Design and Implementation of an Interoperable Solution of a Mobile Field Hospital Dedicated to the Oil and Gas Industry

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DEDICATION

"Dedicated to the cherished memories of
my parents and elder brother, whose
unwavering trust and sacrifices brightened
my academic journey"

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LIST OF ABBREVIATIONS

ABM	Agent-Based Model/Modelling
ABMS	Agent-Based Modelling and Simulation
BPMN	Business Process Management and Notation
CSV	Comma Separated Values
CT	Computational Thinking
DES	Discrete Event Simulation
DRTRPG	Disaster Response Tabletop Role-Playing Game
Eds	Emergency Departments
GUI	Graphical User Interface
M&S	Modelling and Simulation
MFH	Mobile Field Hospital
MWT	Mean Wait Time
ODD	Overview, Design of Concept and Details
OR	Operating Room
OR/MS	Operations Research Management Science
Pre-OP	Pre-operating Room
RH	Regional Hospital
RPG	Role-Playing Game
S1	First Order Sobol' Index
S2	Second Order Sobol' Index
SA	Situation Analysis/Sensitivity Analysis
SALib	Sensitivity Analysis Library
S.D	Standard Deviation
SD	System Dynamics
ST	System Thinking/Total Sobol' Index
TRPG	Tabletop Role-Playing Game
WoS	Web of Science

RÉSUMÉ DE THÈSE

Aperçu

L'utilisation des technologies de modélisation et de simulation pour prévoir et comprendre le fonctionnement des services d'urgence des hôpitaux en cas de catastrophe est essentielle pour la préparation, la gestion efficace des ressources, la coordination des interventions et la sécurité des patients. La technologie de simulation peut être un outil précieux pour la formation des professionnels de la santé, l'identification des domaines d'amélioration des soins et l'optimisation des interventions d'urgence et des processus de soins de santé. L'interopérabilité des processus systémiques dans les scénarios d'urgence peut être examinée à l'aide de la modélisation et de la simulation basées sur les agents. Cela permet d'expliquer comment les décisions des agents affectent leur efficacité et comment ces décisions sont liées à différents niveaux. Par conséquent, cette étude utilise une approche interdisciplinaire qui combine la gestion des catastrophes et des urgences, la simulation sanitaire et la gamification pour apporter des réponses aux questions de recherche examinées.

Questions de recherche

Les deux questions de recherche examinées dans cette étude sont les suivantes :

- Comment pouvons-nous modéliser l'interaction entre un hôpital régional (RH) et un hôpital mobile de campagne (MFH) ou un hôpital de campagne dans une situation de catastrophe dans l'industrie pétrolière et gazière ?
- Comment les jeux de rôle sur table pour les interventions en cas de catastrophe (DRTRPG) peuvent-ils être utilisés pour vérifier/valider la représentativité du processus de réponse de l'agent d'un modèle ABMS dans le contexte d'un scénario d'intervention en cas de catastrophe ?

Méthodologie

La méthodologie utilisée dans cette étude intègre la conception de processus, les techniques de simulation et la gamification pour simplifier, documenter et modéliser un scénario de

catastrophe nécessitant l'intervention des services d'urgence. À l'aide du Business Process Model and Notation (BPMN), les activités et les flux de processus entre les systèmes régionaux et mobiles d'hôpitaux de campagne en interaction (modélisés comme un service d'urgence simplifié) et les sous-systèmes dans le scénario de catastrophe ont été détaillés. NetLogo 6.3.0 (outil de modélisation et de simulation basé sur des agents) a été utilisé pour simuler les interactions entre les paramètres des systèmes en interaction. Enfin, un jeu de rôle sur table de réponse aux catastrophes (DRTRPG) a été développé et mis en œuvre pour fournir une plateforme permettant de valider les simulations par le biais d'exercices basés sur des scénarios et de s'assurer que les réponses du modèle étaient réalistes et efficaces.

Résultats clés

L'application NetLogo 6.3.0 a démontré comment modéliser et tester la prestation de services d'urgence et l'intervention dans un scénario de catastrophe. Le modèle mis en œuvre a été utilisé pour expérimenter l'impact des stratégies de répartition des ambulances sur la mortalité et les temps d'attente moyens dans les services d'urgence. Ces expériences ont produit des résultats significatifs et ont mis en évidence le potentiel des techniques de simulation dans la gestion des catastrophes, la simulation des services d'urgence et l'optimisation des processus. Les résultats montrent également que les jeux de rôle peuvent contribuer de manière significative à la formation à la préparation aux catastrophes en améliorant la compréhension par les participants des systèmes complexes et des processus de prise de décision. Toutefois, le défi consiste à concevoir le jeu de manière à représenter pleinement la complexité et l'interaction du modèle ABMS, ce qui limite le niveau de validation du modèle. Néanmoins, les jeux de rôle se sont révélés inestimables pour offrir des possibilités d'apprentissage par l'expérience et identifier les domaines à améliorer dans la réponse aux catastrophes.

Contributions de l'étude

Les contributions de cette étude interdisciplinaire à la communauté scientifique peuvent être résumées en quatre domaines :

- Identification des domaines à améliorer : L'étude a identifié une lacune critique dans les connaissances en matière de réponse aux catastrophes qui peut guider la recherche future en donnant la priorité aux efforts spécifiques à chaque domaine. C'est ce que montrent les résultats sur l'effet et l'importance des stratégies de sauvetage dans un scénario de catastrophe entre les services d'urgence en interaction.
- Meilleure compréhension des systèmes complexes : L'intégration de l'ABMS dans cette recherche a permis de mieux comprendre la dynamique de la réponse aux catastrophes pour les systèmes hospitaliers en interaction. L'approche adoptée dans cette étude a mis en évidence des facteurs critiques tels que l'allocation des ressources et la coordination de la réponse, qui sont essentiels pour améliorer les capacités de réponse aux catastrophes.
- Formation et éducation : Le modèle de simulation et le jeu de rôle développés dans cette étude peuvent servir d'outil de formation efficace pour les intervenants d'urgence et peuvent être des outils précieux pour les équipes d'intervention d'urgence et les prestataires de soins de santé. Le jeu développé et mis en œuvre a permis d'améliorer les compétences des participants et de faciliter l'apprentissage par l'expérience des systèmes d'intervention en cas de catastrophe.
- Pratiquer la coordination et la communication : Le scénario du jeu sérieux souligne l'importance d'une coordination rapide et efficace entre les différents établissements de soins de santé et les services d'urgence et fournit une plateforme pour pratiquer et affiner les compétences des joueurs (en particulier par le biais de la formation). Les décideurs politiques et les praticiens de la santé publique peuvent utiliser les résultats de cette étude pour formuler des propositions visant à relever des défis équivalents en matière de réaction aux catastrophes.

Conclusion

Cette étude met en évidence la nécessité de plans d'intervention d'urgence efficaces, en particulier dans l'industrie pétrolière et gazière, qui est exposée à des catastrophes industrielles majeures. L'étude démontre les résultats potentiels et l'impact des stratégies d'intervention sur la mortalité et les temps d'attente. Bien que la recherche soit basée sur un scénario

hypothétique, elle souligne l'importance de l'étalonnage du modèle et de la poursuite des recherches pour obtenir des résultats optimaux. La combinaison des techniques NetLogo (ABMS) et DRTRPG fournit une approche pour évaluer les plans d'intervention d'urgence et une plateforme de simulation réaliste pour la prise de décision et la formation des ambulanciers. Les résultats de l'étude soulignent également la nécessité d'améliorer les stratégies d'intervention d'urgence et de réduire les taux de mortalité et les temps d'attente pour les patients dans les situations de catastrophe. L'étude peut être particulièrement utile aux gestionnaires de catastrophes et aux travailleurs de la santé, y compris les organisations, pour améliorer les plans, les normes et les politiques d'intervention d'urgence.

Travaux futurs

Cette étude exploratoire sert de travail préliminaire à de futures recherches sur l'amélioration des systèmes de soins de santé par la modélisation des interactions entre les systèmes hospitaliers dans les situations de catastrophe. La recherche future devrait se concentrer sur la modification du modèle pour tester des scénarios équivalents en utilisant des données réelles. Il est également nécessaire de convertir l'outil de jeu de rôle en une version en ligne afin d'améliorer le réalisme et de réduire les biais dans les protocoles de décision, de générer des ensembles de données plus robustes et d'améliorer la validation du modèle.

CHAPTER 1

1.0 INTRODUCTION

1.0.1. Overview of the study

The need to use modelling and simulation technology to predict and understand how hospital emergency departments would function in a disaster situation is critical for preparedness, effective resource management and patient safety. Simulation technology can be helpful in training healthcare professionals, identifying areas for improvement in care, and optimizing processes (Munira Ibrahim *et al.*, 2018; Shirazi *et al.*, 2022). To investigate the interoperability of systems in a disaster response scenario, agent-based modelling and simulation can be used. This helps explain how agents' decisions affect their effectiveness and how these decisions are linked at various levels (Pescatore & Beery, 2022).

1.0.2. Background of the study

Disasters may strike at any time and in any location, causing effect on human (even death) and material damage on critical infrastructures. They also represent a threat to environments that are not well maintained and need quick emergency response while dealing with limited resources (Uhm *et al.*, 2019). Table 1 shows the categories of natural and anthropogenic disasters that impact substantial number of people annually. The potential for major adverse events to cause catastrophic loss of life and physical injuries is high. Communities can be left in shock as these events are often unexpected. Despite best efforts in healthcare, disasters and major incidents still pose a challenge in providing adequate care for those affected. Recent findings

show that, natural, and anthropogenic events alone caused fifty thousand deaths and affects around 97 million persons (Massazza *et al*., 2019; Murphy, 2021).

Table 1: Categories of disasters and major incidents

Category	**Subcategory**	**Examples**
Natural	Meteorological	Cyclones, storms
	Geophysical	Earthquakes, tsunamis, landslides
	Hydrological	Floods, avalanches
	Climatological	Drought, wildfires, extreme temperatures
	Biological	Epidemics/pandemics (toxic materials or living things)
Anthropogenic	Technological	Food supply, transportation, telecommunications, energy
	Antagonistic	Terrorism, shootings, cyber-attacks
	Major accidents	Transport emergencies, extensive fires, chemical, nuclear, radiological, and explosions

Sources: (Chaudhary & Piracha, 2021; Makhutov, 2013; Mijalkovic & Cvetkovic, 2014)

Pre- and post-disaster phases are commonly used to classify disaster management. While efforts to provide goods and services, coordinate humanitarian assistance resources, and protect infrastructure are the focus of post-disaster efforts, pre-disaster studies aim to minimize damage by assessing potential hazards. This methodology covers the four phases of disaster management: response, recovery, mitigation, and preparation (Altay & Green, 2006; Aringhieri *et al*., 2022; Boonmee *et al*., 2017; Shiripour & Mahdavi-Amiri, 2019). Research on disaster management draws on findings from a diverse range of scientific domains, including disaster medicine (Tintinalli, 2015), to public policy and politics (Birkland, 2009).

The goal of disaster management is to improve coordination and preparedness in times of crisis (González, 2022). It can involve conducting simulation exercises to validate response

plans and improve systems for all hazards (Mahdi *et al*., 2023). Furthermore, during the response phase, power dynamics, reconfigurations and interactions between different actors are the focus areas of disaster response management (Coles & Zhuang, 2011). Figure 1 shows the disaster management continuum which includes a component that deals with response management.

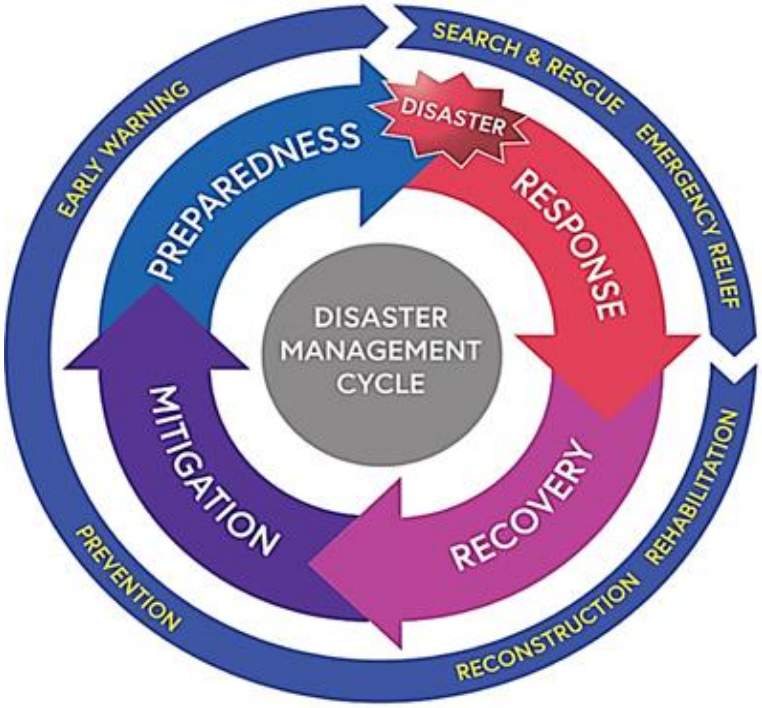

Figure 1: The disaster management continuum (FutureLearn, 2023).

Effective disaster response involves meticulous planning, organization, and deployment of resources to protect property and human life. Key activities include supporting search and rescue efforts, delivering medical aid and essential supplies, setting up evacuation zones and security perimeters, and repairing infrastructure. The main objectives are to stabilize survivors physically and mentally, recover deceased individuals, and restore essential utilities like water and power. This "response" phase precedes other phrases like "recovery," "mitigation," and "preparedness." (‘Background of Disaster Management’, 2023; Disaster Management, 2024).

Particularly given the impact of a disaster on critical hospital systems, the response phase of the event is important in managing the situation. This presents challenges including increasing patient volume, limited resources, space and staffing of the hospital due to the influx of patients. Involving hospital physicians in emergency planning and incident response is critical to coordinating and managing crises (Persoff *et al*., 2018). Building on this established background, the study shifts focus to defining the problem of this study.

1.1. Definition of the problem (disaster response for oil and gas industry)

Despite safety measures and technological advances, the oil and gas industry continue to experience accidents that harm both people and the environment. These incidents often lead to fatalities and strain emergency systems and medical facilities, particularly due to the industry's remote and harsh conditions. Figure 2 shows the trend of the number of fatalities underscores the urgent need for improved emergency preparedness and response. Traditional methods may fall short, highlighting the necessity for specialized interventions tailored to the unique demands of the industry.

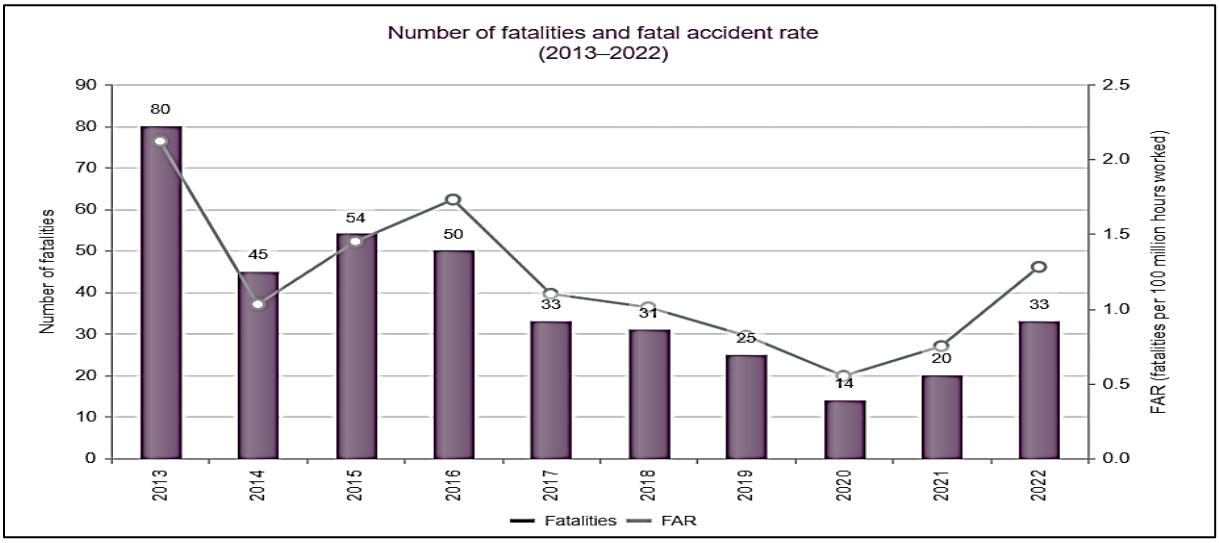

Figure 2: Fatality rates among oil and gas extraction workers 2013-2022 (IOGP, 2023).

According to the International Association of Oil and Gas Producers (IOGP) annual reports for 2013 to 2022, the death toll from onshore and offshore activities is currently increasing. This rise raises concern as it is projected to continue. For oil and gas drilling crews, activities in this sector are heavily related to life-threatening risk concerns. Inadequate safety and health legislation and preventative measures have resulted in hundreds of mishaps and fatalities at onshore and offshore drilling sites (Department of Occupational Safety and Health - 2014, 2014). The environmental dynamism and uncertainty in the oil and gas industry often pose unique challenges for healthcare systems. For example, following a disaster, healthcare responders might have to deal with scarce resources, secondary contamination and health related issues, which are characteristic of the oil and gas industries (Deinkuro *et al*., 2021; Kostyuk *et al*., 2020; Olalekan *et al*., 2018).

Simulation techniques are essential for improving coordination, preparedness, and response times during emergencies in the petroleum industry. By utilizing agent-based simulation modeling (Yousefi & Ferreira, 2017), in-situ simulation-based assessments (Abulebda *et al*., 2018), the petroleum industry can enhance training, resource allocation, and emergency planning through these techniques. By evaluating distinct designs, performance levels, and response capacities, these methods foster the development of more effective emergency response systems.

Emergency Departments (EDs) are undoubtedly one of the top priorities in the healthcare system. In emergency rooms, seriously ill or injured patients are cared for around the clock. Emergency departments are inherently complex, just like other parts of the healthcare system. To address these issues, methods such as System Dynamics (SD) and Discrete Event Simulation

(DES) are becoming increasingly popular (Brailsford, 2007; Gul & Guneri, 2015; Gunal & Pidd, 2006; Koelling & Schwandt, 2005). Furthermore, Agent-Based Modelling and Simulation (ABMS) is also becoming increasingly popular as a simulation modelling technique in emergency department studies. In addition to managing non-urgent patient schedules and predicting hospital admissions, it is also used as a tool for public health interventions and infection prevention in hospitals (Bruballa *et al*., 2020; Encinas *et al*., 2021; Jones *et al*., 2021)**.** These tools have proven useful in emergency departments and in modeling and simulating disaster response scenarios.

1.1.1. What are possible impacts of the problem?

Inadequate or inefficient collaboration between hospital systems in the event of an oil and gas explosion disaster can have several impacts. These impacts may include the following:

1. **Poor patient care:** In emergency situations, a lack of response coordination and/or patient severity information can lead to gaps and errors in understanding patient care needs. This can have a negative impact on the overall well-being of the affected persons.

2. **Ineffective utilization of healthcare resources:** If communication between systems and stakeholders is poor, health resources may not be used effectively in disaster relief. This can lead to increased costs and inefficient processes.

3. **Delay in emergency response:** Worker health and safety can be significantly affected by delays in disaster response, which may be due to inadequate coordination among various systems and stakeholders.

The design and evaluation of interoperable health systems that can help understand the best possible response strategies can be facilitated by using modeling and simulation to predict the complex dynamics of disaster response scenarios. The design of healthcare systems that consider human decision-making and performance can be enhanced by this approach's ability to illuminate human variables and their impact on effective system interactions. Therefore, to improve coordination and real-time response capabilities during emergencies, research on interoperability between an MFH and a RH is required. Simulation technology helps us find and fix problems in medical and logistical operations, which can improve the efficiency and coordination of important healthcare services.

1.1.2. Purpose of the study

The aim of this study is to develop and implement a health system solution for disaster relief in the context of the oil and gas industry using simulation technology to study and predict patient outcomes. The study seeks to evaluate the impacts of critical parameters, utilizing established modeling and simulation concepts to offer insights into methods that can improve the seamless integration and efficiency of healthcare system operations following disasters. This is achieved through enhanced coordination of responses and better resource allocation. The target of this study is expected to be beneficial and relevant to the oil and gas sector by expanding upon computational concepts to draw attention to gaps that are anticipated to exist in emergency response plans.

To give evidence-based insights into the efficacy and cost-effective application of computational tools in disaster response management and healthcare simulation, this study examines and evaluated important characteristics in a disaster scenario via the use of simulation

techniques and virtual environments. These insights can guide the development of policies and regulations related to interoperable healthcare systems for disaster response and propose policy recommendations that promotes standardization and coordination among different stakeholders involved in disaster response in the oil and gas industry and hospital systems optimization.

1.1.3. Aims and objectives

This study aims to contribute to existing knowledge by examining the challenges of interaction between health systems in disaster environments, focusing on disaster planning and response using mobile field hospitals as a support mechanism. Furthermore, the study attempts to bridge the gap between theoretical simulations and real-world applications, thereby helping to develop decision support before deploying expensive healthcare resources. This research is dedicated to the design and implementation of a solution based on the impact of using a mobile field hospital in disaster situations in the oil and gas sector.

The primary aim of this study is to improve the interoperability between a regional hospital and a mobile field hospital by detailing the process of interaction between the systems.

To answer the study's aim, the following objectives have been proposed:

1. Detail the system and sub-systems of a Mobile Field Hospital via a modelling language-Business Process Model and Notation (BPMN),
2. Model, simulate and implement the interactions between the systems parameters by utilizing Agent-Based Modelling and Simulation (NetLogo),
3. Conduct industrial explosion scenario-based exercises via Disaster Response Tabletop Role-Playing Games (DRTRPGs) to validate the model agents' response decisions.

1.1.4. Research questions

The goals and objectives of a study serve as the basis for developing research questions. They serve as a guide to the methodology, data collection and analysis procedures that are essential for finding solutions. The following research questions were developed for this study:

1. **Research question 1**: "How can the interaction between a Regional Hospital (RH) and a Mobile Field Hospital (MFH) in a disaster setting, and dedicated for oil and gas industry be modelled"? (Objectives 1 and 2),
2. **Research question 2:** "How can a Disaster Response Tabletop Role-Playing Games (DRTRPGs) be used to verify/validate the representativeness of an ABMS model agents' response process in the context of the disaster response scenario"? (Objective 3).

This mixed-methods study is underlined by the research questions that emphasize a process-oriented investigation. The focus is on explaining the step-by-step procedures for modelling and simulating interactions between hospital emergency departments within a hypothetical disaster scenario. In addition, the processes underlying the development and implementation of scenario-based exercises are examined. The aim is to formulate and further develop effective strategies for understanding and communicating the results of complex systems.

1.1.5. Significance of the study

In this study, the significance of modeling and implementing an interoperable healthcare system for the oil and gas industry is outlined as follows:

1. **Knowledge:** This study's findings enhance the knowledge base within the academic and research sectors by deepening insights into healthcare systems interactions, disaster response strategies, and the use of modeling and simulation. This investigation offers a starting point for studying how ABMS can be applied in a disaster context to healthcare simulation while also inspiring fresh perspectives and strategies for resolving challenges related to disaster response. For other researchers or professionals involved with disaster responses. This study serves as a critical point-of-reference that promotes knowledge-sharing while fostering academic collaborations around various topic areas, that is ABMS application to predict and manage disaster outcomes.

2. **Preparedness:** Natural disasters such as hurricanes or earthquakes, along with human-caused disaster including oil spills, explosions, are just some of the hazards experienced in the oil and gas industry, which has led to serious health issues and loss of life. The need for investing in specialized healthcare systems and optimizing response interventions before crisis events can be emphasized by this study's findings. Improving disaster preparedness via pre-disaster simulations will enable industries visualize and understand the possible outcomes in a post disaster setting. This can help create effective response measures with minimal negative effects on human health and safety or environmental damage while also minimizing overall economic loss.

Simulation technology has the potential to improve training and quality control in hospital emergency departments during disasters. However, overcoming organizational and technological barriers requires managerial support, including from the management side and in terms of data sharing. Effective implementation of disaster response and business continuity

strategies could lead to improved planning, execution and management that takes decision-making and human behaviour into account (Kanno *et al*., 2023; Shirazi *et al*., 2022; Umemoto *et al*., 2023). This is important for healthcare operations in a disaster setting as it supports decision-making, saves costs that may arise due to unforeseen errors, and, as a result, delivers high-quality services. The use of simulation techniques in healthcare management is promising because it enables the identification and testing of various potential service designs through quantitative, evidence-informed analysis This method shows potential to improve health outcomes and effectiveness of care by addressing quality, safety, and cost concerns (Kelton, 1996).

The utilization of BPMN to detail and then simplify the process of flow of personnel and resources in the scenario being investigated, can help give healthcare executives a consistent description that allows them to see the processes in the systems. Implementing BPMN as a workflow in healthcare organizations can streamline complex hospital processes and improve the quality of care. BPMN simplifies healthcare processes through an understandable and simple presentation. It offers a simplified view of system behavior and the various resources that support successful processes. Its implementation can also improve the exchange of health reports, thereby enhancing patient care and clinical operations (Faturahman, 2021; Sbayou *et al*., 2017).

To further strengthen and validate the modelling and simulation of the processes, a scenario-based Disaster Response Tabletop Role-playing Game (DRTRPG) is designed to simulate stakeholder's response in real-life like setting. To get the most out of the DRTRPG sessions and to maximize learning, the DRTRPGs are designed to capture as much as possible the critical components of the scenario of interaction within the scene of an industrial accident and the

interaction between the MFH and the RH with needs, time constraint, limited resources, and ethical dilemma of typical emergency responders. This can be an important lesson for triage and some of the critical decisions that must be made in crisis decision situations.

The main idea of the model is to allow professionals and researchers alike to observe how system agents make decisions under pressure and then make them aware of the impact of those decisions. The purpose of this research is not to create a complex replica of a real system using modeling and simulation. Rather, it focused on a simplified hypothetical situation often faced by disaster responders to represent, experiment, and evaluate the possible consequences of decisions made in the aftermath of a sudden onset of a disaster. From the disaster response tabletop role-playing games, the study attempts to find how the situation awareness and decisions from the teams resulted in outcomes, leading to some useful lessons. This will assist other researchers with both similar or different situations to understand and partition their own model and game-based exercises to align with their objectives. In other words, this exploratory research gives future researchers a shoulder to stand on to take the next steps, by showing how to connect the different components in the context of applying simulation methodology in a disaster setting, thus allowing them to decide which aspect is of interest to be added to their model.

1.1.6. Motivations of the study

Healthcare systems encounter various challenges such as difficulties in interaction, a lack of real-time data sharing and analysis, and the demand for patient safety and response efficiency in an intricate and dynamic environment. This underscores the necessity for:

1. **Enhancement of response plans and coordination in emergencies** (Kostyuk *et al*., 2020)**:** The ability to coordinate responses during or after an emergency is a critical component of disaster management as it can significantly increase the effectiveness of disaster response efforts. The enhancement of response coordination involves several aspects, including stakeholder identification that will be involved in the intervention, a defined centralized command center, updated and effective operating procedures, and regular exercises and training (scenario-based simulations).
2. **Assessment of the impacts of key factors in disaster response** (George & Kumar, 2022) **:** Enhancing the effectiveness of disaster response efforts relies on evaluating key factors in the disaster setting. These factors encompass resource availability, response coordination systems, the interactions and interferences among these elements, and the preparedness of the response team. The identified factors can then be modelled to simulate their impact in various scenarios, which can reveal gaps in the response intervention.
3. **Identification of gaps in disaster response plans** (Goniewicz *et al*., 2021)**:** The minimization of the effect of a disaster is highly dependent on the effectiveness of its disaster plans, especially in hazardous and complex operation environments such as the oil and gas industry, which can have serious effects on worker safety, the economy, and the environment. A comprehensive risk assessment determines the need for efficient implementation of the disaster response plan, and an effective plan includes a detailed assessment of available resources and their performance. It is essential that response plans be tested (through drills, exercises, and simulations).

1.2. Definition of terms in healthcare simulation and crisis domain

A variety of sub-themes must be considered for the design and implementation of the interaction between a Mobile Field Hospital facility and a Regional Hospital dedicated for response in a hypothetical disaster scenario for the oil and gas industry. To improve understanding of the fundamental ideas and their application in disaster response and healthcare simulation, it is essential to identify and define these terms to clearly delineate the language used in this area of study. Some of these concepts that have been defined include disaster response (including, disaster response coordination, resource allocation), mobile field hospital, regional hospital, interoperability, agent-based modelling and simulation, situational awareness, surge capacity, location for use, business process management and notation etc.

1.2.1. Disaster response

Disaster response is a crucial component of overall disaster management, involving immediate actions to manage the effects of the disaster and reduce its risks. It forms one segment of a four-stage cycle that also includes preparation, recovery, and mitigation. In the response phase, emergency managers work together to organise and implement measures aimed at safeguarding health and safety, providing essential services, and restoring stability. This phase is characterised by the mobilisation of emergency resources, medical aid provisions, and the establishment of shelters (Klein & Irizarry, 2020). Addressing new threats and challenges in system interaction demands enhanced coordination and institutional adaptability. To build sociological resilience, it is essential to establish cross-scale linkages tailored to the disaster's scope and needs. Engaging in participatory planning with institutional actors from initial response organizations and long-term recovery institutions can foster the development of linkages that

enhance legitimacy and trust, thus supporting more integrated and coordinated emergency responses (Baker & Refsgaard, 2007).

When it comes to disaster response efforts, mobile hospitals are valuable resource that can provide much needed medical assistance and support quickly. However, future improvements to these facilities could include the development of intelligence capabilities along with rapid deployment and retrieval features as well as modularization. By focusing on these areas, we could make considerable progress in enhancing mobile hospital performance (Chen *et al*., 2020). Response coordination and resource allocation are two of the critical aspect of disaster response.

1.2.1.1. Coordination in disaster response

Coordination in disaster response refers to interorganizational coordination and network governance that is made up of emergency support functions and interorganisational networks. The resource allocation in the disaster response coordination process is through an optimal distribution of resources to local agencies, national or international organizations and restoration of local agencies as well (Kapucu *et al*., 2022; Sarma *et al*., 2022). To address coordination issues in disaster response, (Guo & Kapucu, 2015), using Petri net computer simulation, investigated coordination in disaster response. A model based on stochastic petri nets was developed as the study focused on interorganizational processes. The performance of collaborative disaster response was demonstrated in the simulation using process analysis. According to (Hossain & Kuti, 2010), a coordination model based on social network is required to explore the potential for distributed coordination in emergency situations, such as emergency

response management. Such a model has potential to enhance emergency response management effectiveness.

By utilizing simulation, Comfort *et al* (2005) was able to evaluate the resilience of an actual disaster response system and identified its breaking point. The findings of their research showed that adopting a simulation-based approach to access core information enhances the efficiency of response actions and boosts coordination across the network of responding organizations. These methods based on simulations highlight the importance of cognitive agents in social system simulations.

1.2.1.2. Resource allocation in disaster response

The placement and distribution of emergency personnel and resources in view of emergencies is the focus of a disaster resposne operations. The distribution of resources, including patient cases such as the hospital mass casualty, is an aspect of the disaster response allocation (Jiang & Ouyang, 2021; Umemoto *et al*., 2023). Due to the increasing frequency and severity of natural disasters on a global scale, it is imperative to improve resource distribution in affected areas. Using a national resource inventory, it will be possible to distribute personnel, facilities, supplies and equipment more effectively across affected areas. By using an agent programming model, this process can be optimized, and response times can be significantly increased (Altay, 2013).

Using their discrete event simulation model in a fictional disaster scenario, Cao & Huang (2012) evaluated four primary resource allocation approaches to determine how to efficiently manage resources during emergency operations. Various asset combinations were examined.

According to the study's findings, random sampling strikes a balance between ethical and practical considerations when allocating limited medical resources during natural disasters.

Sulis & Di Leva (2018) found that process analysis and computer simulation are useful tools for public health management in disaster response scenarios. From a business process management and notation perspective, they compare the results of discrete event and agent-based simulations with real data from an emergency room in a post-disaster scenario. This includes patient arrivals, activities, and resources. According to the authors, once validated, simulations can provide suggestions and different approaches to emergency management problems during disasters. The use of agent-based modelling and simulation to reduce disaster risk in a Pakistani urban area was also demonstrated in the study by Maqbool *et al* (2020). The model focuses on resource allocation for first responders and leverages Geographic Information System (GIS) maps. In a hypothetical disaster scenario, the study compared the resource allocation of two interacting emergency departments based on basic emergency protocols using NetLogo (NL) algorithms. The aim of the model is to evaluate each approach in the context of a disaster simulation and to improve knowledge of resource allocation and collaboration strategies in emergency scenarios.

1.2.2. Agent-Based Modelling and Simulation (ABMS)

Agent-based modeling and simulation (ABMS) is a computational method that simulates the actions and interactions of an individual agent in a predefined environment. This makes it possible to analyze emergent properties from the perspective of the system level (Kraner *et al*., 2023; Wallinger *et al*., 2023; Zschaler & Polack, 2023). Depending on the situation, the word “agent” can have different meanings. When discussing dynamics, the term “agent" usually refers

to the material that causes density changes within gravity flows, such as: temperature, salinity, or volume fraction of the sediment (Salinas *et al*., 2023). On the other hand, in computer science and artificial intelligence, an agent is characterized as something that communicates with itself and other agents. An arrangement of agents working together to solve a widespread problem is called a Multi-Agent System (MAS) (Pérez-Pons *et al*., 2022).

An example of a typical agent interaction model is shown in Figure 3. The agents interact with each other, collect information from their environment and are influenced by both the environment and the other agents through the actions they take.

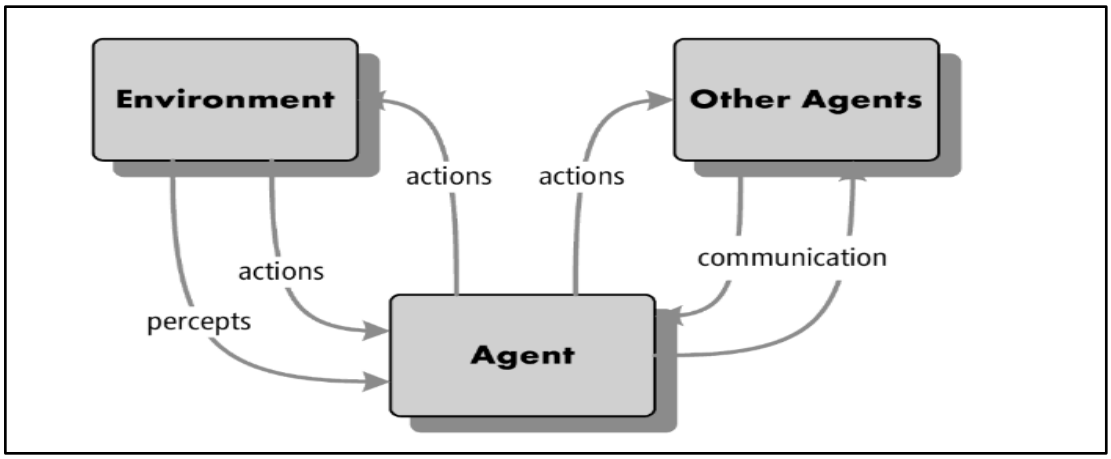

Figure 3: Agent interaction model (Salamon, 2011)

The concept of Agent-Based Modeling (ABM) or Individual-Oriented Modeling (IOM) defines systems primarily through the interactions of their autonomous agents. While ABM draws from fields like robotics, Artificial Intelligence (AI), and Multi-Agent Systems (MAS), its core emphasis lies in modeling human social interactions and individual decision-making (Bonabeau, 2002). The ABMS methodology, which is part of Operational Research Management Science (OR/MS), is becoming increasingly popular due to its ability to link individual behaviour with emergent behaviour that arises from the collective nature of systems. The goal of ABMS is to

understand a problem entity, which can be an actual system, a phenomenon, or policy in place as well as an idea that has not been fully developed (Sargent, 2013).

1.2.3. Mobile Field Hospitals (MFH)

A mobile field hospital is a "A mobile, self-contained, self-sufficient health-care facility capable of rapid deployment and expansion or contraction to meet immediate emergency requirements for a specified period. It can be set up in an existing structure or in a structure, tent or similar, that is brought in with a Foreign Medical Team" (Rossodivita, 2011). Mobile hospitals are hospitals set up to implement prompt treatment of casualties in disasters, and can provide medical aid in natural disasters, but more research is needed to evaluate their interventions and outcomes (Sheerazi *et al*., 2022).

When disasters occur in a complex environment with effect on a considerable number of persons, it is recommended that the kind of response that should be deployed must be adapted to the needs of the affected people. Also, depending on their capabilities, specialized treatments can also be performed. Some of the key features of a conventional mobile hospital include an intensive care unit, technical unit, patient ward unit, emergency unit, medical unit etc. Such a medical system is referred to as a mobile field hospital.

In comparison, the structure, architecture, and application of field hospitals, in a way differ from conventional hospitals. Unlike fixed hospitals, which are designed to address day-to-day health challenges, the health services provided by MFHs are temporary. MFHs are made up of interconnection of both internal and external elements. In the event of a disaster, they provide immediate medical assistance with the aim of minimizing the number of victims, preventing disabilities, and reducing the risk of epidemics by providing on-site medical services such as

diagnosis and treatment. This helps prevent the escalation of injuries and associated costs (Marom *et al.*, 2014; Ramasamy *et al.*, 2009; Zaboli *et al.*, 2016).

1.2.4. Regional Hospital (RH)

A hospital is an institutional facility that offers medical care to individuals suspected of or afflicted with various illnesses or injuries. This care may take the form of observational, diagnostic, therapeutic and rehabilitation services (Islam, 2019). Regional hospitals offer healthcare services to patients situated within a particular geographic area, and in rural or suburban locations they may provide essential medical care to the local population. Examining factors that determine firm mark-ups and evaluating tele-rheumatology service outcomes provided to outpatient clinics are some research studies related to regional hospitals (De Silva *et al*., 2018; Ramathuba & Ndou, 2020; Romero-Brufau *et al*., 2020; Tardivo *et al*., 2017; Wang *et al*., 2014).

1.2.5. Interoperability in healthcare domain

Interoperability refers to the ability of entities to operate together effectively as a group, encompassing various domains from technical to business-related aspects. Over the past decade, interoperability has transitioned from Information Technology (IT) focus to a more business-oriented concern, with its evaluation becoming increasingly important. Its implementation aims to enhance organizational agility, enabling swift adjustments to information systems to facilitate growth and address emerging business needs. This involves identifying potential challenges and exploring practical solutions. As a result, such an evaluation establishes their current condition and gives a roadmap to their future state, assisting businesses in developing tailored reforms and improving their situations. In addition, interoperability refers to the management and exchange

of electronic products and project data between the systems used by collaborating companies for design, construction, maintenance, and business processes, as well as between systems used by other companies. It refers to how effectively systems can use and exchange information (Gallaher *et al*., 2004; Leal *et al*., 2019; L. Liu *et al*., 2020).

In the context of healthcare, interoperability refers to the ability of different healthcare systems to communicate and efficiently use patient data once they receive it. It ensures that medical technology and devices can reliably share, interpret, and present health data in an understandable manner, regardless of where a patient is being treated. This seamless exchange of health information between healthcare providers improves decision-making and requires electronic access to external patient data while integrating care records with Electronic Health Records (EHRs). However, there are significant differences in interoperability between hospitals of varied sizes, which impact both the achievement of universal interoperability and the delivery of high quality and equitable healthcare. The difference between larger and smaller, resource-constrained hospitals is exacerbated by the fact that larger hospitals often devote more resources to implementing advanced features (Healthit.gov, 2013; Pylypchuk *et al*., 2019).

As reported by (Aloui *et al.*, 2006), interoperability is defined as the ability of different elements - people, machines, and applications - to interact with each other to achieve the following goals:

1. **Effectiveness:** This implies that the component must accomplish its task under standard operating conditions.

2. **Stability:** The component should possess resilience to withstand disruptions originating from within the organization or its environment, including other components and the broader system context.

3. **Consistency:** The system should maintain consistency throughout its lifecycle, unaffected by the events and conditions encountered.

The interoperability of a system improves when the resilience of that system is strengthened, and systems become capable of exchanging and cooperating in any scenario. Using agent-based models to predict interactions between hospital systems can provide particularly important insights to emergency response, enabling responders to know what is required during disaster response and what should be done. This proactive approach allows responders to develop intuition and understanding, thus improving preparedness for unprecedented events (Wang *et al.*, 2012). This study examines the process-workflow interoperability that exists between health systems (regional and mobile field hospitals) in a hypothetical disaster response scenario. The goal is to improve response coordination and resource allocation activities through effective patient outcome-focused strategies.

1.2.6. Role-Playing Game (RPG)

Role-playing games (RPGs) are a broad category of interactive media in which users take on the roles of imaginary characters and tell stories together (Thorens *et al*., 2016). These games are designed to improve a variety of skills, including problem solving, collaboration, and strategic thinking (D'água *et al*., 2023). RPGs serve as effective tools for teaching, training, and communication in various contexts, including sustainable resource management and environmental education (Shimabukuro *et al*., 2022). They facilitate learning and skill

development by providing an environment in which users can immerse themselves in different scenarios, make decisions, and experience the consequences of those decisions (Ozpolat *et al*., 2007).

RPGs are designed to teach, guide, and prepare players to overcome a specific obstacle by simulating actual events (Bowman, 2011; Rye & Aktas, 2022). In other applications, Guyot & Honiden (2006) argue that RPGs can be integrated with ABMs and applied in a variety of ways, including but not limited to: (i) Educating stakeholders on decision-making in challenging or extreme scenarios; (ii) Fostering group learning and negotiation among stakeholders; and (iii) Validating and refining model design through observation of stakeholder behavior. The final aspect explored in the use of RPGs constitutes the subject and focus of this study. According to d'Aquino & Bah (2014), when the research objective is to model a particular case, RPG players may be selected from key stakeholders at the case study site. However, participants can be selected from the wider population if the study aims to test a hypothesis, enabling comparisons between distinct groups (Anand *et al*., 2016).

1.2.7. Situational awareness

Situational awareness (SA) is the capacity to perceive, integrate, and make predictions about notable features and qualities of an environment. The goal of SA is to grasp what is going on around you: the main concept is to use previously learned information to detect, analyze, and comprehend the current situation. Time, capital, and human resources are all restricted, thus limited materials and employees must be mobilized swiftly and efficiently. Emergency managers must have a thorough grasp of the situation on the ground to mobilize effectively, especially

amongst organizations with different interests and objectives (Abate *et al*., 2014; Kedia *et al.*, 2022; Stroud *et al.*, 2010).

One of the most crucial components for handling complex crises is situational awareness. Levin *et al*. (2012), asserts that it entails the perception of environmental variables throughout a measure of space and time, understanding of their importance, and projection of how they will fare soon. Effective situational awareness has three levels: (1) recognizing important aspects through active sensing; (2) comprehending those critical factors, and (3) predicting the impact soon, utilizing situational information from the preceding two stages. This level necessitates extensive domain knowledge (Kedia *et al*., 2022). Situational awareness refers to information about events on site in the context of disaster management and response (Mohsin *et al*., 2016).

1.2.8. Location for use

The effectiveness of a Field Hospital (FH) is significantly influenced by its location. While scant literature elaborates on the determinants of FH placement, there is a consensus that they should be positioned near existing local health facilities. This proximity facilitates improved integration with local health services and ensures long-term support (Bar-On *et al*., 2020; Demirel, 2014). Demirel (2014) states that other selection criteria include population density in the region, good access to main roads, the ability to quickly set up FH operations and the potential to optimize bed capacity. In 2003, the World Health Organization published guidelines specifying that site selection must consider victims' accessibility, medical needs, and logistical requirements (Bar-On *et al*., 2020).

