Using simulation to investigate impact of different approaches to coordination on a healthcare system's resilience to disasters

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Abstract

Many disasters that have happened in the last decades have caused a shortage of healthcare resources and change in healthcare activities. Coordination of healthcare facilities is one of the emergency medical response strategies to ensure the continued provision of medical services during disasters. The importance of coordination in healthcare systems during disasters is well recognised in the literature, but to the best of our knowledge there has been no review of the published research in this area. In this thesis, a focused literature review of models for the coordination in the healthcare system is provided. Additionally, measures of coordination effectiveness that denote resilience are discussed. In the field of medical management, there are two types of coordination including integrative care and collaborative care. Both types of coordination aim to improve the emergency medical response by ensuring the continuity of medical services and improving healthcare capability during disasters. Integrative care mainly investigates the resource allocation within a common governance, whereas collaborative care is mainly focused on the sharing of healthcare resources across governances. Thus, integrative care is mainly implemented within a healthcare provider setting, while collaborative care is mainly implemented between the settings. However, resilience is usually perceived at community level rather than at an individual institution when responding to disasters. Improving resilience during disasters requires the capability of different healthcare providers, which can be achieved by collaborative care, rather than integrative care. In addition, the literature has commonly addressed collaborative care using optimisation approach, not simulation approach. In this regard, this study presents simulation models for resilience of the healthcare network during disasters. In collaboration with the health authorities and medical staff in Thailand who experienced a number of disasters we investigated real-world activities that took place in emergency medical responses. We developed novel discrete event simulation models of collaboration in an emergency medical response in a healthcare network during disasters with the aim to improve the resilience of the healthcare network. Three strategies for collaboration in the healthcare network were defined including non-collaborative care, semi-collaborative care, and a new proposed collaborative care. Non-collaborative care strategy was in place in response to Tsunami in Phuket in 2004, while semi-collaborative care strategy is the current strategy which was implemented during the boat capsizing in Phuket in 2018. We propose a new collaborative care strategy which is defined by considering the disadvantages of the current semi-collaborative care strategy. It addresses a new collaboration in the network that enables information sharing and the classification of healthcare providers. The strategies differ with respect to the first treatment provision of patients, sharing of resources, and patient transportation The simulation models were validated and verified by using the boat capsizing real-world event. The model validations were in line with the available system outputs including the number of patients in different categories, resource allocation, patient allocation and average patient waiting times at healthcare providers. A generic metric of resilience proposed in the literature was adapted to be used in healthcare context. Our analysis yielded managerial insights into the emergency planning as follows. In all defined scenarios, the new collaborative care strategy had a considerable impact on improving the resilience and enabled faster return to the pre-disaster state of healthcare network than other strategies. The semi-collaborative care strategy frequently provided the worst resilience in almost all the defined scenarios. However, it provided better resilience than the non-collaborative care strategy when the number of affected patients was relatively small. Even though simulation enabled investigation of the impact of different strategies for collaboration in the network on the resilience, the patient allocation might not be optimal. We developed a mixed integer programming model to address the allocation of patients in collaborative care in which ambulances transport multiple patients to healthcare providers in one trip. The developed model will provide further insights into the collaborative care in disasters management.

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Table of contents

Abstract ... i

Acknowledgments ... iii

Table of contents ... iv

List of figures ... vii

List of tables ... viii

Glossary ... ix

Chapter 1 Introduction ... 1

1.1 Terminology ... 1

1.2 Challenge of healthcare system during disasters ... 7

1.3 Importance of coordination in healthcare system during disasters ... 8

1.4 Research motivations ... 9

1.5 Research aim, objectives and questions ... 11

1.6 Research contributions ... 12

1.7 Thesis overview ... 13

1.8 Dissemination of the research ... 13

Chapter 2 Literature review ... 15

2.1 Current reviews of disaster management ... 15

2.2 Scope of the focused literature review ... 18

2.3 Literature search and selection of articles ... 18

2.4 OR approaches to coordination in the healthcare system ... 22

2.5 Resilience measures in healthcare context ... 37

2.6 Summary ... 43

Chapter 3 Research methodology ... 44

3.1 Interviews 44

3.2 Simulation method 46

3.3 Optimisation method 49

3.4 Summary 50

Chapter 4 Strategies for collaboration in response to disasters 51

4. 1 Common characteristics of strategies for collaboration in healthcare network 51

4.2 Activities undertaken under different strategies 55

4.3 Summary 62

Chapter 5 Development of simulation models 63

5.1 Assumptions 63

5.2 Queuing structure and system objects 64

5.3 Flowchart diagrams 65

5.4 Input parameters 84

5.5 Computation setup 87

5.6 Validation and verification 87

5.7 Resilience metrics 92

5.8 Summary 95

Chapter 6 Simulation experiments 97

6.1 Resilience in base case 97

6.2 Disaster scenarios 101

6.3 Managerial insights 108

6.4 Discussion 111

6.5 Summary 112

Chapter 7 A Mixed Integer Programming model for allocation of multiple patients in collaborative care 113

7.1 Introduction.. 113

7.2 Relevant literature... 114

7.3 Problem description and mathematical model...................................... 117

7.4 Summary.. 126

Chapter 8 Conclusions and implications 127

8.1 Conclusions... 127

8.2 Future research.. 130

References.. 137

Appendices 153

List of figures

Figure 1.1 Concept of resilience in an earthquake (Bruneau et al., 2003)........ 5

Figure 2.1 Literature search and selection of articles...................................... 20

Figure 2.2 Number of articles published between 2005 and 2022 21

Figure 2.3 Distribution of articles across journals... 22

Figure 2.4 Time-based measures during disasters 39

Figure 4.1 Patient pathways through the healthcare system during disasters... 58

Figure 4.2 Non-collaborative care strategy (Strategy 1) 59

Figure 4.3 Semi-collaborative care strategy (Strategy 2)................................ 60

Figure 4.4 Collaborative care strategy (Strategy 3).. 61

Figure 5.1 The screenshot of TMU activities 90

Figure 5.2 The screenshot of HP activities.. 90

Figure 5.3 The screenshot of network-level activities 91

Figure 6.1 Resilience metrics in base case 97

Figure 6.2 Resilience metrics in base case in the first 24 hours 100

Figure 6.3 Effect of different time between patient arrivals on resilience metrics.. 102

Figure 6.4 Effect of different probability of patient category on resilience metrics.. 103

Figure 6.5 Effect of different number of patients on resilience metrics......... 104

Figure 6.6 Effect of small number of patients on resilience metrics.............. 105

Figure 6.7 Effect of different percentage of resource availability on resilience metrics.. 106

Figure 6.8 Effect of different probability of Greens transported using cars on resilience metrics 107

Figure 6.9 Effect of extremely severe disruption on resilience metrics 108

List of tables

Table 1.1 Characteristics of integrative care versus collaborative care 4

Table 1.2 Characteristics of resilience measures 6

Table 2.1 Literature reviews of OR applications in disaster management 16

Table 2.2 Reviewed articles and their characteristics 23

Table 2.3 Main characteristics of the models for integrative care and collaborative care 33

Table 2.4 Resilience measures in healthcare context 42

Table 4.1 Different types of ambulance 53

Table 4.2 Number of patients in a one-trip ambulance in non-disaster environment 53

Table 4.3 Combination of different patient categories in one-trip ambulance in disaster events 54

Table 4.4 Strategies for collaboration in the healthcare network 56

Table 4.5 Characteristics of HPs in different layers 61

Table 5.1 Queuing structure and system objects 64

Table 5.2 Flowchart symbols 65

Table 5.3 Input values for simulation parameters (Boat capsizing for validation and verification) 85

Table 5.4 Input values for simulation parameters (Tsunami for experiments). 86

Table 5.5 Comparative analysis of number of patients in different categories at TMU 88

Table 5.6 Comparative analysis of resource allocation 88

Table 5.7 Comparative analysis of patient allocation 89

Table 5.8 Comparative analysis of average waiting time at HPs 89

Table 5.9 State of healthcare network in the pre-disaster condition ($h(0)$) 95

Table 6.1 $\overline{w}_p(t)$ of strategies 99

Table 6.2 Simulation scenarios 101

Glossary

Abbreviation	Definition
ABS	Agent-based simulation
CMO	Charity/municipal organisation
DES	Discrete event simulation
DOM	Disaster operations management
EMS	Emergency medical service
FCFS	First come first serve
FIFO	First in first out
FJSP	Flexible job shop scheduling problem
FR	First responder
HL1	Healthcare provider in layer 1
HL2	Healthcare provider in layer 2
HP	Healthcare provider
IP	Integer programming
MCS	Monte Carlo simulation
MIP	Mixed integer programming
OR	Operational research
PAP	Patient assembly point
SD	System dynamics
TMU	Temporary medical unit

Chapter 1 Introduction

According to records from the UN Office for Disaster Risk Reduction, 7,255 disaster events took place between 1998 and 2017 (Wallemacq, 2018) worldwide. Natural disasters, technology-related incidents, terrorism events and epidemics formed the majority of these disasters. These disasters caused more than 1.3 million deaths and affected 2.5 billion people. Some of the world's disaster events include the World Trade Centre attack in 2001, the Indian Ocean Tsunami in 2004, the earthquake in Haiti in 2010, and the latest SARS-CoV-2 pandemic in 2020, to mention just a few.

1.1 Terminology

The concept and terminology used in the thesis are presented. Terms include disasters, disaster operations management (DOM), emergency medical response, coordination, and resilience. A part of this terminology, which originated in a medical field, is defined to be used in the operational research (OR) field.

1.1.1 Disasters

We adopt the term *disasters* defined by Galindo and Batta (2013). Their definition encompasses other definitions. They define *disasters* as "*a shocking event that seriously disrupt the functioning of a community or society, by causing human, material, economic or environmental damage that cannot be handled by local agencies through standard procedures*".

