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NAVIGATING HOSPITAL OPERATIONS THROUGH SIMULATION: A STUDY OF URBAN FLOODING DISASTERS AND PHYSICAL DAMAGE IMPACT

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ABSTRACT

This paper presents a discrete-event simulation model of an entire hospital to investigate the impact of urban flooding disasters, specifically focusing on physical damage to the hospital building and its implications for patient care. A novel patient-centred health utility function is introduced to assess patient outcomes and inform patient prioritisation decisions. The model is used to simulate a two-wave disaster scenario: the initial wave represents physically injured patients due to the flooding, while the second wave captures patients with flood-related infections. Additionally, this paper experiments with strategies and policies to respond effectively to the disaster and enhance resilience. Preliminary results demonstrate the model's ability to evaluate hospital resilience and balance the needs of disaster victims and routine patients. This work is intended to lay the foundation for data-driven disaster preparedness and response planning.

Keywords: discrete-event simulation, simulation in healthcare, disaster management

1 INTRODUCTION

Urban flooding represents a serious and growing challenge, often resulting in widespread devastation, economic damages, and the loss of human lives (Halecki and Młyński, 2025). Among all natural disasters globally, floods occur with the highest frequency (Xie *et al.*, 2017) and are projected to increase over the coming decades due to global climate change and rapid urbanisation (Azadgar *et al.*, 2025). Given this context, the importance of modelling and simulating urban flooding disasters cannot be overstated, particularly in understanding their impacts on critical infrastructure such as healthcare facilities.

When urban flooding occurs, it can severely disrupt healthcare infrastructure due to physical damage. Urban flooding is a specific example of natural disasters that can cause such damage to hospitals. Maintaining operational capability becomes a significant challenge for healthcare units, which must continue their operations despite partial damage or destruction. Numerous studies have examined the resilience of hospital systems; however, this research specifically focuses on hospital resilience in the context of disasters that involve physical damage. Relevant studies on such disasters (Shahverdi, Tariverdi and Miller-Hooks, 2020; Mahmoud *et al.*, 2023; Carbonara, Pellegrino and De Luca, 2024) outline how these events can impact healthcare units in critical areas. This includes structural integrity, such as damage to the building framework; non-structural elements, such as damage to interior finishes and fixtures; lifeline support systems, which encompass power or water outages; and medical resources, including damage or failure of equipment and shortages of medical staff. In conducting a review of hospital studies related to disasters involving physical damage, the following gaps in the literature have been identified: notably, no individual study comprehensively covers all the consequences of physical damage on healthcare facilities, and current literature addresses only a narrow scope of damages and losses in their disruption scenarios. Additionally, while existing research has estimated system resilience, there is a lack of studies that design and evaluate specific response policies and improvement strategies beyond merely adding more resources.

The effects of urban flooding extend beyond immediate physical destruction; they also significantly impact the health of affected populations, as well as hospital buildings and operations. Research by Lane *et al.* (2013) and Paterson, Wright and Harris (2018) highlights various pathways through which urban flooding can lead to adverse health outcomes. Initial exposure to flood-related hazards can result in physical injuries and other health risks. Additionally, power outages can lead to severe conditions, such as carbon monoxide poisoning and heat- or cold-related illnesses (Dharmarathne *et al.*, 2024). Following such disasters, secondary hazards also emerge, including waterborne illnesses and respiratory infections due to prolonged exposure to contaminated environments (Mulder *et al.*, 2019; Jang *et al.*, 2024). This multifaceted impact underscores the necessity of understanding how urban flooding affects healthcare infrastructure and the populations it serves.

In addition to the physical and operational challenges posed by urban flooding, patient health outcomes are a critical aspect that warrants attention. The disruption of healthcare services during disaster events can compromise patient outcomes and overall health states. A review of the literature on whole hospital simulation models (Basaglia *et al.*, 2022; Miller-Hooks *et al.*, 2022; Ordu *et al.*, 2023) shows that the performance metrics commonly used are primarily limited to process-based outcomes, such as length of stay, waiting time, and resource utilisation, which focus mainly on the operational efficiency of hospitals. Mortality rate is the only health outcome-related metric typically considered in this literature. Incorporating a patient-centered Key Performance Indicator (KPI) that measures patients' health utility emphasises quality of care, as this KPI also takes health outcomes into account. It transcends conventional process-based KPIs, which are typically used to improve hospital operational efficiency. Additionally, the literature lacks sufficient attention to capturing the competition between routine and disaster patients over hospital resources during a disaster scenario. More importantly, in our context, the patient-centered KPI provides a basis for balancing the needs of disaster victims and routine patients.