According to the study by Deloui & Mofrad (2021), which supports the claims of Bar-On *et al*. (2020) and Demirel (2014), the location of an MFH is of particular importance as it

influences how effective a disaster response operation is. However, they also maintained that several other considerations need to be contemplated when selecting a location for these facilities. These factors include;

1. **Integration with existing healthcare infrastructure:** Whenever possible, mobile field hospitals should work in coordination, with hospitals and clinics complementing and supporting their efforts. By integrating with the existing healthcare infrastructure, the overall response effort can be optimized.
2. **Accessibility:** Roads to be used for the delivery of medical supplies and personnel and for the public must be easily accessible from the hospital. This ensures that victims arrive at the hospital on time for treatment and hospital care runs smoothly.
3. **Safety:** Safety must be the top priority when choosing a location and considering risks such as earthquake aftershocks, floods, or conflict areas. Protecting the environment is critical to protecting healthcare workers and patients.
4. **Proximity to population:** The hospital should ideally be located near places where the affected population is highly concentrated. This shortens travel time. It also allows faster access for patients in need of medical attention. In order not to hinder ongoing rescue and recovery efforts, it is important to strike a balance and ensure that the hospital is located a sufficient distance from the disaster site.
5. **Conditions:** The chosen location should consider the weather and a solid surface for setting up tents or other structures. It should also be free from hazards such as floods or landslides that could affect operations or jeopardize safety.

When designing an ABMS model for a disaster scenario that involves the use of an MFH, it is important to consider as many of these factors as possible. In this way, the operational challenges that arise in a real scenario can be precisely represented in the virtual model. This allows for advance planning and preparation, ensuring that in the event of a Sudden Onset of Disaster (SOD), the mobile field hospital can be placed in the best possible location to treat victims quickly and effectively.

1.2.9. Business Process Management and Notation (BPMN)

Modelling processes in healthcare using Business Process Model and Notation (BPMN) is a recognized standard. By combining BPMN with simulation techniques, it is possible to analyse and improve workflows in the healthcare sector. For example, to simulate medical interventions, a model-based methodology was developed. This methodology creates executable simulation code using BPMN as the process specification (Antonacci *et al*., 2016; Sbayou *et al*., 2017). BPMN can be used to simplify and represent healthcare process flows and components when simulating healthcare disaster scenarios. This helps evaluate process performance, identify issues, perform "what if" analysis, and explore improvements. In healthcare, combining BPMN with simulation techniques can create reliable models for resource management, cost analysis and process optimization. This integration can have significant benefits for certain areas, including treatment, emergency department operations and disease management (Bisogno *et al*., 2016; Tomaskova *et al*., 2019).

Planning resource allocation, patient management, and crisis response coordination is facilitated when BPMN is used in simulation studies that focus on healthcare interactions in disaster scenarios. To do this, a Business Process Model and Notation (BPMN) is used. By using

BPMN for process representation in healthcare modelling and simulation, organizations can improve their preparation and response to events such as disease outbreaks, natural disasters, industrial accidents, and emergency situations.

1.3. Methodology of the study

1.3.1. Introduction

This section provides an overview of the methodology used to achieve the aim of the study. It combines agent-based modeling and simulation methodology (using NetLogo 6.3.0) in a mixed, quantitative, and qualitative strategy and a tabletop disaster response serious game. By employing a comprehensive computational system modeling and simulation framework to investigate the intricate system dynamics involved in implementing the proposed response aligned with the research objectives and utilizing collaborative scenario-based tabletop role-playing to delineate a detailed approach to a hypothetical disaster response scenario, this section elaborates on the rationale behind the chosen strategies. The concluding aspects of the chapter explain the reasons for using a disaster response role play to validate the ABMS prediction capability and how to implement it, including information on how to plan and implement the disaster response scenario game and a summary of this introductory chapter.

1.3.2. Computational system modelling framework

The identification of concepts being studied, and their relationships carried out utilizing a hypothesized model is known as a conceptual framework (Tott, 2013). Moreover, crucial scientific and engineering tools have emerged as models to represent and solve problems involving multi-faceted systems in several fields. To achieve these objectives, I propose use both System Thinking (ST) and Computational Thinking (CT) and incorporate crucial aspects from

related processes and literatures on ST and CT, to propose a comprehensive framework. This framework also shows how these aspects of ST and CT are expressed in computational modeling by showing how every modeling practice incorporates elements of ST and CT to solve problems or clarify phenomena. The purpose of this framework is to provide guidance for researchers and educators in designing effective learning activities that integrate ST and CT into modeling contexts, to enhance skills around study (Shin *et al*., 2022). A representation of the processes involved in computational systems modelling framework is shown in Figure 4 .

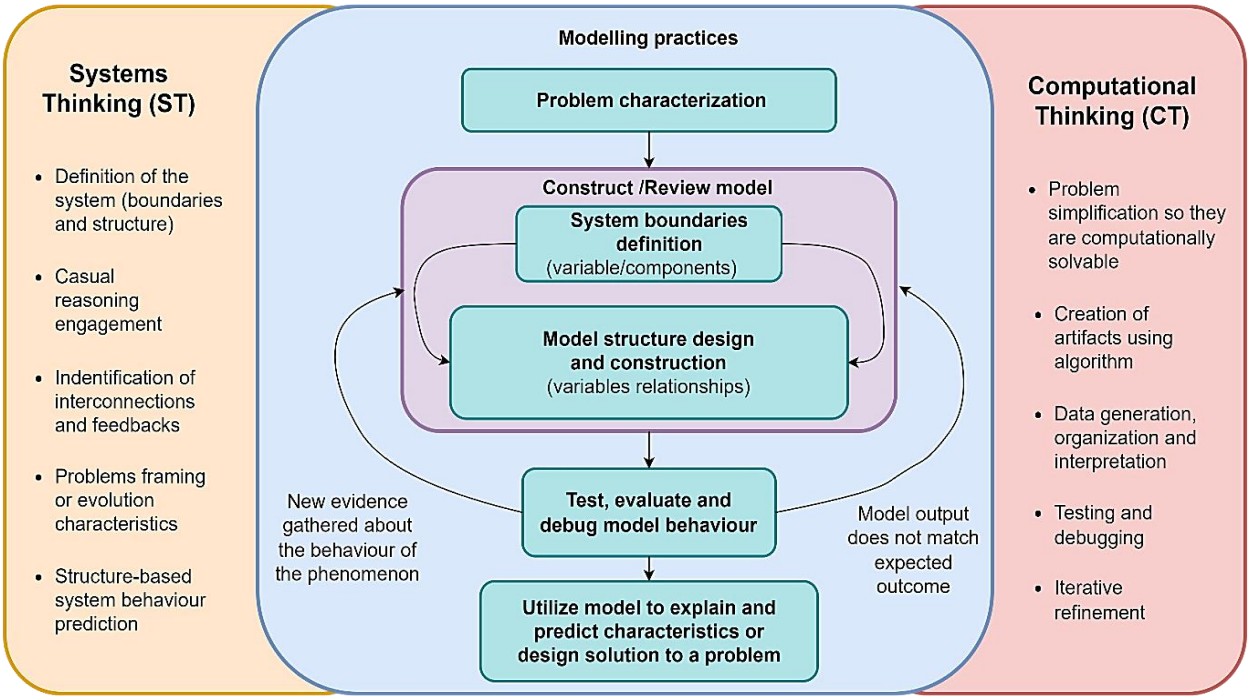

Figure 4: Computational systems modelling framework (Shin *et al*., 2022).

Due to the complex and uncertain requirements in healthcare modeling, especially during disasters, researchers encounter numerous conceptual and methodological challenges. Contemporary trends show an increase in simulation-based research in this field. Conceptual frameworks used in this research provide a robust foundation for modeling the intricate dynamics of public health disaster responses, including interactions among components and the

environment. Open-source agent-based modeling frameworks like NetLogo or Mesa are commonly used to model entities like patients, doctors, hospitals, or clinics.

In summary, the computer modelling method used in this study involves developing, implementing, experimenting, and validating a computer-based model, which can be modified to study other similar or different complex systems depending on the objectives of the study. Other aspects include analysis and refinement, which are essential parts of the computational methodology. This powerful framework enables researchers to increase understanding into the behaviour of complex systems that may be difficult or impractical to study using traditional empirical methods.

1.4. Development of research methodology

It is important to clearly delineate the distinct phases in developing a simulation model to understand the workflow of how critical disaster response factors can impact healthcare systems. This can be achieved through a combination of agent-based modelling and simulation and a role-playing approach. Such exploratory (mixed) research using simulation strategies and a collaborative game in disaster response can be effective in predicting and understanding the intricacies of complex operations and preparing health systems, emergency responders and authorities for actual disaster events. Scenario-based exercises allow teams to realistically respond to different scenarios, increase awareness of real-time threats, and test existing policies and procedures in the most realistic environments possible.

These methods aim to uncover weaknesses in organizational preparation and resource allocation and to help refine plans to effectively deal with emerging disasters. Additionally, they can serve as a valuable resource for policymakers in developing best practices to address the

growing complexity of current disasters. The methodology used in this study to address the intricacies of hospital system interaction design is summarized and illustrated in the methodology block diagram shown in Figure 5. It presents the simplified steps associated with fundamental aspects of the generalized modelling and game-based simulation framework.

Figure 5: Methodology implementation process block diagram (Amakama, *et al*., 2023).

1. A **conceptual model** was first developed based on a hypothetical scenario. The concept considers a RH operating in a location and engaged in routine triaging and treatment of patient. In addition, there is an oil and gas industry operating around the region, which experienced an industrial accident leading to explosion (sudden onset of disaster), prompting the deployment of the MFH as a supporting healthcare system to help reduce mortality outcomes from patients from the incident site.

2. Employing BPMN, the **components and subcomponents** of the MFH) designed for deployment in the oil and gas industry were outlined. This process describes the essential healthcare services required for disaster response interventions, tailored to address the anticipated injuries and illnesses typical in an oil and gas industry scenario.

3. The **concept** was simplified by assuming and equating both healthcare systems as EDs. According to (Sayama, 2023), complex systems must be simplified because of their unique features (networks, self-organization, emergence, nonlinearity) which are rarely understood. This approach is further supported by literature: it is not practical

and also impossible to have a model of every aspects in a hospital (Günal & Pidd, 2010); EDs accounting for at least half of the primary entry point into hospitals; need to address the challenges of EDs preparedness in disaster response; and the need for EDs readiness in response to all types of disaster (Clancy, 2007).

4. Using the conceptual model's assumptions as a foundation, which is supported by literatures, **algorithm/agent-based** model was developed to generate dataset of the emergent outcomes (as patient deaths variation) and then analysed. Furthermore, the modelled scenario was transformed into a scenario-based tabletop role-playing games to generate results to attempt to validate the predictive capability of the ABMS model.

Using these simplified concepts presented in the methodology, the simulation model was developed following detailed methodological processes, discussed in chapter 3 of this document. In this study, I assert that the utilisation of modelling and simulation with focus on emergency departments can provide an effective framework for comprehending and optimising the performance of key healthcare facilities, thereby having a substantial effect on patient outcomes and the wider functioning of other hospital systems.

1.5. ABMS predictive capability validation

The ABMS model developed as part of this research is not intended to replicate the interactions between an existing regional hospital and a mobile field hospital during an oil and gas industry disaster scenario. Rather, its objective is to develop a framework as proposed by (Sargent, 2013), which serves to explore and understand the nuances of a specific problem entity. Furthermore, it illustrates the capacity of ABMS to systematically examine and predict various

contingencies within the domain of disaster response management. The ABMS model is based on a hypothetical case that the I developed and implemented. During the validation process, the ABMS model concepts were transformed into a collaborative and relatable scenario-based exercise, and the results are compared with each other (ABMS and DRTRPG), rather than being compared to the real world or another simulation model of a similar nature.

Several studies suggest that, validating ABMS using the classical empirical methods is particularly challenging, as there is typically a paucity of data and ABMS models are often based on future predictions (Anand *et al*., 2016; Gore *et al*., 2017; Marks, 2007; Onggo & Karatas, 2016; Takadama *et al*., 2008; Utomo *et al*., 2022). The results of these studies also demonstrated the difficulty of validating agent-based models in a classical manner due to features such as path dependence, emergence, and complicated interactions, which are worsened by the lack of micro-level data. The complexity of social processes and the stochasticity of simulations were also cited as reasons for the deviation from carefully monitored experiments.

For this study, a scenario-based Disaster Response Tabletop Role-Playing Game (DRTRPG) was designed, as a validation strategy, which highlights a modified ABMs model validation approach as suggested by (Ligtenberg *et al*., 2010). This is summarized below:

1. Create a foundational ABMS model,
2. Create an RPG version of the basic ABM model and assign roles. The baseline model is transformed into an RPG in which the players are assigned tasks that corresponds to the agents in the ABMS model,
3. Execution of the tasks by the participants. The participants carry out tasks like those in ABM.

4. Collect data with the RPG,
5. Contrast the RPG results with the ABMS model outcomes.

This method compares the results of the ABMS model with the results of the RPG (referred to as Disaster Response Role Playing Game (DRTRPG) in this study) to authenticate their conclusions regarding the representativeness of the agents' decision dynamics relative to the observations made during the DRTRPG. In this approach, if the TRPG outcomes can replicate the outputs of the ABM, the agent's decision rule is deemed credible. According to Ligtenberg *et al* (2010), and Amadou *et al*.(2018), it is possible to compare the ABMS outputs with the RPG outcomes qualitatively or quantitatively, or by employing sensitivity analysis to determine the direction of changes or by using descriptive statistics. The following section outlines the organization of the entire study.

1.6. Organization of the document structure

The document is divided into six chapters, including this chapter, which provide the basic context, aim, objectives, research questions, definition of terms and an overview of the methodological process. Chapter two presents an overview of related literature on the application of BPMN in representing simulation processes for hospital components and various simulation strategies such as system dynamics (SD), agent-based modeling and simulation (ABMS), and discrete event simulation (DES). The aim is to identify gaps and understand the implications to determine the most appropriate strategy for this study.

The third chapter details the systematic process of designing and building the ABMS model for this study. It includes comprehensive descriptions of the concepts, processes, and entities (agents) to be modeled as well as their interactions with each other (agent-agent

interaction) and with the environment (agent-environment interactions). In addition, the chapter presents the criteria for selecting ABMS for the study and the assumptions made in model development.

Chapter four presents the ABMS model implementation carried out in NetLogo, the experimentation process and the simulation results for the study, including the developed simulation graphical user interface and the analysis performed on the generated data from the BehavioralSpace function within the NetLogo programming tool. In addition, a sensitivity analysis for the examined disaster response factors (effects of ambulance policy on mortality and wait times outcomes) is presented in the context of the interacting regional and mobile field hospitals for the disaster response scenario. The chapter ends with a discussion and implications of the results.

Chapter Five provides details of the disaster response role play developed and implemented to validate the predictive capability of the ABMS model developed in NetLogo presented in Chapter four, including a summary of the goal, objectives, guidelines and methodology used in the design and implementation of the exercise, data generation, analysis and discussion of the implications of the results compared to the ABMS results.

The concluding chapter (chapter six) provides a summary of the most important results resulting from the methods used to provide answers to the research questions. In addition, the contribution of the study to the scientific field is presented and the challenges and limitations encountered are also discussed. Furthermore, my conclusions regarding the study are presented by contextualizing the answers to the research questions formulated for the study. Finally, the chapter offers recommendations and perspectives for future research initiatives.

1.7. Chapter summary

Chapter one introduces the research context and provides an overview and background of the area of study. It describes the problem statement, scope, primary research aim, objectives, research questions, significance, and motivations. It also presents definitions of important terms and concepts used in the following chapter. The chapter concludes with an overview of the methodology used to answer the research questions and explores the concept of improving workflow interoperability between a regional and a mobile field hospital for the oil and gas industry. This structure of the document is intended to guide readers and future researchers through the research process.

CHAPTER 2

2.0. MODELLING AND SIMULATION FOR HEALTHCARE SYSTEMS IN DISASTER SETTINGS: A REVIEW

2.1. Introduction

Modelling and Simulation (M&S) is central to understanding the dynamics of various systems, particularly healthcare systems. These methods provide fresh perspectives on system dynamics, resource allocation, decision-making of system which in turn improve the efficiency and effectiveness in health care. Chapter 1 provided an overview for this study with a definition of the problem that underpin the necessity for the conduct of the study. The goals and objectives established in the previous chapter bridges the gap between the study 's overall purpose and method adopted its investigation.

This chapter is divided into two parts. The first part reviews previous studies on how BPMN is used to represent complex healthcare systems. The second part examines the importance and application of simulation techniques in operations research management sciences (OR/MS). It provides a detailed overview of common modelling and simulation methods and highlights their use and impact in healthcare, with a focus on disaster relief and hospital emergency departments, to identify any gaps and explain the rationale for the approach and focus of this study.

2.2. Application of BPMN in representing hospital emergency department processes

Business Process management and Notation (BPMN) are valuable tools for visualizing patient flow, identifying bottlenecks, and conducting scenario analysis within the hospital

emergency departments (Sulis & Di Leva 2018a). They are great at enhancing healthcare processes by representing the various elements of an ED. BPMN facilitates the modeling of patient pathways, streamlining workflows, and enhancing performance metrics (Ajmi *et al*., 2018). According to Ajmi *et al.* (2018), optimizing workflow through BPMN representation of ED components in simulation studies decreases average wait times by 11% while enhancing patient care quality. Onggo *et al*. (2018) discovered that BPMN enhances modeling procedures and increases engagement in healthcare simulation studies, by developing an efficient extension model (BPMN4SIM) for describing healthcare processes.

Another study conducted by Sbayou *et al*. (2017) revealed that the implementation of BPMN in healthcare resource management enhanced the quality of care in hospital emergency departments. Additionally, as indicated by Liu *et al*. (2017), the integration of BPMN with ABM offers a diverse perspective on patient distribution, organizational networks, and resource utilization in healthcare environments. The research demonstrates the capability of the proposed model to replicate various emergency departments. This framework within the healthcare sector facilitates the optimization of intricate operational processes.

According to Contreras *et al.* (2022), using a combination of BPMN and agent-based simulation techniques can lead to a thorough understanding of business processes incorporating complex phenomena such as social interactions, human behavior, and nonlinear dynamics. Employing agent process modeling with BPMN enables the organization of agent behavior through process models, thereby enhancing decision explainability and verification (Ramos-Merino *et al.*, 2019). In this research, BPMN was utilized to simplify the interactions within the emergency departments of interacting hospital system, to facilitate the communication of the

ABMS model to stakeholders and users. The subsequent section explores the purpose and utilization of M&S methodologies for modeling and simulating emergency departments in disaster settings.

2.3. The purpose of simulation models

Simulation models serve as powerful tools in business and management research by reflecting real-world dynamics, providing abstract illustrations, and incorporating plausible behavioral assumptions to address complex study problems (Tram, 2022). Figure 6 shows the role of simulation models that depend on the understanding of the system being modelled.

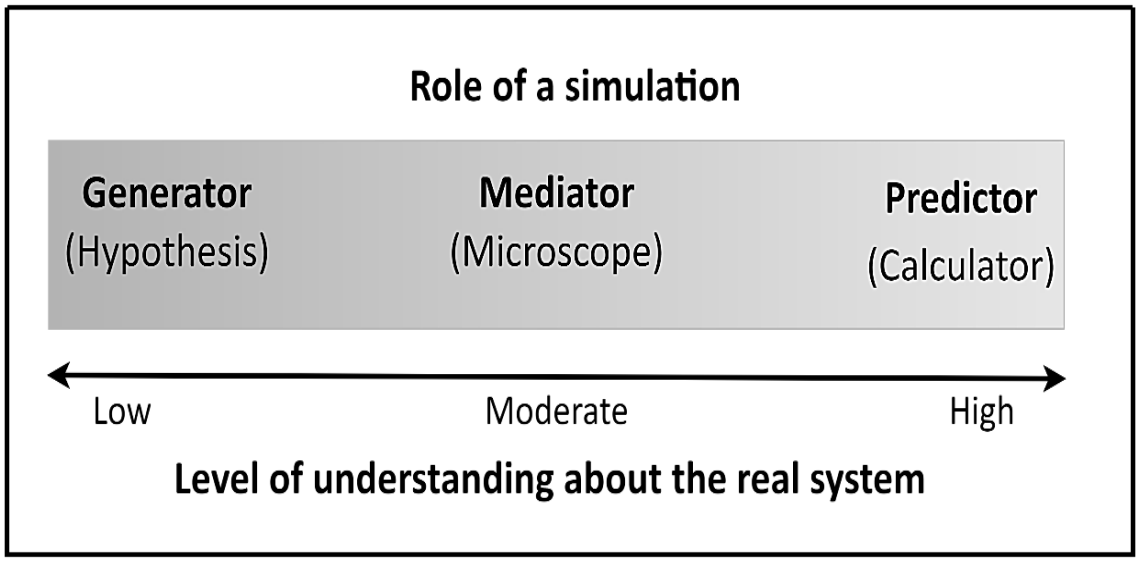

Figure 6: The purpose of simulation models (Katsaliaki & Mustafee, 2011)

The authors explained that simulation acts as a "predictor" when the system is fully understood, like a calculator that accurately predicts the outcome. Conversely, when understanding of the real system is lacking, simulation acts as a "mediator," providing representation rather than precise operations. In cases with very little information, the simulation acts as a "generator" that formulates hypotheses about system behavior. Although they propose theories and hypotheses, the authors assert that simulation as a generator pursues

the same goal as other media: to assess whether the conceptual model or theory accurately reflects the hypothesized system behavior. These three simulation purposes are not mutually exclusive.

In the study of Zi-jian (2005), the author supported the use of simulation as a *"generator"* by stating that simulation research can be beneficial for theory and hypothesis generation since it is a convenient, safe, cheap, and avails an opportunity for exploration of complex systems, data generation, predictions testing and for guiding experiments. The author stated that, the development of generative models of a system;

1. Can assist researchers **understand** the underlying mechanisms of a system's behaviour, which is essential for theory development, adjusting parameters, observing changes, and essential to inferring causal relationships,
2. Provides the opportunity to **manipulate** variables and observe outcomes that would be impractical or impossible to assess in the real world,
3. Is **cost-effective** than real-world experiments, especially when dealing with high-cost or rare events, eliminating the need for physical materials, and reducing the time required to conduct studies,
4. Allows the **forecasting** of the behaviour of systems under various conditions. This can lead to the generation of new hypotheses that can be tested in future research,
5. Can **generate** data that may not be available through empirical research due to ethical, practical, or temporal constraints. Theoretical and hypothetical frameworks can be developed and improved with this data.

6. Can help **guide** the design of practical experiments by determining the range of conditions to be tested and the most relevant variables.

Furthermore, according to Berg *et al*. (2023) and Kanno *et al*. (2020), simulation studies that focuses on hypothetical systems can help in improving disaster preparedness and response in rural setting. They argued that in such setting, simulation studies can help improve disaster resilience, aid in the efficient design and management of hospital exercises and serve as a decision support tool in resource-limited environments. In this current study, I developed and implemented an adaptable and modifiable agent-based model to improve the workflow interoperability between interacting EDs of hospital systems in a disaster setting for a hypothetical case, by leveraging on the capabilities of both BPMN and simulation technique, including a disaster response tabletop role-playing game (validation). The goal is to be able to generate theory and guide future research directions.

2.4. The application of modelling and simulation in healthcare

Modeling and simulation are widely used in healthcare and serve as essential tools for understanding and improving the intricacies of healthcare systems. Myriad studies emphasize the transformative impact of simulation-based learning on holistic improvements in healthcare ecosystems. These methods facilitate research, understanding and refinement of health management and policy formulation (Lamé & Simmons, 2020; Saleem & Khan, 2023). M&S have emerged as an indispensable tool, ensuring preparedness and resilience in crisis settings (Basaglia, Spacone, van de Lindt, *et al*., 2022; Berg *et al*., 2023; De Rouck *et al*., 2023). The results of these studies offer numerous benefits: from assessing the effectiveness of emergency plans to stress testing response capabilities to simulating patient flow within hospital districts.

Furthermore, they emphasize the potential for restructuring disaster plans with computer simulations to improve disaster management strategies and ensure smooth coordination in crisis situations.

Discrete Event Simulation (DES), System Dynamics (SD), and Agent-Based Modelling and Simulation (ABMS) find extensive applications within healthcare systems, serving as dynamic methodologies to enhance resource management and simplify operations, particularly in resource-limited contexts (Mwanza *et al*., 2023). In this study, the authors assert that DES, SD, and ABMS can be used in the development of effective response plans for healthcare facilities and serve as cost-effective tools for intervention planning and performance forecasting. DES has wide application in modeling and simulating various aspects of healthcare systems, including waiting times, patient flows, and resource optimization. It supports the representation of problem scenarios within a system, integration of components and identification of solutions (Vázquez-Serrano *et al*., 2021; X. Zhang, 2018). Simulation techniques such as DES, SD and ABMS are becoming increasingly common in healthcare. These approaches support decision-making and effectively address the complex, multi-layered structure of healthcare systems. The application of these simulation methods is discussed in the following sections, with emphasis on their use in EDs.

2.5. Discrete-event simulation in modelling Emergency Departments (EDs)

Current research in the field of healthcare simulation maintains that the focus for implementing Discrete Event Simulation (DES) is in emergency departments (EDs) (Castanheira-Pinto *et al*., 2021; Palomino Romani *et al*., 2023). These studies demonstrate the flexibility of DES in addressing healthcare challenges, particularly in hospital emergency departments where resource allocation and patient flow management are critical components. Several other studies

have also demonstrated the popularity of DES for simulating disaster response scenarios and in optimizing resource allocation (Y. Liu *et al*., 2023), simulating patients flow (Forbus & Berleant, 2022) and in the prediction of patients wait times in hospital systems (Basaglia, Spacone, Van De Lindt, *et al*., 2022). DES promotes efficiency and reduces patient waiting times by supporting the evaluation of techniques such as centralized resource allocation and First-In-First-Out (FIFO)-based planning (De Santis *et al*., 2023). In Figure 7, we see the representation of research papers (2004-2023) related to the use of DES in OR/MS research area, for ED.

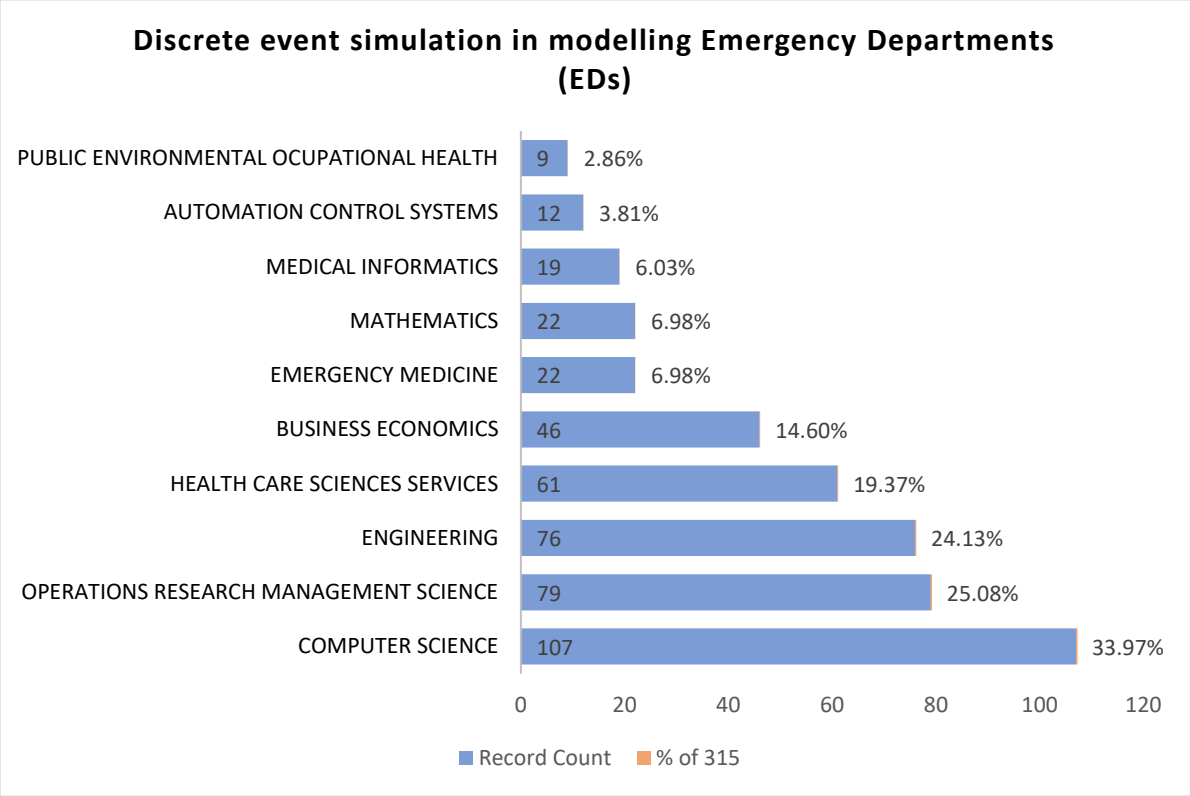

Figure 7: Discrete event simulation in modelling Emergency Departments (EDs).

The use of DES in OR/MS for ED is well documented, with 79 papers accounting for 25.08% of the 315 records searched. This highlights the role that DES plays in optimizing processes, allocating resources, and improving system performance in ED settings. Computer Science (CS) again produced the greatest number of papers with 107 records representing 33.97%. This

indicates an incorporation of computer science principles in modelling and simulating ED operations due to its relevance to DES related aspects such, as software development, algorithm design and data processing.

Despite the established advantages and widespread use of DES in modelling healthcare systems there are still challenges to overcome during the implementation phase. According to a study conducted by Vázquez-Serrano *et al* (2021), less than 10% of DES applications in healthcare result in implementations after the modelling stage. This indicates a gap between the development of models and their practical application, which emphasizes the need for research and development in this area. Additionally, as mentioned by Forbus & Berleant (2022), although DES is an effective tool, it may not encompass all aspects of healthcare systems. As a result, hybrid simulation models that combine DES with methods such, as SD or ABMS have emerged to address this limitation; however, this integration introduces complexity. ABMS has gained popularity as a method for modelling healthcare systems and in evacuation-type simulations.

Nevertheless, the application of M&S to ED modelling has not been directly investigated in disaster response scenarios involving the deployment of a mobile field hospital to assist in triage, transport, treatment, and outcome assessment following an oil and gas explosion disaster. The following section describes the areas and extent of use of SD and ABMS in EDs for disaster response scenarios.

2.6. System dynamics in modelling Emergency Departments (EDs)

The EDs for disaster response settings have been improved through the effective application of system dynamics simulation. Emergency physicians can optimize outcomes by using this approach to model patient flow, resource allocation, and response strategies. Applying

system dynamics also helps emergency physicians create effective communication frameworks such as the Incident Command System (ICS), ensure coordinated responses to emergencies, pinpoint bottlenecks in the triage process, and provide insights into improving patient wait times and overall quality of care (England *et al*., 2023; Farcas *et al*., 2021; Ferreira *et al*., 2020; G. Zhang *et al*., 2021). The application of SD in various research fields, shows a rising trend. Literature search yielded a total of 61 results related to the application of SD in OR/MS for EDs in disaster setting as shown in Figure 8.

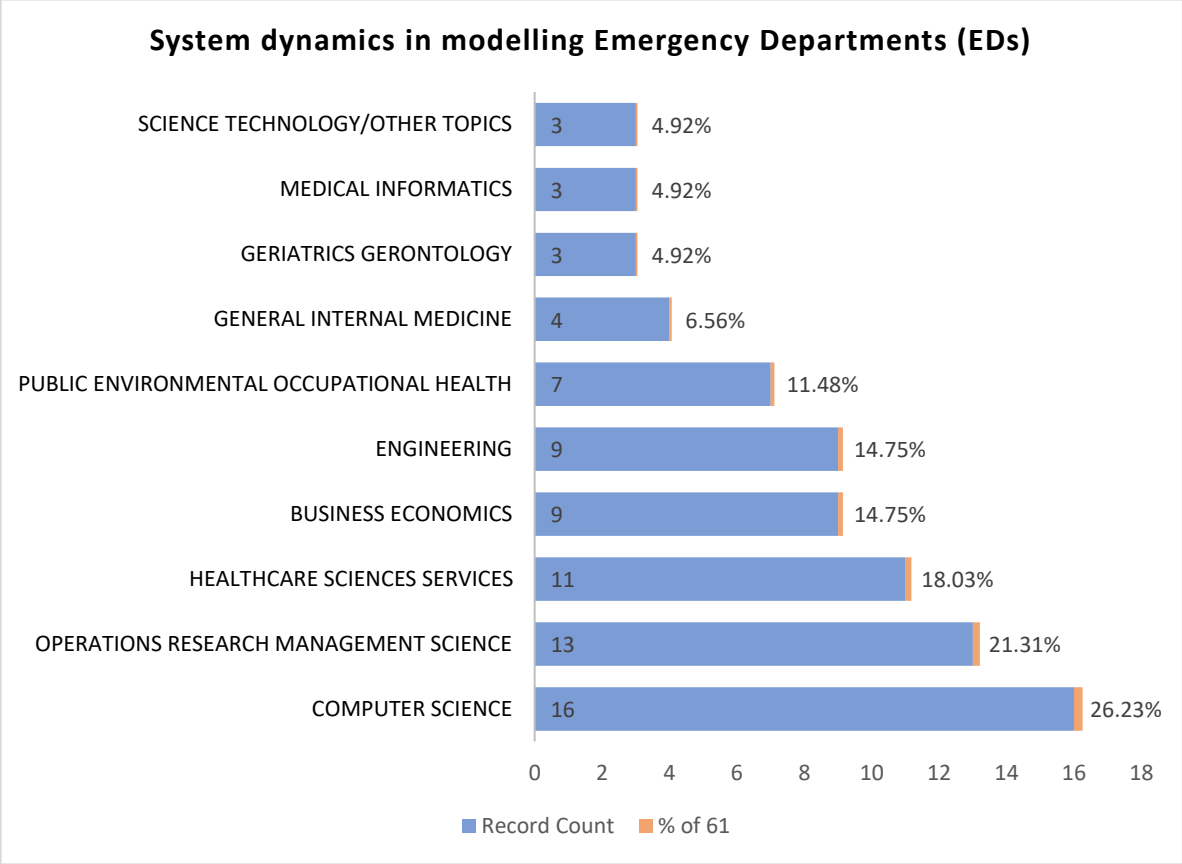

Figure 8: System dynamics in modelling Emergency Departments (EDs).

As anticipated, the use of SD in computer science-related studies for EDs holds the highest record, accounting for 26.23% of the total studies conducted. This indicates that when it comes

to modelling emergency departments, the field of computer science is commonly associated with system dynamics. It also suggests that computational approaches and algorithms play a significant role in this study area. OR/MS represents 21.31% of the total records, suggesting a considerable level of system dynamics application within the domain. The high percentage in OR/MS compared to other fields implies that system dynamics modelling is more heavily utilized for its analytical and optimization capabilities rather than solely focusing on medical or age-specific considerations within the context of emergency departments.

However, it is widely recognized that statistical modelling at a level as permitted by SD may not be suitable for capturing the complexities of diverse populations at an individual level. This limitation becomes particularly relevant when modelling EDs, as the characteristics of both clinicians and patients along with their individual interactions play a crucial role in representing various aspects of ED performance. According to Gullett *et al.* (2023), SD may be unsuitable for capturing the intricacies of diverse populations at an individual level due to their emphasis on system-level processes and feedback loops. Hence, it is understandable that there is no substantial evidence regarding the application of SD in this context. A more significant research study tends to focus on exploring the connection between individual behaviour and ED performance, to which DES and ABMS are better suited for.

2.7. Agent-based modelling and simulation application in OR/MS

Modelling techniques in operations research management science have a wide range of applications, with certain approaches being preferred due to their effectiveness in solving specific types of problems. Discrete event simulation and system dynamics are more common in healthcare modelling compared to ABMS (Robertson, 2016). As with DES and SD, results from

literature search shown in Figure 9 reveals that Computer Science (CS), having a total of 29,531 (41.97%) studies is the subject area with the greatest number of papers. The results obtained for OR/MS regarding ABMS usage shows that there is lesser popularity in the application of agent-based methodologies with a 5.97% of the overall records. This low application of ABMS is understandable as ABMS techniques have deep foundation in computer science related development. For instance, in computer science, the concepts of object-oriented programming and distributed computing aligns well with ABMS principles

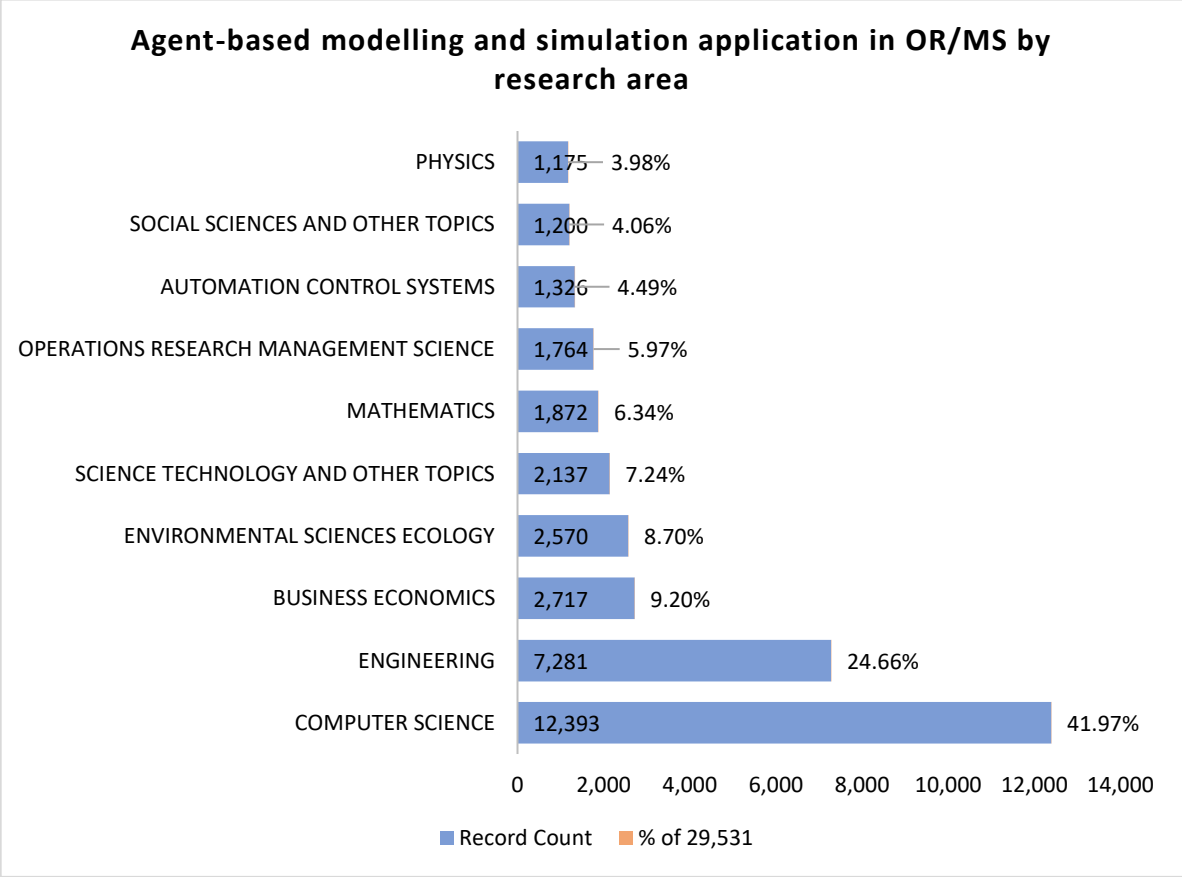

Figure 9: Agent-based modelling and simulation application in OR/MS by research area.

According to Halaška & Šperka (2018), ABMS is highly effective for depicting human behaviours in systems cantered around human interactions. However, its application in OR/MS

remains limited. This is partly because ABMS deals with complex systems, such as EDs, where patient flows are unpredictable and intricate. Additionally, ABMS relies on equation-based modelling, which differs from the graphical notations employed in established simulation methods like SD and DES used in OR/MS. This difference in modelling approaches contributes to the slower adoption of ABMS in this field. Despite these challenges, ABMS has demonstrated potential in fields such as intelligent transportation systems, where it has been successfully applied to model urban traffic control systems (Pilla & Patel, 2009).

Another reason is that developing a model in ABMS often requires extensive data on individual behaviours and interactions. However, such detailed information may not always be available or necessary for the issues being addressed. Agents can represent data or processes that interact within an environment, making ABMS an ideal choice for studying complex systems such as social networks, ecological systems, and market behaviours, where individual components function autonomously and complexly.

In contrast, the focus of OR/MS has traditionally focused on optimization and efficiency within predictable and controllable systems. Therefore, although ABMS provides opportunities to examine emerging behaviours and system characteristics resulting from individual actions, it may not always align with the goals or parameters of typical OR/MS modelling projects. Nevertheless, agent-based modelling and simulation has also shown promising growth in usage in Operations Research/Management Science (OR/MS). As techniques and data accessibility continue to advance, these methodologies are expected to address complex, and dynamically evolving problems characterized by individual agents' interactions.

2.7.1. Agent-based modelling and simulation in modelling Emergency Departments (EDs)

Studies have highlighted the increasing use of ABMS methodologies in the modelling and simulation of EDs. In a review carried out between 2007 to 2019, on the use of simulation-based optimization methods for hospital EDs, the 38 analysed studies identified areas for further research (Yousefi *et al*., 2020). In another study by Su *et al*. (2021), ABMS was developed to simulate emergency room evacuation while assessing rescue strategies and their impact on traffic and evacuation times.

A systematic literature review by Barghi Shirazi *et al*. (2022), identified the aspects and elements that play the most crucial role in the simulation of EDs during crises and disasters. The review highlighted several factors such as human resource management, medical services, resource allocation etc. The study goes further to highlight the different applications of ABMS in solving various problems in hospital EDs, including power reduction, the development of evacuation plans and strategies, and patient scheduling. Figure 10 shows this study's WoS review of literatures on the application of ABMS in modelling and simulating EDs, between 2004-2023.

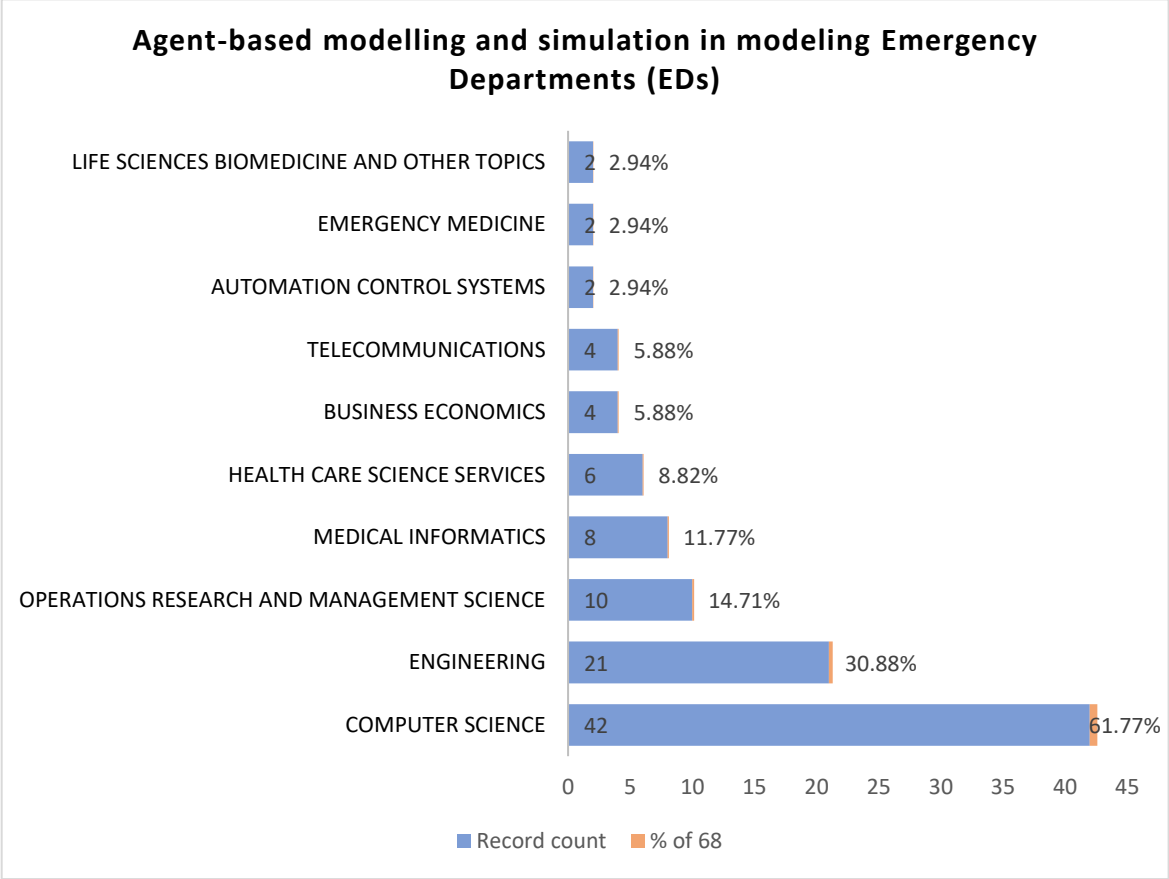

Figure 10: Agent-based modelling and simulation in modelling Emergency Departments (EDs).