1.1.2 Stages of DOM

There are four stages of DOM, including mitigation, preparedness, response, and recovery (Altay & Green, 2006). The mitigation stage aims to predict potential dangers as well as to develop necessary action plans in order to alleviate the effects of upcoming disaster events. The goal of the preparedness stage is to reduce the potential economic, social and physical impacts of a disaster as well as to facilitate the use of resources for response and disaster relief. In the response stage, available resources are allocated, coordinated and managed, with the efforts to enhance the post-disaster survival rates and economic growth. The recovery stage aims to restore some resemblance of normality after a disaster.

Interested readers can refer to Altay and Green (2006) for more details about objectives and activities of different stages.

1.1.3 Emergency medical response

Altay and Green (2006) define the term emergency response as "*response to catastrophic and disaster events and do not consider daily response of ambulance, police, or fire departments*". They claim that the emergency response is needed when the event is more harmful; for example, when resources are in shortage, when non-standard procedures have to be implemented to save lives, or when special authorities have to be appealed to manage the event. Therefore, we adapt their definition and define the term *emergency medical response* to refer to either non-standard activities of medical services that are implemented, or standard activities of medical services that need to be adjusted to save victims in the events where healthcare resources become stressed due to a disaster.

1.1.4 Coordination

According to the World Health Organisation, healthcare system consists of organisations, people and actions whose main aim is to promote, restore or maintain the health of individuals and communitites (WHO.int, 2022) The term *coordination* in the healthcare system is defined by Boon et al. (2009) who examine the coordination of interdisciplinary healthcare teams for the good of patients. They define two different terms, namely *integrative care* and *collaborative care*, to describe the corresponding coordination by considering the characteristics of workforce sharing and work dependency. Both terms are originally described as an interaction among medical staff working together in order to deliver medical services. Integrative care emphasises a closer interaction on a regular basis, which is subsumed into a single entity. Medical staff from different disciplines work dependently under a common governance structure resulting in less autonomy. In contrast, collaborative care allows medical staff to work together for a specific purpose during a period of time in order to deliver medical services. However, medical staff under collaborative care still work independently because they have their own administrative structures. Consequently, they maintain their autonomy while working together.

Collaborative care is perceived as a precondition for integrative care. We believe that a strong collaboration is likely to be a steppingstone towards an integration because an integration requires greater inter- dependency. However, the difference remains unclear since only workforce sharing, and work dependency are considered. The sharing of other healthcare resources including medical equipment and beds as well as the decision-making processes in integrative care and collaborative care are not defined. Thus, we introduce additional characteristics as follows. The sharing of medical equipment and beds in integrative care normally occurs under a common governance structure to enable better medical service quality. In contrast, in collaborative care these are usually implemented across governance structures. Such sharing will only be implemented for a period of time, especially during disasters, in order to improve the healthcare capability of the whole healthcare network. The healthcare network refers to a group of healthcare providers offering medical services to their target population. The decision about the medical service provision during disasters should be made in a timely manner. All members under integrative care generally design both practice guidelines and treatment plans in advance since they work dependently under a common governance structure. Consequently, such guidelines and plans are perceived as a common agreement among members when decision making on provision of medical services is required. Conversely, the decision on provision of medical services under collaborative care is made on demand basis since medical staff only work together for a specific purpose. It requires a sharing of information among medical staff in the decision making in order to provide proper medical services. The characteristics of integrative and collaborative care are summarised in Table 1.1.

Table 1.1 Characteristics of integrative care versus collaborative care

Characteristics	Integrative care	Collaborative care
Sharing of healthcare resources	Interdisciplinary team of medical staff working together on a regular basis as part of a single entity	Interdisciplinary team of medical staff working together for a specific issue/goal during a period of time
	Sharing of medical equipment and beds for a better allocation within the common governance structure	Sharing of medical equipment and beds to increase the healthcare capability across governance structures
Dependency	Common governance structure	Independent administrative structure
	Work dependency	Work independency
	Less autonomous while working together	Maintain autonomy while working together
	Requires collaboration	Precondition for integration
Decision making	Cooperative sharing of information	Cooperative sharing of information
	Decision on medical services is planned in advance	Decision on medical services is made on a demand basis
	Decision making follows common practice guidelines and treatment plans	Requires a sharing of information in the decision making

Note: Adapted from Boon et al. (2009)

1.1.5 Resilience

A concept of resilience is introduced by Bruneau et al. (2003). They define resilience as *"the ability of system to reduce the opportunities of shock, to absorb impact of earthquake if it occurs, and to recover quickly after such an earthquake. Resilience is perceived as the feature of a system allowing to respond to disasters, and then to resume normal operations as quickly as possible"*. Although their definition relates to earthquake, it can be applied to other types of disasters because all types of disasters often adversely affect the community. Figure 1.1 presents a concept of resilience in an earthquake. The resilience is expressed in a prespective of the quality of infrastructure of a community. The graph gives an illustrative example of how the quality of the infrastructure of a community (Q_t) varies over time during an earthquake, with Q_t ranging from 0 – 100%. The value of 0% means the total loss of infrastructure and 100% means no damage in the infrastructure quality. If an earthquake occurs at time t_0 , it can cause a damage to the infrastructure; Q_t is then immediately reduced from 100% to 50%. The restoration of infrastructure is expected to occur over time until time t_1 when it is completely repaired and functional. At this point, Q_t is improved to 100%.

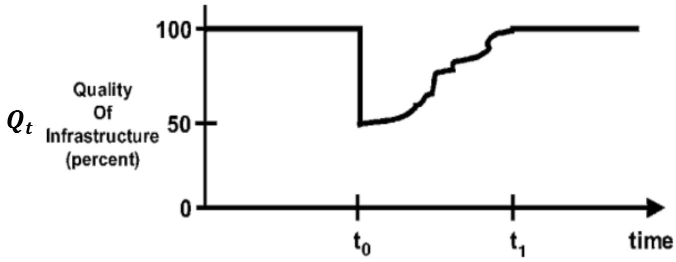


Figure 1.1 Concept of resilience in an earthquake (Bruneau et al., 2003)

Bruneau et al. (2003) state that four dimensions of resilience including robustness, redundancy, resourcefulness, and rapidity are required in response to an earthquake. *Robustness* considers the ability to carry out the designated functions and to withstand the disasters without a loss of functions. *Redundancy* considers the ability to provide the backup resources to sustain activities such as alternative plans. *Resourcefulness* considers the ability to measure the impact during disasters, as well as the ability to manage both material and human resources to cope with any damage. *Rapidity* considers the ability to meet the prioritised goals in a timely manner.

In the field of medical management, some studies use the term resilience to describe the coordination effectiveness in the healthcare system and address different stages of DOM in their definitions. For instance, Crowe et al. (2014) define resilience as the ability of the healthcare system to reduce the potential impact of disasters and to meet the needs of population. These measures of resilience served as objectives in the preparedness stage. Liu and Zhao (2015) define resilience as the ability of multi-HPs in the network to recover its operational state, as well as the ability of sustaining its medical services to save people during disasters using available healthcare resources of the network. A coordination of HPs and the management of available resources in the network are the activities carried out in the response stage. Kruk et al. (2015) define resilience as the capacity of healthcare organisations to prepare for and effectively respond to disasters; to maintain core functions during disasters, and to reorganise functions if required. This definition includes both preparedness and response stage of DOM. It is apparent that resilience is commonly perceived at the network level where the coordination of HPs is required during disasters.

We define *resilience* as the ability of a healthcare network to respond to the impact of disasters and to adapt its emergency medical activities in order to meet better the patient demands during disasters.

The primary concern of resilience is to maximise the provision of emergency medical services as well as to minimise negative healthcare outcomes (Bruneau et al., 2003). It is advocated that the resilience measures should be *outcome-based* describing the reduction in morbidity and mortality of the survivors (Rådestad et al., 2013). The measures are sometimes referred to as patient outcome because they are used to evaluate the improvement of population's health during disasters (Fries et al., 1980; Fitzpatrick et al., 1998).

We define the characteristics of resilience measures based on the framework proposed by Kruk et al. (2017). The framework includes a set of resilience indices for the healthcare system during disasters. The framework specifies that the resilience measures should reveal the population health, reveal the quality of healthcare-network performance, serve as a benchmark for resilience that is comparable across different strategies of emergency medical response, and provide the information for decision makers on the required actions to improve emergency medical response. Berg et al. (2018) suggest that the resilience measures should concern the system performance as a whole rather than the performance of individual components. The characteristics of resilience measures are summarised in Table 1.2. These characteristics aid to define the adapted resilience metrics to be used in disasters.

Table 1.2 Characteristics of resilience measures

Characteristics	Description
Population health	Reveal the health conditions of population in the affected area.
Quality of healthcare-network performance	Reveal the quality of medical services during a particular time.
	Evaluate the effectiveness of collective medical response during disasters.
	Concern the system performance as a whole rather than performance of individual components.
Benchmark	Enable the comparison of different strategies for medical response during a particular disaster.
Information for decision maker	Provide information for the decision maker or policy maker on patients' outcome as well as the required actions of collective medical response to improve it during disasters.

