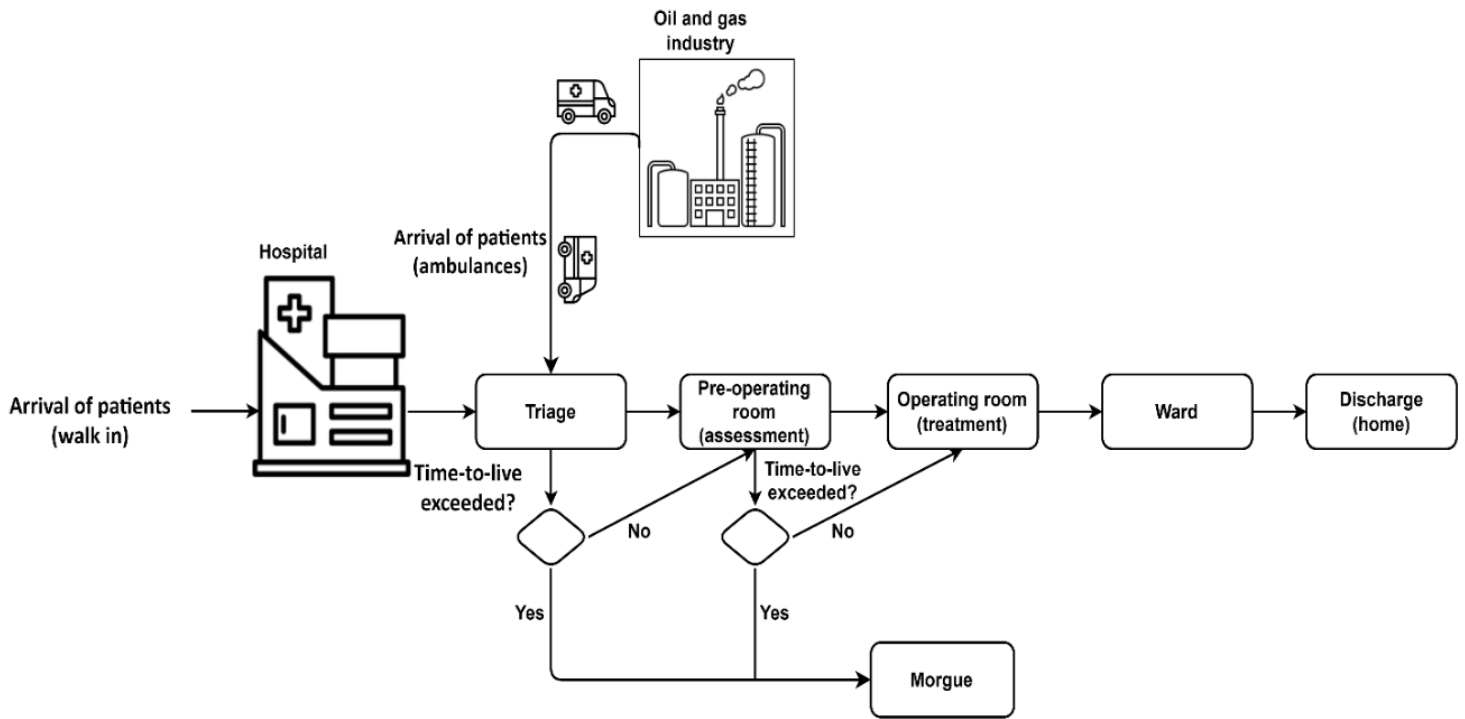


Figure 1

The hypothetical disaster response scenario (the conceptualized problem)