Based on the hits returned for this review, ABMS finds application in approximately 14.71% of all WoS recorded studies. The data presented in the chart indicates a growing interest in the utilization of ABMS to address operational complexities in ED in a several OR/MS research areas. The results further highlight the interdisciplinary approach on the use of ABMS in improving patient care in emergency situations, by improving operational efficiencies, and overall patient care.

Other studies have utilized ABMS in similar and related domains to maximize patient flow in ED resource planning and recommended the integration of DES and ABMS (Y. Liu *et al*., 2023). ABMS have also been shown to play a critical role in the improvement of the emergency communication, and evacuation plans, especially in high-risk and heterogeneous crowd

situations (Naim *et al*., 2021). One further example of a higher-level application of ABMS is the development of an ABMS simulation for an emergency department by Liu *et al* (2017). They designed a tool to aid in policy analysis, understand intricate behaviours, and productivity enhancement. The actions of patients and staff were replicated in their model that utilized basic ifs rules. Their model primarily addressed agent actions, activities, waiting times, and staff scheduling.

Finally, Kanagarajah *et al* (2008) developed and examined a hypothetical agent-based model and simulation of an emergency department. The primary objective was to evaluate the influence of economic factors and workload fluctuations on patient safety. The model included various agents including patients, doctors, nurses, technicians, treatment rooms and managers. Each active unit is programmed to mitigate adverse events with a focus on favourable patient outcomes. The model determines a patient's treatment based on the severity of their disease. However, the rules that govern the behaviour of the agents in the model only take external factors into account and ignore the internal states of the agents.

Based on these premises, we can conclude that agent-based modelling and simulation can also be used for other important hospital components as well as hospital operations. When considering their application in disaster scenarios, it is important to examine how ABMS models have been adapted and applied to overcome the difficulties of providing emergency care under disaster conditions. The gap that this study fills in the use of agent-based modelling and simulation in improving interoperability between EDs in a disaster response operation is discussed in the following section.

2.8. Gap in literature

This review highlights the use of BPMN and M&S techniques in the representation and simulation of healthcare operations during disasters, specifically examining its utilization in EDs. Previous studies have modeled observable processes such as arrivals, queues, and interactions to assess emergency department dynamics. However, compelling evidence is lacking on the impact of strategic factors like evacuation and ambulance strategies on these operations. DES, SD and ABMS have been extensively used in computer science than in operational OR/MS methodologies which are more common in healthcare. Within healthcare, ABMS has been applied more to study disease prevention and epidemiology, rather than at the policy level to model emergency department responses to disasters.

The slow adoption of ABMS in healthcare, especially in disaster settings, is attributed to its high computational demands and the complexity of developing models involving multiple agents. It should be noted that ABMS software may also require in-depth programming knowledge and a comprehensive understanding of ABMS theories. Other challenges that may need to be addressed include data collection and preparation or the complete lack of data. The use of ABMS in the study of complex systems also includes data cleaning and manipulation, which requires a certain level of expertise in secondary data analysis tools. This study used the NetLogo 6.3.0 ABMS toolkit to examine how ABMS can be used to model emergency responses within an oil and gas industry's disaster response framework. The aim is to improve workflow interoperability in the interaction between a regional and a mobile field hospital.

2.9. Chapter summary

This chapter reviewed relevant literature and examined how previous studies have used business process management and notation and simulation methods to improve healthcare delivery, particularly in hospital emergency departments in disaster scenarios. The focus was on the application of simulation techniques such as DES, SD and ABMS. These methods have been investigated for several objectives, e.g., staffing, optimization, coordination, waiting times, patient evacuation, etc., with emphasis on their application in emergency rooms and crisis situations. The results of the literature review conducted in this chapter demonstrate how well these simulation methods are integrated into the study and improvement of various components of disaster preparedness, resource allocation, and coordination in health systems. However, studies that specifically focus on rescue strategies do not appear to receive widespread attention. The following chapter covers the ABMS model creation process and describes the phases and underlying assumptions used in designing and implementing the simulation model using the NetLogo ABMS toolkit.

CHAPTER 3

3.0. THE MODEL DEVELOPMENT AND DESIGN PROCESS

3.1. Introduction

The previous chapter examined how BPMN and simulation techniques are used in healthcare, focusing on their applications in hospital emergency departments and disaster response scenarios. The importance of these approaches for improving health services and understanding complex systems was highlighted. This chapter focuses on the agent-based modelling and simulation development process of this study, drawing on findings from previous studies. The content of this chapter serves as a foundation for understanding the nuances of ABMS model development, particularly as it relates to improving workflow interoperability between emergency department processes and disaster response protocols. The aim is to give readers an insight into the ABMS development process for simulating disaster health systems. It highlights the various aspects of the model development process, such as the definition of model requirements, the conceptual model, the platform-specific model, the simulation, and the underlying assumptions of the ABMS model.

3.2. ABMS development process

Simulation methods such as agent-based modelling, system dynamics and discrete event simulation all share a common development approach. These common properties help improve the effectiveness of simulation methods in applications such as process validation and verification and reduce time and costs during development (Klingstam & Olsson, 2000; Marchetti *et al*., 1998). However, the iteration design may vary between the various M&S techniques

(Robinson, 2014; Tako & Robinson, 2009). One of the most important aspects of conceptual modeling, which represents a crucial component of both modeling and simulation, is the conceptualization of the simulation model from the system under study (Al-Fedaghi, 2016; Freebairn *et al*., 2016; Robinson, 2015). This aspect of the M&S design and development process (conceptualization) is typically considered the least understood, but is a crucial part of simulation studies (Durán, 2020).

The conceptual model development phase of the model design process includes concept formulation and evaluation. The next phase involves translating the conceptual model into a computer-based version using appropriate computer software. Another crucial aspect in the model development process is the verification and validation of both the conceptual and computational model through comparison with real or alternate data sets. This concept of integrating conceptual and computational strategies is what defines the Systems Thinking (ST) and Computational Thinking (CT) framework described by Shin *et al* (2022) in subsection 1.3.2 (Figure 4). After the model design phase, the computer model is used to generate and collect new data about the behavior of the phenomenon under study to deepen the understanding of the modeled concept.

In the methodology used to design the ABMS model for this study, Salamon (2011) outlines a detailed, step-by-step approach to developing ABMS simulation models in four phases, as shown in Figure 11. These phases are "requirements definition." "Conceptual model," "platform-specific model" and "simulation model." Each phase consists of specific steps that contribute to the overall modeling approach. The first two phases include the conceptual modeling phase, while phases three and four focus on the simulation procedures.

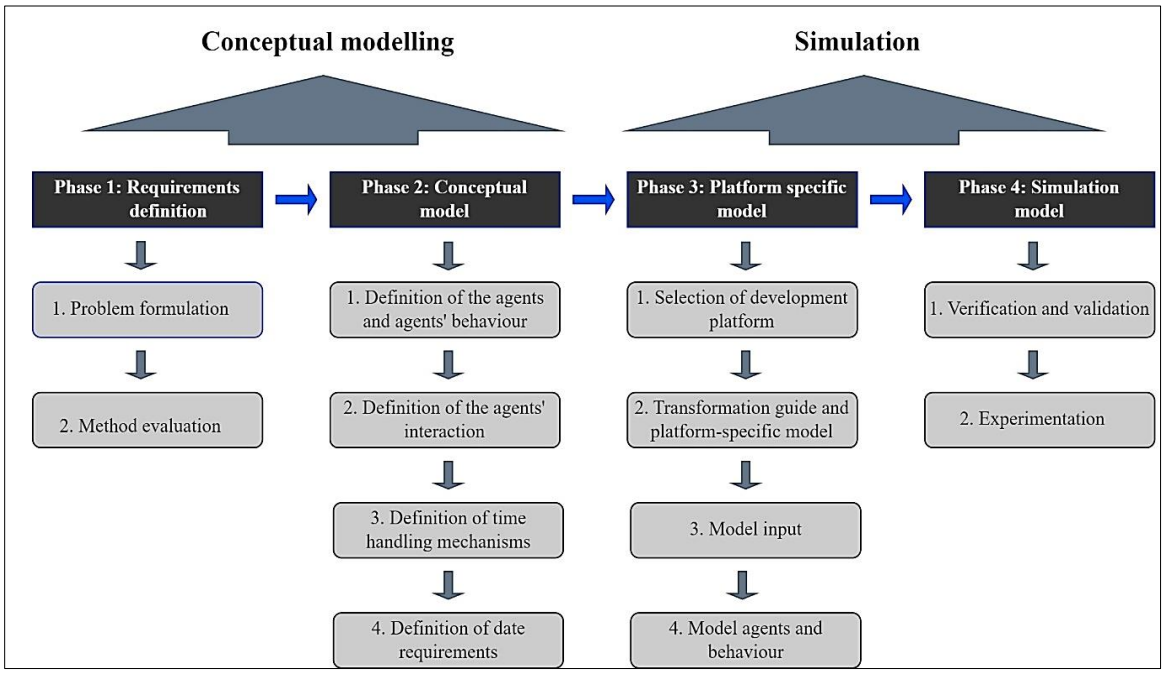

Figure 11: Methodology for ABMS process development. Adapted from Salamon (2011).

3.3. Phase 1: requirements definition

From the more general requirements definition phase, we focus on the first step of problem formulation, where we clearly define and express the problems this study aims to address. This step serves as a bridge and shifts the focus of the study from a broad perspective to the specifics of the model development process.

3.3.1. Step 1: problem formulation

Characterization of the problem under study using ABMS is the first step in this phase, regardless of the software application used, as described in (Salamon, 2011). At this point it is important to consider six aspects: **“The problem:** give an overall description of the problem”, **“The model processes:** identify the processes”, **“The model entities:** describe the entities involved in the processes and their properties and define what they want and what they do and how they interact with each other", **"The model environment:** Explain the characteristics of the

environment and their interrelationships and interactions with the entities", "**The objective:** define the purpose of the study, what measured should be, how it should be measured and what questions should be answered", "**The validation:** how to evaluate and test the developed model".

The model problem

In earlier chapters, it was mentioned how EDs are intricate and ever-changing environments. EDs serve as the primary entry point for hospitals, accounting for more than half of all admissions (Uriarte *et al*., 2015). The challenge lies in the fact that emergency rooms must not only handle emergencies but also manage, evaluate, prioritise, and treat patients alongside those seeking care. This leads doctors to navigate between meeting their patients' clinical needs and working within the constraints of their resources. As a result, the various scenarios that unfold during healthcare delivery constantly influence the decisions made by healthcare professionals. These complexities are represented in the context of this study as a hypothetical response scenario, with EDs of a regional and mobile field hospital interacting.

The hypothetical disaster response scenario

As part of a test case modelling and simulation study scenario as shown in Figure 12, this study considered an oil and gas industry explosion resulting from routine operations needing intervention from healthcare systems. The scenario begins with a Regional Hospital (RH) conducting routine activities (triage, treating, hospitalization etc.). Also, happening simultaneously in an oil and gas industry, are routine daily activities, including cutting, welding, grinding activities, which results in an explosion. The RH is prompted to respond to the victims of the explosion (first responder), however, sensing surge and delay (wait times for patients to be treated) in attending to victims from the incident site (due to distance, resource limitations etc.),

request is made for assistance from a Mobile Field Hospital (MFH) to assist in the transportation, triage and treatment of the victims.

The implemented model I developed addressed cases of both a fixed and/or normally distributed number of injured individuals, one to six available ambulances, and the location of the RH and MFH without initialization of their positions based on real/local data. The location for use of the MFH is set up at a distance of 0.3 hours (18 minutes) from the site of the explosion, to assist the RH (0.9 hours/54 minutes from the incident site) in response to the disaster with the theory of the MFH deployment, location and assistance expected to reduce the overall mortality outcome and waiting times of the victims. The MFH is modelled to become operational four hours after the request for assistance, located closer to the incident site etc. as suggested by Bar-On *et al* (2020); Deloui & Mofrad, (2021); and Demirel (2014) to satisfy the critical factors necessary for the location and use of MFH in a disaster response case (Section 1.2.8). For instance, the UMPEO (the Multipurpose Mobile hospital Europe Occitanie), an innovative mobile hospital that is designed for deployment as emergency centres or intensive care units, has the capability to be mobilized within one hour. It is transportable by truck and autonomous for a span of over two hours, successfully providing medical assistance to 266 patients over a two-week period (Houze-Cerfon *et al*., 2023). Furthermore, as mentioned by Rezapour *et al* (2018), the overall survival rate of sudden-onset disasters can be increased by proportionately optimizing the allocation of emergency units to affected sites.

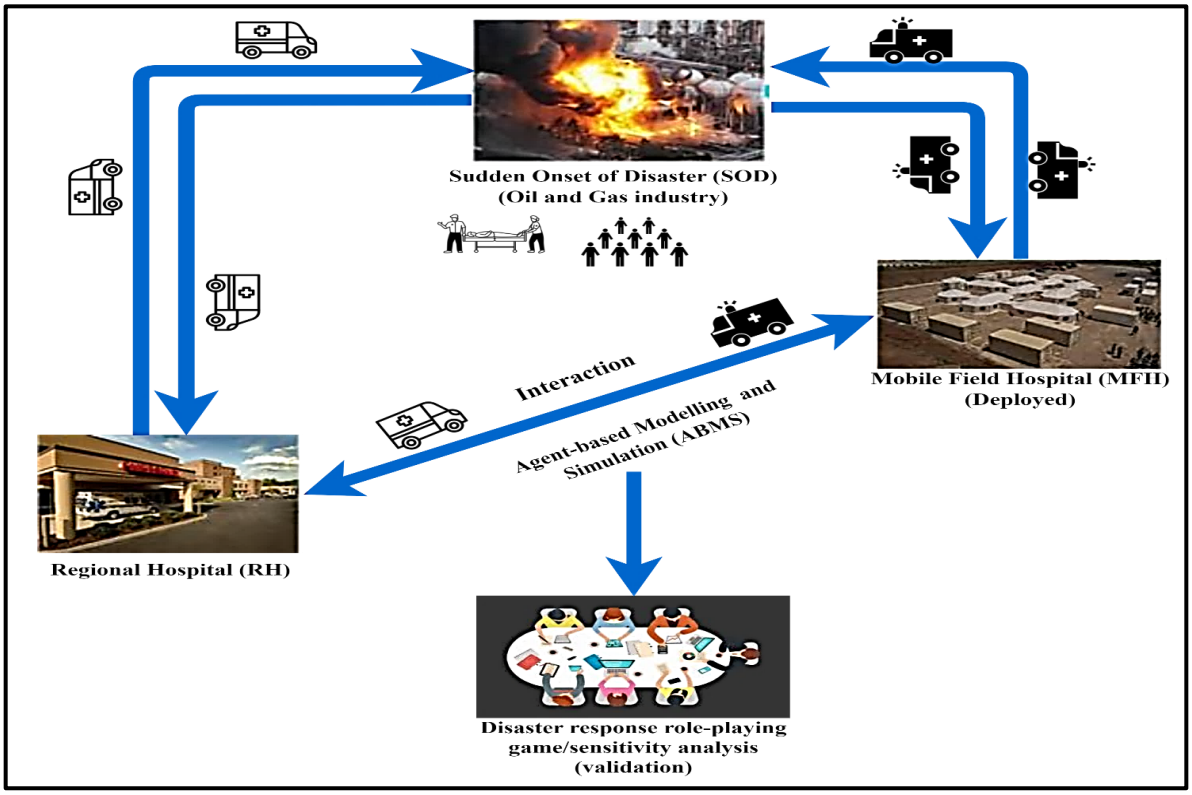

Figure 12: The hypothetical disaster response scenario (Amakama, *et al*., 2023b).

The distribution of the patient's severity is assumed and set at 20%, 30%, and 50%, for severe, moderate, and mild injuries, respectively. The distribution of victims preceding a disaster are either obtained from historical data, epidemiological modelling, experts' opinions, or outcomes of simulation experimentation (Guha-Sapir *et al*., 2015). However, according to Ouhmidou (2020), EDs are a category of healthcare institutions where intensive services must be provided to victims of a disaster, irrespective of prior knowledge of the severity distribution of the patients. Therefore, the choice of severity distribution in this study is justified. It examines how ambulance policies affect deaths and mean patient waiting times in a disaster response scenario involving two interacting health systems functioning as simplified emergency departments.

1. The model processes

Figure 13 shows a simplified outline of the ambulance-patient flow in the EDs to and from the incident site and via walk-in as a chain of activities represented in Figure 12. New patients are typically sent from the triage room to the preoperative room or to the preoperative room based on their severity index. In this triage scheme, a color-coding system is used to identify patients' needs blue indicates non-urgent care, orange indicates patients of moderate urgency, and red indicates patients requiring urgent and immediate attention.

The process of attendance to the patients follows four simple rules, the First-In-First-Out (FIFO), ambulance deployment strategy, and triage-prioritization that is based on the time left to live of the patient (Al Halabi *et al*., 2022; Fava *et al*., 2022; Sigle *et al*., 2023; Van Barneveld *et al*., 2018). Both the patients with severe and moderate conditions have limited time to live if not attended to, however, the mild case patient that are assumed to have injuries or illnesses that are not life threatening are not expected to die. When the pre-set time elapses without treatment being achieved, the patients (severe and moderate severity) die off and are moved to available the morgues. Also, death can occur at any stage in the process, including at the incident site and throughout the EDs processes, but not at the operating rooms or wards.

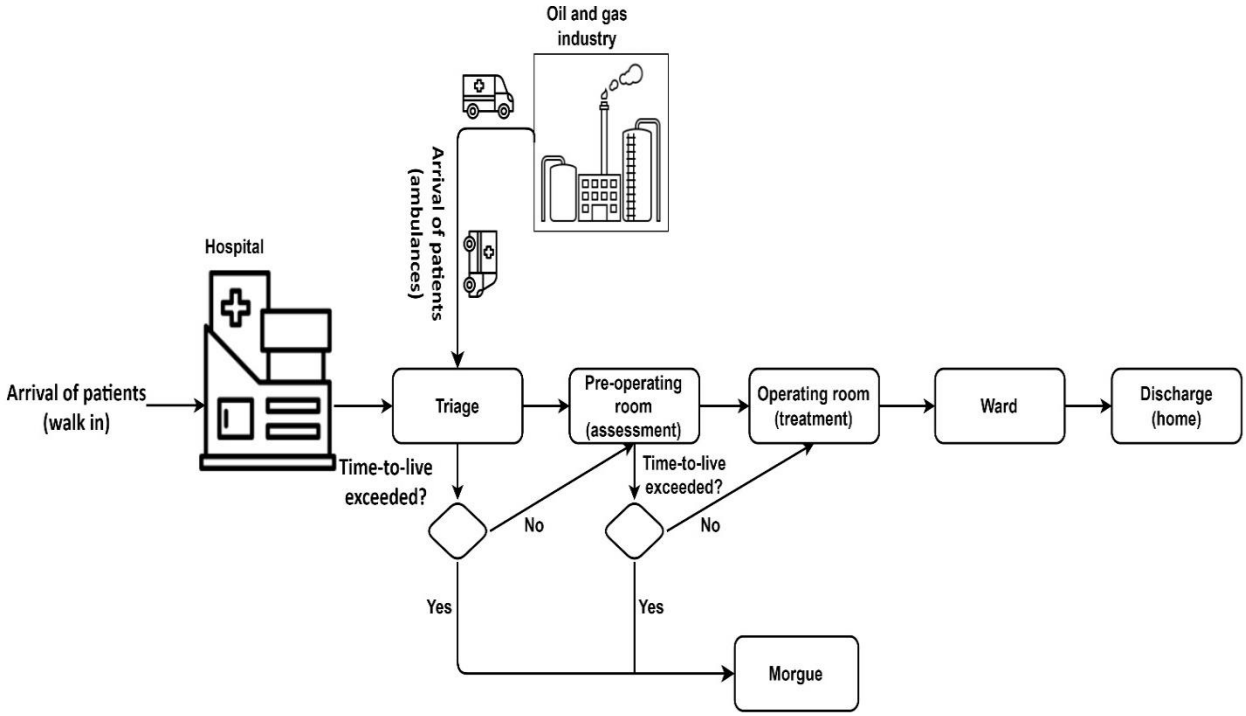

Figure 13: Process flow for the interacting incident site-hospital system.

With respect to the interaction with the incident site (oil and gas industry), the process is designed with 1,2,3,4,5, or 6 ambulances starting at the RH just after the incident when the clock starts ticking on hours-to-live for the patients, that are created at the site (room), alongside other patients that can be set to trickle through the EDs at pre-set rate. Until the MFH arrives, the ambulances would be evacuating patients from the incident site to the RH. However, once the MFH arrives, the ambulances would take the most severe patients there first until the expected waiting time to be seen at the MFH is longer than the time needed to take the serious patients directly to the RH, then the ambulances run would skip the MFH and go directly to the RH.

2. The model entities

The key entities modelled in the process are:

1. The room/stage where the patients are arriving from (e.g. incident site) or goes to (triage, pre- operating rooms, operating rooms) for treatment are agents, having their awareness and decisions that is based on their objectives,
2. The ambulances/vehicles are agents with awareness and decisions based on their defined protocols and objective, which is dependent of the activities of other agents in the process.

The overall system can also be viewed as a unit, potentially functioning as an Incident Command System (ICS) for a disaster response environment to manage and coordinate the response to a sudden onset of a disaster. This includes a clear chain of command, established roles and responsibilities, and specific procedures for communicating, assessing the situation, and responding to the emergency.

3. The model environment

A range of factors contribute to this uncertainty, including patient demand and the length of service process activities. Additionally, the conditions of the environment evolve as decisions are made by entities, which are characterized by three dynamic features. First, the influx of patients into emergency departments (whether through walk-ins or ambulances), fluctuates over time. Second, the workload in triage, pre-operating, and operating rooms can vary based on agent conditions and severity at any given moment. Thirdly, the availability of resources like ambulances for patient evacuation to EDs may vary depending on patient volume or their time to live within the system.

4. **The model aims**

The ABMS model in this study was developed to understand the value of incorporating a disaster scenario into simulating interactions between emergency departments as part of the study objective. Specifically, the model aims to simulate the impact of introducing a mobile field hospital to collaborate with an existing regional hospital on patient outcomes during disaster response, evaluating how well the two hospital systems can interoperate. This model simplifies the essential components of typical emergency departments, depicting interactions between patients (as agents) seeking treatment for their medical conditions based on severity and the resources needed to transport and care for victims at the disaster site using ambulances.

5. **The model validation**

To generate data and conduct predictive tests that may be useful as a baseline model that can be adopted and manipulated to guide future research, the ABMS model developed in this study demonstrates how disaster response settings can be incorporated into health simulation for an ABMS model hypothetical case. The goal is not to replicate the interactions of EDs in a disaster scenario for a real-world scenario. Therefore, the validation process included performing a sensitivity analysis on the generated dataset. Critical elements of the ABMS model were then converted into a Disaster Response Tabletop Role-Playing Game (DRTRPG) to evaluate the results of the ABMS model using game results rather than a real system as suggested by Ligtenberg *et al.* (2010).

3.3.2. Step 2: method evaluation

This step of the model development process presents the method used in evaluating the model design. Section 3.3.2.1 defines the requirements and criteria that verify the use of ABMS

in studies. This provides the basis for ensuring that the decision to use ABMS in the study is both appropriate and applicable.

3.3.2.1. Criteria for ABMS utilization

This stage in the development of the ABMS model focuses on assessing if agent-based approach is suitable for modelling the problem outlined in Section 3.3.1. Identifying a suitable simulation technique does not adhere to a singular procedure to ascertain if one method is more appropriate than another for addressing a specific problem. Nevertheless, specific criteria can offer guidance in selecting one simulation method over another. To determine whether an agent-based method is appropriate for a particular area of interest given the objectives of the study, Salamon (2011) proposes a series of questions that, if answered in the affirmative, can be immensely helpful. These questions include;

1. "**Are there entities that can make decisions**"? In this study's simulation, various individuals such as patients, medical professionals and emergency services personnel are constantly making decisions at distinct stages. For instance, once the ambulances are informed about the state at the MFH, they must assess whether to proceed with transporting patients to either the RH or MFH based on factors like severity of condition and treatment resource availability at both EDs,
2. "**Are there different types of decision-making entities or different types of decisions**"? This model involves various decision-making entities, such as patients, ambulances, clinicians (portrayed as stages in the process) and others. Each of these entities makes a variety of decisions, from patients entering the EDs or progressing to the next stage for

clinician evaluation based on severity, to ambulances choosing to transport a moderately ill patient from the scene rather than a severely ill patient with limited time left,

3. "**Does the system appear to have dynamic characteristics**"? The model for in this study has memory and information that is based on their objectives that affects their future behaviours and the overall outcome of the process in a dynamic manner,
4. "**Is it difficult to describe the whole situation as an activity (with a diagram)**"? Process diagrams such as BPMN can be used to delineate specific elements of the problem being modelled. However, because decisions are made at an individual micro-level, such diagrams may not fully capture the interactions and activities between the parties involved.
5. "**Do we feel a need to treat the overall behaviour of the whole system on a macro level**"? The design of the model is done to meet the objectives of the agents at the individual level. Each of the agent relies on its current and past conditions, as well as environmental information to make decisions,
6. "**Is it difficult to 'count-up' the entities into lump sums and then work solely with such amounts**"? Since different entities are involve in decision-making in the model, it is only possible to group those having similar traits (example ambulances). Nevertheless, individual characteristic plays a role in the overall system behaviour,
7. "**Are spatial factors of the environment important for the simulation**"? the use of spatial features in the model, such as the representation of the EDs and incident site are merely for visualization and does not result in any improvement of system interactions.

By utilizing these seven criteria, all questions within the scope of this study yields positive responses. Thus, it is easy to infer the suitability of agent-based methodology as the platform for the modelling and simulation of the outline problem.

3.4. Phase 2: conceptual model

Agent-based conceptual modelling involves developing a comprehensive overview of the system being analysed. This includes detailing the components, interactions, and behaviours of the agents and their environment. This phase is crucial as it lays the foundation for constructing the computational model. Conceptual modelling aids in defining the objectives of the simulation, identifying key factors, and understanding the dynamics among the agents (Salamon, 2011). According to Robinson (2008), the subjective nature of conceptual models as art implies that there is no singular "correct" model for a given problem. Robinson suggests that the goal should focus on creating a framework that facilitates communication, consultation, and consensus in the design of conceptual models, while leaving room for creativity in the modelling process.

A predominant conceptual framework for various ABMS approaches is the Unified Modelling Language (UML), which is implemented on an object-oriented system (Bauer & Odell, 2005). The use of UML offers the advantage of using symbols that facilitates the model's verification and validation process. Software developers employ UML, a standardized visual modelling language, to design, visualize, and document systems. According to Aslam (2023), the use of UML has application in various industries such as customer relationship management system, education sector, and heterogeneous high-performance computing. However, Business Process Management Notation (BPMN) has proven to be a valuable tool for representing agent-

based models, which is becoming increasingly popular in various areas despite the lack of formal semantics (Halaška & Šperka, 2018).

Using BPMN diagrams when representing activities in ABMS provides a way to simplify the complexity of ABMS processes and make it easier to identify bottlenecks, inefficiencies, and optimization opportunities within the ABMS framework (Sulis *et al*., 2019). The BPMN representation ensures a clear and consistent representation of business processes. When integrated with ABMS, it serves as a valuable tool to visually represent agent interactions and workflows within systems, improving communication and understanding. This can assist organizations to simulate agent's behaviour within business processes, facilitate scenario testing and system performance evaluation (Onggo & Foramitti, 2021; Tour, 2023). For example, when representing entity interactions and activities for the ABM/S approach, the BPMN schema proves to be a valuable tool for simplifying and communicating the entire ABMS model structure. This is demonstrated in the generalized representation of ABM/S using BPMN, as shown in Figure 14.

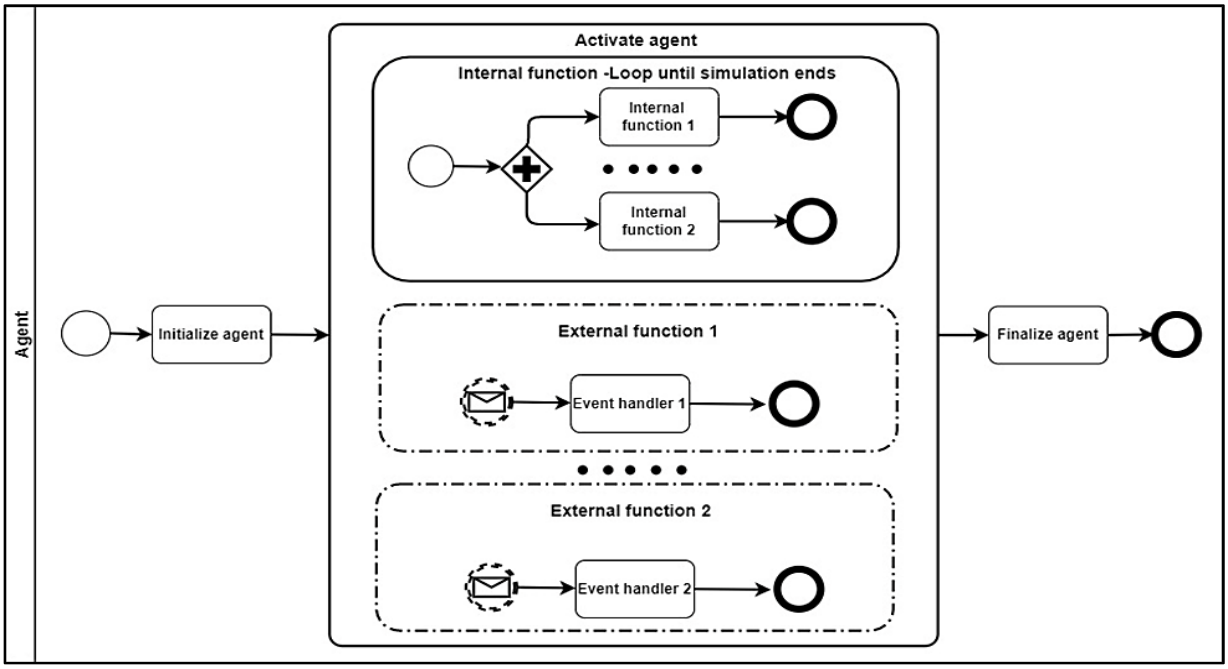

Figure 14: Representation of ABMS process activities using BPMN diagrams (Onggo, 2012).

Specifically, the proposed representation of ABM/S includes two types of BPMN diagrams: the collaboration diagram and the conversation diagram. The collaboration diagrams represent interactions between model agents and are used to illustrate the interactions between two or more agents, while the conversation diagram provides a general overview (Onggo, 2012). This study focuses on the use of collaborative diagrams to represent agents' interaction with the system using simple BPMN objects.

3.4.1. Agents' interactions representation using BPMN

The representation used for the simplification of the various agents' interaction in the model are represented using BPMN flow notations. Figure 15 illustrates some of the fundamental notations widely employed in BPMN activity diagrams utilized for this study.

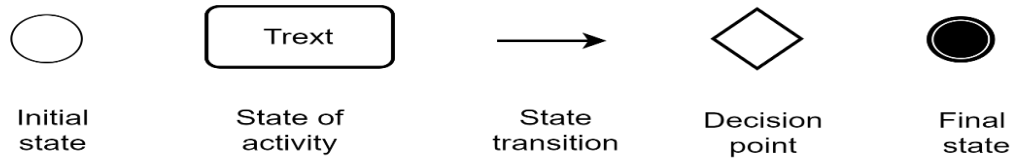

Figure 15: BPMN activity diagrams notation

For example, as part of this simulation study and the applied concepts and methods, the I developed a model using the basic BPMN notations to represent the workflow of the interacting MFH and RH for the disaster scenario, as shown in Figure 16.

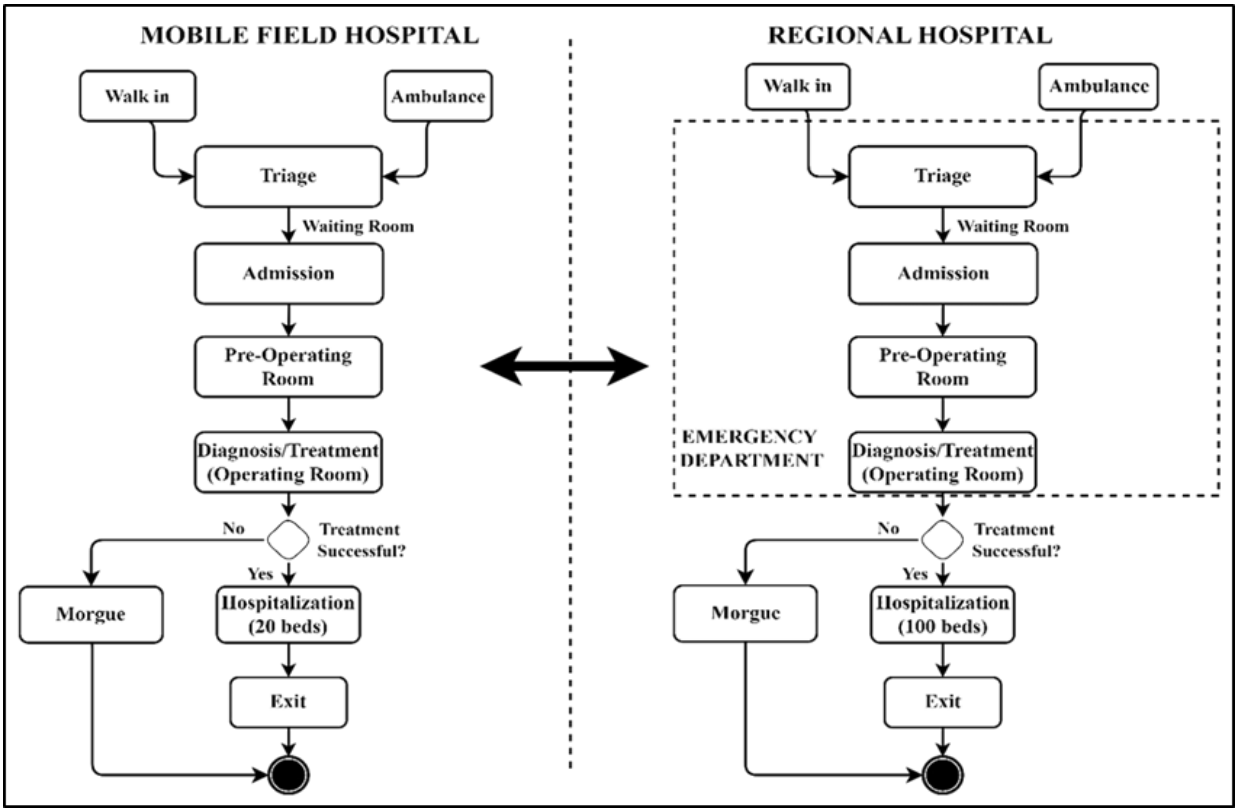

Figure 16: Process workflow for interacting MFH and RH as EDs (Amakama, *et al.*, 2023)

In this scenario, the hypothetical setting (as shown in Figure 16) consists of entities that interact within it. These entities include patients, rooms (like the incident site, triage area, pre-operating room, operating room, wards, and morgues), and ambulances. Each entity follows

simple rules and objectives. For example, until the MFH arrives, the ambulances will keep transporting patients to the RH. However, once the MFH is deployed based on a predefined time, the decision-making process (method, technique, procedure, system) of where to transport the next cohort of patients is influenced by determinants such as the criteria of the patients (time left to live) and the waiting times in pre-operating and operating rooms.

Because the ABMS tool (NetLogo) utilised in this study is not object-oriented (Dickerson, 2011), the I had to use BPMN representation, and structured programming practices as much as possible, to keep all the data structure as easy as possible. Object-oriented programming is to reduce the amount of work it will take to develop a good model. Based on the developed and implemented model, I assert that there is nothing too intricate that requires the application of object orientation activity diagram such as UML for the process representation 9class diagrams), making BPMN sufficient for the study.

3.4.2. The agents and agents' behaviour

Agent-based models are characterized by their ontological correspondence (Gilbert, 2007), which suggests that the entities described in the first phase that represent the modelled system are directly connected to the agents in the model. The agents in this study could read data from the environment and other agents, as well as observe the surroundings using the information they have stored. Agents interpret their surroundings distinctively based on their objectives and present condition. Their decision-making mechanisms can be classified as either deliberative or reactive. In deliberative decision making, an agent evaluates its perceptions, internal state, and goals before deciding. In contrast, when an agent makes a reactive decision,

the pre-set sensor directly influences the agent's behaviour (for instance, the deployment time the MFH uses).

Agents possess the capacity to sense and perceive their surroundings, transition between stages of a process, transmit and receive messages, engage with the environment through resource utilization, and determine appropriate actions. Simple if/then rules make up the reactive behaviour. Patients, rooms, and other entities are specified by the agent of the ABMS model, which eliminates the need for them to make complex decisions and reduces their actions to simple ones like moving and activity. However, when ambulances are simulated as agents, their behaviour becomes more complex as they can make decisions not only about the current states of the system, such as patient deaths, but also about their own internal states and perceptions of the system.

The first activity is to direct patients to the triage room via walk-in (Figure 16). This activity involves interaction between the patient and the triage nurse/triage room (agent). When patients are in the queue for triage or the maximum space for patients is reached, the other patients join the queue and wait for their treatment or die out if the distribution is in the severe or moderate category and the time-to-live is exceeded. Patients check whether there are any vacancies in the next phase and go there to be seen by the pre-operative doctor.

If the incident begins at time t=0, ambulances assess the condition of the emergency responders on site and go there to transport patients. From the scene of the incident, patients are taken to the triage room where they can either join the queue, be given priority over patients with minor illnesses or, in severe cases, be declared dead and taken to the mortuary. If there are no more patients at the scene, the ambulances will either remain there and wait for another

patient to appear, or they will either return to the RH or the MFH (if they are on duty) or, if necessary, they will remain at the RH/MFH was the last Position when the last patients were taken over by other ambulances. For simplicity, all patients are assumed to be of the same undetermined age and gender.

3.4.3. Handling the time factor

Before implementing the model on a specific platform, it is important to consider the model's approach to time management. In agent-based models, simulation typically runs at discrete time intervals during which agents perform specific tasks. The process continues until agents complete all tasks or are removed from the simulation. The model then moves on to the next time interval. Nevertheless, several challenges can arise when formulating a simulation model that uses discrete time increments. The study by (Gilbert, 2007) discusses three of these issues that can arise in handling time factors in simulation models:

1. **Synchronicity:** This refers to the possibility that different agents need to perform different actions at a given time (or step). The model may need to run in a specific order for each action to be invoked. For example, when the simulation begins, the ambulances must update their status and decide what to do. However, when an agent updates its status (the deployed MFH), the ambulances update their status according to the new destination detected by the system. If this goal is not achieved, an error may occur that leads to the simulation being terminated because not all requirements are met.
2. **Inactivity periods:** There are phases in which the agents in the simulation are inactive and cannot carry out any further actions. The simulation then goes through several steps and

checks whether something needs to be done. However, nothing happens until the pre-set sensor shows current activity.

3. **Time calibration:** It is crucial to determine the connection between the simulation time and the modelled scenario. In particular, the modeler should evaluate the importance of each phase of the simulation.

Certain events such as the start of the simulation at the beginning of the incident - occur at regular intervals. However, there are active and inactive times. For instance, the ambulances have a period of high activity at the beginning of the incident, but the intensity of these activities diminishes as the number of patients at the incident site tends to zero. With no patients available at the incident site, the activities of the ambulances come to a stop, while anticipating the next activity to response to in the environment. In the absence of accessible real-world or local datasets that align with the specifications of this study, time (modelled as ticks-per-hour) is assumed and set to 10. In other words, one “go” step (tick) represents (1 / 10) hour (0.1 hour/6 minutes), and reported in decimal hours formats (e.g., 4.2).

3.4.4. Model data source(s)(input/output)/requirement

In this study, I decided against using real data because of the difficulty of data access and to have the freedom to control the specific properties of the generated dataset. Other factors include reducing biases that may exist in utilizing real data, as well as reducing the cost and time required to collect, clean, and prepare the datasets. Since there were no local datasets suitable for the needs of this study, the development of synthetic data proved to be an essential option and strategy to facilitate the investigation and to achieve the study's objectives. The conceptual framework outlined in Sections 3.3 and 3.4 describes a hypothetical system that is likely to occur

in the event of a crisis in the oil-rich Niger Delta region (NDR) of Nigeria. An algorithmic/agent-based model was developed based on the basic principles of this conceptual framework. After the data generation using the BehaviorSpace feature of the NL interface, factors influencing ambulance strategy were examined considering the generated results (e.g., patient deaths). Although the model is valid for its intended purpose, I do not anticipate that stakeholders, organizations, or individuals will use the results of this study as a basis for critical decision making (until calibrated and tested against real-world data).

The goal of the model is to provide valuable insights to stakeholders, including researchers in related fields, by demonstrating that in scenarios with specific shortages, patient accumulation is likely to occur, potentially leading to mortality. Additionally, factors such as ambulance policy are expected to produce promising results. For example, by reducing the capacity of operating rooms, we can estimate the resulting impact on mortality rates. For instance, the implementation of the hospitalist care model (HOS) in an ED led to a significant 50% decrease in mortality rates, demonstrating the model's effectiveness in improving patient outcomes (Yang *et al*., 2019). Unlike typical simulation models, the goal of this study is not to monitor the input distribution and its impact on the output. Studies have shown that overcrowding and long waiting times in EDs can lead to increased hospital stays, negatively impacting patient care and hospital performance (J. Collins, 2021; Mistarihi *et al*., 2023) The model for this study examines the consequences of operating in a scenario with limited or no information. With relevant data, the optimal approach would be to set up input variable monitors and analyse the outputs against the actual target system.

3.4.5. Supplementary assumptions of the model

Building generator models that are based on hypothetical cases often involves making assumptions to simplify complex systems and processes. Other important assumptions made in building the model include:

1. **Assumptions regarding patients:** No health condition depends on the age or sex of the patients, other known "pre-existing conditions" or "co-morbidities." All patients have a specific limit of time they will wait around to be "admitted" after which they will simply move until they get to the home room or die off. This time limit varies by patient, by injury severity, and by each patient's prediction of how long it will be before they are seen.
2. **Assumptions regarding injuries:** Similar kinds of injury exist for all patients which vary only in severity. Both the MFH and RH can treat the different severity of injury. More severe injuries require more time vis-a vis the time the patient will spend in the Operating Room (OR) and recovery room (ward) before discharge. The total number of injuries at the accident scene is defined by a normal distribution characterized by a specified mean and standard deviation. The beta-distribution is asymmetric with the long-tail on the less-severe side. The size (headcount) and severity distribution might be related or independent. The mean, standard deviation and beta-distribution parameters are variables.
3. **Assumptions on time-to-die:** This is the time that a patient must live if treatment is not administered. Patients with time-to-live of less than or equal to 4 hours are color-coded red, those with 8 hours-to-live are coded orange, and those with up to 1000 hours-to-live are coded blue (such patients are assumed to have none-life threatening mild injuries),

4. **Assumption on recovery/ward:** Recovery/ward is where patients go after surgery/treatment. There are a finite number of beds in recovery which cannot be expanded. If the recovery room is full, no patients can be moved from preop to the OR, and the capacity of the ward is fixed at 15 for the MFH and 100 for the RH.