1.2 Challenge of healthcare system during disasters

One of the most prominent systems in disaster response is the healthcare system. Healthcare systems have encountered extreme pressures from disasters (Yi et al., 2010). One of the vital organisations in the healthcare system are healthcare providers (HPs), which are generally recognised as a centre of medical services during disasters (Cimellaro et al., 2010; Vanvactor, 2011; Achour et al., 2014; Kruk et al., 2015). Their roles in providing timely and good quality treatments to both existing and new patients affected by a disaster are critical during disasters (McDaniels et al., 2008). Disasters have an impact on both healthcare resources and healthcare activities as follows. First, in many situations, such as Tsunami in 2004, HPs allocate some medical staff to the shelters set up at the disaster scene in order to provide the initial treatments (Lodree et al., 2017). HPs, thus, need to ensure a sufficiency of medical staff at their settings in order to maintain healthcare capability during disasters (Yi et al., 2010; Becker et al., 2018). Healthcare capability refers to the ability to provide medical services. Second, HPs often provide a patient transportation, especially during natural disasters. Due to a limited number of available ambulances, they need to make multiple trips during such events (Repoussis et al., 2016). Third, a sudden surge of emergency patients causes a shortage of healthcare resources, resulting in a lower healthcare capability for a period of time (Achour & Price, 2010). In particular, a shortage of emergency beds can result in higher waiting time for severe-injured patients (Xiang & Zhuang, 2016). Lastly, disasters change healthcare activities. The admission and discharge protocols are modified in order to increase the ability to accept new patients who require emergency medical services (Zhang & Howard, 2015). To better respond to future disasters, HPs and institutions for social care, in both private and public sectors, need to prepare contingency plans for medical response (Boyd et al., 2012; Starr & Matinrad, 2016). For instance, after the Indian Ocean Tsunami in 2004 with more than 225,000 casualties, HPs around the world started planning the emergency medical response for natural disasters (Altay & Green, 2006).

1.3 Importance of coordination in healthcare system during disasters

The importance of coordination in healthcare systems during disasters is well recognised in the literature. Coordination allows pooling of healthcare resources to ensure the continued provision of medical services in the healthcare network during disasters (Rolland et al., 2010; Kruk et al., 2015). The lack of coordination of multiple healthcare facilities for emergency medical response can result in managerial confusions and ambiguity of authority in the collective response during disasters (Espíndola et al., 2018). The practice of coordination in healthcare systems, for example, has proved to be very useful during the SARS-CoV-2 outbreak. When the medical supplies at Wuhan Red Cross were in shortage, Red Cross in other cities in China shared with them respirator masks, medical protective suits, and some medicine in order to enhance the healthcare capability in the city and to reduce the spread of COVID-19 in China (CNN.com, 2020). The HPs in Italy shared their testing kits, beds, and ventilators in response to a surge of infected patients and coordinated the development of protocols and procedures of healthcare activities and medical treatments in order to mitigate the impacts of COVID-19 on the healthcare system (Carenzo et al., 2020). When the United States experienced an increase in the number of infected patients, there was a need to manage the ventilator allocation at the national level, resulting in a sharing of ventilators between states (covidanalytics.io, 2020). States which had available ventilators were required to allocate some ventilators to the states that were expected to have ventilator shortages in the upcoming weeks. The higher-income countries shared COVID-19 vaccines and syringes with medium- and low-income countries through the COVAX scheme in order to achieve global herd immunity (BBC.com, 2021; UNICEF.org, 2021; WHO.int, 2021).

Studies on disaster management claim that a highly proactive and functioning healthcare network is needed. Disaster response plans require a collective effort from multiple HPs rather than an individual effort from a single HP (Rolland et al., 2010; Vanvactor, 2011; Kruk et al., 2015; Ogawa et al., 2016). The National Health Service in the UK advocates that coordination with other agencies to provide emergency medical response enhances the ability to respond to disasters (GOV.uk, 2019). There is a limit to what any individual institution can achieve without support from other institutions. For instance, disaster responses that assess each healthcare facility in isolation fail to account for patient reallocation from one facility to another, and ultimately affect the ability of the healthcare system to admit new patients (Zhang & Howard, 2015). For example, independent participation of different organisations during two major floods in Mexico and their independent decision-making caused an ineffective response and an inefficient use of resources (Espíndola et al., 2018). The lack of coordination among humanitarian organisations during natural disasters can cause higher operational costs, response times, and inefficient emergency resource allocation (Pazirandeh & Maghsoudi, 2018).

1.4 Research motivations

In the field of medical management, there are two types of coordination: integrative care and collaborative care (Boon et al., 2009). The focus of integrative care is on resource sharing under a common governance structure, thereby being commonly implemented within a HP. In contrast, collaborative care is mainly focused on resource sharing across different governance structures. It is commonly implemented between HPs (Tippong et al., 2022)

Although integrative care has been developed to enhance the healthcare capability in a HP when responding to a disaster, it may not improve resilience at the healthcare-network level because the resilience improvement requires the joint capabilities of different HPs (Holling, 1996; Bruneau et al., 2003). When responding to disasters, the resilience is perceived at community level rather than at an individual institution (Kruk et al., 2015; Rohova & Koeva, 2021).

Several studies have addressed collaborative care between HPs in response to disasters. However, the research about the effectiveness of collaborative care remains unclear. From the methodological perspective to the best of our knowledge, there have been no attempts to use simulation approach to quantify the potential impact of collaborative care. From the application perspective, the literature has not taken into consideration some real-world aspects of collaborative care as follows.

- The literature has not addressed the healthcare resources in the facilities which are not affected by a disaster from external network. We use the term *internal* to refer to the affected areas, whereas *external* refers to outside the affected areas. In real-world, the external medical staff and ambulances from outside the affected area are generally allocated to the affected healthcare network in order to enhance the healthcare capability during disasters, especially natural disasters.

- The literature has not paid attention to the ambulance sharing for multiple patient transportation. The literature on patient transportation so far has always assumed that only one patient could be carried in one ambulance trip, but has not considered sharing of an ambulance between multiple patients. However, this would increase the utilisation of ambulances during disasters. There has been a recognition of the importance of ambulance sharing in real-word disaster operations management. For instance, WHO.int (2008) reports that one of ambulance types, called patient transport ambulances, is suitable for transportation of one or more patient(s) on stretcher(s) and/or chair(s), particularly in post-disaster logistics when fast transportation of patients to healthcare facilities is of utmost importance. Boness & Mayes (2018) state that Australia developed a plan for sharing an ambulance to carry out the transportation requests. An ambulance picks up all the patients for the common route before dropping them off. BBC.com (2018) reported that an increase in demand for ambulances requires the ambulance sharing. However, the constraints that an ambulance could stop for an additional patient only if it is clinically safe for the patient on board should be carefully modelled.

Although simulation enables investigation of the impact of different strategies for collaboration in the network on the resilience, the allocation of patients may not be optimal as the simulation itself is not the optimisation tool. An optimisation model is required to address patient allocation in collaborative care in which an ambulance transports multiple patients to one of the HPs in one trip.

Furthermore, the interviews that we conducted with the health authorities and medical staff in Thailand, who experienced the Tsunami disaster in 2004, proved the importance of collaborative care between HPs in such event. HPs in the affected areas were disorganised while allocating the disaster victims because there was no collaboration agreement in response to Tsunami. This provided further motivation for our study.

1.5 Research aim, objectives and questions

The study aims to develop discrete event simulation (DES) models of different strategies for collaboration in an emergency medical response in a healthcare network. The DES models include relevant real-world aspects of collaborative care missing in the literature including external resource sharing, and ambulance sharing for multiple patient transportation. In addition, the study aims to present the resilience metric in healthcare context and to perform the quantitative analysis to reveal the impact of different strategies on resilience improvement during a disaster. Furthermore, the study aims to develop a mixed integer programming (MIP) model for multiple patient allocation in collaborative care. The MIP model addresses the ambulance sharing for multiple patient transportation in one trip.

The research objectives of this thesis are

1. To develop simulation models to investigate the impact of different strategies for collaboration in the network on the resilience. The models will include relevant real-world aspects of collaborative care missing in the literature.
2. To develop metrics of resilience in healthcare context that can be used in the quantitative analysis of different strategies.
3. Apart from the simulation models, to develop an optimisation model to address the allocation of multiple patients using ambulance sharing.

In particular, we seek to address the following questions.

1. How can DES models be used to develop strategies for effective collaboration in a healthcare network in response to disasters?
2. How can we measure the resilience of a healthcare network during disasters?
3. How can the resilience of healthcare network be improved by using strategies during disasters?
4. How can an MIP model be used to optimally allocate multiple patients to HPs using ambulance sharing?

1.6 Research contributions

In our study, three strategies for collaboration are defined. These strategies include non-collaborative care strategy, semi-collaborative care strategy, and a new proposed collaborative care strategy. The strategies differ with respect to the first treatment provision of patients, sharing of healthcare resources, and patient transportation. We compare the effect of these strategies on the resilience of the healthcare network. We collaborate with the health authorities and medical staff in Thailand who experienced the Tsunami disaster in 2004 to investigate real-world activities that take place in an emergency medical response. These activities include treatment provision of patients, healthcare resource sharing, and patient transportation. The healthcare authorities were involved in model validation and verification as well as the design of disaster scenarios.

The contributions of our study are as follows.

- This is the first example of developing and using DES models to investigate different strategies for collaboration in the healthcare network. Our DES models simulate the strategies following the real-world activities of collaboration in an emergency medical response and cover relevant real-world aspects which are missing in the literature. These aspects include external resource sharing and ambulance sharing for multiple patient transportation.
- A generic metric of resilience proposed in the literature on system safety is adapted for use in the healthcare context.
- Insights about the resilience of a healthcare network under different strategies for collaboration are generated. Ultimately, the study provides an important opportunity to advance the understanding of collaborative care development and resilience improvement. These can support emergency planners in the development of a more effective strategy for collaboration in response to disasters.
- We develop a first MIP model to optimally allocate of multiple patients to HPs using ambulance sharing. The model considers the ambulance capacities and the possible combinations of different patient categories in one-trip ambulance which are missing in the literature.

- Apart from the models, we provide the first focused review of OR articles that discuss the coordination of integrative and collaborative care in healthcare network during disasters. We classify the articles by the research problems they addressed, disaster types, and the methodologies they developed/ used. The main characteristics of mathematical models for integrative and collaborative care which have been developed and published so far are analysed. We also define the characteristics of measures for the resilience of a healthcare network based on a framework proposed in the literature. These characteristics aid to review the resilience measures proposed in the literature and are used to define adapted resilience metrics to be used during disasters.