Urban flooding disasters pose significant challenges for hospitals, causing physical damage to infrastructure, straining resources, and compromising patient outcomes. However, existing studies often overlook the multifaceted impact of disasters, including the absence of patient-centred KPI designed to assess patient health outcomes, and the need to balance the competing demands of disaster victims and routine patients. This research aims to address this gap by building a comprehensive Discrete-event Simulation (DES) model of an entire hospital under urban flooding disaster conditions. The model incorporates a novel patient-centred health utility function and simulates a realistic two-wave disaster scenario. This paper also designs response policies that can be used to experiment with the hospital simulation model during disaster scenarios and periods of hospital congestion. The ultimate goal is to provide managerial insights at the hospital level to prioritize patients, balance the needs of existing and disaster victims, and maintain quality of care during and after a major disaster.

The rest of this paper is organised as follows: Section 2 presents the simulation model of an entire hospital, including the design and framework of experiments, and proposes the patient-centered indicator. Section 3 presents the preliminary results. Finally, Section 4 concludes the study by summarising how the developed simulation model captures hospital operations and the impact of disasters, highlights the design of a health utility function, and discusses the next steps in completing this ongoing work.

2 HOSPITAL SIMULATION MODEL

2.1 Simulation Model Overview

A DES model of a hospital was developed using AnyLogic software. This model captures patient flows and resource dynamics across the entire hospital, including Accident & Emergency (A&E), outpatient, and inpatient care services. Inpatient care is further divided into surgical and medical wards. Figure A-1 illustrates a high-level flowchart of the patient flow process within the hospital. The hospital operates 24/7, every day of the week. Patients are assigned attributes such as Emergency Severity Index (ESI), age, gender, entry point, and exit point. Patient arrivals in the A&E are time-dependent, influenced by the specific hour of the day. Additionally, outpatient and inpatient arrivals vary according to the day of the week, reflecting the absence of elective patients on weekends. The model run length is set to 9 months with 10 replications. Furthermore, a warm-up period of 50 days is determined using Welch's method (Welch, 1981). The model is validated using face validity and extreme condition tests.

2.2 Experimentation Design

Two categories of experiments have been designed. The disaster scenarios reflect the real-world effects of urban flooding on the hospital and the population, while the response policies are strategies aimed at enhancing hospital resilience. In this study, we conduct three experiments as follows:

Experiment 1 (Baseline). This scenario represents the normal arrival patterns in hospital operations and usual rules policy under routine conditions, as explained earlier in 2.1.

Experiment 2 (Two-Wave Disaster Scenario and Usual Rules Policy). This scenario reflects the impact of immediate and secondary health implications of the disaster on the affected population. This scenario is designed based on insights from literature (Paterson, Wright and Harris, 2018), and real-world case studies (Mulder *et al.*, 2019; Musacchio *et al.*, 2021; Ziliotto, Chies and Ellwanger, 2024). The disaster strikes from day 150 and lasts for 10 days. The first wave of the disaster results in victims who are physically injured as a result of direct exposure to the flood and require surgery. In the second wave of the disaster, arriving patients have contracted respiratory infections and waterborne diseases and are admitted to the medical ward for treatment. This scenario also takes into account the specific demographic characteristics, such as the age profile of the disaster arrivals.

Experiment 3 (Two-Wave Disaster Scenario and Elective Cancellation Policy). One response policy to enhance hospital resilience during a disaster or surge in demand is the temporary cancellation of elective patient admissions (Nehme, Puchkova and Parlikad, 2022). This strategy involves suspending the inflow of planned outpatient and inpatient treatment cases, allowing the hospital to redirect its resources toward managing disaster arrivals and patients with emergency care needs. Implementing this policy scenario is a promising approach for addressing patient demand in the Two-Wave Disaster Scenario. By stopping elective admissions to both the inpatient and outpatient wards, the hospital can free up resources to better handle the high demand generated by the two disaster waves presented in this scenario. Therefore, reducing the influx of elective cases can help alleviate the expected congestion in the inpatient and outpatient wards.

2.3 Health Utility Function

Typically, models in the literature focus on process-based outcomes, such as length of stay, waiting times and resource utilisation, with mortality being the only health-related outcome considered. A major contribution of this model is that it incorporates health outcomes for all patients. To assess the patient outcomes, a health utility function is introduced in this paper, capable of evaluating patient health utilities at the population level within a hospital setting. The function assigns a utility score on a numerical scale from 0 to 1, where 1 represents perfect health and 0 indicates death, for each patient throughout their hospital stay. Based on findings from the literature (Needleman *et al.*, 2011; Kuntz and Sülz, 2013; Brazier *et al.*, 2017), several factors are considered in calculating health utility, including:

Base Utility. This reflects the patient's well-being upon arrival at the hospital and is dependent on gender and age.