3.5. Phase 3: the platform specific model

Phase 3 focuses on the platform-specific toolbox in the model development process, which represents an essential phase that includes both theoretical and practical considerations. Creating a transformation guide and selecting an appropriate development platform are the focus of steps 1 and 2 of these phases. By following these steps, it is important to ensure that the model developed properly addresses all specific aspects of the defined problem.

3.5.1. Step 1 and 2: development platform/transformation guide/model-specific platform

This section explains the context for the selection of the model-specific platform (NetLogo 6.3.0) by examining the reasons for its suitability as a modelling software for translating the conceptual model into logical codes. It demonstrates the effectiveness of NetLogo as a robust ABMS tool and highlights its features, capabilities, and applications.

3.5.1.1. NetLogo 6.3.0 (ABMS) tool: features, capabilities, and applications

NetLogo (NL) is an interactive tool for modelling and simulating dynamic processes within complex networks. It enables the study of emerging properties, supports the teaching of complexity science, promotes the conceptualization of creative networks, and finds application in modelling and simulating various scenarios, including emergency evacuation (Chatterjee *et al*., 2023; Wahyudiono *et al*., 2022). NL has a non-object-oriented structure, which can lead to

efficient use of computational resources, especially in scenarios like emergency department optimization where computational efficiency is crucial (Dickerson, 2011).

The program facilitates the development and examination of agent-based models. Originating from the Center for Connected Learning, it utilizes StarLogoT1, compatible with Mac OSX, and StarLogo2, a creation of MIT's Media Laboratory. It is StarLogo2 that has notably shaped NetLogo's programming language, Logo3, which draws upon the traditions of the Lisp programming language family. Reflecting on the history of Logo offers valuable insights into NetLogo's philosophical underpinnings (Arnaud *et al*., 2015). Due to its transparency, stability, capacity, and most significantly, because it is an open-source program that can be configured to communicate with various third-party applications, this software was chosen above other simulators for this study. It can simulate not only the process's net result, but also how the result is produced through an incremental stepwise simulation if needed.

The NL platform conforms to a simulation technique known as "in time-discrete intervals", which means it causes a set of entities to evolve in equal-length time intervals. The corresponding modelling method entails selecting the entities to be included in the model and then characterizing their behaviour over time intervals. This strategy focuses on the entities involved, often known as agents. The metamodel in NL distinguishes three categories of entities: (i) The environment: a rectangular area with a regular grid of n x m square tiles (patches); (ii) The turtles (mobile agents): these are the objects that move around in the environment and interact with it and with one another; and (iii) The links: these are generated dynamically between the turtle agents. There is also a distinct agent known as the observer (modeller). The role of the observer is to supervise and regulate the simulation's execution. The observer (agent) develops

and controls the simulated behaviour of all the entities in the model (patches, turtles, and links) (Arnaud *et al*., 2015).

3.5.1.2. Why NetLogo as a tool for modelling and simulation?

The NetLogo software was chosen over other simulators for this study because of its transparency, stability, capacity, convenience of use, and, most importantly, since it is an open-source programme that can be set to interface with numerous third-party applications. NL is capable of simulating and representing a wide range of spatial phenomena that include mobile agents. The software can simulate not only the overall performance of the process, but also, if necessary, the way in which the result is achieved, through an incremental, step-by-step simulation. It is especially suitable for examining the connection between the micro-level actions of individual agents and the macro-level spatial patterns that result from their interactions (J. Gao, 2022). Other justifications for choosing NL are stated below;

1. **Acceptance:** There is considerable evidence that NL is increasingly being used in research and education. The application has been downloaded by thousands of individuals. Currently, there are about 50 downloads every day. There are more than 5,000 users on the announcements list. There are around 1,600 members in the NL discussion group, and it posts about 100 times a month on average. The discussion group's traffic has increased fivefold since 2002 (Wilensky & Rand, 2015).

2. **Reproducibility:** Since one of NL's primary design goals is for results to be scientifically reproducible, it is imperative that models operate deterministically. To achieve true parallel computing programmes must be written appropriately to prevent nondeterminism. As a result, a NL model always executes the same steps in the same

order and produces the same results if the random number generator is "seeded" in the same way regardless of the machine used to run it (Wilensky & Rand, 2015).

3. **Extensibility:** NetLogo (NL) offers two main options for extended communication: the NL Extension API, allowing creation and access of Java objects within NL, and the NL Controlling API, for controlling NL through Java calls from external programs. These APIs are pivotal for NL's successful integration with other software. Continuous improvements in formats, tools, and data sources enhance its extensibility, bridging the gap between user-friendly integrated modeling environments and more complex, versatile modeling toolkits (Wilensky & Rand, 2015).

Using the conceptual model presented earlier in this chapter, a computer simulation model is created as part of the transformation guide. First, the structure of the model was represented by the BPMN diagram, and then the computer model was created using logical instructions. The various parts of the system are then represented through a graphical user interface designed to help stakeholders understand and communicate with the interactions between the model units.

3.5.2. Steps 3 and 4: model input/output

In the context of this NetLogo model development, the model (referred to as MFH-06-6-2) (NL model created specifically for this research) has been structured to facilitate paired runs, which have been named “matching sets”. This suggests that everything stays the same in each set (“pair”), including the random-seed value, so that the difference in the runs is the ambulance policy that is being compared. It implies that a new routine assigns a sequential number to both of a paired run, and then for one of the sets of ambulance-policy to either "always to go RH" and

for the other one of the pairs sets ambulance-policy to "Alternate". It also implies that the number of cases (i.e., say "injured") is random overall, but identical for the “pair” of runs, so what is seen is the impact of the different ambulance dispatch policy.

Using matching set suggests that, in the BehaviorSpace function (for experimentation) of the NL interface, the specific values of input (“ambulance policy,” “injured,” “number of ambulances”) and output variable(s) (“total deaths,” “mean wait”) are easy to track. The code dynamically configures the behavior of the model, ensuring robust and flexible exploration. Consequently, the generated coma separated values (CSV) file contains only the variables necessary to generate statistics and confirm that the correct case matches.

Furthermore, the code executes a difference of the "deaths" count between the different policies to see the improvement that one policy, say "Alternate" policy has over "Always go to RH", and produces charts for easy visualization. In this study, i decided to use the term "matching" instead of "pairs" because in the future, it is expected that there may be need to compare other policies already captured in the code (“always go to MFH”, “shortest wait” or “flip a coin” etc.), to see what the outcome would be and compare to determine the best response policy. The general model agents and their behaviour have already been addressed in sub-section 3.4.2.

3.6. Phase 4: simulation model

The simulation model MFH-06-6-2 (the NL model developed specifically for this study) aims to demonstrate the basic principles of simulating the impact of a disaster on coordination between a regional hospital and a mobile field hospital using ABMS. This model is structured around a hypothetical situation outlined in Sections 3.3 and 3.4 and does not represent any

current system. Hence, the MFH-06-6-2 model executed in NetLogo is not designed to be a precise representation of a functional ED. Several types of NL-specific structured commands such as agent sets, lists, arrays, turtles, patches, links, and global variables have been used to specify how activities should be performed. The model's actions and consequent simulation were defined using procedures, commands, and conditionals (such as 'ifs' and 'else'), and loops ('while' and 'repeat').

3.6.1. Step 1: verification and validation process

In any simulation study, ensuring the accuracy and reliability of the simulation results is essential. Verification and validation play a key role in increasing confidence in the outcomes. Verifying agent-based models is aimed at validating that the agents perform as intended. The validation process often involves the use of model checking and runtime verification techniques (Ferrando & Malvone, 2022). Consequently, the goal of models, which is usually defined at the start of the simulation study, is associated with the conception of simulation precision. There are six types of verification and validation methods used in computing techniques. These include conceptual model validation, data validation, verification, black box validation and white box validation. The focus of this study is on conceptual, black box and white box validation.

It is important to recognize that evaluating an ABMS can be a significant challenge. There have been numerous studies to validate ABMs, but the lack of data and the fact that ABMS models are based on future predictions hinder the validation of ABMs models using traditional empirical approaches (Anand *et al*., 2016; Gore *et al*., 2017; Onggo & Karatas, 2016; Takadama *et al*., 2008; Utomo *et al*., 2022). The research on validating ABMS models highlights the challenges in verifying agent-based models. Studies on these challenges in validating agent-based

models show that traditional empirical validation faces these difficulties at the micro level due to issues such as path dependence, emergence, complex interactions, and limited data availability. In addition, they highlighted the complexity of the processes and the randomness of the simulations as other aspects of concern. These factors may cause the results to differ from those of a controlled experiment.

In this study, validation of the conceptual model was enabled through unit testing of the process logic. The goal of the process was to ensure that every logic from the conceptualized model appeared in some form in the ABMS model. The rationale behind the white box validation is that the concept that the model's logic replicates the operations of the emergency department during a disaster response scenario. The validation process was aimed to confirm that the model accurately represented the patient flow process as outlined in the BPMN conceptual model and that the agent's actions adhered to the decision rules described in the code. To accomplish this, the model underwent debugging at various phases of the development process, with its graphical user interface facilitating the evaluation of the model's behaviour at each stage.

The model's overall performance was assessed using black-box validation, emphasizing functional testing. This method focuses on evaluating the model's functionality without using the code. Techniques such as error estimation, equivalence partitioning, and boundary level analysis were employed to assess the system's behaviour from an end user's viewpoint, typically concerning issues like functionality gaps, usability, and compatibility. The ABMS model data underwent 720 iterations for the analysis, averaging 20 minutes per iteration. Additionally, *Alternate* runs (1,200, 5,000, 20,000, etc.) were conducted to verify the model's consistent and stable behaviour across varying numbers of iterations. For the experiment (the final phase in the

development of the ABMS), the BehaviorSpace feature of the NL program was used and the update graphics button was disabled for large iterations to reduce runtime and speed up model execution.

3.7. Chapter summary

This chapter provides a detailed discussion of the design process for the NetLogo MFH-06-6-2 model developed for this study. It utilizes the generalized framework for computing systems development as proposed by Shin *et al*. (2022), along with the phases of the ABMS design methodology outlined in the step-by-step approach by Salamon (2011). The objective of this chapter is to enhance comprehension of the problem structure by emphasizing the conceptual and simulation dimensions of the model. Through the fusion of a broad system thinking framework with an agent-based modeling approach, this study suggests that the feasibility of constructing a more intricate and instructive model that includes both the macroscopic and microscopic components of complex systems can be achieved. This combined approach enables a deeper understanding of system interactions, which can help make more informed decisions during model design.

The following chapter outlines the final stage of the development phase (Phase 4 – simulation model) within the methodology of the model development process. This also includes a BPMN representation of the model structure and implementation process as well as the results of the experiment, the analyzes carried out and discussions on the factors examined as part of the study.

CHAPTER 4

4.0 EXPERIMENTATION, RESULTS, ANALYSIS AND DISCUSSION

4.1. Introduction

The development and design of the NetLogo MFH-06-6-2 model for this study, which aims to improve workflow interoperability between regional and mobile field hospital emergency departments in a hypothetical disaster response scenario, was covered in Chapter 3. The distinct phases of the model development process were explained, starting from the conceptualization of the model to the simulation phase. This model design approach is holistic and captures both microscopic and macroscopic system dynamics based on established methods and frameworks. This chapter begins by introducing the final phase and step of the model design and development process (experimentation). It then goes into detail and presents the BPMN diagram of the experimental setup and the graphical user interface of the implemented model. This is followed by a presentation of the results, analyses, and discussions, including the implications of the results in the context of the research. Therefore, this chapter highlights the interactions and consequences that can occur between hospital emergency departments in the event of a disaster.

4.2. Phase 4-step 2: experimentation

In this part, we will briefly discuss the final component of the design and development of the model within the adopted ABMS methodology suggested by Salamon (2011). Before implementing the NetLogo MFH-06-6-2 model, agents were modelled to have simple reactive and deliberative rules and goals based on their protocol:

1. The ambulances start heading to the site of the incident as soon as the simulation is started (they receive information about the explosion),
2. The ambulances transport patients from the site, based on their severity distribution, information about the environment and time left to live of the patients,
3. Patients who exceed their total time to live, die off and move to any of the available the morgues,
4. If patients are waiting to go to the next stage (pre-operating room, operating room etc.), then the one with the highest triaged severities goes first (first-in-first-out-severity rule)
5. If the patient gets into the operating rooms on time, they get treated and go on to the wards for recuperation and then go home.

The experiments conducted in this study evaluate the impact of ambulance policies on mortality outcomes and mean patient wait times by examining the interaction between RH and MFH. An ambulance policy is a set of guidelines that govern emergency response times, patient care, ambulance dispatch, performance, and other aspects of an emergency response system. These policies can be optimized using Markov decision process models, which help determine the best ambulance to dispatch to each patient based on various factors like urgency and patient needs (Albert, 2023). A Dell Latitude 5520 11th Generation Intel (R) Core i5 CPU-1135G7 at 2.40 GHz with 16 GB RAM was used for the experiments and synthetic data was generated using the BehaviorSpace feature within the NetLogo 6.3.0 modelling interface.

Figure 17 shows the Graphical User Interface (GUI) of the implemented model. This interface is intended to enable dynamic interaction between the user and the simulation by providing immediate visual feedback on the effects of the changes made and allowing real-time

monitoring of the parameters. The configuration is customizable and can be adjusted to model similar healthcare disaster response scenarios and test different strategies.

Figure 18 shows the BPMN diagram for the setup process for performing simulation runs. It begins with an initial process that requires the user to decide what type of experiment they want to perform. This also includes setting the sliders (e.g. background, matching sets, incident formula, severity distribution, etc.). After the initial setup is complete, the model setup moves to the execution phase (simulation). The "Start/Stop/Step" button starts the simulation process. When patients are present at the scene, the flow of ambulances to and from the scene to the RH and/or MFH (provided the set response time is achieved) is triggered. Data export begins, generating the output in the form of an Excel file and/or Comma Separated Values (CSV) in a designated folder for analysis. Patient status decision points are part of the execution phase, which includes managing patient flow from triage to Operating Room (OR), Pre-Operating Room (Pre-OP), discharge, etc. At the same time, morgues also record deceased patients at any time. To provide visual feedback on the progress of the simulation, the graphics and model clock are continuously updated to show the passage of time in ticks.

The *BehaviorSpace* experimentation step-by-step setup for data sampling and synthetic data generation is described in detail and presented in Appendix B1 to B4. The source code for the model, including comments about the reasons for certain coding decisions and details about how the model works and instructions for its use, is available on my GitHub page at: https://github.com/MFHproject/MFHrepo/blob/main/mfhmodels/MFH-06-6-3.nlogo.

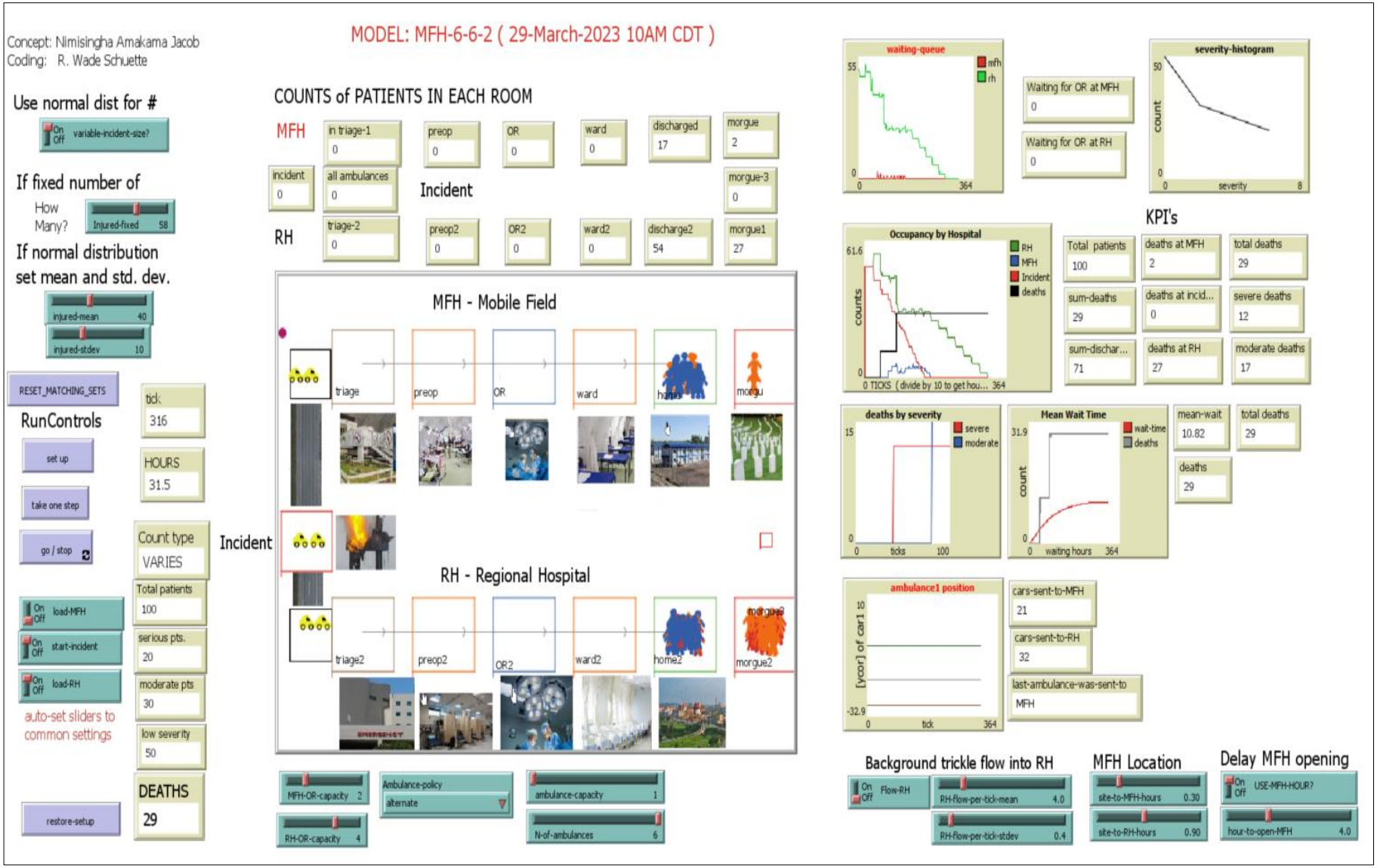

Figure 17: NetLogo (6.3.0) MFH-06-6-2 Graphical User Interface (GUI) (Amakama *et al*., 2023).

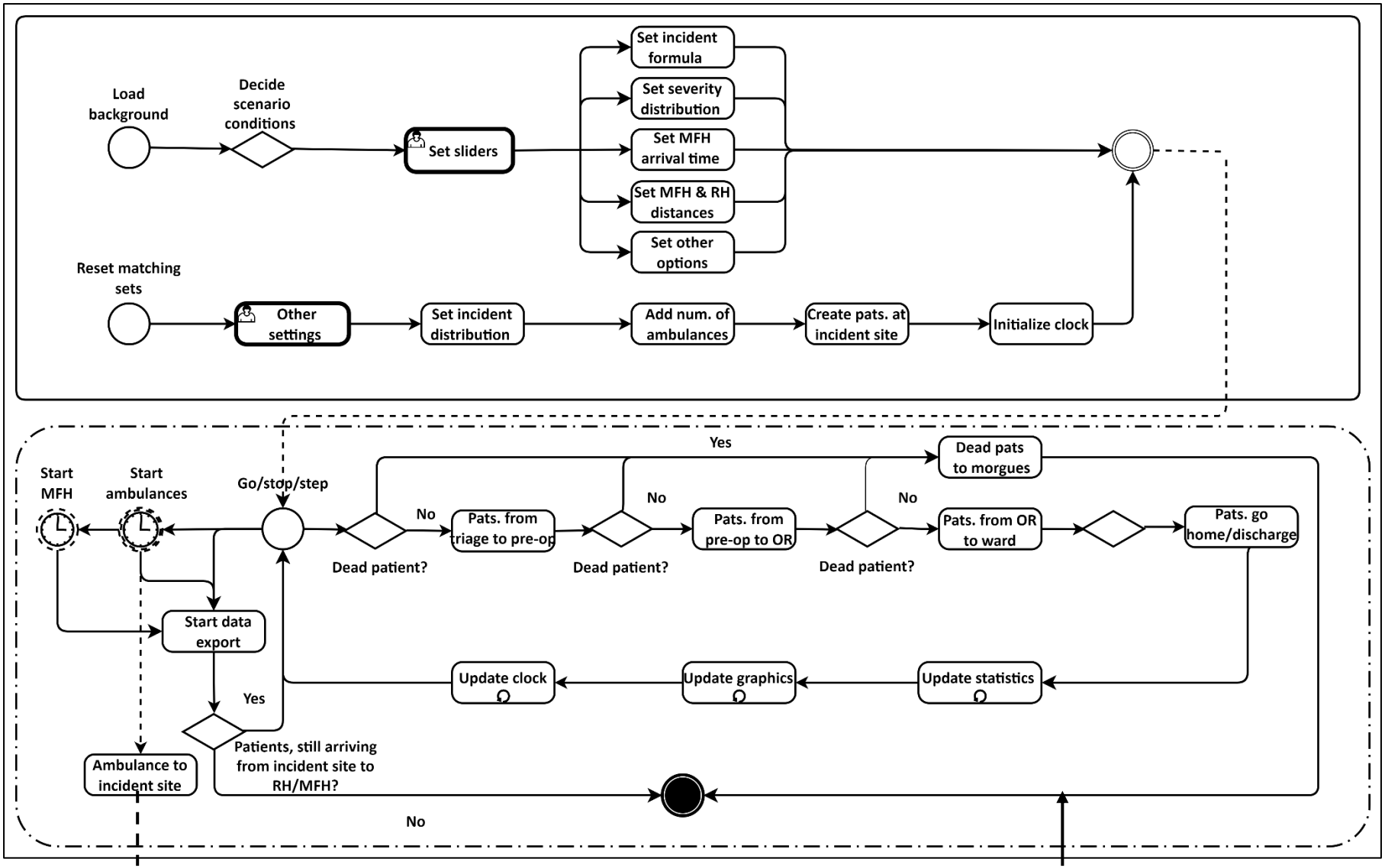

Figure 18: BPMN diagram for MFH-06-6-2 GUI simulation set up (Ambulance-policy)

Continued

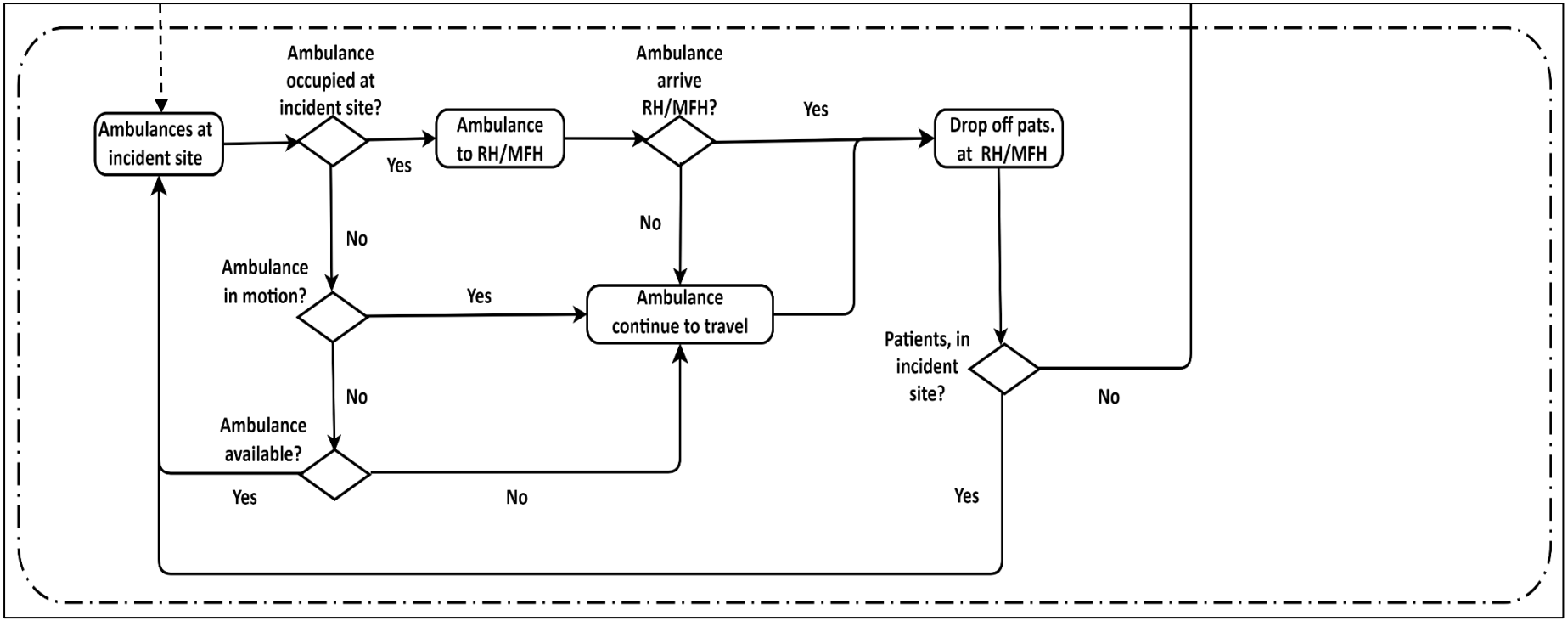

Figure 18: BPMN diagram for MFH-06-6-2 GUI simulation set up (Ambulance-policy)

4.3. Data generation, results, 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 a combination of software tools. With NetLogo 6.3.0, the data sets for the system were generated through simulation experiments (BehaviorSpace). The Python libraries from Pandas, which are based on the Anaconda programming language for scientific computing, were used for data cleaning, filtering, and aggregation - including sensitivity analysis. The analysis conducted to determine how ambulance policy affects model behavior, mortality outcomes and mean waiting times is presented in the following subsections with explanations and graphics.

4.3.1. Model behaviour on effect of ambulance policy on mortality and mean wait time

In Figure 19 we see the effects of two different ambulance deployment strategies on patient outcomes in the simulations. The x-axis shows the number of runs (720 iteration runs) that generated the dataset shown in the Figure 19 and the influence of the different number of ambulances (Num Amb) has on the overall performance of the emergency department in terms of average deaths. The average number of deaths is a function of the sum of the deaths for each run, divided by the total number of deaths in the total iterations. The y-axis shows the total number of patients affected by each response intervention. Since the modelled scenario is unpredictable and variable, the simulations were created to reflect a wide range of the emergency scenario combinations. Each iteration contributes to the overall result of how the different policies might work in real-world situations. The metrics examined in this comparison

include indicators such as: mortality rates as a direct measure of patient outcomes, which is a function of the resource utilization efficiency, and response capacity of the interacting EDs.

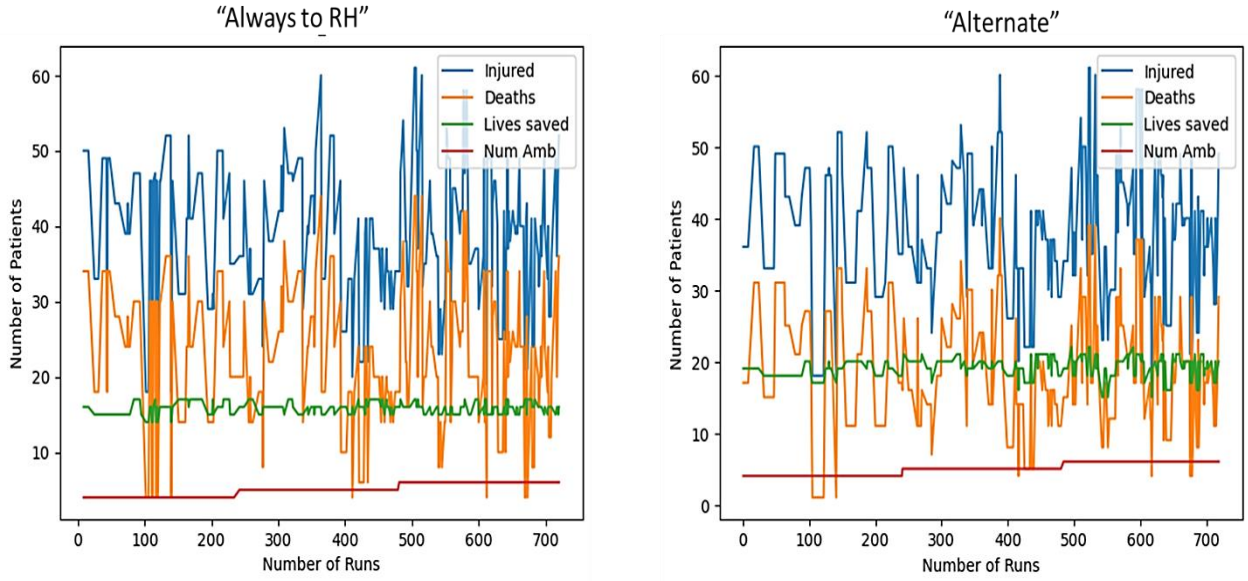

Figure 19: Model variability behaviour on patients' mortality outcomes (ambulance policies).

The first variation chart in the ambulance policy ("Always go to RH") is based on a traditional dispatching approach where ambulances are dispatched based on patient severity and availability, with only the RH available. The second variant ("Alternate") involves a more dynamic approach by using a mobile field hospital to strategically support the RH in the scenario.

Figure 20 shows the influence of the ambulance policies ("Always go to RH" and "Alternate") on the Mean Wait Time (MWT) variation. The MWT is a function of the total sum of wait times for each individual run, divided by the total number of iterations. The x-axis represents data from 720 iterations and also indicates the number of ambulances deployed (Num Amb), while the y-axis shows the number of patients (injured) for each run under the respective ambulance policy.

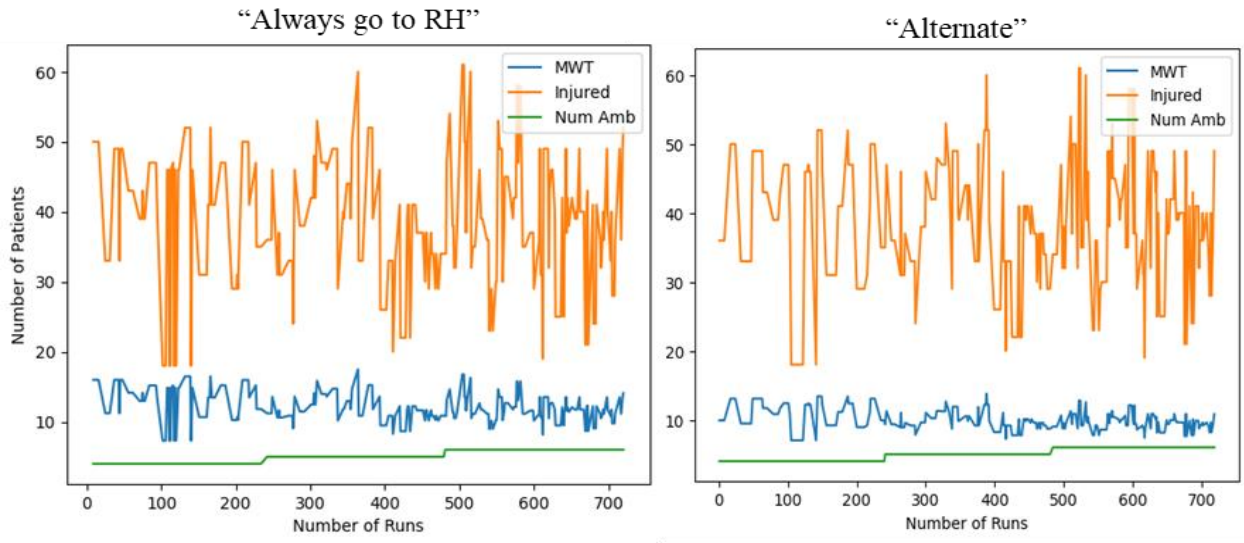

Figure 20: Model variability behaviour on patients' mean wait times (ambulance policies)

The aim of the simulations is to recreate an operational environment, considering the different demands for emergency services and the use of ambulances. The substantial number of simulations runs guarantees a complete data set reflecting a wide range of outcomes, thereby increasing the validity of the comparative analysis. Further comparisons and quantifications of these effects can be found in the following sections.

4.3.2. Effects of ambulance policy on mortality outcomes

To achieve the goal of this study, we examined how ambulance policies affect patient mortality outcomes from both the interaction or lack of interaction of a regional and mobile field hospitals (modelled as basic emergency departments) in a hypothetical disaster scenario. "Always go to RH" describes a policy used by the regional hospital to respond to the disaster; on the other hand, the term "Alternate" describes the use of the mobile field hospital in collaboration with the regional hospital to support emergency operations. Figure 21 shows two boxplots of the impact of ambulance policy on mortality outcomes from the simulation experiment runs.

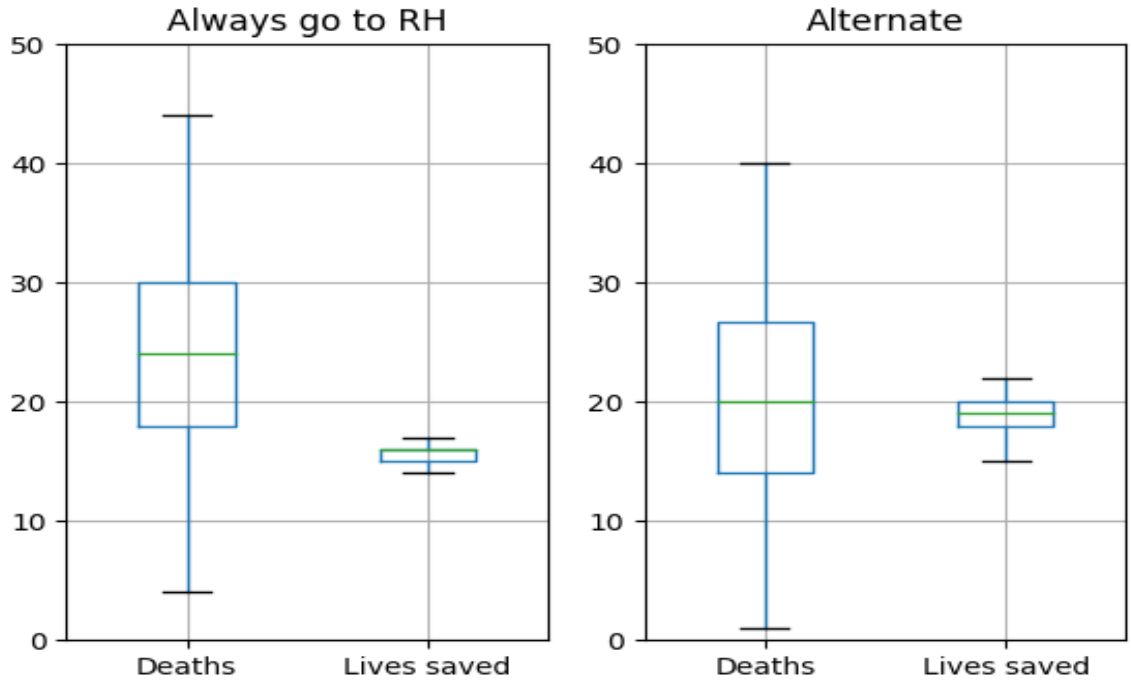

Figure 21: Effect of ambulance policy on mortality outcomes for interacting EDs.

Boxplots are great statistical tools that provides visual analysis of the distribution of the datasets. By using boxplots in analysing the 720 iterations (runs) for each ambulance policy, a thorough visual and quantitative comparison of the policies' performance can be achieved, improving the clarity and depth of the results.

4.3.3. Effects of ambulance policy on patient's mean wait times

Figure 22 shows two boxplots comparing the mean wait times for the two ambulance policies, "Always go to RH" and "Alternate". These charts are helpful in displaying the data distribution. The codes used to analyse and visualize both the effects of ambulance policy on mortality outcomes and mean wait times is available on Github at: https://github.com/Nimisingha/Ambulance_Policy_RPG.

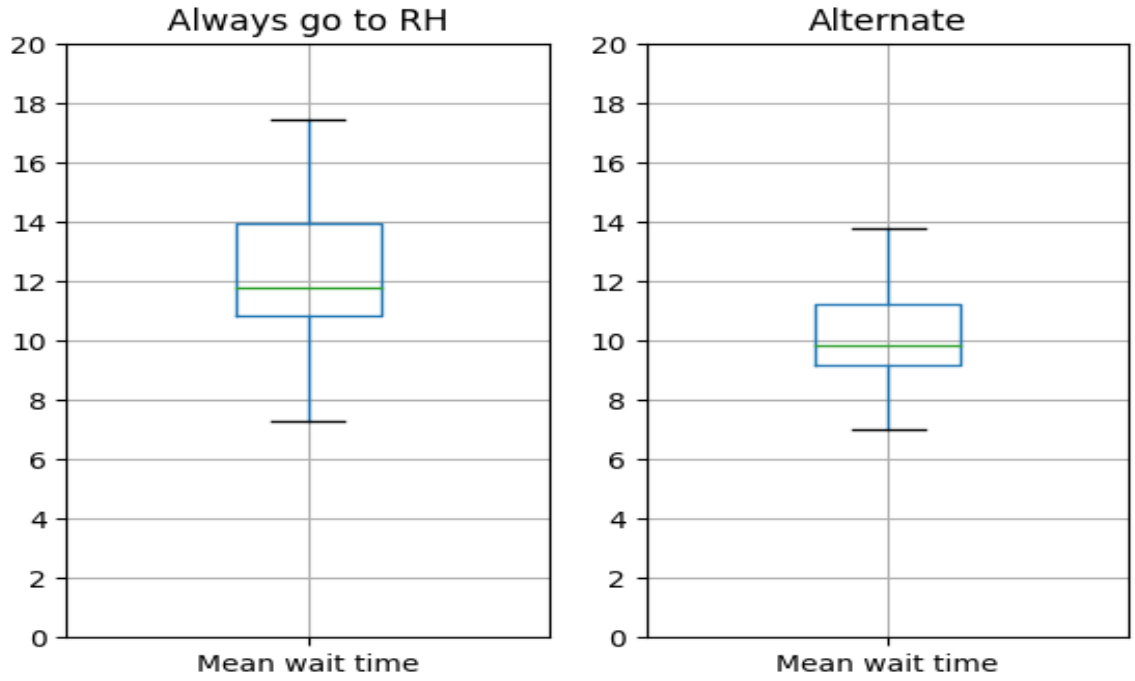

Figure 22: Effect of ambulance policy on patients mean wait times for interacting EDs.

The behaviour and interactions of agents are determined by a variety of parameters that make up ABMs. Because the effects of model parameters on output is methodically studied, sensitivity analysis is an essential step in understanding the behaviour of the output variable(s) from the interactions of the input variables and subsequent usage of ABMs. The methodology used to conduct the sensitivity analysis for the model results and outcomes is presented in the following section.

4.3.4. Sensitivity analysis (effects of ambulance policy on mortality and MWT outcomes)

Understanding the behaviour of the variables of agent-based models' dataset can be facilitated by conducting sensitivity analysis. Many sampling and global sensitivity analysis techniques are available through the open-source Python-based sensitivity analysis library SALib. Fourier Amplitude Sensitivity Test (FAST), Morris, Sobol, and Delta Moment Independent Measure (DMIM) are some of these methods (Herman & Usher, 2017).

4.3.4.1. Criteria for sensitivity analysis technique

To facilitate the selection of the most appropriate Global Sensitivity Analysis (GSA) method for problems and models, Iooss & Lemaître (2015) proposed a decision tree that considers the unique characteristics of different Sensitivity Analysis (SA) methods as shown in Figure 23. Although the decision tree can be particularly useful in simplifying the concepts and requirements for the various SA techniques, caution should be exercised when using this diagram.

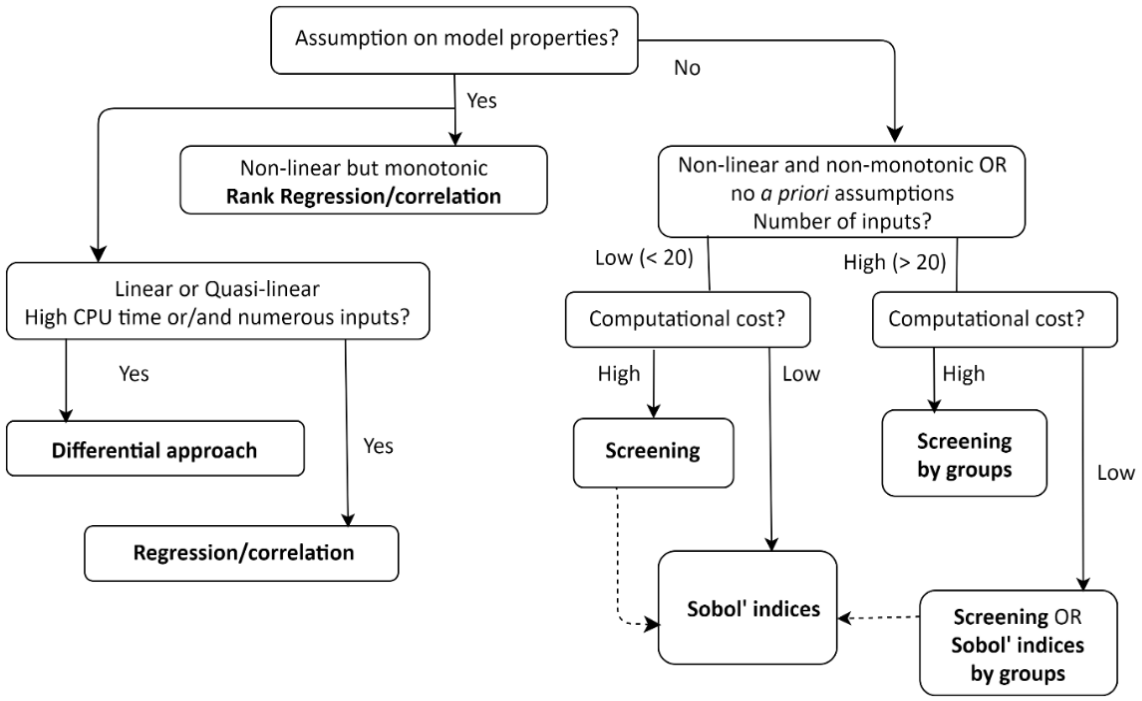

Figure 23: Decision tree for selection of Sensitivity Analysis (SA) technique (Radišić *et al*., 2023).

Considering the decision tree (Figure 23), the purpose of the investigation, and the characteristics of the data set, this study selected the Sobol global sensitivity analysis (GSA) as the optimal technique to improve the understanding of the model's core dynamics and variability. This choice is based on the use of Sobol indices that quantify variance decomposition.

Typically, Python's SALib (sensitivity analysis libraries) are used for this. All SALib's methods can be accessed through a single interface known as a `ProblemSpec` (problem specification).

4.3.4.2. Sobol's indices: functional decomposition of variance

According to Radišić *et al* (2023), Sobol' indices are a widely accepted method to express how sensitive a model output is to the input parameters. When examining how input parameters affect output variance, the Sobol approach is inherently variable.