1.7 Thesis overview

The thesis is organised as follows. Chapter 2 provides a focused literature review of OR contributions on the topic of coordination in healthcare systems. It presents the literature search, reviews the literature on coordination and resilience measure in healthcare system, and highlights the gaps in the literature. Chapter 3 sets out the research methods used in the thesis, including interviews, simulation and optimisation. Chapter 4 presents the description of strategies for collaboration in the healthcare network and their activities. The development of DES models is described in Chapter 5. The design of different disaster scenarios and the resilience of a healthcare network using different strategies obtained in these scenarios are given in Chapter 6. Also discussed in Chapter 6 are the managerial insights into collaborative care. The MIP model of multiple patient allocation in collaborative care is presented in Chapter 7. Chapter 8 provides the conclusions and suggests future research.

1.8 Dissemination of the research

The dissemination of this research includes the following publications and presentations:

- Tippong, D., Petrovic, S., & Akbari, V. (2022). A Review of Applications of Operational Research in Healthcare Coordination in Disaster Management. *European Journal of Operational Research*, 301(1), 1-17.

- Tippong, D., Petrovic, S., & Akbari, V. (2022). Collaboration in healthcare for resilience improvement during disasters, paper reviewed and presented at the 48th EURO Working Group on Operational Research Applied to Health Services (ORAHS), Bergamo, Italy, 17 – 22 July.
- Tippong, D., Petrovic, S., & Akbari, V. (2022). Collaborative response for healthcare resilience improvement in disasters, paper reviewed and presented at the 32nd EURO Conference, Espoo, Finland, 3 – 6 July.
- Tippong, D., Petrovic, S., & Akbari, V. (2019). Healthcare resilience improvement using collaborative care during disruption, paper reviewed and presented at Health Challenge Thailand 2019, London, United Kingdom, 28 – 30 June.

Under review:

- Tippong, D., Petrovic, S., & Akbari, V. (R&R). A simulation study of healthcare resilience improvement using collaborative care in response to disasters. *European Journal of Operational Research*.

Chapter 2 Literature review

This chapter presents a focused literature review of OR contributions on the topic of coordination in healthcare systems during disasters.

2.1 Current reviews of disaster management

OR has been employed to a variety of problems to support decision making in healthcare systems during disasters. A reasonably large number of literature reviews of disaster management have been offered by numerous OR scholars. Table 2.1 presents a summary of exiting reviews of OR applications in disaster management and positions our review with respect to these. The columns in the table show the authors, the review focus, the stages of DOM, the disaster types, and the time period of articles covered in the review. The last column shows the level of details presented in the review. The existing reviews covered only some parts of disaster management.

Altay and Green (2006) reviewed the articles on DOM which covered all stages of DOM. Simpson and Hancock (2009) reviewed the articles on emergency responses in both urban and disaster services. They defined urban services as municipal services that can be provided by a single organisation, whereas disaster services referred to large-scale emergency services. Caunhye et al. (2012) reviewed the optimisation models proposed for emergency logistics problems, which included the facility location, stock pre-positioning, relief distribution and casualty transportation. Galindo and Batta (2013) analysed the trend of articles in DOM and compared them with the review by Altay and Green (2006). Their review also identified the most frequent assumptions presented in the reviewed articles. Anaya-Arenas et al. (2014) reviewed the articles in the relief distribution network focusing on logistics perspectives. Gul & Guneri (2015) reviewed the application of simulation methods in an emergency department in their normal functioning and during disaster events. The review mainly presented the frequency of use of simulation methods. Key performance indices and simulation software used in the reviewed articles were presented. Özdamar and Ertem (2015) provided a comprehensive review of amathematical models for mass evacuation, casualty transportation, and relief distribution.

Table 2.1 Literature reviews of OR applications in disaster management

Author(s)	Focus of literature review	Scope of study			Review includes
		Stages of DOM	Types of disaster	Period surveyed	
Altay and Green (2006)	- Disaster operations management	Mit, Pre, Res, Rec	Nat, Man	1980 – 2004	Sol
Simpson and Hancock (2009)	- Emergency response in urban services and disaster services	Res	Nat, Man	1965 – 2007	Sol
Caunhye et al. (2012)	- Optimisation models for emergency logistics	Mit, Pre, Res	Nat, Man	1980 – 2010	Par, Var, Obj, Cons
Galindo and Batta (2013)	- Evaluation of the trend of articles on DOM and comparison with the review by Altay and Green (2006)	Mit, Pre, Res, Rec	Nat, Man	2005 – 2010	Assump, Sol
Anaya-Arenas et al. (2014)	- Relief distribution network focusing on logistics perspective - Models for location-network design and humanitarian aid transportation	Res	Nat, Man	1990 – 2013	Obj, Cons, Sol
Gul & Guneri (2015)	- Simulation models in an emergency department	N/A	Nat, Man	1968 – 2013	Obj
Özdamar and Ertem (2015)	- Models for mass evacuation, casualty transportation, and relief distribution	Res, Rec	N/A	1998 – 2014	Obj, Cons, Sol
Gutjahr and Nolz (2016)	- Multicriteria optimisation in humanitarian aid - Optimisation criteria in humanitarian aid	Mit, Pre, Res, Rec	Nat	2007 – 2015	Par, Obj, Sol
Ahmadi-Javid et al. (2017)	- Healthcare facility location in both non-emergency and emergency situations - Models for healthcare facility location	N/A	N/A	2004 – 2015	Par, Var, Obj, Cons, Sol
Esposito Amideo et al. (2019)	- Optimisation models developed for shelter location and evacuation routing - Challenges in developing applicable optimisation models for these problems	Res	Nat, Man	1980 – 2016	Par, Obj, Cons, Sol
Mishra (2019)	- Simulation models in disaster management	Mit, Pre, Res, Rec	Nat, Man	2000 – 2016	Sol
Farahani et al. (2020)	- Casualty management	Res	Nat, Man	1977 – 2019	Assump, Par, Var, Obj, Cons, Sol
Sabbaghtorkan et al. (2020)	- Prepositioning and allocation of healthcare supplies	Mit, Pre	Nat	2000 – 2018	Var, Obj, Cons
Our review	- Coordination in the healthcare systems - Measures of healthcare resilience	Res	Nat, Man	2005 – 2022	Par, Var, Obj, Cons

Note: Mit - Mitigation, Pre - Preparedness, Res - Response, Rec - Recovery, Nat - Natural, Man - Man-made, Assump - Main assumptions, Par - Parameters, Var - Key decision variables, Obj - Objective functions, Cons - Main constraints, Sol - Solution approach, N/A - Not applicable

Gutjahr and Nolz (2016) provided an in-depth review of articles which addressed multi-criteria optimisation for humanitarian aid. The multicriteria deterministic and stochastic optimisation models for different stages of DOM were presented. Ahmadi-Javid et al. (2017) reviewed articles on healthcare facility location in both non-emergency and emergency situations, presenting the main characteristics of the models and optimisation methods. Esposito Amideo et al. (2019) reviewed optimisation models developed for shelter locations and evacuation routing. The review also discussed the challenges in developing realistic optimisation models by considering the applicability of models in real-world cases. Mishra et al. (2019) reviewed the applications of simulation methods in disaster management. The review mainly presented a broad analysis of different simulation methods in the context of disaster management. Farahani et al. (2020) reviewed articles about casualty management in humanitarian activities which included resource dispatching, search and rescue, on-site medical activities and patient transportation. Sabbaghtorkan et al. (2020) reviewed articles which investigated prepositioning and allocations of healthcare supplies.

Most of them consider logistics management in their review including facility locations, stock pre-positioning, relief distribution network, evacuation routing, and casualty transportation. Only a few of them considered the operations management of entire activities in different stages of DOM (Altay and Green, 2006; Galindo and Batta, 2013; Gutjahr and Nolz, 2016; Mishra 2019). Most of them covered all types of disasters, whereas a few reviews covered only natural disasters.

Although the existing literature reviews of OR approaches have included the perspective of healthcare management, they focused mostly on the application of OR in disaster operations and logistics management. The importance of coordination in healthcare systems during disasters is well recognised in the literature, but to the best of our knowledge there has been no review of the published research in this area. Therefore, a focused literature review of OR applied to the problem of coordination in healthcare systems during disasters was undertaken.

2.2 Scope of the focused literature review

The terminology defined in Section 0 helps in highlighting precisely the scope of the review as follows.

2.2.1 Disasters

The review is not limited to any particular type of disasters because healthcare systems have encountered extreme pressures from different types of disasters, including natural disasters and man-made disasters (Yi et al., 2010). All these disasters have created a surge of demands for medical services and caused a shortage of healthcare resources in the affected areas.

2.2.2 Stages of DOM

Our review is focused on the response stage of DOM. When disasters happen there is often a shortage of healthcare resources even if some emergency medical plans have been developed in advance. The healthcare environment during disasters is characterised by high level of variations which drive the need for adaptation plans (Fairbanks et al., 2014). For instance, a surge of patient demand, and an inappropriate staffing are common variations in the conditions of work and require adaptation. The changes in clinical pathway to meet a surge of demands as well as the flexible medical staff assignment to perform medical services have to be implemented for a better disaster response (GOV.uk, 2019). Therefore, devastating impacts of disasters on the healthcare systems require an efficient emergency medical response and the adaptation of healthcare activities to meet a surge of disaster victims.

2.2.3 Emergency medical response

According to the definition of emergency medical response presented in Section 0, daily responses to routine emergency calls are excluded.