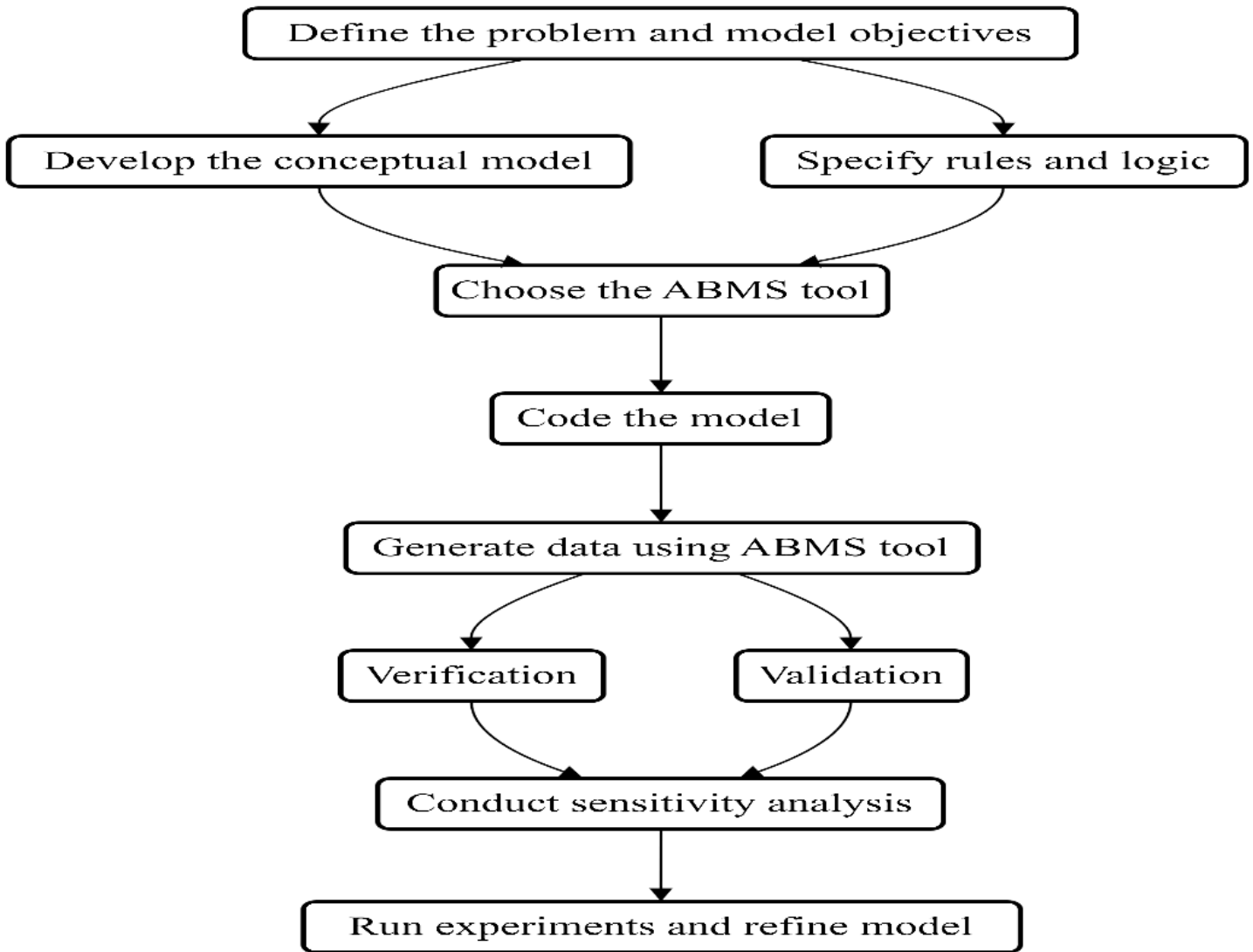


Figure 2

The ABMS model development process

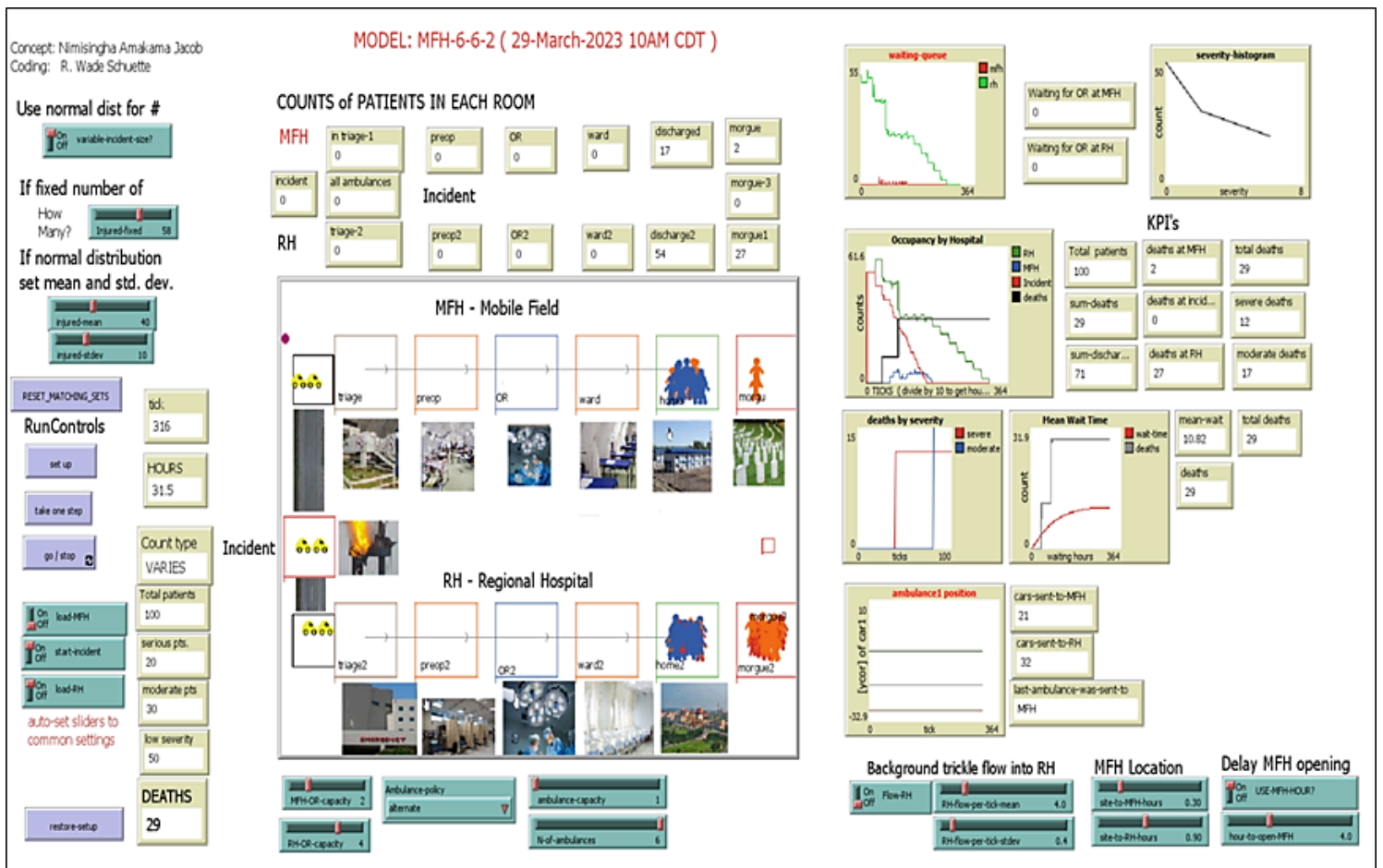


Figure 3

NetLogo (6.3.0) Graphical User Interface (GUI) on effect of response policy on patients mean wait times (Amakama et al., 2023, 2024).