Let D be the model output's variance, Y as shown in Equation 1:

$$D = Var(Y) \tag{1}$$

Given the input parameter X_i, let D_i , Equation 2 represent the expected output's variance.

$$D_i = Var(\mathbb{E}[Y \mid X_i]) \tag{2}$$

Sobol' (2001), defines the input parameter's first-order Sobol' index X_i as the proportion of the conditional variance to the output's overall variance as shown in Equation 3:

$$S_i = \frac{D_i}{D} \tag{3}$$

With the specified set of input parameters $\{X_{i1}, \ldots X_{is}\}$, $D_{i1\ldots is}$ denotes the variance of the expected output variables corresponding to these input parameters. For every subset of these input parameters, the variance of the expected output variables can be expressed as follows in Equation 4:

$$D_{i1\ldots is} = Var(\mathbb{E}[Y \mid X_i, \ldots X_{is}]) - \sum_{\mathfrak{T}s} D_{i1\ldots ik}\,, \tag{4}$$

Where, $\mathfrak{T}s = \{\{i_1, \ldots i_k\}\} : \{i_1, \ldots i_k\} \subsetneq \{i_1, \ldots i_s\}$

The Sobol' index for higher-order interactions among input parameters $X_i, \ldots X_{is}$ can be similarly expressed as shown in Equation 5: it denotes the ratio of the total variance in output to the conditional variance of the output linked to a particular parameter set. This calculation subtracts the variances of the output conditioned on other subsets of the parameter being examined.

$$S_{i1\ldots.is} = \frac{D_{i1\ldots.is}}{D} \tag{5}$$

The input parameter's overall Sobol' index, X_i is determined by adding together all the Sobol' indices of the sets that contain it.

The input parameter's total Sobol' index X_i is calculated by summing all the Sobol' indices for the sets that include it, using Equation 6.

$$S_{Ti} = \sum_{\mathfrak{T}s} \frac{D_{i1\ldots.is}}{D} \tag{6}$$

Where, $\mathfrak{T}s = \{\{i_1, \ldots i_k\}\}: \exists k, 1 \leq k \leq s, ik = i\}$

An alternate definition for the entire Sobol' index is represented in Equation 7 as follows: Since all first and higher order Sobol' indices add up to 1.

$$S_{Ti} = 1 - S_{\sim i} \tag{7}$$

$S_{\sim i}$ is the total of all Sobol' indices $S_{i1\ldots.is}$, excluding index i. First-order Sobol' indices and total Sobol' indices exemplify the advantageous characteristics of Sobol' indices.

These indices effectively illustrate the impact of a parameter alone or in conjunction with others. However, estimating them can be challenging, especially for large models with numerous

input parameters and simulations that require significant computational resources. In this study, the sensitivity indices are denoted as ST for total sensitivity, S1 for first-order sensitivity, and S2 for second-order sensitivity.

4.3.5. Sensitivity analysis of effect of ambulance policy on outcomes

The results of the Sobol' sensitivity analysis for the MFH-06-6-2 model are shown in Figure 24. This analysis identifies input parameters that significantly influence the model's output, thereby improving the understanding of the dependencies and sensitivities within the model framework. The results shown in the figure deepens our understanding of how adjustments to the input parameters can affect the overall behaviour and performance of the model.

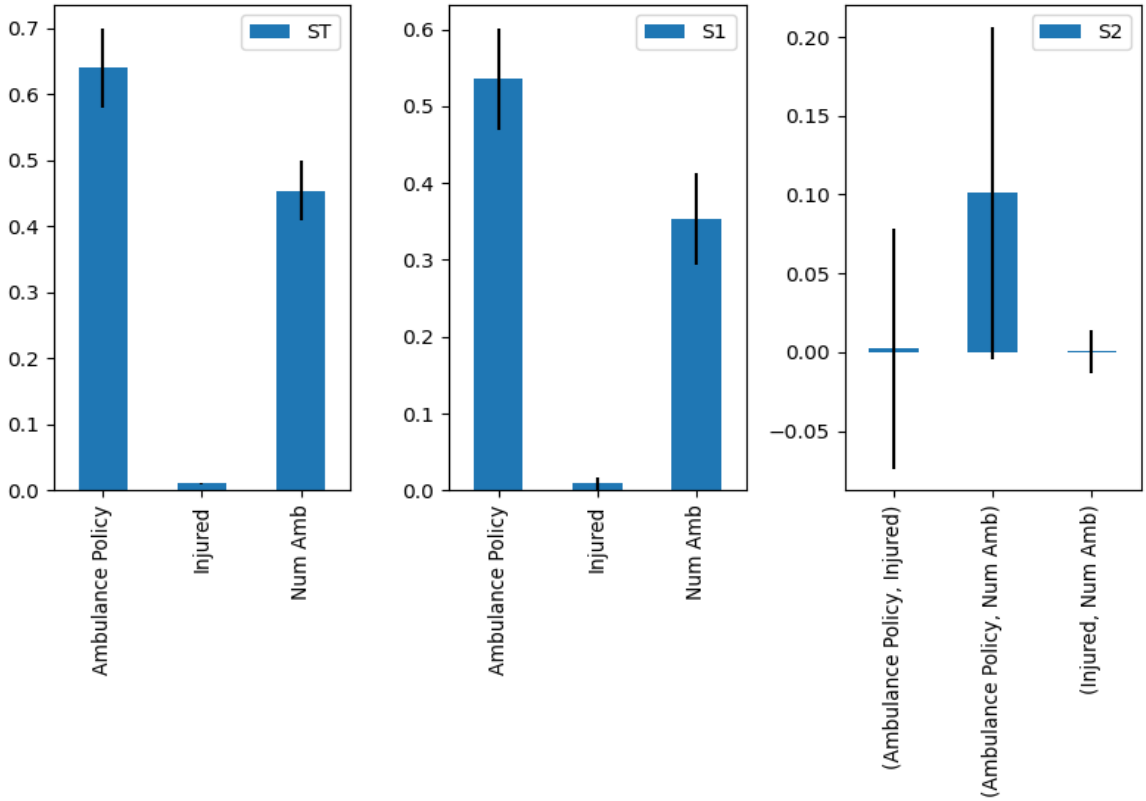

Figure 24: Sensitivity analysis of the effect of ambulance strategy outcomes

Sobol's sensitivity analysis is a technique for evaluating how various sources of uncertainty in model inputs affect the uncertainty in the output. This is particularly useful when it comes to simulating complex systems, be it mathematical or computational. The overall Sobol' index (ST) considers both the main effects of components and their interactions with other inputs to assess the extent to which each input accounts for the output variance. The first-order Sobol' index (S1) shows how much an input variable independently influences the output variance and helps identify the key influencing variables responsible for the output variability. In addition, the second-order sensitivity index (S2) evaluates the contribution of interactions between input variables and output variance, revealing how the joint variation of two inputs can affect output variance beyond their individual effects. Further explanation of these results can be found in Section 4.4.

4.4. Discussion

Because the operations of healthcare systems are complex, it is often difficult to predict emergency room outcomes in the event of a disaster. However, by modeling the behavior of individual agents, the interaction of such system elements can be simulated, which makes them indispensable in disaster response. In this problem case, NetLogo, an agent-based modeling and simulation platform, proved effective in predicting mortality outcomes and mean wait times. A detailed discussion of the research results is presented below, considering the given problem context.

4.4.1. Effects on ambulance policy on mortality outcomes

This aspect of the analysis compared two disaster response policy for an oil and gas explosion-type scenario, specifically examining the effects of the collaboration (or lack) between

a Regional Hospital (RH) and a Mobile Field Hospital (MFH) (Figure 21). In the first policy ("Always go to the RH"), the response depends on the RH for transport, triage, and treatment of the injured patients. The second policy ("Alternate") involves utilizing both the RH and MFH for response efforts.

While the mean value of mortality outcome for the policy "Always go to RH" is 23.22 with S.D of 8.98, the interquartile range — approximately 50 % of the data – is between 18 and 30 deaths suggesting variability in the distribution of the average number of deaths. The low standard deviation from the average life saved of 15.85 is 0.79 reveals that the policy "Always go to RH" in the number of lives saved is consistent. In this case, the minimum and maximum mortality outcome is from 4 to 44 with 50 % of deaths falling in the range between 14 and 29. Conversely, the Average number of deaths for the "Alternate" policy is 19.75 with SD 8.27 recording a significantly lower mean number of deaths compared to "Always go to RH". While the S.D of 1.30 is slightly higher implying even higher variability, its mean number of lives saved is also higher. The "Alternate" policy reduces the average number of deaths by approximately 14.94% when implemented in comparison to "Always go to RH" policy. Conversely, the "Alternate" policy also increases the average number of lives saved by 17.32%.

These findings highlight how ambulance policies impact mortality outcomes during disasters when emergency departments interact. Simulation methods have effectively showed that the function of emergency department, especially coordination and resource allocation under such conditions can be enhanced. For example, Fu *et al.* (2022) modelled emergency scenarios using simulation to evaluate the effect of ambulance strategies on death rates. Their study considered hospital schemes for emergency medical services; specifically, how operational

influences optimize such services. Z. Liu *et al.* (2014), employed NetLogo modeling to virtually recreate different accident and emergency areas. Their computational design allowed evaluating and improving emergency care quality.

In a related investigation, Azimi *et al*. (2017) employed multi-agent modelling to maximize emergency centre space allocation. The model they proposed successfully reduced ambulance response times by 36.7%. Laker *et al*. (2018) emphasized the role of computer simulation in improving utility systems and discussed the use of the widely used M&S techniques in emergency scenarios. Their work was particularly focused on how ambulance deployment strategies can impact mortality outcomes in emergency departments. Another study by Ogie *et al*. (2022), also suggests that the application ABM is beneficial in modelling and simulating changes in crisis settings, and in optimizing crowdsourcing for disaster response.

4.4.2. Effects of ambulance policy on mean wait times

This aspect of the results analysed examined the two different disaster response policies but focuses on how the policies affects the mean wait times. The boxplot shown in Figure 22 reveals that the “Always go to RH” policy produces a longer mean wait times compared to the “Alternate” policy (12.34, 10.20) and a higher standard deviation (3.11,2.06) (descriptive statistics). The “Always go to RH” policy also has a larger interquartile range, indicating greater variability in MWT. This is indicated by the length of the boxplot. The minimum wait times of the two policies are similar, however the maximum MWT of the “Always go to RH” policy (17.48) is higher than that of the “Alternate” policy (13.81). From the results, implementing the “Alternate” policy reduces the average wait time of patients in the treatment process by 16.68%. From this results, one can infer that under a comparable disaster response situation, the implementation

of the “Alternate” policy, which involves the deployment of a Mobile Field Hospital to collaborate with the Regional Hospital in place, could reduce the waiting times for the disaster victims and improve the quality of care and patients’ outcomes.

Studies using M&S techniques have produced similar or related results. For example, the hybrid model developed by Y. Liu *et al*. (2023) combining simulation methodologies (ABS and DES) effectively reduced patient waiting times through optimizing resource planning. Using their strategy research results, the effect of "FIFO+Centralized" hospitalization is cut by 3.75%, while under "Random+Centralized" conditions, it falls to 0.57%.In another study by Yousefi & Ferreira (2017), ABS combined with group decision making led to a 12.7% reduction in average waiting time at emergency departments and a 14.4% decrease in the proportion of patients who leave after being seen, thereby improving the overall performance of such systems.

Furthermore, Z. Liu *et al*. (2014) created a model for generalized ABMS-based simulation and optimization of various ED scenarios in the NetLogo environment. They argued that this model allows for a more comprehensive understanding of response planning and response strategy by analyzing patient wait times in emergencies. Similarly, Z. Liu & Luque (2015) stated that NetLogo has the potential to simulate emergency room wait times during a disaster to enable efficient disaster relief planning. In contrast, Taboada *et al*. (2013) reported that simulation helps clinical staff make better decisions for patient flow and optimal resource utilization. These authors conducted a simulation in NetLogo to evaluate the impact of patient deviation policies on ED outcomes.

Data analysis of the hypothetical scenario shows that collaboration between RH and MFH can effectively reduce mortality rates and MWT, resulting in higher effectiveness and efficiency

of the response measures. The comparison between the “Always go to RH” and “Alternate” policies can be seen as creating a more flexible and dynamic framework that can improve the system's responsiveness to emergency situations. Consequently, flexibility and adaptability are particularly notable features of disaster response frameworks as they form the basis for establishing disaster response measures and policies. Therefore, applying agent-based modeling and simulation to disaster management planning, resource allocation and policy effectiveness evaluation is helpful to evaluate the influence of different policies.

The better results of the “Alternate” policy in terms of MWTs and survival rates also suggest that the “Alternate” strategy may be more versatile and applicable to a wider range of disaster scenarios. However, a comprehensive analysis of these results must rely on the distribution of the data sets. Significantly, the Alternate policy indicates a minimum of 1 for mortality, signifying its potential utility in certain circumstances, and provides a smaller maximum for this metric. The results confirm the utility of a collaborative disaster response approach for the best possible outcome.

It is also possible that improvements in responsiveness, efficient resource allocation, or triage and treatment protocols, which only appear to benefit from the more collaborative approach, are responsible for the “Alternate” policy results. The greater variations in the number of lives saved by the “Alternate” measures could represent a more heterogeneous environment in terms of coordination, thus providing the possibility for optimal outcomes or, conversely, greater setbacks in the logistical system of the disaster response continuum. Here RH and MFH must work together and exchange the necessary resources and information. Conversely, the “Always go to RH” strategy provides consistent performance, albeit with extreme limitations on

all outcomes, as suggested by the lower variance, fewer lives saved, and longer average times. This could be since MFH deployment allows for rapid delivery of life-saving interventions, as the RH infrastructure and procedures are only capable of efficiently serving a certain number of specific cases and therefore are not as scalable or flexible.

Deploying an MFH in addition to the existing RH could be a critical decision in the event of an oil and gas explosion disaster response. In the critical first hours after the explosion, the MFH's mobility and proximity to the explosion site could mean the difference between life and death. The agent-based model thus draws attention to the complexity and variability of disaster scenarios. This also suggests that while certain measures are consistently implemented, there are significant differences in the effectiveness of disaster response efforts in terms of mortality outcomes and wait times. Therefore, in this context, there is a need for a more thorough analysis of the strategies in future simulation studies, to test and optimize comparable or different disaster scenarios.

4.4.3. Sensitivity analysis on effect of ambulance policy on outcomes

The use of global sensitivity analysis and particularly Sobol' in this study helps us to expand the knowledge of the results as it helps us to understand the system behavior, the characteristics, and the influence of the system agent's behavior on the overall result. Such sensitivity analyzes also help reveal the key factors that impact the efficiency of the disaster response model: hospital coverage and effective deployment and transfer times for injured patients (Alrehaili *et al*., 2022; Çağlayan & Satoglu, 2022; Hierink *et al*., 2020). The given results in Figure 24 portray the following results in the form of Sobol's total sensitivity index: ST, Sobol's first-order sensitivity index: S1, and Sobol's second-order sensitivity index: S2.

The total index (ST) calculates the total effect of the input variables on the variance of the output by considering both the main effects and the interactions of the input variable with other variables. The first-order sensitivity index (S1) evaluates the direct effect of each input variable on the output variance and identifies the variables that have the greatest influence on the variation. The second-order sensitivity index (S2) shows that simultaneous changes in inputs can have larger effects on output than their individual effects suggest. This is achieved by evaluating the effects of interactions between two variables on the output variance.

- **Total sensitivity index (ST):** "Ambulance policy" has the highest ST value at 0.64, meaning that it is the most crucial factor influencing all performance indicators (total deaths and MWT). "N Ambulances" also has a significant ST value (0.45), indicating the extent to which this also determines the model results. These ST values reveal the proportion of the variance of each input variable that is attributed to the output variable.
- **First-order sensitivity index (S1):** This index shows that of all input variables, ambulance policy has the largest impact on performance, as measured by total deaths/wait times, with the highest S1 value of 0.54. "N Ambulance" has the second largest correlation to output power with the following S1 value (0.35). The S1 values provide information about the individual contribution of each of the input variables to the variance of the output.
- **Second-order sensitivity index (S2):** The pair "N Ambulances" and "Ambulance Policy" has a positive S2 value of 0.11, indicating a stronger joint effect on the output variable. However, for other combination pairs ("Ambulance Policy," "Injured") and ("Injured," "N-Ambulances") there are negative to near zero values, indicating that little interaction leads to the model results.

These results show that “Ambulance policy” has the strongest influence on the model outcomes, indicating that it has a significant impact on performance of the model capability both individually and collectively. As significant ST and S1 values show, the number of ambulances (“N-ambulances”) also has a major influence. In the context of a real situation, decision makers should give priority to optimizing “Ambulance policy” to influence the outcomes while considering the function of “N-ambulance directly and significantly.”

The effectiveness of using the Sobol method in the analysis of ABMs is demonstrated by Borgonovo *et al*. (2022), who found that ABMs can be effectively evaluated by applying the Sobol sensitivity technique, which can improve the reliability of the model and its applicability in emergency decisions. According to Gao *et al*. (2023) and White *et al*. (2023), Sobol's sensitivity analysis can be highly effective in ABMS robustness assessment by helping to identify all essential elements in the model, providing an understanding of system interaction and influencing factors, and helping to predict the direction of change in a system. They claim that such analysis can be helpful in optimizing response strategies, improving decision-making processes, and improving the performance of EDs in disaster response scenarios.

4.5. Chapter summary

The results of this chapter demonstrate how modelling EDs using agent-based modelling in NetLogo can integrate and enable experimentation in a hypothetical disaster scenario. In addition, the implemented MFH-06-6-2 model was described and shown how experiments on the impact of ambulance policy on mortality outcomes and mean waiting times provided promising insights and a basis for further research. This refers to the application of computational techniques in disaster response, emergency department simulation and process optimization issues. While NetLogo's agent-based modelling has proven to be a helpful tool for realistic and

complex behavioural representation of simulation models, simulating entities in a disaster situation can be a daunting task that can be influenced by several factors such as the validation process. In addition, the level of complexity of the model could have an impact on the realism and reliability of the results. It is critical that model validation is carried out carefully to ensure that simulated results match potential reality.

To validate the predictive ability of the ABMS model (MFH-06-6-2), I designed and implemented a Disaster Response Tabletop Role-Playing Game (DRTRPG). DRTRPG is a strategy that can serve as a valuable tool for validating ABMs, training in disaster response, and expanding healthcare workers' knowledge, including communication and collaboration. This is discussed in detail in the next chapter.

CHAPTER 5

5.0. DISASTER RESPONSE TABLETOP ROLE-PLAYING GAME (DRTRPG)

5.1. Introduction

Building on the findings of the previous chapter, this chapter examines the development and implementation of a Disaster Response Tabletop Role-Playing Game (DRTRPG). The previous chapter demonstrated how Agent-Based Modelling Simulation (ABMS), particularly with the NetLogo modelling toolkit, can be modelled and effectively used to represent and integrate complex behaviours of EDs in a disaster scenario. In addition, the implementation of the NetLogo (MFH-06-6-2) model was simulated and promising results from experiments on the effects of ambulance policy on mortality outcomes and Mean Wait Time (MWT) were presented for the studied case. To validate the decision dynamics protocols of the ABMS model agents, the game-based approach presented in this chapter will not only test the predictive capability of the ABMS model but also provide a platform for further studies on disaster response and simulation optimization in healthcare disaster response management.

5.2. Disaster Response Tabletop Role-Playing Game (DRTRPG)

Disaster response tabletop role-playing games have been investigated as a potential teaching tool for disaster preparedness. Tabletop disaster exercises or simulations have been shown to significantly improve healthcare workers' understanding of disaster management (Suleman *et al*., 2022). Role-playing games have also been used in the validation process of various ABMS. One of the variations in using games as a validation strategy is participatory simulation (A. J. Collins *et al*., 2024; Szczepanska *et al*., 2022). Additionally, games such as PREDIS

allow both experts and non-experts to simulate decision-making in disaster management and assess their choices (Rye & Aktas, 2022).

The Disaster Response Tabletop Role-Playing Game (DRTRPG) developed for this study is a TRPG that utilized the analytical and predictive capabilities of an ABMS model to design a collaborative and interactive role-playing game. The aim is to create an environment in which participants can take on roles in a situation that represents aspects of the interactions within the ABMS simulated system. This combination can be particularly useful in areas where understanding complex systems and human behavior in decision-making situations is essential.

Several factors highlight the importance of using a DRTRPG to verify/validate the predictive ability of the NetLogo MFH-06-6-2 model developed and implemented for this study. This includes:

1. **Cost-effective:** Using tabletop role-playing games, training, educating people/organizations about disaster response and validating ABMs can be achieved at an exceptionally low cost. TRPG do not require the same resources as large-scale disaster simulations or exercises.
2. **Data collection:** This involves observing and recording players interactions, decisions, and actions during gameplay. This data can then be used to examine the decision protocols of the agents in the model.
3. **Scenario testing:** TRPGs focused on disaster response can be valuable tools for evaluating the effectiveness of different disaster scenarios in one model. By using these games, any defects or errors in the model can be located and corrected.

4. **Expert validation:** Disaster response experts can monitor the game and provide comments on the realism and accuracy of the model. By using their comments, the model can be expanded and improved.
5. **Analytical comparison:** It is possible to compare the results of the model with those of the tabletop role-playing game. This makes it possible to detect and correct errors or inconsistencies in the model or game.

This study's RPG integrated components from a validation strategy for ABMs suggested by Ligtenberg *et al* (2010). To confirm the ABMS model's accuracy in representing agent behavior and game outcomes, the method initially translates pertinent ABM elements into an RPG. Subsequently, it contrasts the outcomes of the RPG with those from the ABMS model. If the RPG can produce results akin to those of the ABM (whether visual, statistical, or otherwise), it suggests that the model agent's decision-making rule is dependable.

5.2.1. The DRTRPG planning and development process

The planning and development of tabletop role-playing games for this study includes various aspects that contribute to the design of an interactive and collaborative gaming experience. The development process includes detailing and simplifying aspects of the ABMS model and in-game implementation. This includes clear communication of the aim, objectives, guidelines, methodology, including the design concept, principles and experimental design, participant role(s), metrices, materials, data collection and analysis. All these aspects are elaborated in the following sections.

5.2.1.1. Aim of the DRTRPG exercise

One aim is to shape the design and implementation of the DRTRPG. This is related to answering the second research question of this study (and consequently dealing with the third objective). The question is: “How can Disaster Response Tabletop Role-Playing Games (DRTRPGs) be used to verify/validate the representativeness of the response process of an ABMS model agent in the context of the disaster response scenario?” The objective is to ascertain if the data produced by the agents' decisions in the game align with the decision-making process of the ABMS model concerning the industrial explosion scenario. This will aid in enhancing the model's effectiveness and accuracy, ensuring it accurately reflects a real disaster response decision protocol.

5.2.2.2. Objectives of the DRTRPG

To address the research question, the following specific objectives were carefully formulated for the DRTRPG:

1. **Objective 1:** To assess the improvement in understanding gained through the trainings and implementation of the DRTRPG through pre- and post-training assessments;
2. **Objective 2:** To assess the effect of ambulance policy on mortality outcomes from the activities of the disaster response teams/agents (players) and visually and/or statistically compare the outcomes of the DRTRPG against the MFH-06-6-2-ABMS model outcomes (validation).

To achieve these objectives, the DRTRPG-specific game rules are followed to ensure that the ABMS disaster response scenario remains central throughout the design process. These guidelines are listed below and are essential to the effectiveness and value of the exercise.

5.2.2.3. The DRTRPG guidelines

The DRTRPG is conducted under the following guidelines, which are based on the traditional guidelines for disaster resposne-type role-playing games:

1. Only players on the same team must communicate and collaborate effectively within their group before making decisions.
2. The MoD/GM provides hints, guidance, and instructions for the game while the observers observe the players' actions and evaluate/record their findings.
3. Discussion in each group will focus on the emergency challenges that require quick decision-making. This promotes collaboration within teams to complete all aspects of tasks.
4. The game has a time limit on the scenario tasks, forcing players to make quick decisions and allocate resources.
5. The game includes consequences for decisions (e.g., death consequences) to encourage thoughtful decisions and increase realism.
6. The game's design incorporates the concept of limited resources (ambulance, operating room, etc.) that players must use effectively to save lives if possible

The following section describes the methodology used in the game's design and implementation.

5.3. Methodology: disaster response tabletop role-playing game design

The Disaster Response Tabletop Role-Playing Game (DRTRPG), which emphasizes an ABMs model validation approach, as described by Ligtenberg *et al* (2010) was created as a scenario-based validation strategy for this study. This is summarized below:

1. **Create** a foundational ABMS model,

2. **Design** an RPG version of the basic ABMS model and assign roles. The ABMS model is converted into a role-playing game in which the participants play through scenarios like those in the ABMS model,
3. Guide **participants/players** to execute tasks in the game. The participants carry out tasks like those in ABM.
4. **Collect** data with the RPG,
5. **Compare** and **contrast** the RPG findings with those of the ABMS model**.**

The exercise consists of two phases. In the first phase, participants are introduced to the DRTRPG concept in a group setting through preparatory training and exercises. During this phase, several elements of the ABMS model and the game were expanded and improved. In Phase 2, response data were then generated, examined, and compared against the basic ABMS model (again in a group-based setting) and between medical and master's students. The DRTRPG was created between 2023 and 2024 and two exercises (or three training sessions) were carried out during this time. Ten to fifteen people could easily fit into the standard classroom used for tabletop role-playing games at the IMT Mines Ales Clavières location.

According to this design, each group experienced the same crisis response scenario (during the game). Prior to participating in the DRTRPG exercise, participants' knowledge of disaster management and health-related decision-making was assessed using a multiple-choice pre-game questionnaire. Next, a simulation (in-game activities) was conducted that represented components of the ABMS model (in the DRTRPG) by creating an environment (the disaster response case) in which players from each group collaborated and made decisions. While playing the game, each group simultaneously recorded the time spent on each task. At the same time,

observers also observed and evaluated players' actions during the in-game activities. The reason is to be able to generate extensive data in a brief time. The in-game activities are followed by a debriefing as well as a post-game questionnaire and an observer rating assessment answered by the players and observers, respectively.

5.3.1. Participants

Participants in this research with diverse experiences and backgrounds are asked to play the DRTRPG game as members of a team with specific roles (e.g., emergency responders, triage nurses, surgeons, etc.) in a cooperative role-playing environment to respond to a problem to respond to hypothetical explosion events and decide on the best possible medical care. In the first practice session, four groups of fifteen players each (including observers) test the game. In phase 2, a total of 11 participants were divided into just two groups in order to compare the behaviour of students and medical professionals. Using agent-based models and tabletop role-playing techniques, I argue that the DRTRPG increases the validity and effectiveness of disaster response strategies.

5.3.2. The DRTRPG design concepts, principles, and experimental setup

Tabletop role-playing games developed for disaster response are useful resources for confirming the accuracy of agent-based models used in disaster management. Both experts and non-experts can make decisions faster and more accurately with games like PREDIS (Rye & Aktas, 2022). Utomo *et al* (2022) state that data from RPGs can be used to validate ABMS models at both micro and macro levels to accurately represent real-world processes and knowledge in the model. *Figure 17* shows the GUI of the ABMS simulation model underlying the game design (already presented and discussed in sections 4.2).

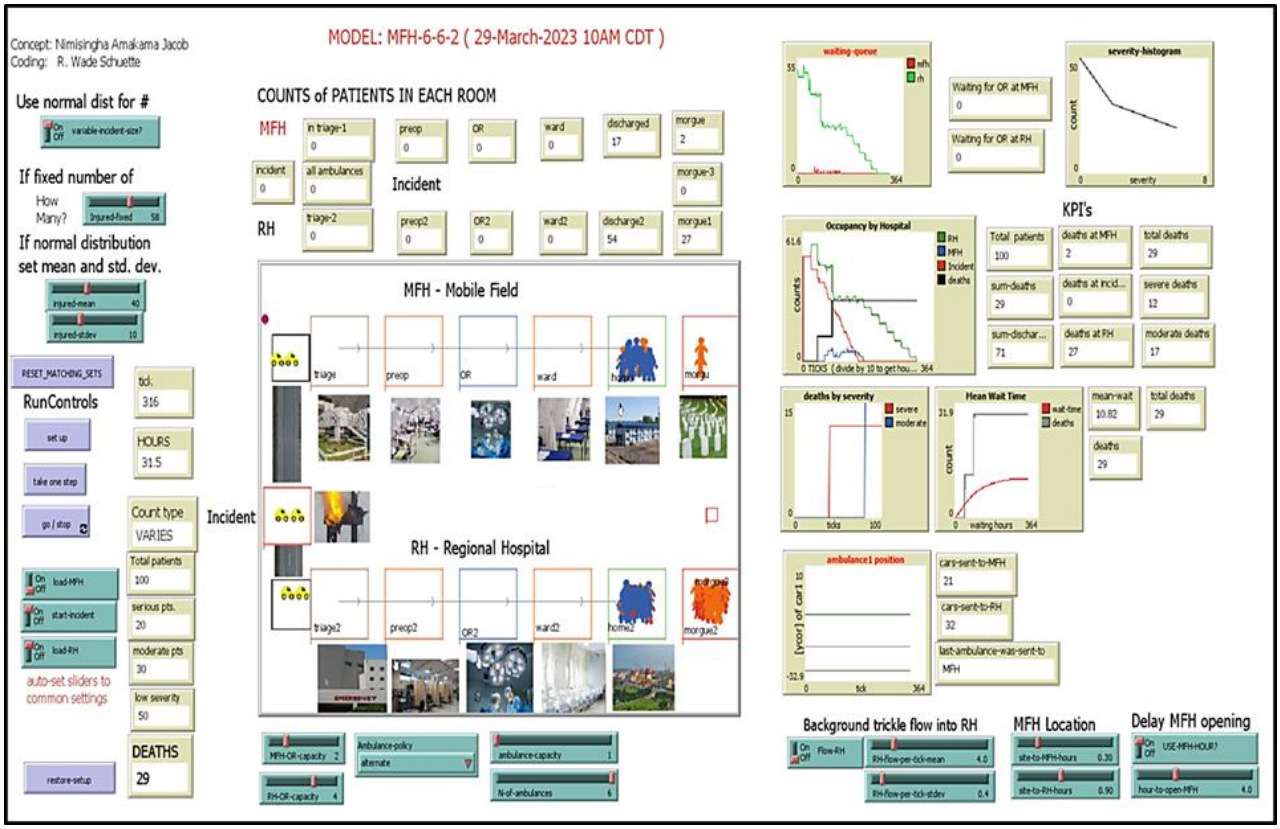

Figure 17: Graphical user interface of simulation used in the DRTRPG design (Amakama,2023a).

The simulated crisis scenario provides the components of the disaster response role-playing game's design found in the ABMS model's Graphical User Interface (GUI). Just as the agents (having defined roles) in the ABS collaborate to respond to an explosion in the oil and gas industry, players assume different roles in collaborate in the DRTRPG to deal with similar scenario. These roles represent simplified aspects of the ABMS simulation. In addition to other considerations of each of the key elements (game elements, game roles, and simulations) that were required to define and design the game. Table 2 provides a summary of the game design guiding principles.

Table 2: DRTRPG components, design choices and considerations

Game elements	Game description	Game design decision	Game playing considerations
Game storyline	A scenario modeled on the ABMS model and based on a simulated oil and gas industry disaster to validate response interactions and outcomes in a regional and mobile field hospital. Pre- and post-game questionnaires to evaluate knowledge gained from the game.	- The game follows the parameters and guidelines of the ABMS model as much as possible to ensure accurate representation - Adapt the game in real time to address player concerns as they arise. - Storyline of the scenario can examine various “what if” scenarios.	- The degree of accuracy with which the game captures the dynamics of the ABMS-modeled scenario. - The degree to which the game scenario and model are representative of a possible real-world scenario.
Game roles	Participants assume roles adapted from the ABMS model such as: emergency dispatcher, triage nurse, surgeon, etc.	- Clearly define the responsibilities and decision-making procedures of the roles. - To assess performance, certain quantifiable metrics are used. - In DRTRPG design, players should feel the impact of their role interactions	- Making sure a role is playable even if it might be complex enough to test the model. - The roles' impact on the thorough model validation procedure. - The requirement that participants learn the ABMS protocols through instruction.
Simulations	A series of ABMS-derived simulations that replicate the oil and gas explosion event and its aftermath, with an emphasis on collaborative response and decision making via in-game tasks	- The simulations include scenarios and exercises that call for the application of disaster management techniques - Create recurring game loops that allow validation of the model through repeated trials. - Provide statistical or graphical comparisons between the impact of DRTRPG decisions and ABMS results.	- Ensure game simulation provides useful/robust data for model validation. - Finding a balance between the simplicity of the game and the complexity of the ABMS. - Clearly convey the objectives and design of the basic ABMS model to participants and other relevant parties.

For tabletop role-playing exercises intended to provide instruction, validation, and training in disaster response and healthcare simulation, this table can serve as a three-step design guide. Next comes the experimental setup of the game.

5.3.3. Experimental set-up

The course of the experiment can be summarized in five progressive steps: (i) describing the DRTRPG plot, rules, and goals to the participants; (ii) assigning roles; (iii) simulation activities (in-game action); (iv) debriefing; and (v) player feedback presented in Table 3.

Table 3: Experimental implementation steps (DRTRPG) (estimated time: 2hrs:15 minutes)

Actions	Resources	Duration (est.)
The GM/MoD explains and discusses the plot and the rules of the game to the participants, including its objectives	Presentation (PowerPoint)	30 mins
Each participant is assigned a role by the GM/MoD (typically pre-selected into a group based on the participant's background).	Printed label/computer online selection	10 mins
The participants (each group) deliberate about the particulars of their respective roles).		5 mins
The GM/MoD presents the possible outcomes of the scenario as hypothetical truths and begins the simulations.	Presentation (PowerPoint)	10 mins
Participants take part in simulations of scenario tasks. By directing the story and generating relevant dialogue with tasks, the GM/MoD makes the game easier. The game leader makes sure that everyone follows the rules.	Cards, phones, PowerPoint presentation	60 mins
Debriefing discussion, initiated by the GM/MoD with the observers and players.	Presentation (PowerPoint)	10 mins
After the experiment, participants receive a short post-experience questionnaire to complete to assess their expanded knowledge and insights gained.	Questionnaires designed in Microsoft Form (online)	10 mins

The GM(s)/MoD describes the environment at the beginning of the experiment. Each player is then assigned a role that determines their tasks for the duration of the game. Before the in-game simulation activities begin, players in each group are given a few minutes to interact so that everyone becomes familiar with their roles and can assign any other sub-role to a group member. The GM guides the players by giving them hints, initiating relevant conversations, and introducing important plot points according to the DRTRPG rules. To facilitate debriefing after the experiment, the research team observers documented and scored their observations. My research shows that a playgroup with eight to sixteen participants would be perfect. To generate meaningful datasets to validate the ABMS model, the game should have more activities.

5.4. Metrics and data generation

The DRTRPG activity scoring chart as shown in Table 4 was used to evaluate team decisions in the disaster scenario, with a focus on estimating mortality outcomes based on response times (performance metrics). Points are awarded to encourage competition and effective decision-making between groups (does not affect results). One tick in the ABMS model corresponds to the estimated six minutes for each task.

Table 4: Game activity scoring chart

Decision time conditions	**Estimated outcomes (deaths)**	**Outcome points**
Team decision taken at T ≤ 2 minute	All mild patients are saved. Mortality outcome, **d ≤ 5** from moderate and severe	10
Team decision taken at 2 < t ≤ 4 minutes	All mild patients are saved. Mortality outcome, **5 < d ≤ 10** from moderate and severe patients	5
Team decision taken at 4 < t ≥ 6 minutes	All mild patients are saved. Mortality outcome, **d ≥ 10** for moderate and severe patients	0

Based on the ambulance policy for this task, this study estimated mortality outcomes using this scoring table and recorded response times for each group. This implies that faster response times could be a sign of better decision making and coordination within the team.

5.4.1. Data collection and analysis

In the ABMS validation phase, the data collected from the role-playing experiments can be used in various ways. One method is to examine the results and compare them with the ABMS results. However, these comparison results can be divided into two types; myopic or hyperopic. The myopic comparative data focuses on the decisions made by participants in the scenario game, with emphasis on the characteristics of each decision. To analyze how often both the simulated agents and role players make similar decisions, detailed micro-level myopic comparative data can be used (A. J. Collins *et al*., 2024). In contrast, hyperopia comparison data focuses on the possible outcomes of the situation, specifically determining whether both exhibit comparable overall behaviour. A macro-level hyperopic comparison can be difficult to perform because the role-playing scenario may only cover a small percentage of the simulated scenario (A. J. Collins *et al*., 2024). This study considers the hyperopia comparison strategy using basic tabletop materials for the game implementation and data collection.

5.4.2. Materials for the DRTRPG

For the success of any tabletop role-playing game, it is important to select materials that enhance the experience. Each material that makes up the DRTRPG's resources has a specific function within the game's ecosystem. The following are the basic materials of the exercise:

1. Maps of the disaster response scenario, based on the in-game tasks

2. DRTRPG presentation slides

3. In-game tasks response record form

4. Pencils/pens/stopwatches

5. Pre/post assessment test/observer's evaluation forms

The DRTRPG was designed to assess the impact of rescue efforts on mortality outcomes using data from games and to validate the predictive power of the ABMS model. The results were then compared visually and statistically with the results in Section 4.3 regarding the impact of ambulance policy on mortality ABMS results. The aim is to assess whether the decision-making processes in the two approaches correspond qualitatively and/or quantitatively. Figure 25 shows an overview of the DRTRPG configuration.

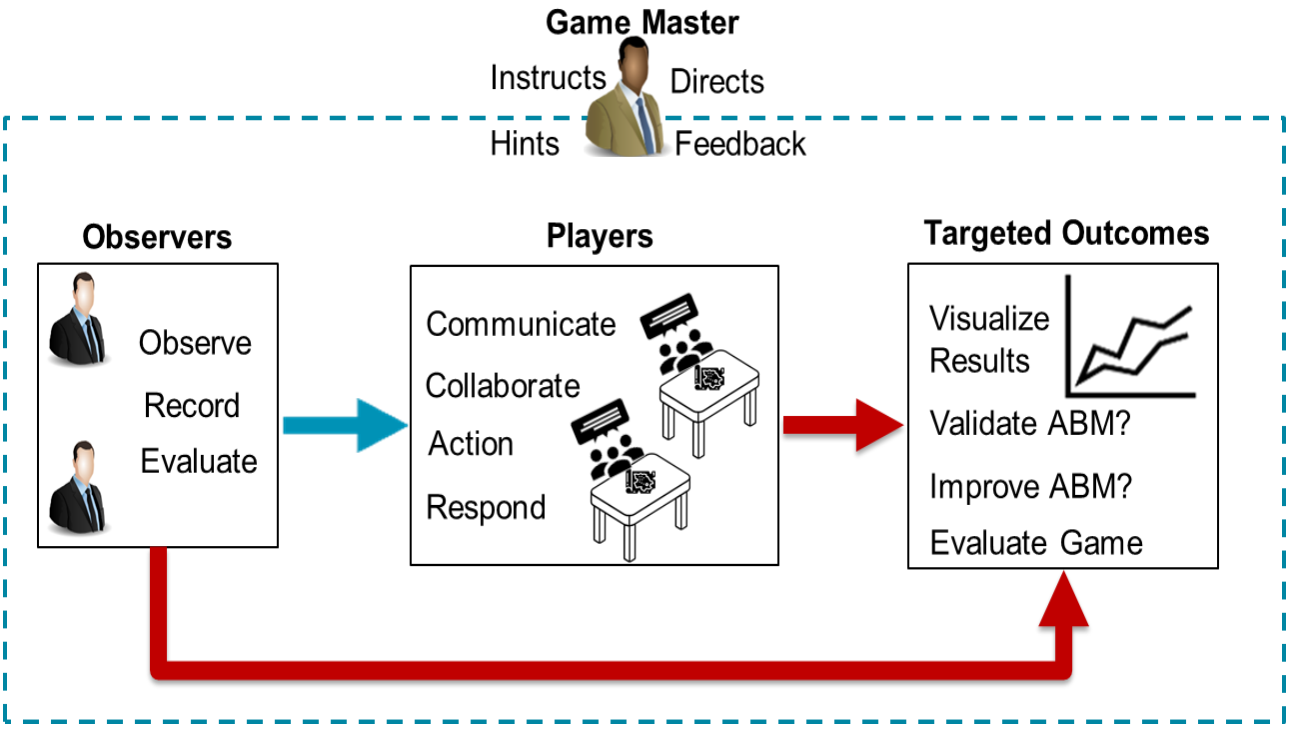

Figure 25: Disaster Response Tabletop Role-Playing Game (DRTRPG) process setup summary

During this experiment, two teams (A and B) compete against each other by completing a set of 18 emergency tasks in a disaster scenario with different patient counts, response times, and severity distributions. The exercise is conducted using predetermined rules and procedures designed to reproduce the developed ABMS NetLogo model. The DRTRPG setup and in-game action sessions are shown in Figure 26.

Figure 26: (a) - (d): DRTRPG players interaction and collaboration (a) the group stakeholder's tabletop setup, (b)-(c) the second experiment for students and medical doctors (7 March 2024) and (d) the first experiment (6 March 2023). (Amakama *et al*., 2024)

5.5. Results

Sixteen participants (split into four groups) and two observers participated in the tabletop test experiment. Nine master's students, one doctor, one emergency responder, one PhD student, and one postdoctoral student make up the distribution of participants based on their backgrounds and experiences. The last DRTRPG exercise involved 10 participants (in two groups), along with 2 observers. There was a 100% response rate (8 out of 8) on the pre-(12 multiple choice) and post-(13 multiple choice) DRTRPG evaluation test questions to assess whether the game resulted in knowledge gain.

5.5.1 Pre and post DRTRPG tests

For the doctors (Group A), the pre- and post-assessment test shows an 11.5% (64.5% to 72.9%) increase in knowledge from the game about disaster management and health interactions, but on average there was no increase in the time, required to complete the tests (11.5 minutes out of an estimated 15 minutes for both assessment tests). The pre- and post-assessment of the DRTRPG for Group B (students without a medical background) shows a slight increase in knowledge (3.1%) based on the correctly answered assessment test questions. However, there was a slight decrease between pre- and post-assessment response times (15:05 to 14:30 minutes).

In the post-game survey answered by participants regarding team challenges and how they were overcome during the game, the physicians' (Group A) reflections showed a pattern focused on group members' difficulty in reaching consensus, which was attributed to their medical background became experiences. The team addressed this problem with strategies such as assigning roles to less engaged members and adaptive leadership, which led to improved coordination and unified decision-making. For the students, their reflections show that their challenges lay in resource management and understanding some technical terms. The group overcame these obstacles through effective communication and scenario resource tracking.

Both groups agreed that the guidance and support from the Game Master/Master of Disaster (GM/MoD) was helpful, and the tabletop exercise was an effective tool for understanding the modelled disaster management concepts. Additionally, observer ratings during and after the game (using the forms in Appendix C2-C3) indicate that both teams

demonstrated elevated levels of engagement and communication skills. However, time management presented some challenges for both groups, indicating room for improvement. Overall, both teams were rated by the observers as competent in terms of their performance in the various criteria. However, to achieve the second objective of DRTRPGs (validation of the predictive ability of the ABMS model), this study collected and analysed data from the in-game activities on the impact of ambulance policy on mortality rates.

5.5.2. Effects of ambulance policy on mortality outcomes (validation)

An ambulance policy is a group of regulations that govern the performance, deployment, and other aspects of emergency response systems in addition to patient care. A boxplot is used to represent the distribution of data from the teams participating in the game activity (Figure 27b) to compare the results of the ABMS model and evaluate the effectiveness of the response measures. This evaluation uses the results (shown in Figure 27) for the two policies ("Always go to RH" and "Alternate"). Figure 27(a) shows the ABMS results, which simulate the behavior and interactions of autonomous agents using computational techniques to generate data about the agents' interactions in the disaster scenario and analyze them using Pandas. Figure 27(b) shows the results of the DRTRPG experiment, which utilizes a more participatory and interactive simulation technique by using RPG to reproduce aspects of the decision protocols of the ABMS model.