2.3 Literature search and selection of articles

Our review focuses on articles published in OR and OR-related journals, which presented research into coordination in the healthcare system during disasters. We refer to OR-related journals as the journals that do not focus on OR in their scope, but they present articles describing OR approaches. The utilised databases include *Web of Science, Scopus, and Google Scholar.* Conference proceedings, book chapters, books, working papers, theses, conceptual frameworks, and practitioner magazines are not included in our review. To the best of our knowledge, none of book chapters publishes the coordination in the healthcare system during disasters. In addition, the review aims to identify, evaluate, and integrate what have been investigated by individual studies on the same subjects. The review requires the detailed research problems, methodologies and new findings/knowledge of the individual studies, which are available in articles, but not in book chapters. Book chapters are likely a collection of knowledge arising from many studies on the same subjects. They are often in the informative format and may be a repetition of findings from articles published in journal. Thus, book chapters are not included in the review. Only publications in English are considered. Our study covers the timeframe 2005 – 2022, because prior to 2005, OR articles address mostly the mitigation phase of disaster management. Only after 2005, there have been more research interests and advancements in the response phase of disaster management. We believe that Tsunami in 2004 caused an increase in OR articles in the medical management. In the initial stage of our article selection, we considered articles where the following keywords were used anywhere in the articles: "integrated", "collaboration", "coordination", "sharing", "allocation", "resilience" or "resiliency", together with one of the terms "emergency", "disasters", "COVID", "hospital" or "healthcare". We proceed to select the candidate articles, which fit into our scope. Our screening process is divided into three stages, which is similar to the review by Gutjahr and Nolz (2016); and Mishra et al. (2019). First, the titles and their abstracts are checked if they present an OR approach to the coordination in the healthcare system during disasters. Second, the articles that pass the first screening test are kept if they address the coordination for activities of medical services (not physical space sharing) in their abstracts. Third, the last filtering is done based on the introduction and the problem description of articles, which have to address the coordination in emergency medical response (not in the collapse of buildings and the failure of information technology network). The steps taken in the review methodology are given in Figure 2.1.

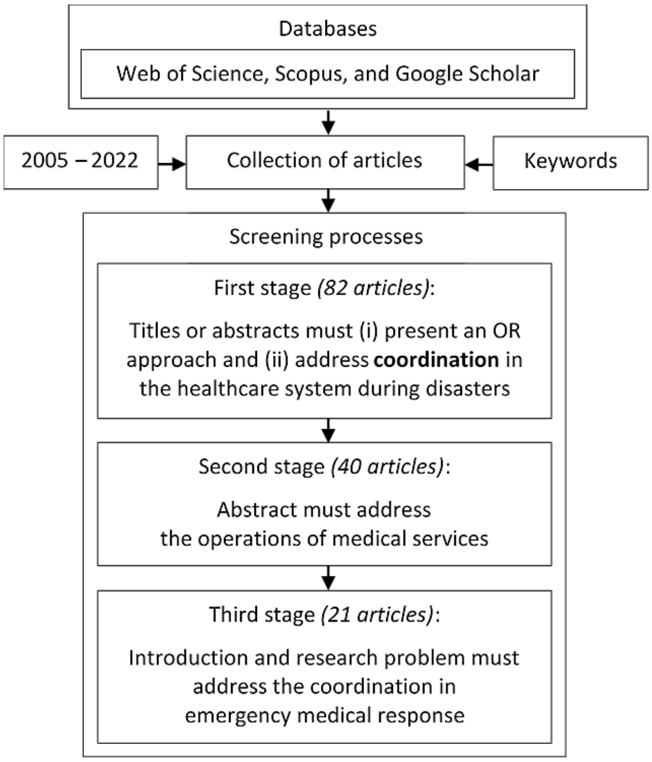


Figure 2.1 Literature search and selection of articles

Our search reveals that it is not always straightforward to determine whether the subject of an article should be classified as a disaster. For instance, the terms "disruption", "overcrowding events", and "crowded demand" are used in the literature to address different issues. In these situations, the following questions are considered: (1) Does the event cause a surge in patient demands? (2) Are the healthcare resources of multiple departments or organisations in shortage during the event? The articles are retained if research problems address the surge in patient demand and the shortage of healthcare resources. In addition, the focus of this thesis is on the collaboration in an emergency medical response in a healthcare network. The goal of the preparedness stage in DOM is to reduce the potential economic, social, and physical impacts of a disasters as well as to facilitate the use of resources for response and disaster relief. The outcome of preparedness stage is likely an emergency medical plan for upcoming disasters. However, these plans that have been prepared in advance are often adjusted to the situations during disasters in order to enhance the post-disaster survival rates. For example, clinical pathway is typically changed in order to relieve overcrowding in emergency departments. Ambulances, which normally carry one patient in non-disaster environment, transport multiple patients in one trip due to a shortage of ambulances during disasters. Thus, articles have to address the medical management of the response stage of DOM. However, this aspect is sometimes difficult to evaluate precisely because some models presented in the articles could be applied in either the preparedness stage or the response stage of DOM. In the latter case, they are included in the review.

The first stage resulted in 82 articles. Figure 2.2 shows the number of published articles based on the year of the publication. It can be noticed that research interests in coordination in the healthcare system during disasters have increased gradually in the last decade. The number of articles published between 2014 and 2019 almost doubled. However, the number is still relatively small considering the breadth and depth of research potentials in this topic as well as the complexity of the healthcare system.

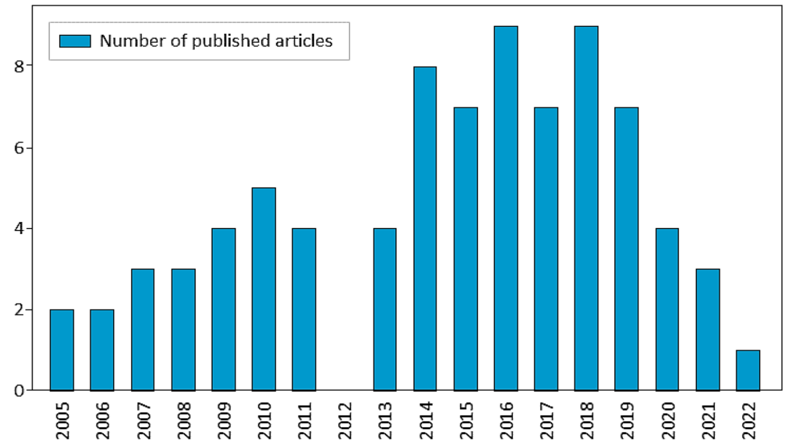


Figure 2.2 Number of articles published between 2005 and 2022

Only 40 of the retrieved articles address the activities of medical services in the abstract. They are published in *European Journal of Operational Research (EJOR)*, *Journal of the Operational Research Society (JORS)*, *Operations Research for Health Care (ORHC)*, *Annals of Operations Research*, *Health Systems*, *Journal of Simulation*, *Production and Operations Management Journal (POM)*, *Computers and Operations Research (COR)*, *Health Care Management Science (HCMS)*, *Artificial Intelligence in Medicine*, *Operations and Logistics*, *Decision Support Systems*, *Naval Research Logistics (NRL)*, *Journal of Healthcare Informatics Research*, *Computers & Industrial Engineering (CAIE)*, *Operations Management Research (OMS)*, and *Journal of Scheduling*. Figure 2.3 illustrates the distribution of published articles across these journals. There are 42 articles published in non-OR journals, mostly in medicine and engineering related journals, including *Journal of Prehospital, Disaster Medicine* and *Earthquake Spectra*. Their focus is on physical space sharing. In all of them, the research into how the undamaged hospitals can support the damaged ones by allocating their free space during disasters was reported. These articles do not fit into our scope, i.e., do not address the activities of medical services. Thus, we exclude these 42 articles.

In total, 21 articles in which the introduction and research problem address the coordination of emergency medical response are kept being reviewed. Figure 2.3 shows the number of reviewed articles across journals. EJOR and ORHC published the largest number of papers followed by Annals of OR. In the third stage, we exclude 19 articles because all of them investigate the provision of medical services under the coordination of healthcare infrastructure during the collapse of buildings and the failure of information technology network. Collapsed buildings and failed information technology network are out of the scope of our study, which address insufficient healthcare resources where the resources include medical staff, beds, medical equipment, and medical supplies.

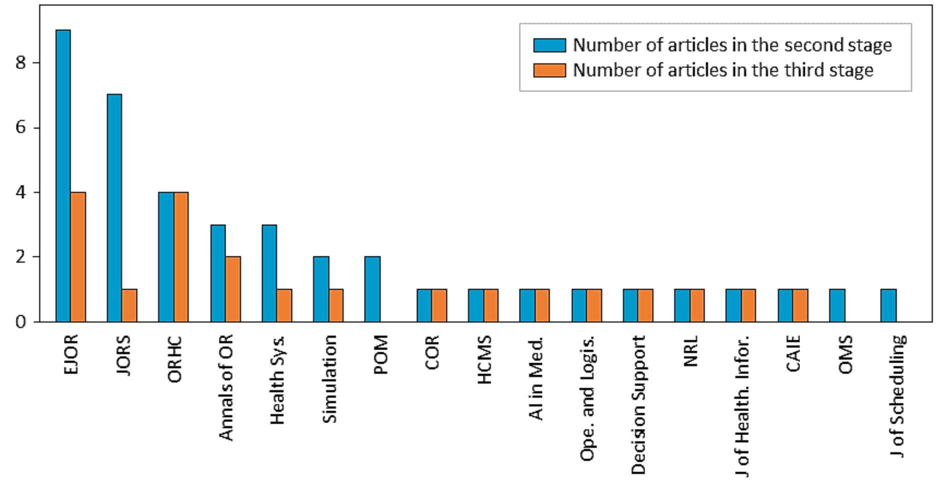


Figure 2.3 Distribution of articles across journals

2.4 OR approaches to coordination in the healthcare system

The characteristics of the reviewed articles are given in Table 2.2 and are discussed in detail in the remainder of this section.