Reason for Admission. This accounts for the temporary condition that has led to the patient's illness.

Utility on Admission. This is derived from the two factors mentioned above. Utility on Admission is calculated using the formula presented in Equation (1):

$$\textit{Utility on Admission} = \textit{Base Utility} * \textit{Reason for Admission} \qquad (1)$$

Curability. This factor assesses whether the patient has an acute or chronic condition, or if they have sustained an injury that results in permanent disability.

Effect of Delay. This reflects any delays the patient may experience in receiving treatment compared to the standard timeframe.

Effect of Treatment Quality. It reflects the adequacy of available resources and is quantified by the staff-to-patient ratio.

Final Utility. This measures the final health utility value for individual patients at discharge and is compared with Base Utility and Utility on Admission. Equation (2) outlines the formula proposed to calculate the health utility function:

$$\textit{Health Utility Function} = \textit{Base Utility} * \textit{Curability} * \textit{Effect of Delay} * \textit{Effect of Treatment Quality} \qquad (2)$$

The health utility function is incorporated into the hospital simulation care paths, spanning from patient entry to discharge, and is used as an output KPI.

3 PRELIMINARY RESULTS

The simulation model was run for the three experiments outlined in 2.2. The patient-centred health utility function was used to assess the impact on patient outcomes across different patient categories.

Table 1 presents the average final utility scores for routine patients, including emergency admissions, direct referrals, and elective admissions. In Experiment 1, which represents the normal operations of the hospital, the average final utility score of 0.77 exceeds the utility on admission, which is 0.48. This indicates that most patients experienced an improvement in their health states compared to when they were admitted. The final utility score is below the base utility of 0.81, suggesting that while patients generally improved during their hospital stay, not every patient fully returns to their original health state.

However, under Experiment 2, the final utility drops to 0.48, 0.60, and 0.64 for emergency, direct referral, and elective patients, respectively. This decline in utility scores highlights the significant impact of the disaster on routine patient outcomes.

Table 1 Average Final Utility for Routine Patient across Different Experiments

			Emergency	**Direct Referral**	**Elective**
	Base Utility	Utility on Admission	Final Utility	Final Utility	Final Utility
Experiment 1	0.81	0.48	0.77	0.77	0.77
Experiment 2	0.81	0.48	0.48	0.60	0.64
Experiment 3	0.81	0.48	0.56	0.74	0.76

Experiment 3, designed to mitigate the impact of the disaster, shows improvements in final utility scores compared to the disaster scenario. While the utility scores remain lower than the baseline for emergency patients, the elective cancellation policy demonstrates its effectiveness in balancing the utility score of different routine patient groups during the disaster. The current model does not consider the impact of treatment delay due to the cancellation. This will be addressed in our future work.

Table 2 focuses on the disaster victims, categorised into first wave and second wave arrivals. Under Experiment 2, the final utility values for first wave and second wave disaster victims are 0.43 and 0.41, respectively. These low utility scores emphasise the severe impact of the disaster on the health outcomes of disaster victims.

Experiment 3 shows a notable increase in final utility scores for both first wave and second-wave disaster victims compared to Experiment 2. The final utility for both first wave and second-wave victims increases to 0.77. This suggests that the elective cancellation policy not only helps balance utility values among routine patient groups but also significantly improves outcomes for disaster victims by freeing up resources to address their immediate medical needs.

Table 2 Average Final Utility for Disaster Victims across Different Experiments

			First Wave Disaster Arrivals	**Second Wave Disaster Arrivals**
	Base Utility	Utility on Admission	Final Utility	Final Utility
Experiment 2	0.81	0.48	0.43	0.41
Experiment 3	0.81	0.48	0.77	0.77

4 DISCUSSION & CONCLUSION

This study developed an entire hospital simulation model that captures both hospital operations during disasters and the presence of scheduled patients. It also examines the impact of two waves of disaster, focusing on the initial and secondary health implications of urban flooding on the population. A distinctive aspect of this research is the creation of a health utility function, which serves as a patient-centric indicator for measuring health outcomes. This approach allows the system to be evaluated and improved not only through traditional process-based indicators but also via this patient-centred indicator that emphasises individual health utility. By integrating this health utility function into the simulation model, the study enables the tracking of each patient's health outcomes throughout their entire treatment journey within the hospital and enables the model to explore potential health-related trade-offs between disaster and routine patients under different response policies.

The preliminary findings from this paper demonstrate the potential of using utility measures to assess the impact of disasters and response policies on different patient groups. Although model parameters are currently being refined using literature and publicly available datasets to obtain more accurate values, the initial results show promising applications. The utility function enables hospital managers to prioritise patient groups based on their health needs and to allocate resources effectively to balance the utility across all patient categories. By comparing utility scores across scenarios, decision-makers can identify the patient groups most severely affected by the disaster and tailor response strategies accordingly.