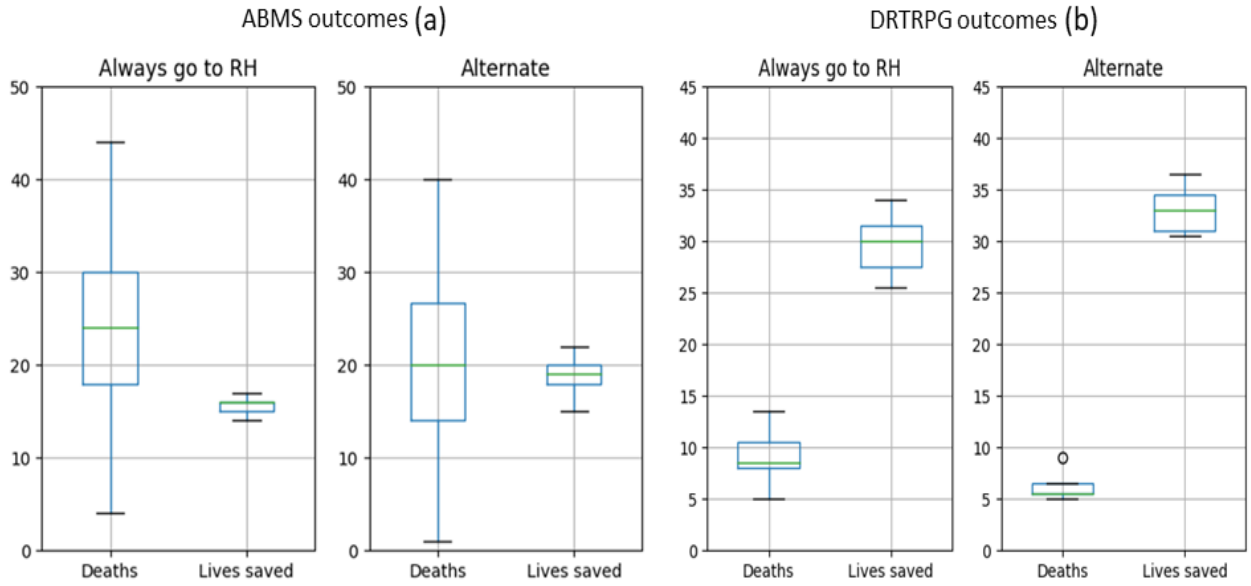

Figure 27: Effects of ambulance policy on morality outcome for (a) ABMS model, (b) DRTRPG

This study's comparison of results offers insights into the efficacy of each response policy by using role-playing methods to validate agent-based models. It achieves this by comparing the outcomes of the two approaches. The subsequent sections delve into the interpretation and implications of these findings.

5.6. Discussion of the results

The validation and communication of the results of the ABMS model in this study differs slightly from widely used traditional techniques. This study chose to compare the simulation results of an ABMS model qualitatively (visually) and statistically with the results of a disaster relief role-playing game, rather than comparing the accuracy of the model results with an equivalent model in the real world. The aim is to increase stakeholder confidence in the predictive power of the model. Conversely, the goal is to examine the ability of the DRTRPG to replicate tasks of individual agents and analyse the results of group decision-making processes.

During the study period, a hypothetical ABMS scenario was first modelled and then doctors and students took on the role of agents in the DRTRPG since it was not possible to obtain experimental or real data during this period. This enabled various observations to be made and controlled experiments, analytical comparisons, and scenario-based tests to be carried out cost-effectively. For the simplified class case of the study, using the group-based collaborative approach to data generation and validation of the ABM appears to provide promising results that are understandable to both the modeler and the role-playing participants.

The results of the DRTRPG show that the game contributes to increasing knowledge about disaster management in interacting emergency departments, especially for people with a medical background. While there was a slight increase in knowledge among students (Group B), there was a significant increase in knowledge among doctors (Group A). The fact that players who had experience with medicine or disaster relief appeared to benefit more from the game suggests that the questions were appropriate to their level of experience. However, the reduced time to complete the post-test assessment in Group B may be due to an adjustment in practice rather than a notable improvement in disaster management knowledge. Players recognized that the game could be used as a teaching tool for disaster management and generally found it educational and useful. I emphasize that the background of the participant should be considered when designing the game in order to optimize learning success.

A nuanced assessment of team performance is supported by the observers scores on game activities and feedback ratings. Both teams were perceived as very collaborative and communicative. Observers recognized that time management was a minor weak point for both

teams, suggesting an area for improvement in subsequent exercises. Team B received higher ratings overall, suggesting that observers placed slightly more weight on role connection than on situational awareness, an area in which Team A performed particularly well. Additionally, Team B was believed to be more sympathetic to their positions. Across all metrics, no team appeared to be in control, and observers generally rated different competencies differently within each team.

The two strategies (Figure 27) shows that both the ABMS model outcomes and DRTRPG outcomes have similar decision dynamics (the mortality outcomes for the policies). However, it is necessary to conduct additional study on the data using basic statistics as there appear to be significant differences in the data distribution. The “Always go to RH” policy has mean mortalities and S.D for ABMS scores that are 23.22 and 8.98, respectively, higher than the “Alternate” policy values. The policy has consistently resulted in lives being saved, as evidenced by the lower mean of 15.85 and S.D (0.79). There are also some differences in mortality outcomes, as shown by the mean and SD of the “Alternate” policy, which are 19.75 and 8.27, respectively. The median, 25th, and 75th percentiles, located at 20, 14, and 26.75, respectively, show a higher concentration of dataset points below the median.

Regarding the DRTRPG results, the “Always go RH” policy has a slightly higher mean mortality (8.94) than the “Alternate” policy with an S.D. of 2.6, indicating greater variability. The lives saved, on the other hand, show good consistency, although with a mean of 29.72 and an S.D. of 2.86, above that of the “Alternate” policy (33.0, 2.11). The results of the “Alternate” policy show a S.D of 1.19, indicating lower variability and lower mean mortality (6.11) compared to the

“Always go RH” policy. In terms of average number of lives saved, the “Alternate” policy results in a higher number (33 lives saved) with an S.D. of 1.90, showing that this policy consistently saves more lives.

Although the "Alternate" policy has a lower average mortality compared to the "Always go to RH" policy (suggesting that the "Alternate" policy may be a more effective strategy for reducing mortality/saving lives), the " Always go to RH” policy produces more consistent results in lives saved, as evidenced by the lower S.D. for lives saved. For both policies, DRTRPG results consistently show lower mortality and more lives saved than ABMS results, with less variability in results. This could mean that the ABMS overestimates the variability or that the DRTRPG does not fully capture the range of variability encountered in the ABMS model. The maximum values for lives saved in the DRTRPG compared to the ABMS could indicate that the ABMS overestimates lives saved or that the DRTRPG results are overly optimistic.

The notable differences between the results of the DRTRPG and ABMS models highlight the difficulties in validating the predictive power of ABMS through role-playing games. This significant deviation may be caused by the significantly lower number of simulations runs (18) of the DRTRPG compared to 720 of the ABMS model, which limits the statistical robustness of the DRTRPG. This means that the validation process may be uncertain as the smaller sample size may not accurately reflect the scope of the scenario. I therefore recommend adjusting the calibration to better adapt the ABM to the human-interactive dynamics of the DRTRPG and thus improve the validation results.

Additionally, it is possible that the DRTRPG results were influenced by players' knowledge, experience, and bias, which may have resulted in more optimal decision-making than expected. One may have to assume that the DRTRPG represents only a “best case” scenario since the purpose of the study is to validate ABMS model protocols using the DRTRPG. If real data is available, additional analysis could include comparing the models against it to determine which strategy more accurately represents the actual results and determine the reason for the significant difference between the two simulation results.

Several studies have successfully used RPG to validate or understand ABMs in disaster response and related areas. For example, the study by Ramchurn *et al* (2016) used tabletop disaster response RPG to validate ABMs to improve understanding and test the effectiveness of the system in simulating scenarios. In another study, Guyot & Honiden (2006) merged TRPGs with ABMs, improving validation by allowing human participants to control agents, thus bridging the gap between model and real behavior. A tabletop disaster response role-playing game such as RimSim was also used by Campbell & Schroder (2009), to validate ABMs for emergency response training and to improve crisis management strategies through simulations. This approach of using TRPGs to validate ABMs is also supported by Janssen & Ostrom (2006), who claimed that disaster response tabletop role-playing games can be used as an empirical approach to validating ABMs. Finally, Mariano & Alves (2020) also integrated role-playing games such as WaDiGa with ABM in water management to reflect local decision-making and show the correspondence between game and model results.

5.7. Lessons learnt

Responses from both groups highlight the importance of effective communication, leadership, and resource management in disaster response scenarios. For the physicians, their experiences highlight the need for interdisciplinary skills such as team leadership and decision-making under pressure that go beyond their medical expertise. Adapting to assigned roles and leadership adjustments demonstrates the value of flexibility and the ability to learn from experience in a dynamic crisis environment. The master's students' reflections highlight the importance of a clear understanding of the operational environment, including technical languages. Both teams agree that support from the GM/MoD is critical in dealing with complex situations. Additionally, they agree that the use of simulations such as DRTRPGs can be an effective teaching tool that provides practical experience that can be translated into real-world applications. These insights can inform the development of disaster management training programs and protocols, ensuring teams are better prepared to meet the challenges of real-world emergency situations.

5.8. Chapter summary

This chapter discussed the planning, design, and implementation of DRTRPGs as a method to improve knowledge of disaster response management and validate the predictive capability of ABMs in the context of interacting EDs for a disaster response event. By simulating a complex decision-making scenario, the DRTRPGs not only serve to engage participants in the mechanics of the DRTRPG, but also provide a platform for data collection, scenario testing and comparative analysis, bridging the gap between theoretical models and practical application. The insights

gained highlight the crucial role of effective communication, leadership, resource management and adaptability in crisis situations.

Furthermore, the results suggest that RPGs can make a significant contribution to disaster preparedness training and highlight their potential to improve participants' understanding of complex systems and decision-making under pressure. However, the use of RPGs in validating ABMS models is challenging, as it is a daunting task to have a complete representation of the ABMs implemented in RPGs. The closing chapter summarizes the study and describes in detail its contributions, challenges, conclusions, and recommendations. The aim is to provide a comprehensive overview of the research implications and future directions in the areas of disaster management, simulation-based studies, and collaborative simulation games.

CHAPTER 6

6.0. SUMMARY, CONTRIBUTIONS, CHALLENGES/LIMITATIONS, CONCLUSION AND RECOMMENDATIONS

6.1. Introduction

In this final chapter, I share my thoughts and insights from the data analysis performed using various tools, including Microsoft Excel, Pandas from the Anaconda libraries, and others, on the data produced by the applied methods (ABMS and RPG). This chapter also includes a summary of the results of the study, its contribution to the scientific community, its limitations and difficulties, and recommendations for further research.

The previous chapters presented the context of the study, conducted a literature review, and described the model design and development process. In addition, the impact of ambulance policy on mortality and mean waiting times examined using data generated from NetLogo's BehaviorSpace (data generation and experimentation function) and the DRTRPG exercise. The use of Business Process Management and Notation (BPMN) provided a way to simplify and represent the workflow of the interacting MFH and RH as emergency departments (EDs). The analysis of the simulation results provided insights into the phenomenon of complex interaction between the EDs in the hypothetical disaster response scenario. In addition, the DRTRPG results from participants' interaction and collaboration were used to evaluate the predictive capability of the ABMS model and assess its consistency.

6.2. Summary of the study

This study examines the application of computational techniques and disaster response role-playing game to assess the feasibility of developing a reproducible and adaptable simulation model for disaster response and crisis decision-making in healthcare. A crisis management approach is used to deploy resources and evacuate victims from a hypothetical disaster site following a sudden onset of disaster. This approach requires diverse agents and their ability to coordinate and allocate resources effectively. While the model in no way replaces any real system, the simulations and exercise developed and implemented in this study can serve as an analytical tool to support process improvement, training, and decision-making.

The simulation model and game developed for this study analysed the results of both reactive and deliberative agents' decisions, evaluated as mortality, and mean wait time outcomes from interacting emergency departments. The core elements of the developed agent-based model (NetLogo 6.3.0) were then transformed and implemented in a tabletop serious game where participants played through the model's decision-making rules, providing an answer to the study's research questions. This research questions posed in this study are: (1) "How can the interaction between a regional hospital (RH) and a mobile field hospital (MFH) be modelled for a disaster response setting for the oil and gas industry?" and (2) "How can Disaster Response Tabletop Role-Playing Games (DRTRPGs) be used to verify/validate the representativeness of the ABMS model agents' response process in the context of the disaster response scenario?" The aim of this study is to "improve the interoperability between a regional hospital and a mobile field

hospital by detailing the process of interaction between the systems," describing a typical disaster response incident control system.

In the event of an industrial explosion such as that hypothesized in this study, the parameters examined highlighted the uncertainties associated with the complexity of responding to a disaster scenario and the variability due to the crisis context as critical to patient outcomes. The examined indicators can serve two purposes: (1) enable an assessment of the overall effectiveness of disaster response strategies; and (2) draw attention to elements in the context of disaster response management that may have larger and complementary impacts. The need for informed decision-making in disaster situations to reduce patient mortality rates and mean waiting times between interoperable healthcare systems is demonstrated in this study through modelling, simulation, and gamification. Therefore, the potential and effectiveness of using combined techniques to gain valuable insights into the interactions within complex systems is established.

6.3. Contributions of the study

For a study to be successful and useful for a particular area, it must consider both the research purpose and objectives and describe in detail how each objective was achieved. To develop a methodological, interaction-based, and exploratory technique that can guide future interdisciplinary research, this study combined both ABMS and RPG methods. By using datasets generated from both approaches, the feasibility of the proposed technique was validated. Therefore, the form of contributions in this study provides answers to the research questions. ABMS-RPG based exploratory studies that simulate interactions between a RH and an MFH in

emergency situations have enormous potential to contribute to progress in various areas, as outlined below:

- **Knowledge gap identification:** Identifying critical knowledge gaps is a major advantage when conducting exploratory research in the field of disaster response and serves a dual purpose: to guide and inform future research and to facilitate the prioritization of domain-specific efforts in this area. Therefore, the contribution of assessing the impact of ambulance operations in a disaster response scenario between interacting health systems while addressing issues of response coordination and resource allocation is significant to the advancement of future scientific investigations.
- **Improved understanding of complex hospital systems interaction in disaster settings:** By integrating an agent-based model into this research study, a better understanding of the complex systems and dynamics of disaster response for interacting hospital systems was achieved. This approach enabled a better understanding of critical factors such as resource allocation and efficient response coordination, which are crucial to improving disaster response competency in sudden-onset disasters. In addition, it provides a basis for future research aimed at refining the understanding and effectiveness of computational methods for disaster response class problems.
- **Training/Education:** The simulation model and role-play developed as part of this research study can be an effective, versatile training and educational tool tailored to the needs of emergency response teams and healthcare providers and can help practitioners gain a better understanding of disaster response systems. As a result, it can help improve skills

and strengthen preparedness for real-world disasters. Additionally, the simulation model's ability to enable experiential learning about its simulated environment for scenario-based training exercises can help response teams and health care providers improve their preparation and ability to effectively respond to the complex disaster response class problems.

- **Coordination and communication practice:** The game scenario offers the opportunity to improve basic knowledge, but also illustrates how important it is to coordinate various health facilities and emergency services quickly and effectively.
- **Evidence-based policy making:** By closely examining the results of various strategies in both the ABMS model and the game setting, policymakers and public health practitioners can develop more informed and evidence-based policies and protocols that specifically address the disaster response challenges associated with the oil and gas industry.

Additionally, previous work on using NetLogo in modelling and simulating disaster response scenarios with a focus on the mortality outcomes and mean wait times of emergency scenarios was conducted using older versions that may not have taken advantage of the BehaviorSpace feature set to enable numerous sampling combinations. These parameter experiments are carried out automatically and generates very extensive data sets. This study argues that although Netlogo provides a visualization window and basic graphics, it needs other tools for better data manipulation, statistics, and graphics.

To meet this requirement, this study utilized several Pandas upon Anaconda libraries (Python tools) and other statistical tools for data analysis. Although there are articles about using

NetLogo in healthcare and disaster response, this study provides further details on the specific issues a programmer new to Netlogo faces when tackling a crisis and disaster management challenge. This is available in the “code” and “info” tabs for the model and system documentation, along with inline comments explaining the reasoning behind some coding decisions. This study therefore serves as preliminary work to achieve future improvement of healthcare systems by modelling the interaction between hospital systems in disaster situations.

6.4. Challenges/limitations of the study

The validity and applicability of research results are always influenced by the availability and quality of the data; Therefore, it is crucial that any challenges or limitations that may have influenced the results are properly acknowledged. This will help define a clear perspective for future studies. Although I am convinced and confident that both the model and the role-play (with some variations) correctly predict the concept, there is no clear claim that a sufficiently strong relationship exists (until it is tested, calibrated, and validated against a real system), between the outcomes of the investigated strategies and an actual disaster response scenario. According to Collins *et al*. (2024), a simulation can never fully reproduce the system under study; Therefore, comparisons should be limited to the critical elements of the simulated environment. They also noted that the goals of the simulation determine the necessary components and serve as the standard against which all validation efforts are measured.

On the above crucial points, my position is that no individual or organization is recommended to use the results of this study in making important policy decisions. This is because the modelled system is a hypothetical case and therefore the agents decisions are not

based on local data. Therefore, the agent's interactions and the resulting outcomes are based on simple rules and goals based on certain simplified assumptions. In other words, this study investigates the usefulness of the NetLogo 6.3.0 modelling tool and simulation game in testing and evaluating outcomes in a disaster environment based on simply defined rules in emergency situations.

Another limitation of this study is its narrow scope, as it examines only a few selected performance indicators: mortality outcomes and waiting times related to ambulance policy. Therefore, other secondary Key Performance Indicators (KPIs) such as the impact of patient waiting time on system performance in distinct phases were not considered. Additionally, other important aspects in EDs such as patient diagnoses, patient satisfaction, overall quality of care, or physician physical condition were assumed to have been completed in the course of the patient care. For example, studying the impact of physician fatigue on service quality, such as: accurate diagnoses and fewer readmissions. Furthermore, to model the scenario, this study relied primarily on literature reviews and plausibility checks rather than experimental observations of real systems.

Additionally, because the study focuses on predicting mortality outcomes and waiting times in simplified emergency departments, it ignores other factors that could result in other secondary outcomes from the interaction between these systems (e.g., logistics, clinical staff, etc.). Future models could consider integrating additional social decision-making processes of stakeholders (agents) into the system and conduct better classical tests (calibration, validation,

refinement, etc.) based on local data availability to evaluate the feasibility of using the model more effectively for Improve decisions support.

Finally, regarding the challenge of using ABMS for the modelled system, this study showed that a substantial number of computational resources and detailed data are required to achieve better results. As computer power increases, new opportunities for ABMS modelling could emerge. However, running a highly detailed model with hundreds or thousands of agents requires computational resources. ABMS software can also be a challenge to master in a brief period because it requires some basic programming skills in addition to a thorough understanding of the underlying theories. Concerns about patient privacy also posed a major challenge in data acquisition. This research also shows that, data sources may not exist (as this study demonstrates) or may not contain all the necessary information for an accurate and comprehensive ABMS model development and to design a robust role-playing game. Under these circumstances, synthetic data generation became the only way to explore the capabilities of the ABMS toolkit. Additionally, data cleaning and manipulation can be time-consuming.

6.5. Conclusion

The demand for oil and gas resources has made the petroleum industry an important contributor to the global economy. However, statistics on petroleum exploration and production activities have shown that they are prone to major industrial disasters, resulting in injuries and deaths. In disaster situations, an efficient and effective emergency plan is required. This study highlights the need to generate potential outcomes and test how response strategies would influence mortality and waiting times. The research demonstrated how effective procedures can

be implemented for different scenarios, resulting in faster response times and better health outcomes. However, since the results of the study are based on a hypothetical case, further investigation and calibration of the model is recommended to achieve the best results.

The combination of NetLogo (ABMS) and DRTRPG techniques provides a unique approach to evaluating contingency plans, supported by evidence of their significant value from the results. The methodological approach adopted in this study provided not only a realistic simulation, but also a platform that can be adapted for informed decision making and employee training. The use of these tools provided evidence of the need to improve emergency response to disasters and reduce mortality rates in disaster situations.

These collections of generative scientific knowledge led to significant results achieved through the combination techniques and thus provided an important framework for consideration in future studies. The results of this study also showed that the proposed hypothesis that the deployment of MFHs within the first four hours in a post-disaster situation in collaboration with an existing regional hospital can help reduce the mortality rate and mean waiting times of injured patients. Therefore, the importance of policy assessment for improving emergency response strategies and the application of simulation technologies such as NetLogo ABMS and scenario-based RPG for disaster response in modelling, simulating and communicating system interactions is highlighted.

The main findings of the study provided essential information and viable solutions to improve industrial disaster response plans. It also highlights the need for flexible and dynamic response strategies that can successfully mitigate the challenges posed by disaster scenarios

through a thorough comparative analysis between “Always go to RH” and “Alternate” policies. With DRTRPG, simulation exercises are conducted that not only provide the opportunity to validate the predictive accuracy of the response decisions made by the ABMS model agents, but also act as a bridge between theoretical models and real-world applications. Decision makers may utilize the study's findings to prioritize disaster response variables and improve emergency services in high-risk situations.

Based on the results, I suggest that policymakers should think about how response methods affect the consequences of disasters. In this study, I also propose the use of simulation tools to develop, evaluate and improve resilient and adaptive health systems. This study demonstrates the benefits of integrated response strategies in addition to its insights into RH-MFH dynamics in possible disaster scenarios. The study reveals that the “Alternate” policy that utilizes RH and MFH resources, achieve better outcomes and enabled collaborative disaster management to save more lives and subsequently reduced the average waiting times.

Using the DRTRPG validation approach, I developed, implemented and evaluated the predictive ability of the ABMS models while providing empirical data and perspectives to the disaster management literature to improve the forecasting tools. This strategy provides a collaborative framework for problem-solving and decision-making while testing the theoretical foundations of disaster response plans. The research uses ABMS and DRTRPG to improve our understanding of disaster response processes, optimize policies, and provide theory for disaster planning, training, and response education. Thus, this exploratory study serves as a foundation for simulation and game-based disaster response strategies by highlighting the transformative

potential of simulation-based methods in creating robust, effective, and flexible disaster management systems.

6.6. Recommendations for future studies

Further research is needed in this area as the review of the literature highlights the need for additional studies on simulation models for interoperability between healthcare systems in an industrial emergency scenario. Subsequent research could explore topics related to human factors, such as simulating and quantifying the effects of human characteristics such as fatigue on medical systems. Therefore, “How can human aspects related to fatigue and emotions of people be developed and modeled in healthcare systems during emergencies?” would be an interesting research question that would arise from such a study.

In addition, since this study is not based on the development of a comparable, real-world system of an actual emergency department, it would be interesting to investigate the feasibility of developing a generic simulation model for the emergency department that considers human aspects related to service quality, effectiveness of diagnosis and patient satisfaction in health systems. A research question that could be investigated could be: “How can a generic model be developed and used to incorporate emotional and competence aspects such as patient satisfaction and service quality in disaster situations?” A third aspect for further research using simulation techniques would be to use more advanced modeling - and simulation packages such as AnyLogic, which are intended to integrate both ABMS and DES approaches. Such a study would enable better calibration and comparison of hybrid strategies.

While using tabletop role-playing games to validate agent-based NetLogo models presents challenges, it also provides a dynamic approach that promotes a deeper understanding of complex systems. This study therefore highlights the potential benefits of this validation technique (although it focuses on a hypothetical scenario) and recommends that game participants should be included in the ABMS model development structure from the beginning of the project to achieve better calibration and validation results. Both the agent-based model and the serious game should be continuously refined through feedback loops and collaboration between modelers and game developers.

Appendices A2-A6 show BPMN diagrams based on predictions of the severity of consequences of industrial explosions, ranging from polytrauma to influenza-related illnesses. This provides a basic operational planning and decision-making framework for future studies. The purpose of these diagrams is to provide strategic guidance for disaster response mechanisms for MFHs. Future research should attempt to model these processes and focus on improving and empirically testing the proposed BPMN frameworks, focusing on their adaptability and scalability in a range of disaster scenarios. In this way, it will be possible to practically apply the theoretical insights from this research to improve disaster resilience in more complex cases.

REFERENCES

Abate, V., Adacher, L., & Pascucci, F. (2014). Situation awareness in critical infrastructures. *International Journal of Simulation and Process Modelling*. https://www.inderscienceonline.com/doi/10.1504/IJSPM.2014.061451

Abulebda, K., Lutfi, R., Whitfill, T., Abu-Sultaneh, S., Leeper, K. J., Weinstein, E., & Auerbach, M. A. (2018). A Collaborative In Situ Simulation-based Pediatric Readiness Improvement Program for Community Emergency Departments. *Academic Emergency Medicine*, *25*(2), 177–185. https://doi.org/10.1111/acem.13329

Ajmi, F., Ben Othman, S., Zgaya Biau, H., & Hammadi, S. (2018, August). Scheduling Approch to Control the Execution of the Patient Pathway Workflow in the Emergency Department. *The 3th International FLINS Conference on Data Science and Knowledge Engineering for Sensing Decision Support (FLINS 2018)*. https://hal.science/hal-01773708

Al Halabi, A. M., Habas, E., Ghazouani, H., Borham, A. M., Swallmeh, E., & Abou-Samra, A.-B. (2022). Scenarios to Improve the Patient Experience Time in a Tertiary Academic Hospital Using Simulation. *Cureus*. https://doi.org/10.7759/cureus.30751

Albert, L. A. (2023). A mixed-integer programming model for identifying intuitive ambulance dispatching policies. *Journal of the Operational Research Society*, *74*(11), 2300–2311. https://doi.org/10.1080/01605682.2022.2139646

Al-Fedaghi, S. (2016). Conceptual Modeling in Simulation: A Representation that Assimilates Events. *International Journal of Advanced Computer Science and Applications*, *7*(10). https://doi.org/10.14569/IJACSA.2016.071038

Aloui, S., Chapurlat, V., & Penalva, J. M. (2006). Linking interoperability and risk assessment: A methodological approach for socio-technical systems. *IFAC Proceedings*, *39*(3), 585–590.

Alrehaili, N. R., Almutairi, Y. N., Alghamdi, H. M., & Almuthaybiri, M. S. (2022). A Structural Review on Disaster Management Models and Their Contributions. *International Journal of Disaster Management*, *5*(2), 93–108. https://doi.org/10.24815/ijdm.v5i2.27087

Altay, N. (2013). Capability-based resource allocation for effective disaster response. *IMA Journal of Management Mathematics*, *24*(2), 253–266. https://doi.org/10.1093/imaman/dps001

Altay, N., & Green, W. G. (2006). OR/MS research in disaster operations management. *European Journal of Operational Research*, *175*(1), 475–493. https://doi.org/10.1016/j.ejor.2005.05.016

Altevogt, B. M., Stroud, C., Nadig, L., & Hougan, M. (2010). *Forum on Medical and Public Health Preparedness for Catastrophic Events*.

Amadou, M. L., Villamor, G. B., & Kyei-Baffour, N. (2018). Simulating agricultural land-use adaptation decisions to climate change: An empirical agent-based modelling in northern Ghana. *Agricultural Systems*, *166*, 196–209. https://doi.org/10.1016/j.agsy.2017.10.015

Amakama, N. J., Dusserre, G., Cadiere, A., & Schuette, R. W. (2023a, September 5). *Assessing the Impact of Wait Times on Patient Mortality Outcomes in a Hypothetical Oil and Gas Industry Disaster Scenario: An Agent-Based Modeling Approach Using NetLogo*. QPSS 2023 - Qatar Process Safety Symposium. https://imt-mines-ales.hal.science/hal-04199308

Amakama, N. J., Dusserre, G., Cadiere, A., & Schuette, R. W. (2023b, September 5). *Assessing the Impact of Wait Times on Patient Mortality Outcomes in a Hypothetical Oil and Gas Industry Disaster Scenario: An Agent-Based Modeling Approach Using NetLogo*. QPSS 2023 - Qatar Process Safety Symposium. https://imt-mines-ales.hal.science/hal-04199308

Amakama, N. J., Dusserre, G., Cadiere, A., Schuette, R. W., & Zacharewicz, G. (2023, April 13). *Risk Management and Disaster Response In the Oil and Gas Industry: Modelling and Implementation of Interoperable Healthcare Systems Solution for Disaster Response in the Oil and Gas Industry*. Colloque IMT 2023 : « Sécurité et Résilience ». https://doi.org/10.5281/zenodo.7937270

Amakama, N. J., Dusserre, G., Cadiere, A., Schuette, R. W., & Zacharewicz, G. (2024). How Effective are Tabletop Role-Playing (Serious) Games in Understanding and Validating the Predictive Capabilities of Disaster Response Agent-based Models? *American Journal of*

Multidisciplinary Research and Innovation, *3*(4), 49–61. https://doi.org/10.54536/ajmri.v3i4.2937

Anand, N., Meijer, D., van Duin, J. H. R., Tavasszy, L., & Meijer, S. (2016). Validation of an agent based model using a participatory simulation gaming approach: The case of city logistics. *Transportation Research Part C: Emerging Technologies*, *71*, 489–499. https://doi.org/10.1016/j.trc.2016.08.002

Antonacci, G., Calabrese, A., D'Ambrogio, A., Giglio, A., Intrigila, B., & Ghiron, N. L. (2016). A BPMN-Based Automated Approach for the Analysis of Healthcare Processes. *2016 IEEE 25th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE)*, 124–129. https://doi.org/10.1109/WETICE.2016.35

Aringhieri, R., Bigharaz, S., Duma, D., & Guastalla, A. (2022). Fairness in ambulance routing for post disaster management. *Central European Journal of Operations Research*, *30*(1), 189–211. https://doi.org/10.1007/s10100-021-00785-y

Arnaud, B., Christophe, L., & Nicolas, M. (2015). *Agent-based Spatial Simulation with Netlogo*. Elsevier. https://doi.org/10.1016/C2015-0-01299-0

Aslam, A. (2023). *Universal Language Modelling agent* (arXiv:2306.06521). arXiv. https://doi.org/10.48550/arXiv.2306.06521

Azimi, S., Dalavar, M. R., & Rajabifard, A. (2017). Multi-agent simulation of allocating and routing ambulances under condition of street blockage after natural disaster. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 325–332. https://doi.org/10.5194/ISPRS-ARCHIVES-XLII-4-W4-325-2017

Background of Disaster management. (2023). *INSIGHTSIAS*. https://www.insightsonindia.com/disaster-management/background-of-disaster-management/

Baker, D., & Refsgaard, K. (2007). Institutional development and scale matching in disaster response management. *Ecological Economics*, *63*(2), 331–343. https://doi.org/10.1016/j.ecolecon.2007.01.007

Barghi Shirazi, F., Moslehi, S., Rasouli, M. R., & Masoumi, G. (2022). A Systematic Literature Review Identifying the Dimensions and Components of Simulation of the Hospital

Emergency Department During Emergencies and Disasters. *Medical Journal of the Islamic Republic of Iran*. https://doi.org/10.47176/mjiri.36.82

Bar-On, E., Peleg, K., & Kreiss, Y. (Eds.). (2020). *Field Hospitals: A Comprehensive Guide to Preparation and Operation* (1st ed.). Cambridge University Press. https://doi.org/10.1017/9781316493489

Basaglia, A., Spacone, E., van de Lindt, J. W., & Kirsch, T. D. (2022). A Discrete-Event Simulation Model of Hospital Patient Flow Following Major Earthquakes. *International Journal of Disaster Risk Reduction*, *71*, 102825. https://doi.org/10.1016/j.ijdrr.2022.102825

Basaglia, A., Spacone, E., Van De Lindt, J. W., & Kirsch, T. D. (2022). A Discrete-Event Simulation Model of Hospital Patient Flow Following Major Earthquakes. *International Journal of Disaster Risk Reduction*, *71*, 102825. https://doi.org/10.1016/j.ijdrr.2022.102825

Bauer, B., & Odell, J. (2005). UML 2.0 and agents: How to build agent-based systems with the new UML standard. *Engineering Applications of Artificial Intelligence*, *18*(2), 141–157. https://doi.org/10.1016/j.engappai.2004.11.016

Berg, T. A., Marino, K. N., & Kintziger, K. W. (2023). The Application of Model-Based Systems Engineering to Rural Healthcare System Disaster Planning: A Scoping Review. *International Journal of Disaster Risk Science*, *14*(3), 357–368. https://doi.org/10.1007/s13753-023-00492-z

Birkland, T. A. (2009). Disasters, Catastrophes, and Policy Failure in the Homeland Security Era1. *Review of Policy Research*, *26*(4), 423–438. https://doi.org/10.1111/j.1541-1338.2009.00393.x

Bisogno, S., Calabrese, A., Gastaldi, M., & Levialdi Ghiron, N. (2016). Combining modelling and simulation approaches: How to measure performance of business processes. *Business Process Management Journal*, *22*(1), 56–74. https://doi.org/10.1108/BPMJ-02-2015-0021

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the national academy of sciences*, *99*(suppl 3), 7280–7287. https://doi.org/10.1073/pnas.082080899

Boonmee, C., Arimura, M., & Asada, T. (2017). Facility location optimization model for emergency humanitarian logistics. *International Journal of Disaster Risk Reduction*, *24*, 485–498. https://doi.org/10.1016/j.ijdrr.2017.01.017

Borgonovo, E., Pangallo, M., Rivkin, J., Rizzo, L., & Siggelkow, N. (2022). Sensitivity analysis of agent-based models: A new protocol. *Computational and Mathematical Organization Theory*, *28*(1), 52–94. https://doi.org/10.1007/s10588-021-09358-5

Bowman, S. L. (2011). The functions of role-playing games: How participants create community, solve problems and explore identity. *Choice Reviews Online*, *48*(06), 48-3103-48–3103. https://doi.org/10.5860/CHOICE.48-3103

Brailsford, S. C. (2007). Tutorial: Advances and challenges in healthcare simulation modeling. *2007 Winter, Simulation Conference*, 1436–1448. https://doi.org/10.1109/wsc.2007.4419754

Bruballa, E., Wong, A., Rexachs, D., & Luque, E. (2020). An Intelligent Scheduling of Non-Critical Patients Admission for Emergency Department. *IEEE Access*, *8*, 9209–9220. https://doi.org/10.1109/ACCESS.2019.2963049

Çağlayan, N., & Satoglu, S. I. (2022). Simulation analysis of critical factors of casualty transportation for disaster response: A case study of Istanbul earthquake. *International Journal of Disaster Resilience in the Built Environment*, *13*(5), 632–647. https://doi.org/10.1108/IJDRBE-03-2021-0031

Campbell, B. D., & Schroder, K. A. (2009). *Training for emergency response with RimSim:Response!* (D. A. Trevisani, Ed.; p. 73480G). https://doi.org/10.1117/12.819337

Cao, H., & Huang, S. (2012). Principles of Scarce Medical Resource Allocation in Natural Disaster Relief: A Simulation Approach. *Medical Decision Making*, *32*(3), 470–476. https://doi.org/10.1177/0272989X12437247

Castanheira-Pinto, A., Gonçalves, B. S., Lima, R. M., & Dinis-Carvalho, J. (2021). Modeling, Assessment and Design of an Emergency Department of a Public Hospital through Discrete-Event Simulation. *Applied Sciences*, *11*(2), Article 2. https://doi.org/10.3390/app11020805

Chatterjee, A., Cao, Q., Sajadi, A., & Ravandi, B. (2023). Deterministic random walk model in NetLogo and the identification of asymmetric saturation time in random graph. *Applied Network Science*, *8*(1), Article 1. https://doi.org/10.1007/s41109-023-00559-2

Chaudhary, M. T., & Piracha, A. (2021). Natural Disasters—Origins, Impacts, Management. *Encyclopedia*, *1*(4), 1101–1131. https://doi.org/10.3390/encyclopedia1040084

Chen, X., Lu, L., Shi, J., Zhang, X., Fan, H., Fan, B., Qu, B., Lv, Q., & Hou, S. (2020). Application and Prospect of a Mobile Hospital in Disaster Response. *Disaster Medicine and Public Health Preparedness*, *14*(3), 377–383. https://doi.org/10.1017/dmp.2020.113

Clancy, C. M. (2007). Emergency Departments in Crisis: Implications for Disaster Preparedness. *American Journal of Medical Quality*, *22*(2), 123–126. https://doi.org/10.1177/1062860606298915

Coles, J., & Zhuang, J. (2011). Decisions in Disaster Recovery Operations: A Game Theoretic Perspective on Organization Cooperation. *Journal of Homeland Security and Emergency Management*, *8*(1). https://doi.org/10.2202/1547-7355.1772

Collins, A. J., Matthew, K., & Christopher J., L. (2024). *Methods That Support the Validation of Agent-Based Models: An Overview and Discussion*. https://doi.org/10.18564/jasss.5258

Collins, J. (2021). *Improving Emergency Department Throughput: Using a Pull Method of Patient Flow* [Doctor of Nursing Practice, University of St. Augustine for Health Sciences]. https://doi.org/10.46409/sr.CSAP4806

Comfort, L. K., Ko, K., & Zagorecki, A. (2005). Coordination in rapidly evolving disaster response systems: The role of information. In T. Terano, H. Kita, T. Kaneda, K. Arai, & H. Deguchi (Eds.), *Agent-Based Simulation: From Modeling Methodologies to Real-World Applications* (pp. 208–219). Springer. https://doi.org/10.1007/4-431-26925-8_19

Contreras, A., Falcone, Y., Salaün, G., & Zuo, A. (2022). WEASY: A Tool for Modelling Optimised BPMN Processes. In S. L. Tapia Tarifa & J. Proença (Eds.), *Formal Aspects of Component Software* (Vol. 13712, pp. 110–118). Springer International Publishing. https://doi.org/10.1007/978-3-031-20872-0_7

d'Aquino, P., & Bah, A. (2014). Multi-level participatory design of land use policies in African drylands: A method to embed adaptability skills of drylands societies in a policy

framework. *Journal of Environmental Management*, *132*, 207–219. https://doi.org/10.1016/j.jenvman.2013.11.011

D'água, J. B., Cláudio, A. P., Carmo, M. B., Guerreiro, M., Cavaco, A., Piedade, D., Gomes, C. F., Pais, A., Mateus, E., de Lisboa, U., & Moniz, E. (2023). *Pare Vitoria, a virtual assistant to promote education and awareness on juvenile rheumatic musculoskeletal diseases.* https://doi.org/10.1136/annrheumdis-2023-eular.5927

De Rouck, R., Benhassine, M., Debacker, M., Dugauquier, C., Dhondt, E., Van Utterbeeck, F., & Hubloue, I. (2023). Creating realistic nerve agent victim profiles for computer simulation of medical CBRN disaster response. *Frontiers in Public Health*, *11*. https://doi.org/10.3389/fpubh.2023.1167706

De Santis, A., Giovannelli, T., Lucidi, S., Messedaglia, M., & Roma, M. (2023). A simulation-based optimization approach for the calibration of a discrete event simulation model of an emergency department. *Annals of Operations Research*, *320*(2), 727–756. https://doi.org/10.1007/s10479-021-04382-9

De Silva, D. G., Jung, H., & Kosmopoulou, G. (2018). The impact of regional competition on the health care industry. *Applied Economics*, *50*(48), 5135–5141. https://doi.org/10.1080/00036846.2018.1467551

Deinkuro, N. S., Knapp, C. W., Raimi, M. O., & Nimlang, N. H. (2021). Environmental Fate of Toxic Volatile Organics from Oil Spills in the Niger Delta Region, Nigeria. *International Journal of Environment, Engineering and Education*, *3*(3), 89–101. https://doi.org/10.55151/ijeedu.v3i3.64

Deloui, H., & Mofrad, S. S. (2021). *Identification and evaluation of physical indicators affecting emergency accommodation and safe places with physical resilience approach Case study: District 11 of Mashhad*. https://www.semanticscholar.org/paper/Identification-and-evaluation-of-physical-affecting-Deloui-Mofrad/f61b60eff38cc934c4053dc2219ad93fadb6b5a1

Demirel, M. C. (2014). *İSTANBUL TEKNİK ÜNİVERSİTESİ*.

Dickerson, M. (2011). *Multi-agent simulation and netLogo in the introductory computer science curriculum*. https://dl.acm.org/doi/abs/10.5555/2037151.2037175

Disaster Management. (2024). Physiopedia. https://www.physio-pedia.com/Disaster_Management

Durán, J. M. (2020). What is a Simulation Model? *Minds and Machines*, *30*(3), 301–323. https://doi.org/10.1007/s11023-020-09520-z

Encinas, D. O., Maccallini, L., & Romero, F. (2021). An Approach to the Modeling and Simulation of Intra-Hospital Diseases. *Journal of Computer Science and Technology*, *21*(2), e14. https://doi.org/10.24215/16666038.21.e14

England, T., Brailsford, S., Evenden, D., Street, A., Maynou, L., Mason, S. M., Preston, L., Burton, C., Van Oppen, J., & Conroy, S. (2023). Examining the effect of interventions in emergency care for older people using a system dynamics decision support tool. *Age and Ageing*, *52*(1), afac336. https://doi.org/10.1093/ageing/afac336

Farcas, A., Ko, J., Chan, J., Malik, S., Nono, L., & Chiampas, G. (2021). Use of Incident Command System for Disaster Preparedness: A Model for an Emergency Department COVID-19 Response. *Disaster Medicine and Public Health Preparedness*, *15*(3), e31–e36. https://doi.org/10.1017/dmp.2020.210

Faturahman, B. M. (2021). DISKURSUS MANAJEMEN BENCANA ERA COVID-19. *Madani Jurnal Politik Dan Sosial Kemasyarakatan*, *13*(1), Article 1. https://doi.org/10.52166/madani.v13i1.2291

Fava, G., Giovannelli, T., Messedaglia, M., & Roma, M. (2022). Effect of different patient peak arrivals on an emergency department via discrete event simulation: A case study. *SIMULATION*, *98*(3), 161–181. https://doi.org/10.1177/00375497211038756

Ferrando, A., & Malvone, V. (2022). *Towards the Combination of Model Checking and Runtime Verification on Multi-Agent Systems* (Vol. 13616, pp. 140–152). https://doi.org/10.1007/978-3-031-18192-4_12

Ferreira, L. A. F., Santos, I. L. dos, Santos, A. C. de S. G. dos, & Reis, A. da C. (2020). Discrete event simulation for problem solving in the context of an emergency department. *Independent Journal of Management & Production*, *11*(5), Article 5. https://doi.org/10.14807/ijmp.v11i5.1286

Forbus, J. J., & Berleant, D. (2022). Discrete-Event Simulation in Healthcare Settings: A Review. *Modelling*, *3*(4), Article 4. https://doi.org/10.3390/modelling3040027

Freebairn, L., Atkinson, J., Kelly, P., McDonnell, G., & Rychetnik, L. (2016). Simulation modelling as a tool for knowledge mobilisation in health policy settings: A case study protocol. *Health Research Policy and Systems*, *14*(1), 71. https://doi.org/10.1186/s12961-016-0143-y

Fu, X., Krzhizhanovskaya, V., Yakovlev, A., & Kovalchuk, S. (2022). *Modelling Hospital Strategies in City-Scale Ambulance Dispatching* (arXiv:2201.01846). arXiv. https://doi.org/10.48550/arXiv.2201.01846

FutureLearn. (2023). Preparedness and the disaster cycle. *FutureLearn*. https://www.futurelearn.com/info/blog

Gallaher, M. P., O'Connor, A. C., Dettbarn, Jr., J. L., & Gilday, L. T. (2004). *Cost Analysis of Inadequate Interoperability in the U.S. Capital Facilities Industry* (NIST GCR 04-867; p. NIST GCR 04-867). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.GCR.04-867

Gao, J. (2022). *Fundamentals of Spatial Analysis and Modelling* (1st ed.). CRC Press. http://dx.doi.org/10.1201/9781003220527-6

Gao, Y., Sahin, A., & Vrugt, J. A. (2023). Probabilistic Sensitivity Analysis With Dependent Variables: Covariance-Based Decomposition of Hydrologic Models. *Water Resources Research*, *59*(4), e2022WR032834. https://doi.org/10.1029/2022WR032834

George, S., & Kumar, P. P. A. (2022). Indicator-based assessment of capacity development for disaster preparedness in the Indian context. *Environment Systems and Decisions*, *42*(3), 417–435. https://doi.org/10.1007/s10669-022-09856-0

Gilbert, N. (2007). *Computational Social Science: Agent-based social simulation*. http://www.bardwell-press.co.uk

Goniewicz, K., Goniewicz, M., Włoszczak-Szubzda, A., Burkle, F. M., Hertelendy, A. J., Al-Wathinani, A., Molloy, M. S., & Khorram-Manesh, A. (2021). The importance of pre-training gap analyses and the identification of competencies and skill requirements of

medical personnel for mass casualty incidents and disaster training. *BMC Public Health*, *21*(1), 114. https://doi.org/10.1186/s12889-021-10165-5

González, D. P. (2022). Disaster Risk Governance as Assemblage: The Chilean Framework of the 1985 San Antonio Earthquake. *International Journal of Disaster Risk Science*, *13*(6), 878–889. https://doi.org/10.1007/s13753-022-00453-y

Gore, R. J., Lynch, C. J., & Kavak, H. (2017). Applying statistical debugging for enhanced trace validation of agent-based models. *SIMULATION*, *93*(4), 273–284. https://doi.org/10.1177/0037549716659707

Guha-Sapir, D., Vos, F., & Below, R. (2015). *Annual Disaster Statistical Review 201*. http://www.cred.be/sites/default/files/ADSR_2015.pdf

Gul, M., & Guneri, A. F. (2015). A comprehensive review of emergency department simulation applications for normal and disaster conditions. *Computers & Industrial Engineering*, *83*, 327–344. https://doi.org/10.1016/j.cie.2015.02.018

Gullett, H., Brown, G., Collins, D., Mathews, M., Stange, K., & Hovmand, P. (2023). 249 Addressing Structural Racism Using Community Based System Dynamics. *Journal of Clinical and Translational Science*, *7*(s1), 76–77. https://doi.org/10.1017/cts.2023.316

Gunal, M. M., & Pidd, M. (2006). Understanding Accident and Emergency Department Performance using Simulation. *Proceedings of the 2006 Winter Simulation Conference*, 446–452. https://doi.org/10.1109/WSC.2006.323114

Günal, M. M., & Pidd, M. (2010). Discrete event simulation for performance modelling in health care: A review of the literature. *Journal of Simulation*, *4*(1), 42–51. https://doi.org/10.1057/jos.2009.25

Guo, X., & Kapucu, N. (2015). Examining Coordination in Disaster Response Using Simulation Methods. *Journal of Homeland Security and Emergency Management*, *12*(4), 891–914. https://doi.org/10.1515/jhsem-2014-0092

Guyot, P., & Honiden, S. (2006). Agent-Based Participatory Simulations: Merging Multi-Agent Systems and Role-Playing Games. *Journal of Artificial Societies and Social Simulation*, *9*.