Table 2.2 Reviewed articles and their characteristics

Article	Journal	Type	Boundary	Resource	Disaster	Model/Method
Yi and Özdamar (2007)	EJOR	CC	Across	Staff	Nat, Man	DeterOpt (MIP) / Simple split algorithm
Lameris et al. (2008)	AI in Med.	IC	Within	Staff, Bed, Equip	Nat, Man	Sim (MCS) and DynOpt (IP)
Arora et al. (2010)	Decision Support	CC	Across	Equip	Nat	DeterOpt (IP)
Konrad et al. (2013)	ORHC	IC	Within	Staff	Nat, Man	Sim (DES)
Crowe et al. (2014)	JORS	IC	Within	Staff, Equip	Nat	DeterOpt (IP) and heuristics
Sun et al. (2014)	COR	CC	Across	Pat	Nat	DeterOpt (MIP)
Lei et al. (2015)	Annals of OR	CC	Across	Staff	Nat, Man	DeterOpt (MIP) / Greedy heuristic
Liu and Zhao (2015)	Ope. and Logis.	CC	Across	Equip	Nat, Man	DeterOpt (MIP)
Zhang and Howard (2015)	Health Sys.	CC	Across	Pat	Nat	DeterOpt (MIP)
Chen and Wang (2016)	Simulation	IC	Within	Staff, Equip	Nat, Man	Sim (DES) and StochOpt (IP) / Multiobjective swarm optimisation
El-Rifai et al. (2016)	ORHC	IC	Within	Staff	Nat	StochOpt (MIP)
Repoussis et al. (2016)	EJOR	CC	Across	Pat	Nat, Man	DeterOpt (MIP) / Hybrid multi-start local search
Sung and Lee (2016)	EJOR	CC	Across	Pat	Nat, Man	DeterOpt (MIP) / Column generation
Yang et al. (2016)	ORHC	IC	Within	Staff	Nat, Man	Sim (DES)
Lodree et al. (2017)	Annals of OR	IC	Within	Staff	Nat, Man	Sim (MCS)
Becker et al. (2018)	HCMS	IC	Within	Staff	Nat, Man	DeterOpt (IP)
Niessner et al. (2018)	ORHC	CC	Across	Staff	Nat, Man	Sim (DES) and DynOpt (IP)
Mehrotra et al. (2020)	NRL	CC	Across	Equip	Nat	StochOpt (MIP)
Buhat et al. (2021)	J of Health. Infor.	CC	Across	Equip	Nat	DeterOpt (NLP)
Sarkar et al. (2021)	CAIE	CC	Across	Pat	Nat	DeterOpt (MIP)
Thul & Powell (2021)	EJOR	CC	Across	Equip	Nat	StochOpt (IP)

Note: IC - integrative care, CC - collaborative care, Within - within a hospital, Across - across hospitals, Staff - Medical staff allocation/scheduling, Bed - emergency bed allocation, Equip – medical equipment/supplies allocation, Pat - patient flow/allocation, Nat - natural disasters, Man - man-made disasters, DeterOpt - deterministic optimisation, DynOpt - dynamic optimisation, StochOpt - stochastic optimisation, MIP - mixed integer programming, IP - integer programming, NLP - nonlinear programming, Sim - simulation method, MCS - Monte Carlo simulation, DES - discrete event simulation

2.4.1 Research problem

The reviewed articles are classified into groups based on their research problems. Each article is presented in some detail. Overall, the integrative care literature mainly examines the sharing of healthcare resources within a HP setting, whereas the collaborative care literature primarily investigates the sharing of healthcare resources between HPs to address a surge of demands for emergency medical services in the network. The common purpose of coordination is to ensure the continuity of medical services and to improve healthcare capability during disasters. The healthcare resources that are commonly found in the reviewed articles include medical staff, emergency beds, medical equipment, and medical supplies such as syringes, antibiotics, surgical blades, vaccines, and bandages.

Integrative care

The literature on integrative care dealt with *workforce allocation to ensure sufficient staff within a HP*. Some articles proposed models for workforce scheduling with on-call duty to respond to disasters. Becker et al. (2018) developed an integer programming (IP) model of a cyclic workforce scheduling with on-call duties for emergency events. Two sets of medical staff were allocated for the period of time. The first set of medical staff was assigned to provide medical services on a regular basis, while the second set was assigned to perform on-call duties. When patient demand reached the usually available healthcare capability, the second set of medical staff was called in order to increase the healthcare capability during disasters. El-Rifai et al. (2016) also optimised workforce scheduling with on-call duty during a seasonal epidemic. They concluded that such scheduling could save 10% of the total wage cost compared to workforce scheduling without on-calls. Additionally, some articles presented the allocation of extra staff to respond to disasters. Lodree et al. (2017) developed a Monte Carlo simulation (MCS) model to allocate separate medical staff teams to serve different patient categories, for example, severe- and minor-injured patients simultaneously, in contrast to the normal approach where medical staff treated all patients. They found that this strategy can minimise waiting time and patients' queue in an emergency department during mass casualty incidents. Yang et al. (2016) also presented the allocation of extra nurses to the triage station in order to improve the emergency department performance during a demand peak while considering the utilisation rate of medical staff. Konrad et al. (2013) investigated a HP which has encountered emergency department crowding caused by a surge of patient volume. They introduced the concept of split patient flow with an addition of medical staff to improve the Door-to-Doctor time. The split-flow concept classified patients considering their severity and created parallel processes. The severe-injured patients were treated using a normal emergency department process flow, whereas the minor-injured patients were treated in an intake area where emergency beds were not required. This study addressed coordination by sharing the medical staff in a HP setting and the emergency medical response by adjusting the patient flow process. The usual staff were responsible for doing the normal ED patient flow for severe-injured patients, while the additional staff working in a medical response team served minor-injured patients in an intake area. This research is useful in disaster management when the healthcare resources become stressed and HPs in the affected areas need to adjust the emergency department activities in response to a surge of victims affected by a disaster. Both Konrad et al. (2013) and Yang et al. (2016) developed DES models to examine the patient flows under integrative care strategy in an emergency department during the higher patient demands.

Some integrative care studies developed models for *resource integration within a HP* in order to improve healthcare capability during disasters. Crowe et al. (2014) investigated the reallocation of medical staff and medical equipment within a HP in order to minimise unmet demand and improve resilience during flooding. To improve resilience, the availability of care service levels for different patient categories was determined within a HP in order to estimate the shortage levels. Both medical staff and medical equipment were allocated between departments subject to their availability of resources and the shortage levels. A few studies developed a dynamic allocation approach to improve healthcare capability when responding to disasters. In general, dynamic allocation refers to the adaptive allocation of healthcare resources considering the current situations such as patient demands. Lameris et al. (2008) proposed a model of dynamic resource allocation in order to achieve high service levels for all patient categories during disasters. They claimed that such allocation should be adjusted considering patient arrivals, the current and expected events. Chen and Wang (2016) also investigated the allocation of healthcare resources in order to improve an average length of stay and costs related to wasted healthcare resources in an emergency department during overcrowding events. The costs related to wasted healthcare resources were measured by a surplus of healthcare resources in the department.

Collaborative care

The main focus of collaborative care literature was on the *sharing of medical staff between HPs*. Lei et al. (2015) developed an MIP model to allocate the teams of internal medical staff to the different HPs in the healthcare network. Medical teams from home hospitals were allocated to carry out treatments at affected HPs. Once the treatment activities were completed, the medical teams could proceed to the next assigned HPs. The model considered the travel time in order to minimise the total tardiness of the service activities. Medical supplies were included in the model. However, the medical supplies were shipped from multiple distribution centres to HPs to support medical treatments, rather than being shared between HPs in the network. In addition, a dynamic allocation of medical staff to affected areas was proposed in a number of studies. Such allocation aimed to enable fast-relief access and improve survivor rates in the affected areas (Altay & Green, 2006), as well as to reduce congestion at the HPs (Galindo & Batta, 2013). Niessner et al. (2018) developed a DES model for the activities of medical treatments at the site after mass casualty incidents. They developed an IP model to allocate physicians to the treatment stations at the site. The physician reallocation was made based on the demand and the current staff capacity at the treatment stations in order to minimise the total rescue time and number of deaths. Yi and Özdamar (2007) developed an MIP model to allocate the internal medical staff to the shelters during an earthquake. The objective was to maximise the response service level and to reduce congestion in the HPs. The medical staff allocation took into consideration a trade-off between patient demands at the shelters and healthcare capacity at the HPs. Medical staff can also be shifted from shelter to shelter considering the patient demand at the shelters.

Apart from sharing of staff, some of the collaborative care literature included *sharing of medical supplies to enable resource collaboration between HPs*. Liu and Zhao (2015) examined a collaborative scheduling strategy with the aim to improve resilience in the healthcare network. They developed an MIP model for medical supplies sharing between HPs in the healthcare network. They assumed that one HP had a role of the main HP providing medical services, whereas others transferred their medical supplies to it. Arora et al. (2010) examined regional aid by sharing antiviral drugs during a pandemic flu. An IP model was developed to allocate the antiviral drugs for the treatments of the expected infected population to each region in the healthcare network. The objective was to minimise the negative healthcare outcomes such as the number of deaths and infected patients. It was assumed that the pandemic might affect one region more than others, thereby leaving some regions with a shortage of antiviral drugs, and others with an excess. The regions with a shortage could therefore receive aid from regions with surplus. Costs of transferring antiviral drugs between regions and the delay in transfer were also minimised. Mehrotra et al. (2020) developed a multi-period planning model to optimally allocate and reallocate ventilators that were available in the national stockpile to different regions during the SARS-CoV-2 pandemic. The allocation and reallocation of ventilators between regions were implemented by a central agency that acted as a coordinator for ventilator sharing among regions. The aim was to meet patient demands, while minimising total shortfall of ventilators under different expected demand scenarios. The model incorporated the demands for ventilators at each planning period in regions, the initial inventory of ventilators in regions and in the central agency, the availability of additional ventilators through planned production, and the lead time for the ventilator production. Thul & Powell (2021) examined the collaboration between a test centre and a vaccination centre to allocate test kits and vaccines in response to the SARS-CoV-2 pandemic in the United States and Nevada. The test centre allocated the tests kits and received samples of suspected/ infected patients. The information about the infection and transmission rate was sent to the vaccination centre for implementing the vaccine allocation. The model took into account the information flow between these centres in order to minimise the cumulative number of new infections. Buhat et al. (2021) also investigated the collaboration between test centres in response to the SARS-CoV-2 pandemic. They developed a nonlinear programming model to allocate COVID-19 test kits among test centres in Philippines. The aim was to give an equal chance for all people in the country to have an initial test for the virus infection. The objective was to maximise the number of suspected patients in getting tested. The model incorporated distance between test centres and patients' community, number of suspected patients in cities, and capacity of test facilities. Their results served as a guide to healthcare authorities in distributing the test kits in response to the SARS-CoV-2 pandemic.