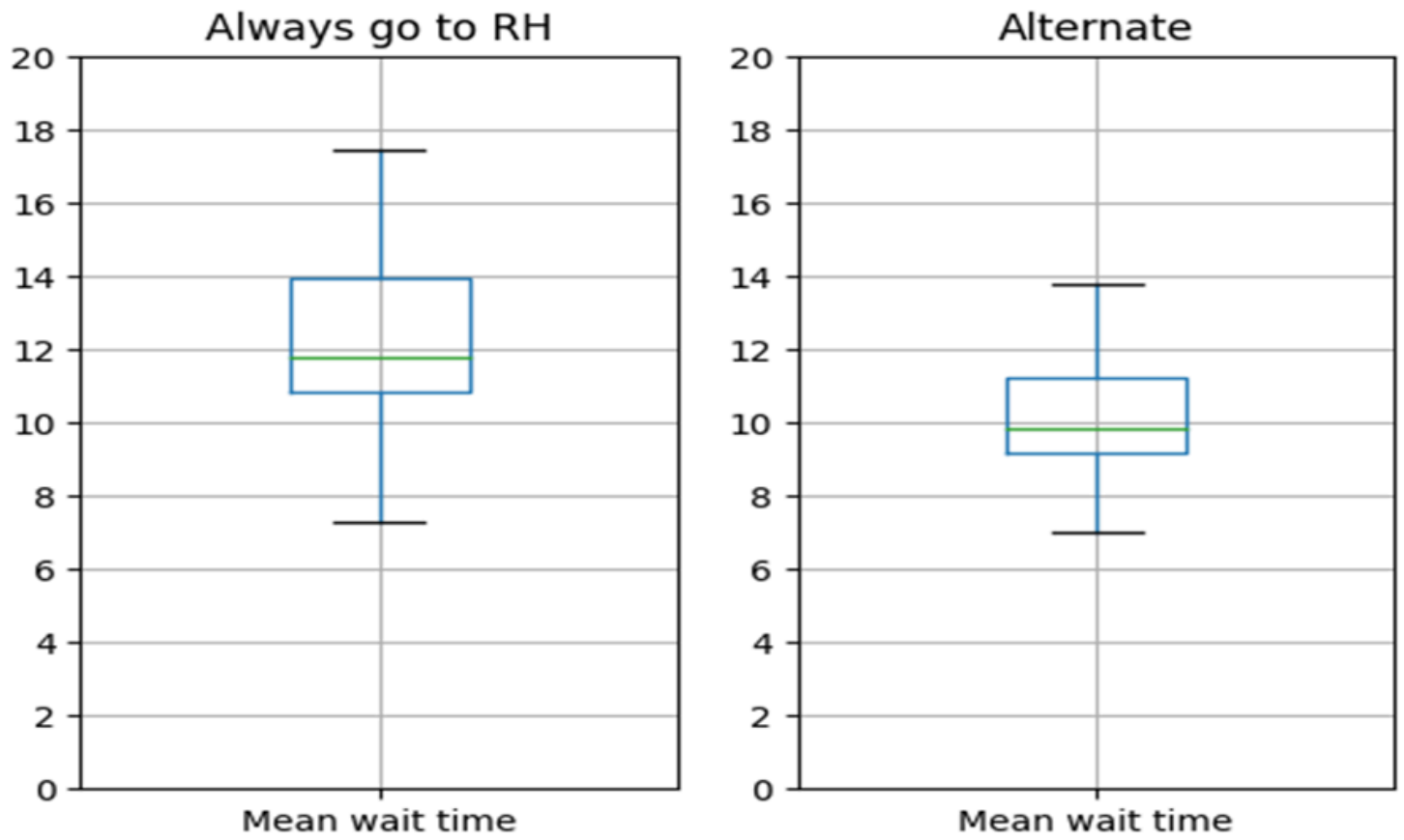
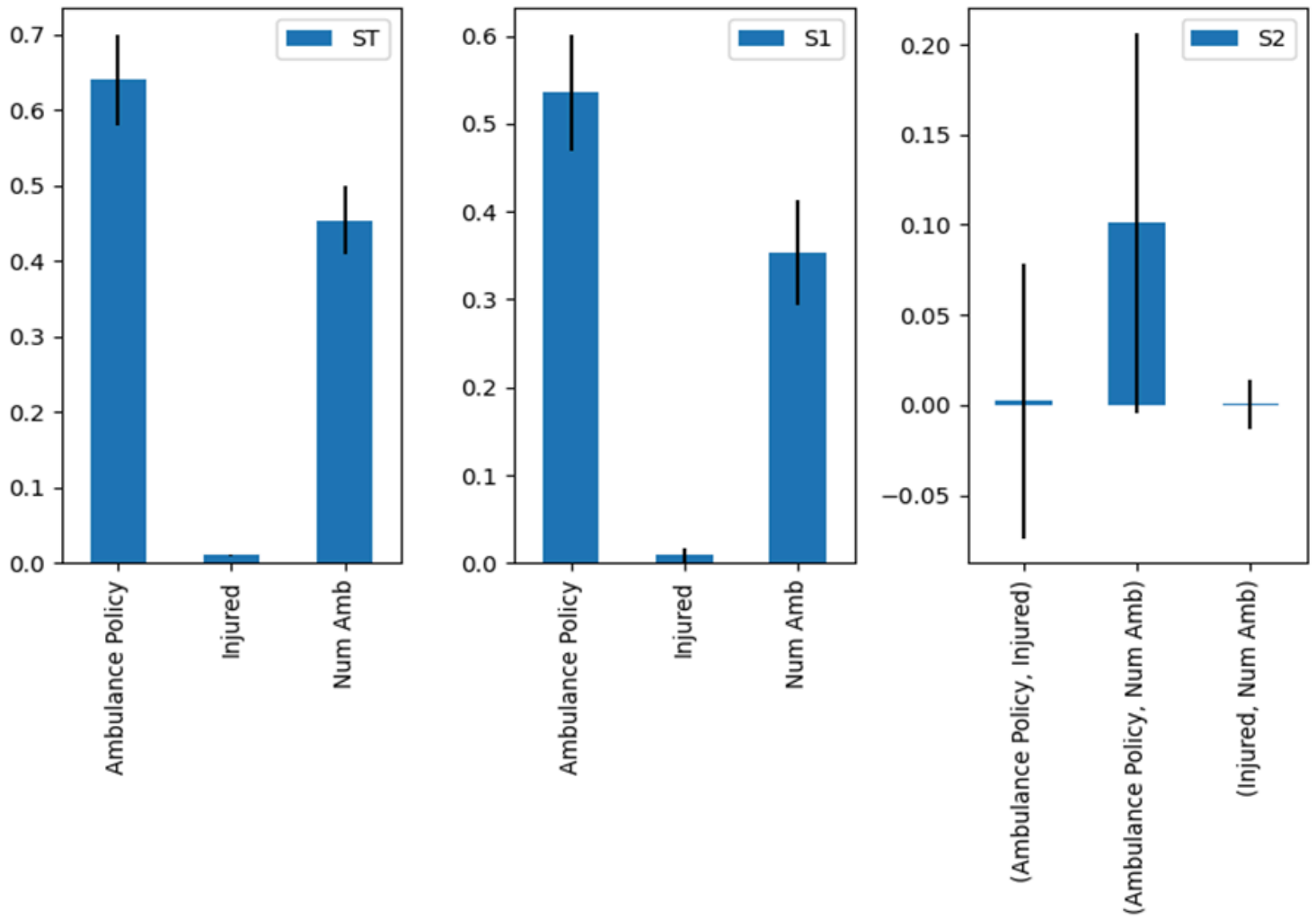


Figure 4

Effect of ambulance policy on patients mean wait times for interacting EDs.



**Figure 5**

Sensitivity analysis of the effect of ambulance policy on outcomes