Halaška, M., & Šperka, R. (2018). Is there a Need for Agent-based Modelling and Simulation in Business Process Management? *Organizacija*, *51*(4), 255–269. https://doi.org/10.2478/orga-2018-0019

Healthit.gov. (2013). *The Path to Interoperability*.

Herman, J., & Usher, W. (2017). SALib: An open-source Python library for Sensitivity Analysis. *The Journal of Open Source Software*, *2*(9), 97. https://doi.org/10.21105/joss.00097

Hierink, F., Rodrigues, N., Muñiz, M., Panciera, R., & Ray, N. (2020). Modelling geographical accessibility to support disaster response and rehabilitation of a healthcare system: An impact analysis of Cyclones Idai and Kenneth in Mozambique. *BMJ Open*, *10*(11), e039138. https://doi.org/10.1136/bmjopen-2020-039138

Hossain, L., & Kuti, M. (2010). Disaster response preparedness coordination through social networks. *Disasters*, *34*(3), 755–786. https://doi.org/10.1111/j.1467-7717.2010.01168.x

Houze-Cerfon, V., Viault, B., Marcou, E., Pardon, T., Ribera-Cano, A., Nouzières, C., & Bounes, V. (2023). An Innovative Mobile Hospital for the Management of a Massive Flow of Victims. *Prehospital and Disaster Medicine*, *38*(S1), s88–s88. https://doi.org/10.1017/S1049023X23002522

IOGP. (2023). *Overall—Fatalities*. https://data.iogp.org/Safety/OverallFatalities

Iooss, B., & Lemaître, P. (2015). A Review on Global Sensitivity Analysis Methods. In G. Dellino & C. Meloni (Eds.), *Uncertainty Management in Simulation-Optimization of Complex Systems* (Vol. 59, pp. 101–122). Springer US. https://doi.org/10.1007/978-1-4899-7547-8_5

Islam, M. S. (2019). Clinical Waste Management Scenario of Private Health Care Establishment in Rajshahi City. *Trends in Civil Engineering and Its Architecture*, *3*(3). https://doi.org/10.32474/TCEIA.2019.03.000161

Janssen, M. A., & Ostrom, E. (2006). Empirically Based, Agent-based models. *Ecology and Society*, *11*(2), art37. https://doi.org/10.5751/ES-01861-110237

Jiang, Z., & Ouyang, Y. (2021). Reliable location of first responder stations for cooperative response to disasters. *Transportation Research Part B: Methodological*, *149*, 20–32. https://doi.org/10.1016/j.trb.2021.04.004

Jones, K., Hadley, E., Preiss, S., Kery, C., Baumgartner, P., Stoner, M., & Rhea, S. (2021). *North Carolina COVID-19 Agent-Based Model Framework for Hospitalization Forecasting Overview, Design Concepts, and Details Protocol* (arXiv:2106.04461). arXiv. https://doi.org/10.48550/arXiv.2106.04461

Kanagarajah, A. K., Lindsay, P., Miller, A., & Parker, D. (2008). An Exploration into the Uses of Agent-Based Modeling to Improve Quality of Healthcare. In A. Minai, D. Braha, & Y. Bar-Yam (Eds.), *Unifying Themes in Complex Systems* (pp. 471–478). Springer. https://doi.org/10.1007/978-3-540-85081-6_58

Kanno, T., Hong, S., Yamashita, T., & Sharikura, S. (2020). The disaster context model and its application in creating disaster scenarios for hospitals. *Human-Intelligent Systems Integration*, *2*(1–4), 75–87. https://doi.org/10.1007/s42454-020-00013-z

Kanno, T., Karikawa, D., Fujino, H., & Ishida, C. (2023). Mini Special Issue on Modeling of Human-Policy-Technology Nexus and Simulation for Disaster Response and Business Continuity. *Journal of Disaster Research*, *18*(2), 87–88. https://doi.org/10.20965/jdr.2023.p0087

Kapucu, N., Okhai, R., & Hu, Q. (2022). Network Governance for Coordinated Disaster Response. *Public Administration Quarterly*, *46*(4), 309–333. https://doi.org/10.37808/paq.46.4.2

Kedia, T., Ratcliff, J., O'Connor, M., Oluic, S., Rose, M., Freeman, J., & Rainwater-Lovett, K. (2022). Technologies Enabling Situational Awareness During Disaster Response: A Systematic Review. *Disaster Medicine and Public Health Preparedness*, *16*(1), 341–359. https://doi.org/10.1017/dmp.2020.196

Kelton, W. D. (1996). Statistical issues in simulation. *Proceedings of the 28th Conference on Winter Simulation*, 47–54. https://doi.org/10.1145/256562.256570

Klein, T. A., & Irizarry, L. (2020, July 22). *EMS Disaster Response*. https://www.semanticscholar.org/paper/EMS-Disaster-Response-Klein-Irizarry/ee77d53301aae234a607df3143d2d123201f839b

Klingstam, P., & Olsson, B.-G. (2000). Using simulation techniques for continuous process verification in industrial system development. *2000 Winter Simulation Conference*

Proceedings (Cat. No.00CH37165), *2*, 1315–1321. https://doi.org/10.1109/WSC.2000.899101

Koelling, P., & Schwandt, M. (2005). *Health systems: A dynamic system-benefits from system dynamics* (p. 1327). https://doi.org/10.1109/WSC.2005.1574393

Kostyuk, A., Tumanov, A., Tumanov, V., & Zybina, O. (2020). Improving Emergency Response Systems in the Oil and Gas Industry To Reduce Environmental Damage. *E3S Web of Conferences*, *221*, 01008. https://doi.org/10.1051/e3sconf/202022101008

Kraner, B., Vallarano, N., Tessone, C. J., & Schwarz-Schilling, C. (2023). *Agent-Based Modelling of Ethereum Consensus* (arXiv:2305.13906). arXiv. http://arxiv.org/abs/2305.13906

Laker, L. F., Torabi, E., France, D. J., Froehle, C. M., Goldlust, E. J., Hoot, N. R., Kasaie, P., Lyons, M. S., Barg-Walkow, L. H., Ward, M. J., & Wears, R. L. (2018). Understanding Emergency Care Delivery Through Computer Simulation Modeling. *Academic Emergency Medicine*, *25*(2), 116–127. https://doi.org/10.1111/acem.13272

Lamé, G., & Simmons, R. K. (2020). From behavioural simulation to computer models: How simulation can be used to improve healthcare management and policy. *BMJ Simulation & Technology Enhanced Learning*, *6*(2), 95–102. https://doi.org/10.1136/bmjstel-2018-000377

Leal, G. D. S. S., Guédria, W., & Panetto, H. (2019). Interoperability assessment: A systematic literature review. *Computers in Industry*, *106*, 111–132. https://doi.org/10.1016/j.compind.2019.01.002

Levin, S., Sauer, L., Kelen, G., Kirsch, T., Pham, J., Desai, S., & France, D. (2012). Situation awareness in emergency medicine. *IIE Transactions on Healthcare Systems Engineering*, *2*(2), 172–180. https://doi.org/10.1080/19488300.2012.684739

Ligtenberg, A., van Lammeren, R. J. A., Bregt, A. K., & Beulens, A. J. M. (2010). Validation of an agent-based model for spatial planning: A role-playing approach. *Computers, Environment and Urban Systems*, *34*(5), 424–434. https://doi.org/10.1016/j.compenvurbsys.2010.04.005

Liu, L., Li, W., Aljohani, N. R., Lytras, M. D., Hassan, S. U., & Nawaz, R. (2020). A framework to evaluate the interoperability of information systems–Measuring the maturity of the

business process alignment. *International Journal of Information Management*, *54*, 102153. https://doi.org/10.1016/j.ijinfomgt.2020.102153

Liu, Y., Moyaux, T., Bouleux, G., & Cheutet, V. (2023). Hybrid Simulation Modelling of Emergency Departments for Resource Scheduling. *Journal of Simulation*. https://www.tandfonline.com/doi/full/10.1080/17477778.2023.2187321

Liu, Z., Cabrera, E., Rexachs, D., & Luque, E. (2014). *A Generalized Agent-Based Model to Simulate Emergency Departments*. https://shorturl.at/iuW37

Liu, Z., & Luque, E. (2015). *High Performance Computing Based Simulation for Healthcare Decision Support*.

Liu, Z., Rexachs, D., Epelde, F., & Luque, E. (2017). An agent-based model for quantitatively analyzing and predicting the complex behavior of emergency departments. *Journal of Computational Science*, *21*, 11–23. https://doi.org/10.1016/j.jocs.2017.05.015

Mahdi, S. S., Jafri, H. A., Allana, R., Battineni, G., Khawaja, M., Sakina, S., Agha, D., Rehman, K., & Amenta, F. (2023). Systematic review on the current state of disaster preparation Simulation Exercises (SimEx). *BMC Emergency Medicine*, *23*(1), 52. https://doi.org/10.1186/s12873-023-00824-8

Makhutov, N. (2013, February 22). *Big disasters analysis in problems of technical systems safety*. https://www.semanticscholar.org/paper/Big-disasters-analysis-in-problems-of-technical-Makhutov/3a5885dd83697aee1e6c5f2809b7b3fb81bca602

Maqbool, A., Usmani, Z. ul A., Afzal, F., & Razia, A. (2020). Disaster Mitigation in Urban Pakistan Using Agent Based Modeling with GIS. *ISPRS International Journal of Geo-Information*, *9*(4), Article 4. https://doi.org/10.3390/ijgi9040203

Marchetti, J., He, Y., Than, O., & Akkaraju, S. (1998). *Efficient process development for bulk silicon etching using cellular automata simulation techniques* (P. J. French & K. H. Chau, Eds.; pp. 287–295). https://doi.org/10.1117/12.323900

Mariano, D. J. K., & Alves, C. de M. A. (2020). The application of role-playing games and agent-based modelling to the collaborative water management in peri-urban communities. *RBRH*, *25*, e25. https://doi.org/10.1590/2318-0331.252020190100

Marks, R. E. (2007). Validating Simulation Models: A General Framework and Four Applied Examples. *Computational Economics*, *30*(3), 265–290. https://doi.org/10.1007/s10614-007-9101-7

Marom, T., Dagan, D., Weiser, G., Mendlovic, J., Levy, G., Shpriz, M., & Albukrek, D. (2014). Pediatric otolaryngology in a field hospital in the Philippines. *International Journal of Pediatric Otorhinolaryngology*, *78*(5), 807–811. https://doi.org/10.1016/j.ijporl.2014.02.019

Massazza, A., Brewin, C. R., & Joffe, H. (2019). The Nature of "Natural Disasters": Survivors' Explanations of Earthquake Damage. *International Journal of Disaster Risk Science*, *10*(3), 293–305. https://doi.org/10.1007/s13753-019-0223-z

Mijalkovic, S., & Cvetkovic, V. (2014). Victimization of people by natural disasters: Spatial and temporal distribution of consequences. *Temida*, *17*(4), 19–42. https://doi.org/10.2298/TEM1404019M

Mistarihi, M. Z., AL-Tahat, M. D., & AL-Nimer, S. H. (2023). Improving Process Efficiency at Pediatric Hospital Emergency Department Using an Integrated Six-Sigma Simulation Methodology. *Processes*, *11*(2), Article 2. https://doi.org/10.3390/pr11020399

Mohsin, B., Steinhäusler, F., Madl, P., & Kiefel, M. (2016). An Innovative System to Enhance Situational Awareness in Disaster Response. *Journal of Homeland Security and Emergency Management*, *13*(3), 301–327. https://doi.org/10.1515/jhsem-2015-0079

Munira Ibrahim, I., Liong, C.-Y., Abu Bakar, S., & Farid Najmudd, A. (2018). Performance Improvement of the Yellow Zone in Emergency Department using Discrete Event Simulation Approach. *International Journal of Engineering & Technology*, *7*(4.33), 102. https://doi.org/10.14419/ijet.v7i4.33.23509

Murphy, J. P. (2021). *DISASTER RESPONSE AND PREPAREDNESS:* https://openarchive.ki.se/xmlui/bitstream/handle/10616/47840/Thesis_Jason_Murphy?sequence=3&isAllowed=y

Mwanza, J., Telukdarie, A., & Igusa, T. (2023). Optimising Maintenance Workflows in Healthcare Facilities: A Multi-Scenario Discrete Event Simulation and Simulation Annealing Approach. *Modelling*, *4*(2), Article 2. https://doi.org/10.3390/modelling4020013

Naim, A., Alimo, R., & Braun, J. (2021). *AI Agents in Emergency Response Applications*.

Official Website Department of Occupational Safety and Health—2014. (2014). https://www.dosh.gov.my/index.php/archive-statistics/2014

Ogie, R. I., O'Brien, S., & Federici, F. M. (2022). Towards using agent-based modelling for collaborative translation of crisis information: A systematic literature review to identify the underlying attributes, behaviours, interactions, and environment of agents. *International Journal of Disaster Risk Reduction*, *68*, 102717. https://doi.org/10.1016/j.ijdrr.2021.102717

Olalekan, R. M., Omidiji, A. O., Nimisngha, D., Odipe, O. E., & Olalekan, A. S. (2018). Health Risk Assessment on Heavy Metals Ingestion through Groundwater Drinking Pathway for Residents in an Oil and Gas Producing Area of Rivers State, Nigeria. *Open Journal of Yangtze Oil and Gas*, *03*(03), 191–206. https://doi.org/10.4236/ojogas.2018.33017

Onggo, B. S., & Foramitti, J. (2021). Agent-based modeling and simulation for business and management: A review and tutorial. *2021 Winter, Simulation Conference (WSC*, 1–15.

Onggo, B. S., & Karatas, M. (2016). Test-driven simulation modelling: A case study using agent-based maritime search-operation simulation. *European Journal of Operational Research*, *254*(2), 517–531. https://doi.org/10.1016/j.ejor.2016.03.050

Onggo, B. S. S. (2012). BPMN pattern for agent-based simulation model representation. *Proceedings of the 2012 Winter Simulation Conference (WSC)*, 1–10. https://doi.org/10.1109/WSC.2012.6465145

Onggo, B. S. S., Proudlove, N. C., D'Ambrogio, S. A., Calabrese, A., Bisogno, S., & Levialdi Ghiron, N. (2018). A BPMN extension to support discrete-event simulation for healthcare applications: An explicit representation of queues, attributes and data-driven decision points. *Journal of the Operational Research Society*, *69*(5), 788–802. https://doi.org/10.1057/s41274-017-0267-7

Ouhmidou, I. M. (2020). *Modelling and Optimizing Hospital Emergency Department Workflow*. 11. https://shorturl.at/GPSW7

Ozpolat, B., Akar, U., Steiner, M., Zorrilla-Calancha, I., Tirado-Gomez, M., Colburn, N., Danilenko, M., Kornblau, S., & Lopez Berestein, G. (2007). Programmed Cell Death-4

Tumor Suppressor Protein Contributes to Retinoic Acid–Induced Terminal Granulocytic Differentiation of Human Myeloid Leukemia Cells. *Molecular Cancer Research*, *5*(1), 95–108. https://doi.org/10.1158/1541-7786.MCR-06-0125

Palomino Romani, G., Blowes, K., & Molina Hutt, C. (2023). Evaluating post-earthquake functionality and surge capacity of hospital emergency departments using discrete event simulation. *Earthquake Spectra*, *39*(1), 402–433. https://doi.org/10.1177/87552930221128607

Pérez-Pons, M.-E., Parra-Dominguez, J., Anzola-Rojas, C., Durán Barroso, R. J., Miguel, I. D., Queiroz, J., & Leitao, P. (2022). A brief review on Multi-Agent System Approaches and Methodologies. *Proceedings of the IV Workshop on Disruptive Information and Communication Technologies for Innovation and Digital Transformation: 18th June 2021 Online*, 35–47. https://doi.org/10.14201/0AQ03153547

Persoff, J., Ornoff, D., & Little, C. (2018). The Role of Hospital Medicine in Emergency Preparedness: A Framework for Hospitalist Leadership in Disaster Preparedness, Response, and Recovery. *Journal of Hospital Medicine*, *13*(10), 713–718. https://doi.org/10.12788/jhm.3073

Pescatore, M., & Beery, P. (2022). Interoperability analysis via agent-based simulation. *The Journal of Defense Modeling and Simulation*, 15485129221111171. https://doi.org/10.1177/15485129221111171

Pilla, V. N., & Patel, N. V. (2009). *Using agent based simulation to empirically examine complexity in carbon footprint business process*. http://bura.brunel.ac.uk/handle/2438/3510

Pylypchuk, Y., Alvarado, C. S., Patel, V., & Searcy, T. (2019). Uncovering differences in interoperability across hospital size. *Healthcare*, *7*(4)). http://dx.doi.org/10.1016/j.hjdsi.2019.04.001

Radišić, K., Rouzies, E., Lauvernet, C., & Vidard, A. (2023). Global sensitivity analysis of the dynamics of a distributed hydrological model at the catchment scale. *Socio-Environmental Systems Modelling*, *5*, 18570–18570. https://doi.org/10.18174/sesmo.18570

Ramasamy, A., Harrisson, S., Lasrado, I., & Stewart, M. P. M. (2009). A review of casualties during the Iraqi insurgency 2006–A British field hospital experience. *Injury*, *40*(5), 493–497. https://doi.org/10.1016/j.injury.2008.03.028

Ramathuba, D. U., & Ndou, H. (2020). Ethical conflicts experienced by intensive care unit health professionals in a regional hospital, Limpopo province, South Africa. *Health SA Gesondheid*, *25*, 1183. https://doi.org/10.4102/hsag.v25i0.1183

Ramchurn, S. D., Huynh, T. D., Wu, F., Ikuno, Y., Flann, J., Moreau, L., Fischer, J. E., Jiang, W., Rodden, T., Simpson, E., Reece, S., Roberts, S., & Jennings, N. R. (2016). A Disaster Response System based on Human-Agent Collectives. *Journal of Artificial Intelligence Research*, *57*, 661–708. https://doi.org/10.1613/jair.5098

Ramos-Merino, M., Álvarez-Sabucedo, L. M., Santos-Gago, J. M., & De Arriba-Pérez, F. (2019). A Pattern Based Method for Simplifying a BPMN Process Model. *Applied Sciences*, *9*(11), 2322. https://doi.org/10.3390/app9112322

Rezapour, S., Naderi, N., Morshedlou, N., & Rezapourbehnagh, S. (2018). Optimal deployment of emergency resources in sudden onset disasters. *International Journal of Production Economics*, *204*, 365–382. https://doi.org/10.1016/j.ijpe.2018.08.014

Robertson, D. A. (2016). Agent-Based Models and Behavioral Operational Research. In M. Kunc, J. Malpass, & L. White (Eds.), *Behavioral Operational Research* (pp. 137–159). Palgrave Macmillan UK. https://doi.org/10.1057/978-1-137-53551-1_7

Robinson, S. (2008). Conceptual modelling for simulation Part I: definition and requirements. *Journal of the Operational Research Society*, *59*(3), 278–290. https://doi.org/10.1057/palgrave.jors.2602368

Robinson, S. (2014). *Simulation: The Practice of Model Development and Use*. Bloomsbury Publishing.

Robinson, S. (2015). A tutorial on conceptual modeling for simulation. *2015 Winter Simulation Conference (WSC)*, 1820–1834. https://doi.org/10.1109/WSC.2015.7408298

Romero-Brufau, S., Wyatt, K. D., Boyum, P., Mickelson, M., Moore, M., & Cognetta-Rieke, C. (2020). Implementation of Artificial Intelligence-Based Clinical Decision Support to

Reduce Hospital Readmissions at a Regional Hospital. *Applied Clinical Informatics*, *11*(4), 570–577. https://doi.org/10.1055/s-0040-1715827

Rossodivita, A. (2011). (A340) The Role of Field Hospitals in Severe Environments—Guidelines to Prepare and Build a Field Hospital during a Disaster. *Prehospital and Disaster Medicine*, *26*(S1), s95–s96. https://doi.org/10.1017/S1049023X11003244

Rye, S., & Aktas, E. (2022). Serious Games as a Validation Tool for PREDIS: A Decision Support System for Disaster Management. *International Journal of Environmental Research and Public Health*, *19*(24), 16584. https://doi.org/10.3390/ijerph192416584

Salamon, T. (2011). *Design of Agent-Based Models*. https://pub.bruckner.cz/titles/salamon

Saleem, M., & Khan, Z. (2023). Healthcare Simulation: An effective way of learning in health care. *Pakistan Journal of Medical Sciences*, *39*(4), Article 4. https://doi.org/10.12669/pjms.39.4.7145

Salinas, J. S., Balachandar, S., Zúñiga, S. L., Shringarpure, M., Fedele, J., Hoyal, D., & Cantero, M. I. (2023). On the definition, evolution, and properties of the outer edge of gravity currents: A direct-numerical and large-eddy simulation study. *Physics of Fluids*, *35*(1), 016610. https://doi.org/10.1063/5.0138187

Sargent, R. G. (2013). *Verification and validation of simulation models*. 16. https://doi.org/10.1109/wsc.1994.717077

Sarma, D., Das, A., Dutta, P., & Bera, U. K. (2022). A Cost Minimization Resource Allocation Model for Disaster Relief Operations With an Information Crowdsourcing-Based MCDM Approach. *IEEE Transactions on Engineering Management*, *69*(5), 2454–2474. IEEE Transactions on Engineering Management. https://doi.org/10.1109/TEM.2020.3015775

Sayama, H. (2023). *Introduction to the Modeling and Analysis of Complex Systems*.

Sbayou, M., Bouanan, Y., Zacharewicz, G., Ribault, J., & Francois, J. (2017, April). DEVS modelling and simulation for healthcare process application for hospital emergency department. *Proceeding ANSS'17 Proceedings of the 50th Annual Simulation Symposium*.

Sheerazi, S., Awad, S., & Von Schreeb, J. (2022). Use of Mobile Health Units in Natural Disasters – A Scoping Review. *Prehospital and Disaster Medicine*, *37*(S2), s88–s88. https://doi.org/10.1017/S1049023X2200187X

Shimabukuro, M., Toki, T., Shimabukuro, H., Kubo, Y., Takahashi, S., & Shinjo, R. (2022). Development and Application of an Environmental Education Tool (Board Game) for Teaching Integrated Resource Management of the Water Cycle on Coral Reef Islands. *Sustainability*, *14*(24), 16562. https://doi.org/10.3390/su142416562

Shin, N., Bowers, J., Roderick, S., McIntyre, C., Stephens, A. L., Eidin, E., Krajcik, J., & Damelin, D. (2022). A framework for supporting systems thinking and computational thinking through constructing models. *Instructional Science*, *50*(6), 933–960. https://doi.org/10.1007/s11251-022-09590-9

Shirazi, F. B., Moslehi, S., Rasouli, M., & Masoumi, G. (2022). Identifying the Challenges of Simulating the Hospital Emergency Department in the Event of Emergencies and Providing Effective Solutions: A Qualitative Study. *Disaster Medicine and Public Health Preparedness*, *17*. https://doi.org/10.1017/dmp.2022.144

Shiripour, S., & Mahdavi-Amiri, N. (2019). Optimal distribution of the injured in a multi-type transportation network with damage-dependent travel times: Two metaheuristic approaches. *Socio-Economic Planning Sciences*, *68*, 100660. https://doi.org/10.1016/j.seps.2018.10.011

Sigle, M., Berliner, L., Richter, E., Van Iersel, M., Gorgati, E., Hubloue, I., Bamberg, M., Grasshoff, C., Rosenberger, P., & Wunderlich, R. (2023). Development of an Anticipatory Triage-Ranking Algorithm Using Dynamic Simulation of the Expected Time Course of Patients With Trauma: Modeling and Simulation Study. *Journal of Medical Internet Research*, *25*, e44042. https://doi.org/10.2196/44042

Sobol', I. M. (2001). Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Mathematics and Computers in Simulation*, *55*(1–3), 271–280. https://doi.org/10.1016/S0378-4754(00)00270-6

Stroud, C., Altevogt, B. M., & Goldfrank, L. R. (2010). Institute of Medicine's Forum on Medical and Public Health Preparedness for Catastrophic Events: Current Initiatives. *Disaster*

Medicine and Public Health Preparedness, *4*(2), 174–177. https://doi.org/10.1001/dmphp.4.2.174

Su, B., Kwak, J., Pourghaderi, A. R., Lees, M. H., Tan, K. B. K., Loo, S. Y., Chua, I. S. Y., Quah, J. L. J., Cai, W., & Ong, M. E. H. (2021). A Model-based Analysis of Evacuation Strategies in Hospital Emergency Departments. *2021 Winter Simulation Conference (WSC)*, 1–12. https://doi.org/10.1109/WSC52266.2021.9715522

Suleman, I., Pomalango, Z., & Slamet, H. (2022). Disaster exercise tabletop media improves knowledge of health personnel about disaster management. *Jambura Journal of Health Sciences and Research*, *5*(1), 90–99. https://doi.org/10.35971/jjhsr.v5i1.16633

Sulis, E., Amantea, I. A., & Fornero, G. (2019). Risk-Aware Business Process Modeling: A Comparison of Discrete Event And Agent-Based Approaches. *2019 Winter Simulation Conference (WSC)*, 3152–3159. https://doi.org/10.1109/WSC40007.2019.9004822

Sulis, E., & Di Leva, A. (2018a). An Agent-Based Model of a Business Process: The Use Case of a Hospital Emergency Department. In E. Teniente & M. Weidlich (Eds.), *Business Process Management Workshops* (Vol. 308, pp. 124–132). Springer International Publishing. https://doi.org/10.1007/978-3-319-74030-0_8

Sulis, E., & Di Leva, A. (2018b). Public Health Management Facing Disaster Response: A Business Process Simulation Perspective. *2018 Winter Simulation Conference (WSC)*, 2792–2802. https://doi.org/10.1109/WSC.2018.8632534

Szczepanska, T., Antosz, P., Berndt, J. O., Borit, M., Chattoe-Brown, E., Mehryar, S., Meyer, R., Onggo, S., & Verhagen, H. (2022). GAM on! Six ways to explore social complexity by combining games and agent-based models. *International Journal of Social Research Methodology*, *25*(4), 541–555. https://doi.org/10.1080/13645579.2022.2050119

Taboada, M., Cabrera, E., Epelde, F., Iglesias, M. L., & Luque, E. (2013). Using an Agent-based Simulation for Predicting the Effects of Patients Derivation Policies in Emergency Departments. *Procedia Computer Science*, *18*, 641–650. https://doi.org/10.1016/j.procs.2013.05.228

Takadama, K., Kawai, T., & Koyama, Y. (2008). Micro- and Macro-Level Validation in Agent-Based Simulation: Reproduction of Human-Like Behaviors and Thinking in a Sequential

Bargaining Game. *Journal of Artificial Societies and Social Simulation*, *11*. http://jasss.soc.surrey.ac.uk/11/2/9.html

Tako, A. A., & Robinson, S. (2009). Comparing model development in Discrete Event Simulation and System Dynamics. *Proceedings of the 2009 Winter Simulation Conference (WSC)*, 979–991. https://doi.org/10.1109/WSC.2009.5429423

Tardivo, S., Moretti, F., Nobile, M., Agodi, A., Appignanesi, R., Arrigoni, C., Baldovin, T., Brusaferro, S., Canino, R., Carli, A., Chiesa, R., D'Alessandro, D., D'Errico, M. M., Giuliani, G., Montagna, M. T., Moro, M., Mura, I. I., Novati, R., Orsi, G. B., … GISIO - Italian Study Group of Hospital Hygien. (2017). Definition of criteria and indicators for the prevention of Healthcare-Associated Infections (HAIs) in hospitals for the purposes of Italian institutional accreditation and performance monitoring. *Annali Di Igiene: Medicina Preventiva E Di Comunita*, *29*(6), 529–547. https://doi.org/10.7416/ai.2017.2183

Thorens, G., Billieux, J., Megevand, P., Zullino, D., Rothen, S., Achab, S., & Khazaal, Y. (2016). Capitalizing upon the Attractive and Addictive Properties of Massively Multiplayer Online Role-Playing Games to Promote Wellbeing. *Frontiers in Psychiatry*, *7*. https://doi.org/10.3389/fpsyt.2016.00167

Tintinalli, J. (2015). *Tintinallis Emergency Medicine A Comprehensive Study Guide*. McGraw-Hill Education. https://lib.hpu.edu.vn/handle/123456789/32417

Tomaskova, H., Kopecky, M., & Maresova, P. (2019). Process Cost Management of Alzheimer's Disease. *Processes*, *7*(9), 582. https://doi.org/10.3390/pr7090582

Tott, G. (2013). *Influence Of Donor Funded Projects On The Social-economic Welfare Of The Rural Communities: Case Of Cadsal In Elgeiyo Marakwet County, Kenya* [Thesis, University of Nairobi]. http://erepository.uonbi.ac.ke/handle/11295/55781

Tour, A. (2023). *Mining Agent-Based Models of Business Processes: Extended PhD Abstract*.

Tram, N. T. B. (2022). Simulation modeling—An effective method in doing business and management research. *HO CHI MINH CITY OPEN UNIVERSITY JOURNAL OF SCIENCE - ECONOMICS AND BUSINESS ADMINISTRATION*, *12*(1), 108–124. https://doi.org/10.46223/HCMCOUJS.econ.en.12.1.1916.2022

Tykhonov, D., Jonker, C., Meijer, S., & Verwaart, T. (2008). Agent-Based Simulation of the Trust and Tracing Game for Supply Chains and Networks. *Journal of Artificial Societies and Social Simulation*, *11*. http://jasss.soc.surrey.ac.uk/11/3/1.ht

Uhm, D., Jung, G., Yun, Y., Lee, Y., & Lim, C. (2019). Factors Affecting the Disaster Response Competency of Emergency Medical Technicians in South Korea. *Asian Nursing Research*, *13*(4), 264–269. https://doi.org/10.1016/j.anr.2019.09.005

Umemoto, M., Kadono, S., Kanno, T., Kajiyama, K., Sharikura, S., Ikari, R., Yoneyama, M., & Chuang, S. (2023). Modeling and Simulation of In-Hospital Disaster Medicine in a Mass Casualty Event for the Resilience Evaluation of BCPs. *Journal of Disaster Research*. https://doi.org/10.20965/jdr.2023.p0104

Uriarte, A. G., Zúñiga, E. R., Moris, M. U., & Ng, A. H. (2015). System design and improvement of an emergency department using simulation-based multi-objective optimization. *Journal of Physics: Conference Series*, *616*(1), 012015. https://doi.org/10.1088/1742-6596/616/1/012015

Utomo, D. S., Onggo, B. S. S., Eldridge, S., Daud, A. R., & Tejaningsih, S. (2022). Eliciting agents' behaviour and model validation using role playing game in agent-based dairy supply chain model. *Journal of the Operational Research Society*, *73*(12), 2670–2693. https://doi.org/10.1080/01605682.2021.2013137

Van Barneveld, T., Jagtenberg, C., Bhulai, S., & Van Der Mei, R. (2018). Real-time ambulance relocation: Assessing real-time redeployment strategies for ambulance relocation. *Socio-Economic Planning Sciences*, *62*, 129–142. https://doi.org/10.1016/j.seps.2017.11.001

Vázquez-Serrano, J. I., Peimbert-García, R. E., & Cárdenas-Barrón, L. E. (2021). Discrete-Event Simulation Modeling in Healthcare: A Comprehensive Review. *International Journal of Environmental Research and Public Health*, *18*(22), 12262. https://doi.org/10.3390/ijerph182212262

Wahyudiono, S., Darmawan, A. A., & Burhan, M. S. (2022). Pemodelan Shift Kerja dalam Proyek Konstruksi menggunakan NetLogo dalam meminimalkan Penyebaran Covid-19. *Jurnal*

Ilmiah Universitas Batanghari Jambi, *22*(2), Article 2. https://doi.org/10.33087/jiubj.v22i2.2465

Wallinger, S., Grundner, L., Majic, I., & Lampoltshammer, T. J. (2023). Agent-Based Modelling for Sustainable Tourism. In B. Ferrer-Rosell, D. Massimo, & K. Berezina (Eds.), *Information and Communication Technologies in Tourism 2023* (pp. 355–360). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-25752-0_40

Wang, Y., Luangkesorn, K. L., & Shuman, L. (2012). Modeling emergency medical response to a mass casualty incident using agent based simulation. *Socio-Economic Planning Sciences*, *46*(4), 281–290. https://doi.org/10.1016/j.seps.2012.07.002

Wang, Y., Sun, B., Yue, H., Lin, X., Li, B., Yang, X., Shan, C., Fan, Y., Dong, M., Zhang, Y., Lin, W., Zuo, X., Su, P., Heng, Y., Xu, J., & Kissoon, N. (2014). An epidemiologic survey of pediatric sepsis in regional hospitals in China. *Pediatric Critical Care Medicine: A Journal of the Society of Critical Care Medicine and the World Federation of Pediatric Intensive and Critical Care Societies*, *15*(9), 814–820. https://doi.org/10.1097/PCC.0000000000000247

White, L., Basurra, S., Alsewari, A. A., Saeed, F., & Addanki, S. M. (2023). *Temporal Meta-optimiser based Sensitivity Analysis (TMSA) for Agent-Based Models: A Children's Services Application*. https://doi.org/10.21203/rs.3.rs-3096058/v1

Wilensky, U., & Rand, W. (2015). *An introduction to agent-based modeling: Modeling natural, social, and engineered complex systems with NetLogo*. The MIT press.

Yousefi, M., & Ferreira, R. P. M. (2017). An agent-based simulation combined with group decision-making technique for improving the performance of an emergency department. *Brazilian Journal of Medical and Biological Research*, *50*, e5955. https://doi.org/10.1590/1414-431X20175955

Yousefi, M., Yousefi, M., & Fogliatto, F. S. (2020). Simulation-based optimization methods applied in hospital emergency departments: A systematic review. *SIMULATION*, *96*(10), 791–806. https://doi.org/10.1177/0037549720944483

Zaboli, R., Toufighi, S., Raiess Zadeh, M., Ghaed Amini, R., & Azizian, F. (2016). Key Performance Indicators in Field Hospital Appraisal: A Systematic Review. *Trauma Monthly*, *23*(1). https://doi.org/10.5812/traumamon.42604

Zhang, G., Shen, X., Hua, J., Zhao, J., & Liu, H. (2021). System Dynamics Modelling for Dynamic Emergency Response to Accidents Involving Transport of Dangerous Goods by Road. *Journal of Advanced Transportation*, *2021*, e2474784. https://doi.org/10.1155/2021/2474784

Zhang, X. (2018). Application of discrete event simulation in health care: A systematic review. *BMC Health Services Research*, *18*(1), 687. https://doi.org/10.1186/s12913-018-3456-4

Zi-jian, L. (2005). Research on Concurrent Design Oriented Assembly Sequence Planning. *Computer Simulation*. https://www.semanticscholar.org/paper/Research-on-Concurrent-Design-Oriented-Assembly-Zi-jian/88fa2122cf42479650001256c9e3640db19ecb33

Zschaler, S., & Polack, F. A. C. (2023). Trustworthy agent-based simulation: The case for domain-specific modelling languages. *Software and Systems Modeling*, *22*(2), 455–470. https://doi.org/10.1007/s10270-023-01082-9

APPENDICES

This section contains a suggestion for additional research as well as additional relevant supporting documents, figures, tables, and screenshots to clarify further points.