Another purpose of collaborative care is to *allocate patients to HPs* during disasters. Zhang and Howard (2015) investigated collaborative responses for creating a healthcare surge capacity in the healthcare network during disasters. They assumed that the skilled nursing facilities were used to expand the healthcare system and they were used to create a surge capacity in the healthcare network. They developed an MIP model to allocate patients to either skilled nursing facilities or HPs in the healthcare network with the aim to relieve overcrowding in the HPs and improve the ability of a healthcare network to admit new severe-injured patients during disasters. Sung and Lee (2016) examined a resource-constrained triage for patient allocation in the healthcare network. An MIP model was developed to allocate patients to the HPs. The model took into account the priority of patients and the change in the patients' chance of survival in order to maximise the number of expected survivals. Sun et al. (2014) developed an MIP model to allocate patients to HPs by considering the shortest total travel distance to the HPs. Repoussis et al. (2016) argued that the patient allocation to the nearest HP might cause a congestion at the HPs, resulting in long waiting time. They thus developed an MIP model to allocate patients to remote HPs in the healthcare network. The objectives were to improve the balance of patient allocation between the HPs and the efficient use of healthcare network capacity. Sarkar et al. (2021) developed a data-driven optimisation model for patient allocation to hospitals in other cities in India with the aim to minimise the transportation cost during the SARS-CoV-2 pandemic. Pareto analysis was conducted using the information on the number of infected patients in the cities. The cities where there were higher number of infected patients were placed in the higher rank. The cities that were in top 80% ranked of all cities were only considered. The information related to these cities including a cooperation level between cities, distances between cities, and number of beds per city was used in patient allocation. The cooperation level was estimated based on a COVID-related governmental policy for patient allocation in different cities. Some cities in India did not accept patients from other cities, while some did.

Types of Disaster

The reviewed articles presented in Table 2.2 are concerned with all types of disasters. Several disasters including Spanish influenza pandemic in 1918, Asian influenza pandemic in 1957, and in Hong Kong in 1968, Swine influenza in 1976, the World Trade Centre bombing in 2001, Tsunami in Indonesia in 2004, Hurricane Katrina in 2005, Haiti earthquake in 2010, and SARS-CoV-2 pandemic in 2019 have drawn OR scholars' attention to use and/or develop models and methods for disaster management. Articles that developed general models/methods and evaluated them on a specific real-world disaster are of particular interest to the OR community. For instance, Repoussis et al. (2016) developed a response model for ambulance dispatching and patient assignment for all disaster situations. They then illustrated the application of the proposed model in the terror attack on the New York Stock Exchange in Lower Manhattan in 2001. The response efficiency was examined by varying the availability of resources including ambulances and emergency beds. The models were developed to support decision making responding to events with many causalities.

2.4.2 Methodology and model development

Table 2.2 shows that development of deterministic optimisation models together with heuristic algorithms to solve larger problems is the dominant approach in the reviewed articles (Yi & Özdamar, 2007; Arora et al., 2010; Crowe et al., 2014; Sun et al., 2014; Zhang & Howard, 2015; Lei et al., 2015; Liu & Zhao, 2015; Repoussis et al., 2016; Sung & Lee, 2016; Becker et al., 2018). We would like to emphasise that a classification of an article to deterministic optimisation does not imply that the underlying problem itself is fully deterministic. Several reviewed articles included the components in the model to handle uncertainties, then solved the problem using a deterministic optimisation approach. This is mainly because, in general, deterministic optimisation methods consume less computational time and hence are able to handle larger instances. Crowe et al. (2014) advised that a simple model must be built in the first instance to reduce the computational burden. Then a more complex model with more realistic assumptions and input data to address stochastic behaviour of the problems in disasters management should be developed.

Due to the nature of the problems, developing an MIP model was a common approach to find the optimal solutions. In these problems, decisions often involved the selection of hospitals for patient allocation and patient assignment to ambulances. Some reviewed articles presenting the MIP models provided the computational costs associated with the approaches used to solve the problems. Yi and Özdamar (2007) developed an MIP model to allocate medical staff to the shelters during an earthquake. They included 20 shelters and solved the problem using a two-stage procedure. In the first stage, they treated vehicles as integer commodity flows rather than binary variables. In the second stage, they used a simple vehicle splitting algorithm to generate detailed vehicle routes and pick up/delivery locations. All instances were solved in the MIP solver CPLEX 7.5 within 2 seconds. They also illustrated the applicability of a two-stage procedure in larger size scenarios with up to 60 nodes for which optimal solutions were obtained within 140 seconds. Sun et al. (2014) developed an MIP model to allocate patients to hospitals during the pandemic influenza. They divided the long planning horizon into several short planning horizons in order to shorten the run time. For example, a 2-month pandemic outbreak was divided into consecutive weekly planning horizons. The output from the previous planning horizon was used as input to the next planning horizon. Specifically, the number of patients who were admitted and the available resources from the previous planning horizon were fed in the new planning horizon as the starting condition. This approach allowed decision makers to update the system state in each weekly planning horizons. The model was solved using LINGO 11.0. Unfortunately, no data about runtime was reported. Lei et al. (2015) developed an MIP model for the allocation of medical staff to different hospitals. They used a rolling-horizon based greedy heuristic to find near optimal solutions. The search process started with a hospital sequence in which hospitals were sorted based on the starting time of their services. In each iteration, a sub-problem focused on the hospitals on the top of the list that needed the additional medical staff was solved, which in turn reduced the size of the problem. This heuristic allowed them to solve the problem with a short time horizon and to quickly obtain a solution for a given group of waiting hospitals. The best feasible solution was obtained within 2 minutes for 40 hospitals and within 12 minutes for 80 hospitals. Repoussis et al. (2016) developed an MIP model for ambulance dispatching and patient assignment during disasters and solved the model using a hybrid multi-start local search. They initially used a greedy randomised algorithm to generate the upper bound of initial solutions. Then, these initial solutions served as the starting points for an iterated Tabu search algorithm. The application of the proposed model was illustrated on large scale problem instances with up to 150 patients. The conclusion was that the iterated Tabu search algorithm considerably improved the initial solutions. Unfortunately, no CPU time required for solving the large-scale instances was given. Sung and Lee (2016) developed an MIP model for patient allocation in the network. They modelled the defined problems as a set-partitioning problem and evaluated the model on 900 instances. A column generation approach was developed which obtained near optimal solutions within a short computation time (but the exact time was not reported).

Simulation was used relatively frequently as well. Simulation was used to investigate the outcomes of a change in strategy, and to evaluate the implementation of alternative plans (Katsaliaki & Mustafee, 2011). DES was most widely used. Konrad et al. (2013) and Yang et al. (2016) developed DES models to examine the patient flows under integrative care strategy in an emergency department during the higher patient demands. In addition, Lodree et al. (2017) developed a MCS model to simultaneously allocate different teams of medical staff to serve different patient classes in an emergency department during mass casualty incidents.

There were two articles which employed a combination of simulation and optimisation methods. Lameris et al. (2008) implemented patient scheduling using MCS, then used optimisation to allocate healthcare resources to patients. These methods were employed sequentially. Chen and Wang (2016) developed a multi-objective stochastic optimisation model to identify the optimal number of healthcare resources at emergency departments. This served as input to a DES model to examine potential solutions to healthcare resource allocation problems. Different resource allocations obtained by DES were analysed by comparing performance indicators including the average patient length of stay and the costs related to wasted healthcare resources.

More details of the developed models for integrative care and collaborative care are given in Table 2.3. In the medical management field, coordination has been implemented for two main purposes: *clinical integration / collaboration*, and *resource integration / collaboration*. The former can be achieved by sharing of medical staff, the latter by sharing of key resources such as medical staff, emergency beds, medical equipment and medical supplies (Gould et al., 2000; Lockhart-Wood, 2000; Bender et al., 2013; Chong et al., 2013; Karam et al., 2018; Johnson & Mahan, 2019). Therefore, the models proposed in the literature are classified into two categories considering the purpose of coordination: sharing of medical staff for clinical integration and clinical collaboration (second and fourth column respectively); and sharing of healthcare resources for resource integration and resource collaboration (third and fifth column respectively). The table shows the relevant objectives, parameters, decision variables, and model constraints.

The models for clinical integration in integrative care (second column) aimed to improve the healthcare performance in an emergency department by sharing staff within a HP. Objectives used in integrative care for clinical integration included minimisation of waiting time (Konrad et al., 2013; Yang et al., 2016), and minimisation of total costs (El-Rifai et al., 2016) in an emergency department. Treatment processes in an emergency department, service times for different processes, and patient arrival rates were taken into account in the models. Service time was defined as the total estimated time for each treatment process. The decision variables included the number of staff allocated to a particular time period. The required number of staff for a shift or a treatment process, the number of available staff and total available working times were normally perceived as model constraints for the allocation of staff.