The simulation model indicates capability for decision support in hospital disaster response. As this research is ongoing, future work should focus on expanding the range of disaster scenarios and response policies. Emphasis should be placed on scenario evaluation, specifically examining the impact of delayed treatment due to the cancellation as well as the impact of flooding on hospital infrastructure in addition to its effects on the population. Additionally, it is important to analyse results across diverse patient groups, such as different age demographics or ESI levels. Future efforts will also aim to provide insights regarding patient prioritisation plans for hospital managers.

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APPENDIX

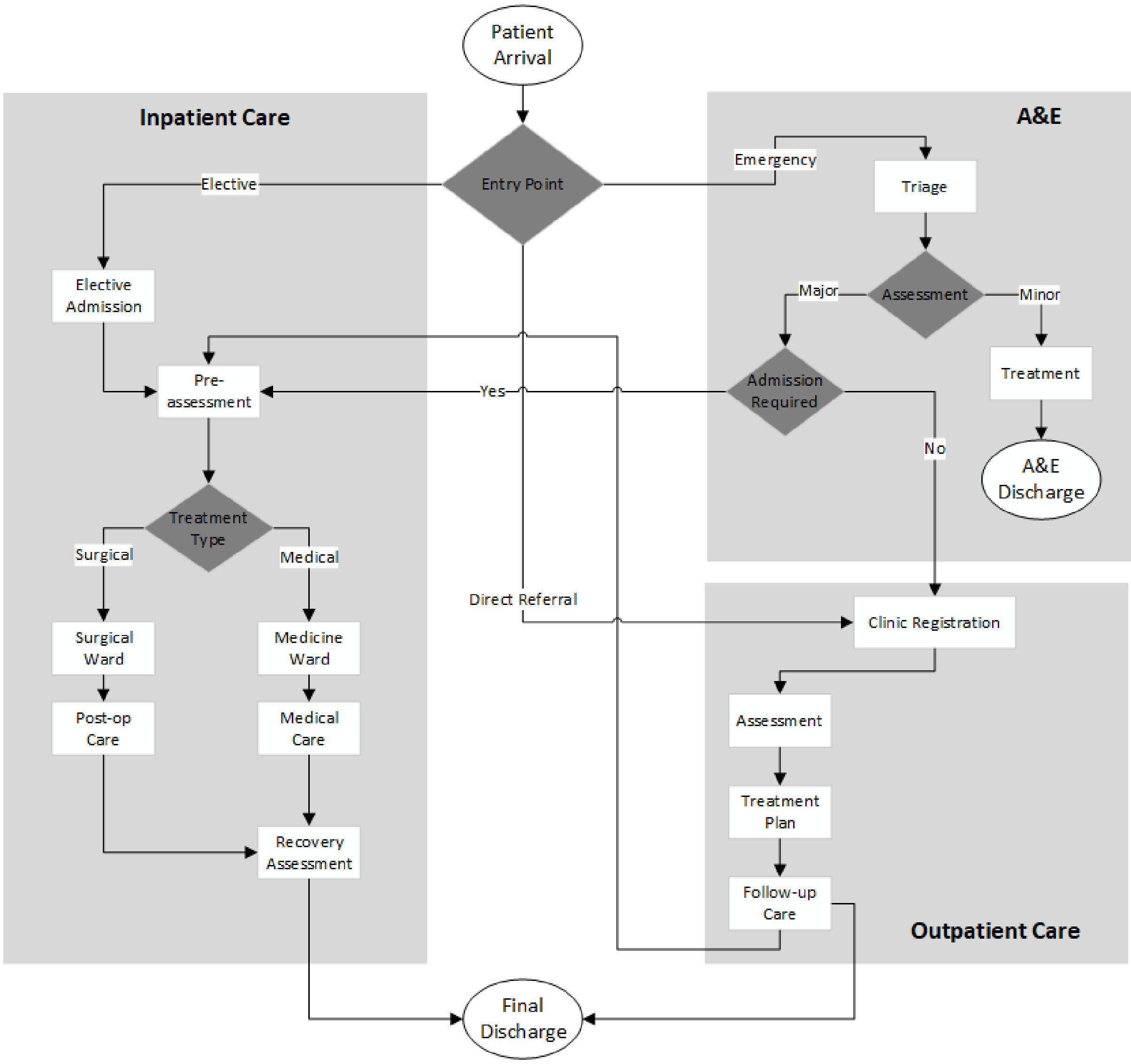

Figure A-1 High-level flowchart of the patient flow process within the hospital

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