Appendix A1: BPMN representation of patients triage flow in MFH

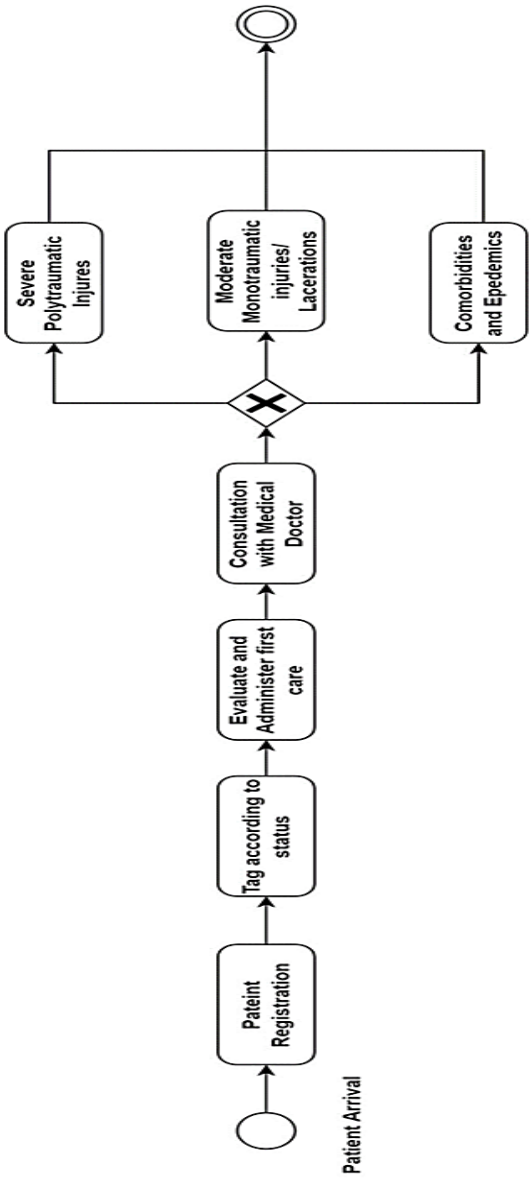

Figure 28: BPMN representation of patients triage flow in MFH

Appendix A2: BPMN diagram of patients flow in MFH (polytraumatic injuries)

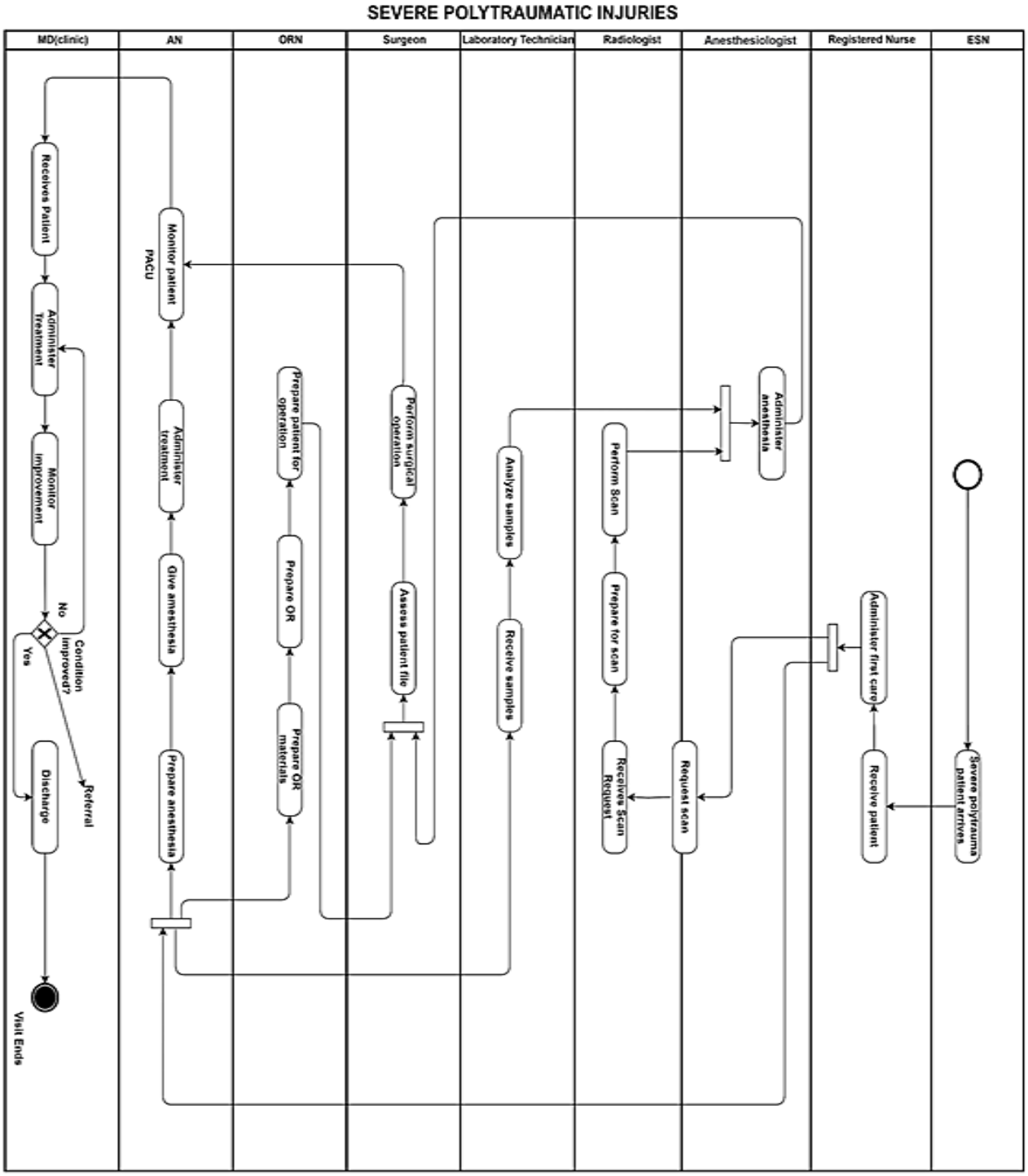

Figure 29: BPMN diagram of patients flow in MFH (polytraumatic injuries)

Appendix A3: BPMN diagram of patients flow in MFH (mono-traumatic injuries)

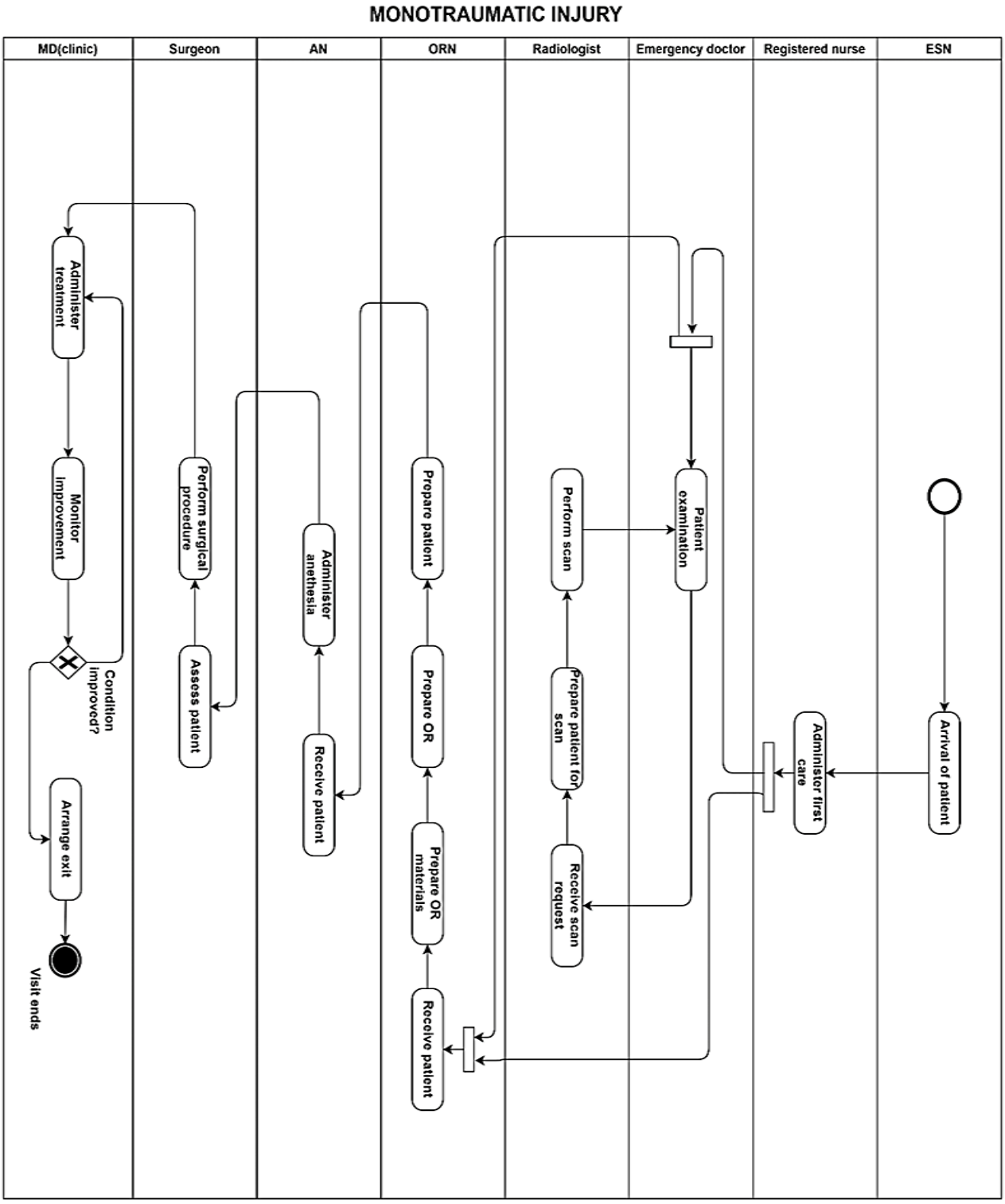

Figure 30: BPMN diagram of patients flow in MFH (mono-traumatic injuries)

Appendix A4: BPMN diagram of patients flow in MFH (minor injuries/lacerations)

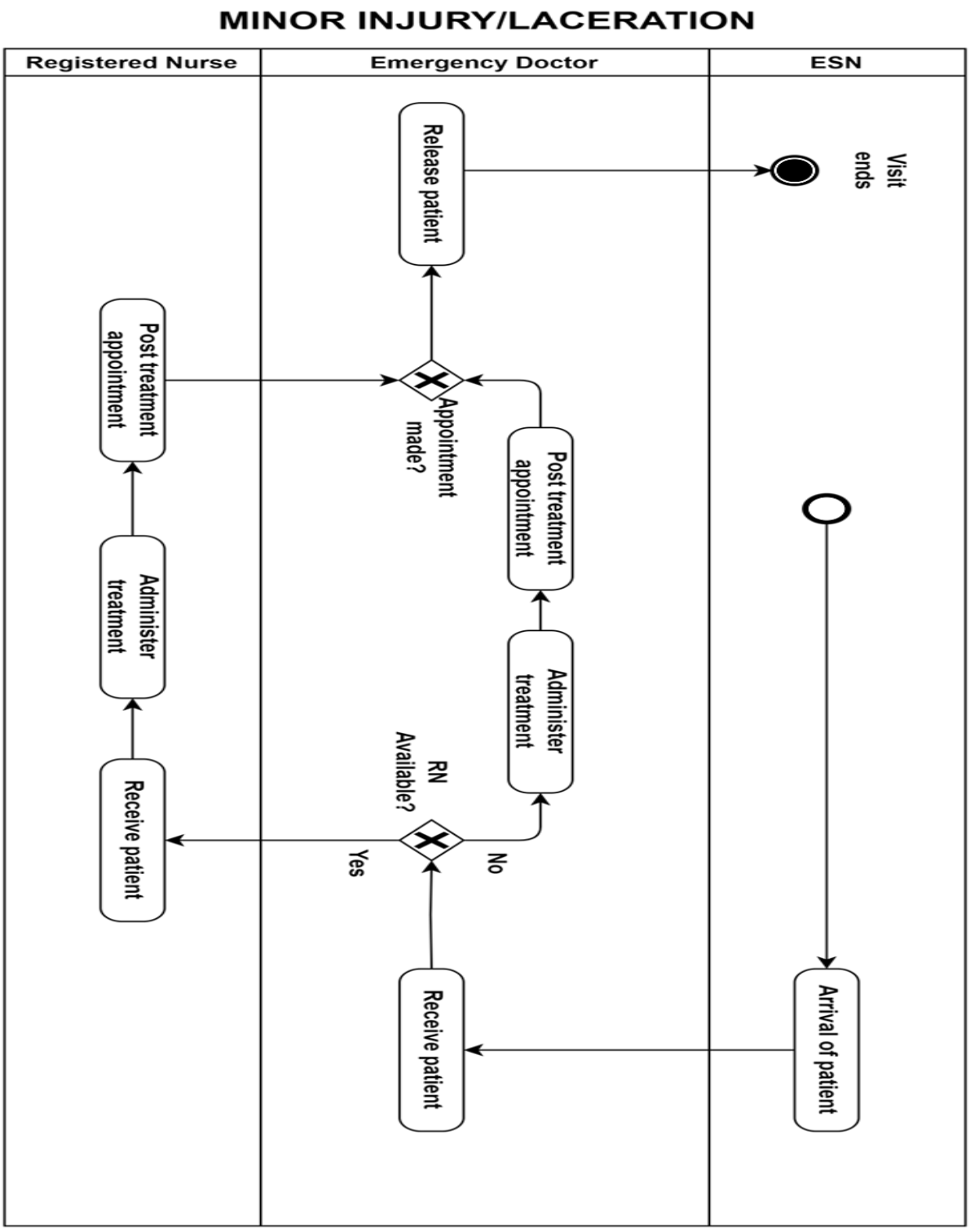

Figure 31: BPMN diagram of patients flow in MFH (minor injuries/lacerations)

Appendix A5: BPMN diagram of patients flow in MFH (other illnesses/comorbidities)

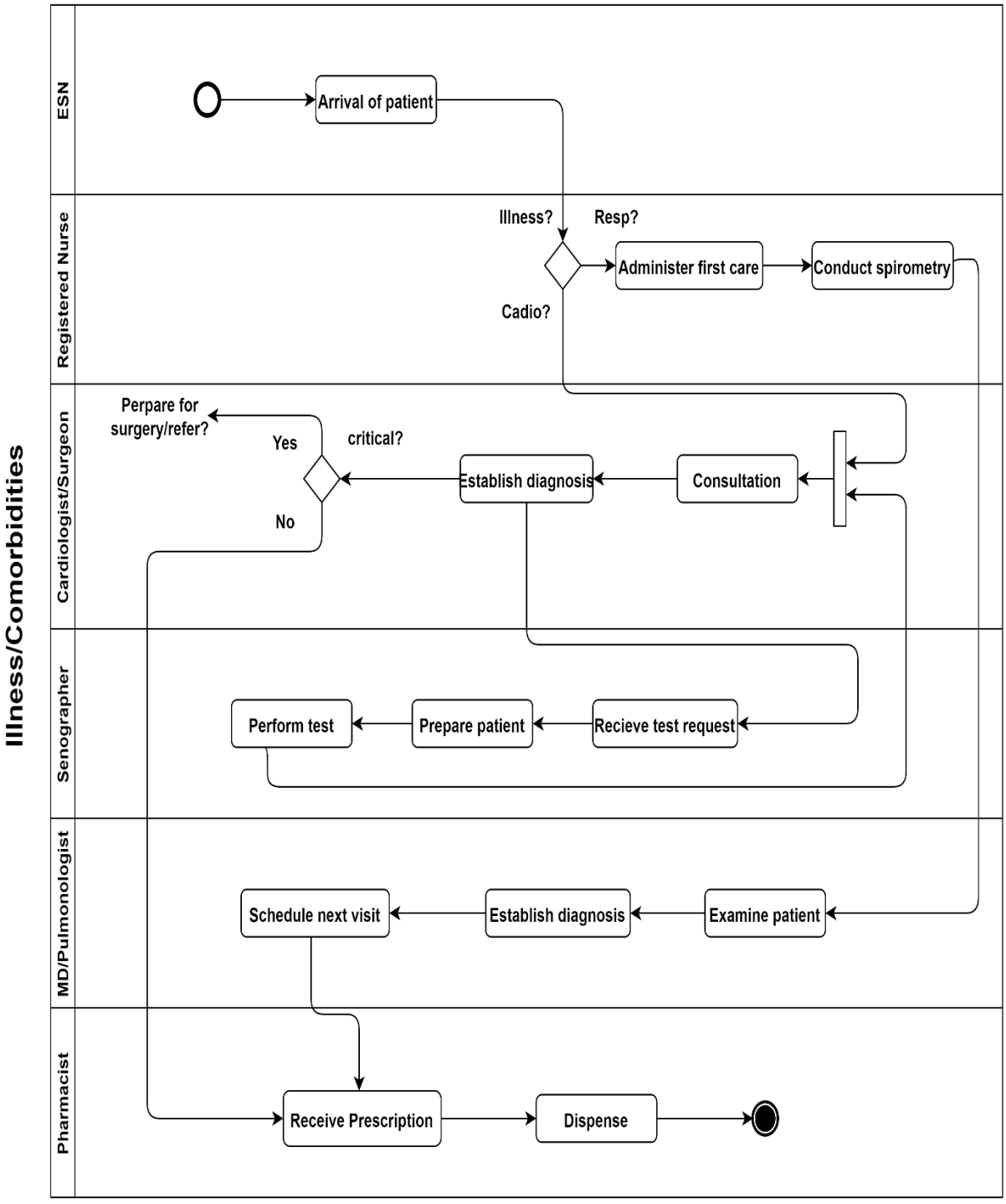

Figure 32: BPMN diagram of patients flow in MFH (other illnesses/comorbidities)

Appendix A6: BPMN diagram of patients flow in MFH (flu related conditions)

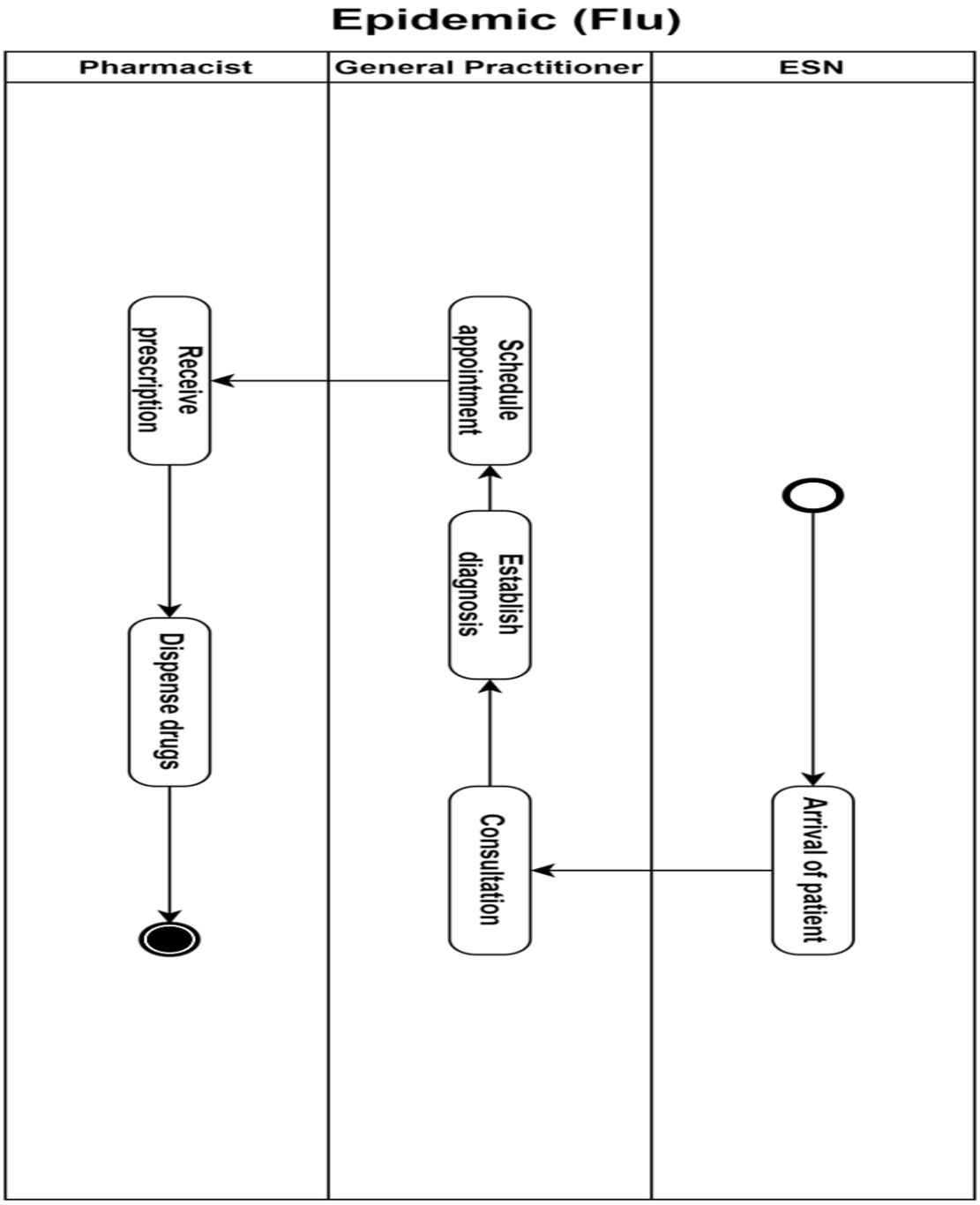

Figure 33: BPMN diagram of patients flow in MFH (flu related conditions)

Appendix B1: BehaviorSpace experimental set up (data sampling and generation) – step1

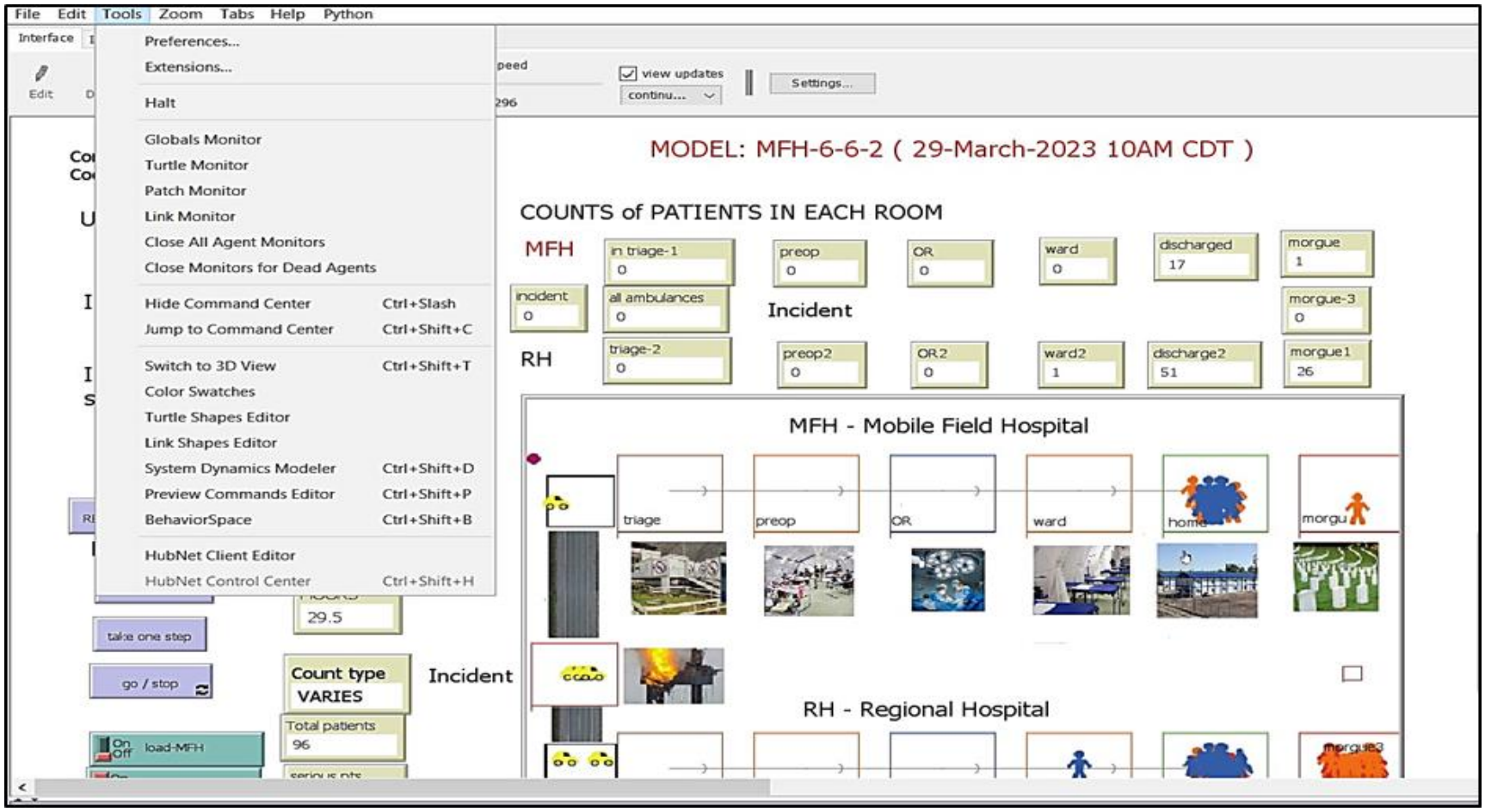

Figure 34:BehaviorSpace experimental set up (data sampling and generation)-step 1

Appendix B2: BehaviorSpace experimental set up (data sampling and generation) – step 2

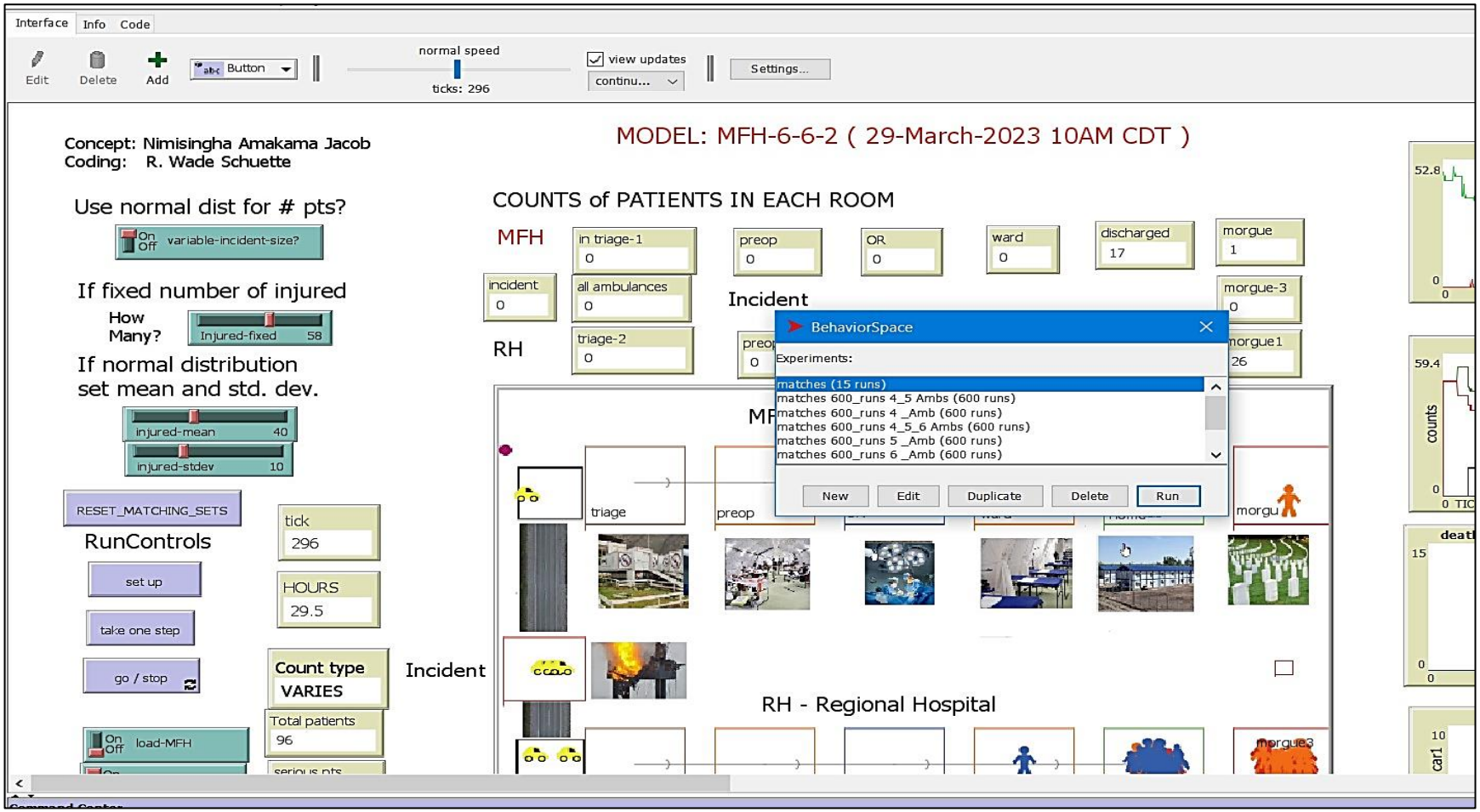

Figure 35: BehaviorSpace experimental set up (data sampling and generation)-step 2

Appendix B3: BehaviorSpace experimental set up (data sampling and generation) – step 3

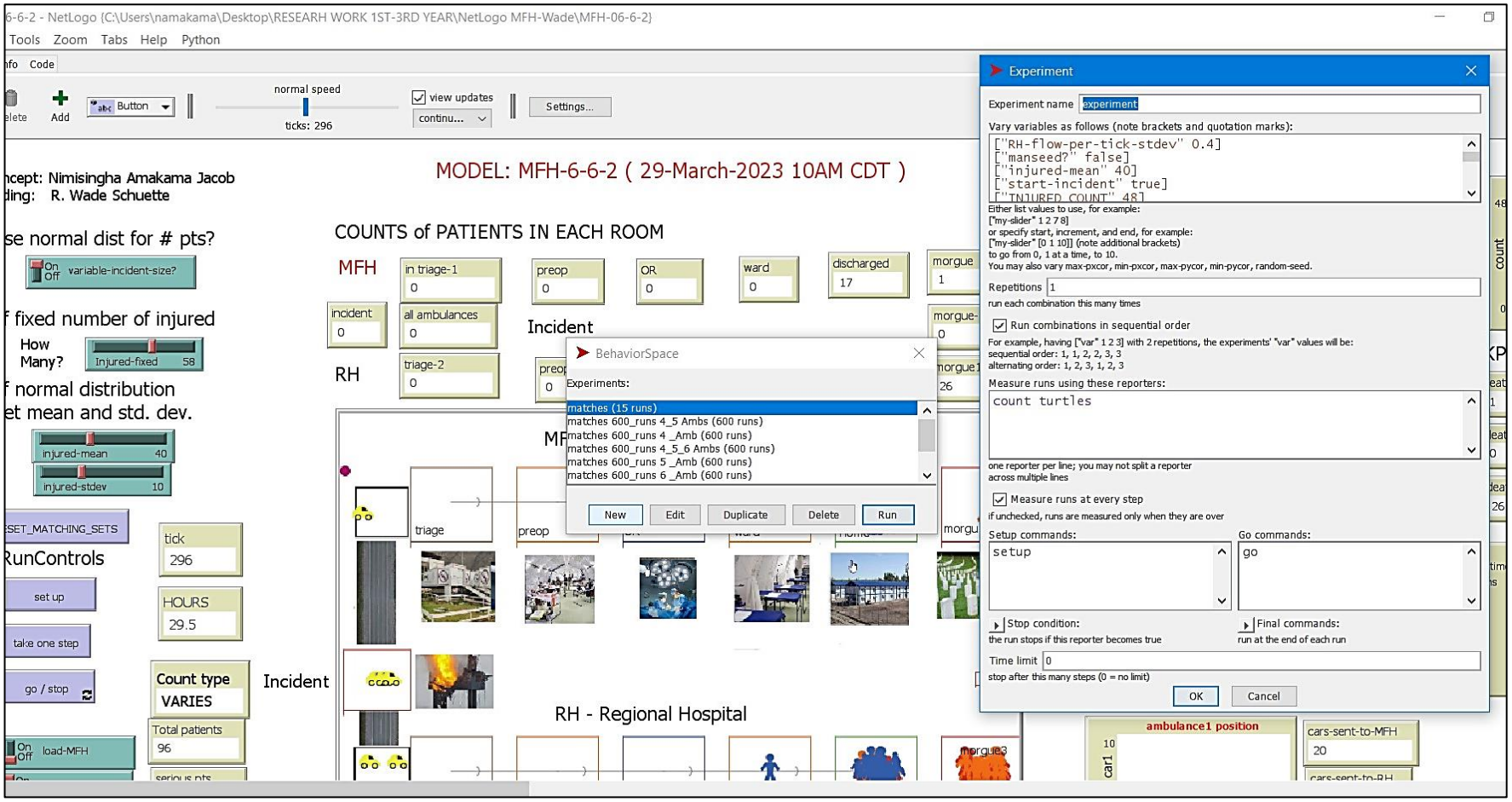

Figure 36: BehaviorSpace experimental set up (data sampling and generation)-step 3

Appendix B4: BehaviorSpace experimental set up (data sampling and generation) – step 4

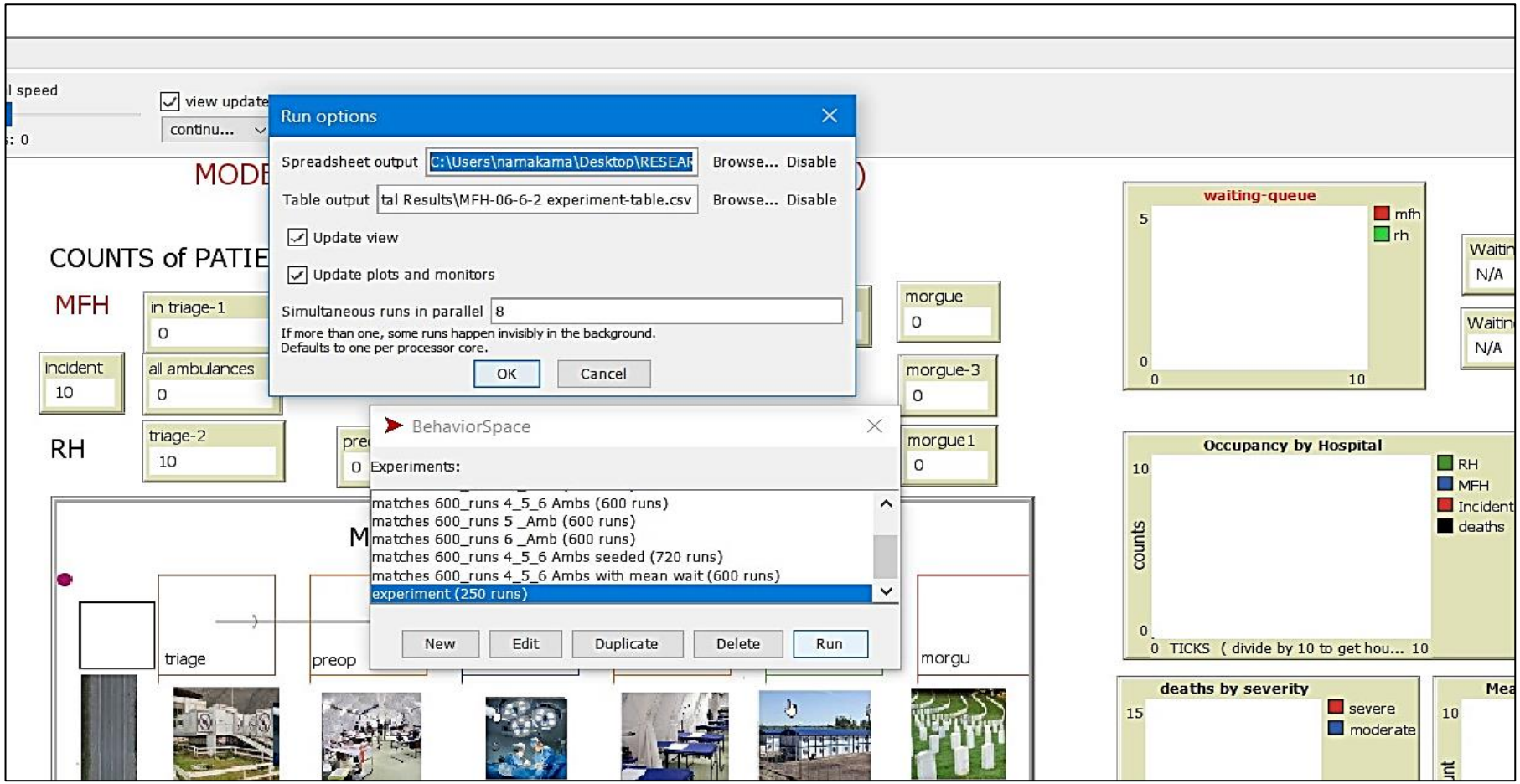

Figure 37: BehaviorSpace experimental set up (data sampling and generation)-step 4

Appendix C1: Disaster response scenario tasks

Table 5: Disaster response scenario tasks

Task #	Scenario tasks requiring team collaboration/communication and response action	Decision taken / rationale
1	Your team receives an emergency call from the Oil & Gas industry (incident site) with **40 injured** (**8 severe,12 moderate and 20 mild**). You have available **3 free ambulances** and **2 free operating rooms** (**ORs**). With only **RH** operational, decide how to respond to the situation?	
2	Your team was alerted of more victims on site. On arrival, triage information shows that **4** out of **39** cases were results of underlining health issues (2 respiratory, 2 cardiovascular), with **9 severe, 10 moderate and 20 mild** cases (result of the explosion). Who amongst the victims would your team prioritize, having **3 ambulances** and **4 ORs** and only the **RH** in operation?	
3	On getting to the incident site (ambulance), triage information reveals **38** injured [**6 severe (2 unconscious), 12 moderate severity, 20 mild victims**]. With only the **RH** still in operation, **3 ambulances** and **1 OR** available for surgery. How will your team respond?	
4	Distress call of **37 patients** (**15 moderate**,**5 severe**, **17 mild**) are expected to start arriving in **45 minutes** in the **RH**. Anticipate the surge, and plan for optimal transport, triage, and treatment of the patients.	
5	**40 patients** (**8 severe, 12 moderates, 20 mild**) need urgent evacuation and treatment. Only **3 ambulances** are available. Decide on the priority and distribution if there is a secondary request for a critical case in a location **30 minutes** away?	
6	**RH** has **3 ambulances** available, but **38 patients** (**10 moderate, 3 severe, 25 mild**) need transport, triage, and treatment. There are **2 available ORs** and **1 Pre-OR**. What decision will your team take to save the most life if **2 moderate** cases become worse and have **118 minutes (about 2 hours)** to live with treatment?	
7	Your team already dispatched **4 ambulances** bearing **3 severe** cases (approx. 1hr.30mins to live without surgery). There are also **8 moderate**, and **28 mild cases** patients on site. Information from the RH indicates **2 OR** is available. What should be your teams resolve to handle the situation?	
8	Ambulances are dispatched by your team from the incident site *en route* the **RH** with **8 severe patients**. Meanwhile patients are still held up in the ORs (**3 patients**) and no bed spaces at the wards. However, there is **1 OR** available. What would be your team's call for action as the patients need to get in for surgery? **13 moderate and 21 milds** are also reported on site.	
9	Your team received an emergency call of **3 patients** needing ambulance service from home **25 minutes**' drive from the RH. While preparing to respond, an update came in from the MFH informing your team of readiness to take in victims for surgery (**38 total injured**). How will your team dispatch the **4 available** ambulances (the other 2 ambulances are heading back to the RH)?	

10	Your team gets the good news of the MFH being fully operational. However, at the incident site, triage reveals **39 injured** (8 **severe, 11 moderates, 20 mild**). There are **5 ambulances available**. How would your team distribute the resources and what decision will be taken about the victims if only **4 ORs** are available (**2 at the MFH and 2 at the RH**)?	
11	There is prediction of a surge at the MFH in the **25 mins**. [(if the remaining victims are transported there, it will take longer for them to be seen (**7 severe**, **12 moderates**, **21 mild**)]. A comparable situation is projected to happen in 3 hrs. at the RH. What would your team do if **3** ambulances were located at the RH and **3** were **10** mins out from the incident site?	
12	Triage personnel on site informs your team of readiness to transport **8 severe** patients and awaits your directive on how to distribute the patients to either system **(RH/MFH).** There are no free **OR** at the **MFH** and **3 OR** at the **RH** with **5 ambulances** available. What decision would your team take, if there are also **11 moderate** and **22 mild** also waiting for medical assistance?	
13	**18 patients** out of the **36 injured** (**7 severe, 11 moderate**) need urgent evacuation. Only **4 ambulances** are available for the RH and MFH. Decide on what will be your team's priority and distribution of the victims.	
14	Your team is receiving a call about the distribution of **40 victims** at the incident site and, there is a sudden disconnection in the line which may take half an hour to fix (**30mins**). What will be your team's decision if you have **2 ORs** at the MFH, **3 ORs** at the RH for surgery and other related issues?	
15	**38 patients** (8 severe, 11 moderates, 19 mild) require various levels of attention. The MFH has **1 OR** for a moderate severity patient. How will your team coordinate the affected patients if **5 severe** patients and **3 moderate** patients require surgery?	
16	**42 patients** (8 severe, 13 moderates, 21 mild) need evacuation and treatment. The **MFH** has **2 ORs** to attend to patients. How will your team coordinate patients if **all ambulances** are between **15-20 minutes** from the incident site and **3** patients have **45 minutes** to live without surgery?	
17	**14** out of the **40 patients** (8 severe, 12 moderates, 20 mild) in the incident site are expected to require hospitalization after treatment. **RH** has separate wards for severe and moderate patients, but the available space is limited. How will your team manage the patients if **7** hospitalization spaces are available at the **MFH** and**,** only **5** bed spaces are in the **RH**?	
18	**37 patients** (7 severe, 11 moderates, 19 mild) require various degrees of medical attention. Only **1 OR** is available at the **MFH** for moderate patients. **RH** has **4 ORs** available. How will your team coordinate the patients if **7 severe** patients and **5 moderate** patients require surgery?	

**Injects 1- 9 describes the scenarios of the intervention carried out only by the Regional Hospital (RH) prior to the deployment, setup, and operation of the Mobile Field Hospital. **Injects 10-18 describes the scenarios capturing the intervention of both the Regional and Mobile Field Hospitals, based on the ambulance policies. This nuanced approach to the scenario design ensures that players are consistently challenged to reassess and apply disaster response strategies in varying contexts, enhancing the educational and training value of the disaster response tabletop role-playing game.

Appendix D1: DRTRPG in-game response time form (data collection)

Table 6: In-games response time form (Group A and B)

# Scenario tasks	Response Time	
	Start	**Stop**
1		
2		
3		
4		
5		
6		
7		
8		
9		
10		
11		
12		
13		
14		
15		
16		
17		
18		

Appendix D2: DRTRPG in-game observers rating form

Date: __7th March,2024__

Team Name: __**A and B**__

Scenario: Disaster/emergency response in an oil and gas industry

Time: __9:30hr – 12:00hr__

Role (observer): The role of the observer in the role-playing game is to assess the performance of the players acting as ambulance dispatchers in the group.

Instruction: Use the scale provided to rate the following items. Additional comments may be added in the spaces provided. Please use circles or ticks to indicate your selections in the box.

This information is to be collected ***during*** the DRTRPG and is intended to help summarize the observer's findings on the participants during the exercise.

Table 7: DRTRPG in-game tasks performance evaluation

		Injects Response Scoring			
	Performance evaluation criteria	**Strongly Disagree**	**Disagree**	**Agree**	**Strongly Agree**
i.	**Involvement:** All members of the group were actively engaged throughout the inject exercise	1	2	3	4
ii.	**Communication:** The group members communicated with each other during the injects/exercise	1	2	3	4
iii.	**Role-playing:** The group stayed in character (ambulance dispatcher) during the injects scenario	1	2	3	4
iv.	**Decision-making skill:** The players were able to make quick decision in the high-pressure situations	1	2	3	4
Additional observations on groups' performance:					

Appendix D3: DRTRPG post-game observers rating form

Date: __7th March,2024__

Team Name: __**A and B**__

Scenario: Disaster/emergency response in an oil and gas industry

Time: __9:30hr – 12:00hr __

Role (observer): This information is to be collected ***after*** the DRTRPG and is intended to help summarize the observer's feedback on the participants engagement in the exercise.

Instruction: Use the scale provided to rate the following items. Additional comments may be added in the spaces provided. Please use circles or ticks to indicate your selections in the box.

Table 8: Observers' post-game evaluation criteria

		RPG Evaluation Scoring			
	Evaluation Factor	**Strongly Disagree**	**Disagree**	**Agree**	**Strongly Agree**
i.	**Situation Awareness (SA):** The team successfully maintains SA through sharing and communicating knowledge across the scenarios?	1	2	3	4
Comment:					
ii.	**Teamwork:** The team effectively collaborated in decision taking throughout the exercise	1	2	3	4
Comment:					
iii.	**Time management:** The team effectively managed the time they had available to them during the exercise	1	2	3	4
Comment:					
iv.	**Role empathy: T**he team effectively empathized with their given role?	1	2	3	4
Comment:					
v.	**Performance:** The team demonstrated good understanding of the objectives for the exercise	1	2	3	4
Comment:					

Appendix E1: Disaster response role-playing game data gathering forms

Table 9: Observers' in-game response rating (*official use*)

	Group A				Group B				Average
Evaluation Criteria	4	3	2	1	4	3	2	1	
Involvement									
Communication									
Role-playing									
Decision-making skill									

Overall score: ----------

Appendix E2: Disaster response role-playing game data gathering forms

Table 10: Observers' evaluation feedback rating (*official use*)

		Group A				Group B				Average
	Questions	4	3	2	1	4	3	2	1	
i	Situation Awareness (SA)									
ii	Teamwork									
iii	Time managements									
iv	Role empathy									
v	Performance									

Overall Score: ----------

***These table gives a standardized rating scale that will be used to assess the performance of the players on each of the criteria mentioned on the observer's form. Scores might reveal game flaws or areas for improvement. If players repeatedly score low in one area, the task or challenge may need to be changed to make it more interesting or demanding in the future.

Appendix F1: DRTRPG observers in-game performance evaluation results

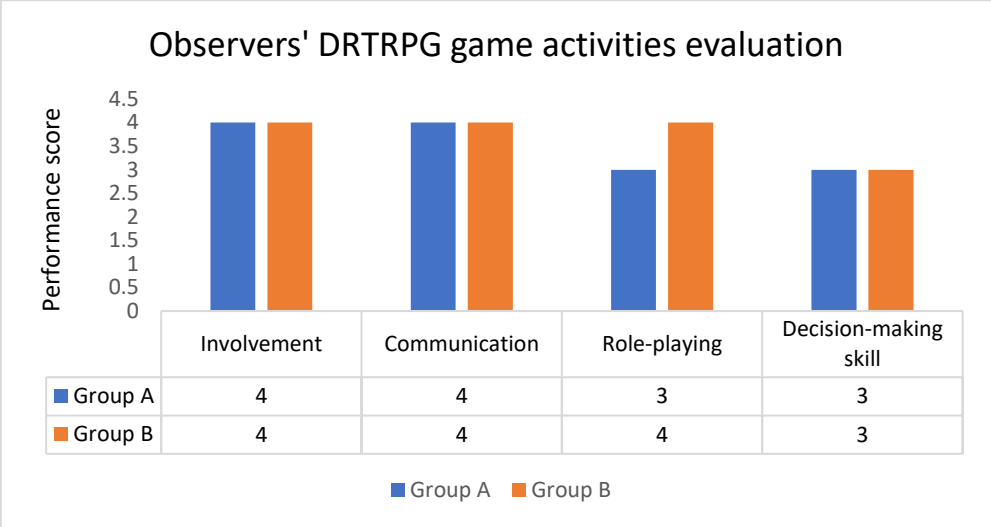

Figure 38: DRTRPG observers in-game performance evaluation results

Appendix F2: DRTRPG observers feedback performance evaluation results

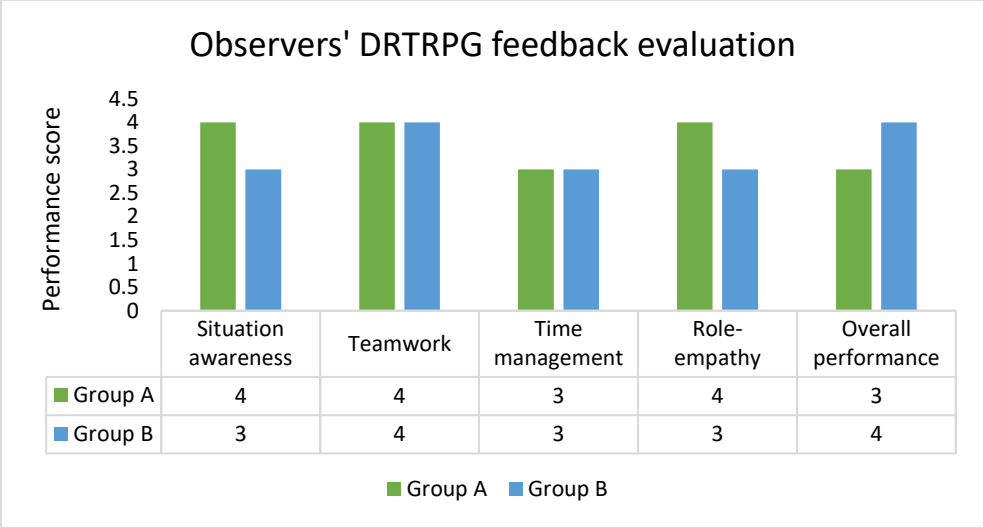

Figure 39: DRTRPG observers feedback performance evaluation results