Table 2.3 Main characteristics of the models for integrative care and collaborative care

	Integrative care (within a HP)		**Collaborative care (in the network)**	
	Sharing of medical staff for clinical integration	*Sharing of healthcare resources for resource integration*	*Sharing of medical staff for clinical collaboration*	*Sharing of healthcare resources for resource collaboration*
Objectives	- Minimisation of the waiting time in an ED (Konrad et al., 2013; Yang et al., 2016) - Minimisation of total cost in an ED (El-Rifai et al., 2016; Lodree et al., 2017)	- Minimisation of the length of stay in an ED (Chen and Wang, 2016) - Minimisation of total cost in an ED (Lameris et al., 2008; Li et al., 2009; Güneş & Yaman, 2010; Chen & Wang, 2016) - Minimisation of untreated patients in different departments (Crowe et al., 2014)	- Minimisation of the times of service activities across healthcare facilitates in the network (Lei et al., 2015) - Minimisation of number of patients waiting for medical services in the network (Yi & Özdamar, 2007) - Maximisation of number of treated patients in the network (Niessner et al., 2018)	- Minimisation of maximum completion times of treatment (Repoussis et al., 2016) - Minimisation of travel times of all patients (Sun et al., 2014; Sung & Lee, 2016; Sarkar et al., 2021)
Main parameters	- Treatment processes in an ED (Konrad et al., 2013; Yang et al., 2016) - Service times for different treatment processes in an ED (Konrad et al., 2013) - Patient arrival rate (Yang et al., 2016; Lodree et al., 2017)	- Treatment processes in an ED (Chen and Wang, 2016) - Amount of resources required to serve different patient categories (Lameris et al., 2008; Chen & Wang, 2016) - Number of patients (Crowe et al., 2014; Chen & Wang, 2016)	- Number of healthcare facilities in the network (Lei et al., 2015) - Travel times between healthcare facilities (Lei et al., 2015) - Number of patients (Yi & Özdamar, 2007; Niessner et al., 2018)	- Number of healthcare facilities in the network (Liu & Zhao, 2015) - Travel times between healthcare facilities or incident scene-healthcare facilities (Sun et al., 2014; Liu & Zhao, 2015; Repoussis et al., 2016; Sung & Lee, 2016; Buhat et al., 2021; Sarkar et al., 2021) - Number of patients (Sun et al., 2014; Repoussis et al., 2016; Sung & Lee, 2016; Mehrotra et al., 2020; Buhat et al., 2021)
Decision variables	- Number of medical staff allocated to a particular period of time (Konrad et al., 2013; El-Rifai et al., 2016; Yang et al., 2016; Lodree et al., 2017)	- Number of healthcare resources allocated to different departments (Lameris et al., 2008; Crowe et al., 2014; Chen & Wang, 2016)	- Number of medical staff allocated to different facilities in the network (Lei et al., 2015; Niessner et al., 2018) - Number of patients assigned to facilities in the network (Yi & Özdamar, 2007)	- Number of healthcare resources transferred from one facility to other (Liu & Zhao, 2015; Repoussis et al., 2016; Mehrotra et al., 2020; Buhat et al., 2021; Thul & Powell, 2021) - Number of patients assigned to facilities (Sun et al., 2014; Repoussis et al., 2016; Sung & Lee, 2016; Sarkar et al., 2021)

	Integrative care (within a HP)		Collaborative care (in the network)	
	Sharing of medical staff for clinical integration	*Sharing of healthcare resources for resource integration*	*Sharing of medical staff for clinical collaboration*	*Sharing of healthcare resources for resource collaboration*
Main constraints	- Medical staff capacity in an ED (Konrad et al., 2013; El-Rifai et al., 2016; Yang et al., 2016; Lodree et al., 2017) - Total working times in an ED (El-Rifai et al., 2016; Becker et al., 2018) - Staff requirement for a shift or a treatment process in an ED (Becker et al., 2018)	- Healthcare resource availability in different departments (Crowe et al., 2014; Chen & Wang, 2016) - Minimum number of healthcare resources required in an ED (Lameris et al., 2008; Chen & Wang, 2016)	- Medical staff capacity in different facilities (Lei et al., 2015; Niessner et al., 2018) - Total number of vehicles available in the network (Yi & Özdamar, 2007) - Load vehicle capacity (Yi & Özdamar, 2007)	- Healthcare capacity in different facilities (Sun et al., 2014; Liu & Zhao, 2015; Repoussis et al., 2016; Sung & Lee, 2016; Mehrotra et al., 2020; Buhat et al., 2021; Sarkar et al., 2021; Thul & Powell, 2021) - Patient demand (Sun et al., 2014; Liu & Zhao, 2015) - Load vehicle capacity (Repoussis et al., 2016)

Note: ED – emergency department

In contrast, the models for clinical collaboration in collaborative care (fourth column) aimed to improve performance of healthcare facilities as a whole by sharing staff across HPs. The examples of objectives included the minimisation of response times across facilities in the network (Lei et al., 2015), minimisation of number of patients waiting for medical services in the network (Yi & Özdamar, 2007), as well as the maximisation of number of treated patients in the network (Niessner et al., 2018). Characteristics of healthcare facilities in the network, travel times between healthcare facilities, and patient demands in the network were typically considered as model parameters. The decision variables included the number of staff allocated to different facilities, and the number of patients assigned to facilities after implementing the clinical collaboration. The number of staff available in different facilities, the total number of vehicles available and their load capacities were normally modelled constraints.

Similarly, to the models for clinical integration, the models for resource integration in integrative care (third column) aimed to improve the healthcare performance in some departments of HPs, for example, an emergency department by sharing healthcare resources within a HP. These models usually considered emergency beds, medical equipment, and also medical staff. The examples of objectives were the minimisation of length of stay and costs in an emergency department (Chen & Wang, 2016) and minimisation of unmet demands in different HP services (Crowe et al., 2014). Again, the models had treatment processes in an emergency department, the resources required to serve different patient categories, and patient demands as model parameters. Decision variables included the number of healthcare resources (staff, emergency beds, medical equipment, and medical supplies) allocated to different departments in a HP. These models mainly took into consideration healthcare resource availability in different departments as model constraints. On the other hand, the models for resource collaboration in collaborative care (fifth column) were concerned with the minimisation of time by sharing of healthcare resources in the whole network. Healthcare resources in different HPs were pooled together in order to allocate patients to HPs where healthcare resources were available, instead of assessing the resources in isolation. The examples of objectives were the minimisation of maximum completion time of treatments (Repoussis et al., 2016), and of total travel times between incident scene and healthcare facilities (Sun et al., 2014; Sung & Lee, 2016; Sarkar et al., 2021). The number of healthcare facilities, travel times between healthcare facilities or incident scene-healthcare facilities, and patient demands in the network were usually considered as model parameters. The optimal solution usually showed the number of healthcare resources transferred from one facility to other; or the number of patients assigned to facilities. The models generally considered the healthcare capacity in different facilities, demand, and vehicle load capacity as model constraints.

To summarise, the models for clinical integration/collaboration include staff only, whereas the models for resource integration/collaboration include the key resources such as staff, beds, medical equipment, and medical supplies. The main difference between integrative care and collaborative care models is that the former are mainly concerned with the allocation and resource sharing within a HP to accomplish treatment tasks, ensure the continuity of medical services and provide the required capacity in a HP, while the latter deal with the sharing of healthcare resources across HPs, and take into account the capacity of healthcare resources in different healthcare facilities, and travel times between facilities to enable an efficient use of healthcare resources in the whole network.

2.4.3 Research gap

The focus of this thesis is on collaborative care between HPs in response to disasters because resilience is usually perceived at community level rather than at an individual institution when responding to disasters (Kruk et al., 2015; Rohova & Koeva, 2021). Improving resilience at healthcare-network level typically requires the collaborative care between multiple HPs (Holling, 1996; Bruneau et al., 2003), rather than an individual effort from a single HP (Deo & Gurvich, 2011; He et al., 2019).

From the overview of the focused literature review, it can be inferred that the current research contributes to the knowledge of collaborative care from both methodological and application perspectives. From the methodological perspective, collaborative care problems are commonly solved using an optimisation approach. From an application perspective, the literature provides the understanding of the internal resource sharing and the patient allocation in the healthcare network. The addressed internal resources include medical staff and supplies. The patient allocation is made under the assumption that one ambulance can transport one patient to a HP in one trip.

Although a substantial body of research work has appeared in the literature, the collaborative care remains overlooked. From the methodological perspective to the best of our knowledge, no effort has been made to address collaborative care using simulation approach. Although one study by Niessner et al. (2018) employed simulation approach to investigate the physician allocation after mass casualty incidents, their DES models addressed treatment activities at the incident site, while the allocation of resources was handled using optimisation. From the application perspective, the literature does not take into consideration some real-world aspects of collaborative care. First, the literature has not addressed the sharing of external resources, whilst in reality HPs outside a particular healthcare network often allocate their resources to the affected healthcare network in order to enhance the healthcare capability during disasters. Second, the literature on patient transportation has always assumed that an ambulance carries one patient in a trip. However, due to a limited number of available ambulances during mass casualty incidents or disasters, one ambulance often transports multiple patients to a HP in one trip.

2.5 Resilience measures in healthcare context

The measures found in the literature can be classified into four different categories: *time*-based, based on *number of patients*, *costs*, and *utilisation rate.*

2.5.1 Time-based

A considerable volume of literature has measured resilience considering *time* including waiting time, Door-to-doctor time, and length of stay. Rolland et al. (2010) claim that time is becoming a critical factor during disasters.

Waiting time is usually identified as the measure of medical service quality related to the availability of healthcare resources (Dansky & Miles, 1997). Waiting time is generally defined as the time elapsed between the received demand for medical service by the HP and the provision of medical service to the patient. Some studies measured resilience during disasters using average patients' waiting time. For example, Cimellaro and Piqué (2016) assigned weights to different patient categories where higher weight was assigned to severe-injured patients. The sum of average weighted waiting time was then used to measure the resilience in an emergency department after an earthquake event. In contrast, Yang et al. (2016) measured resilience using average waiting time for different categories, where all patient categories were assigned equal weights.

The waiting time is sometimes measured in terms of Door-to-Doctor time in order to assess the effectiveness of medical staff allocation. *The Door-to-Doctor time* is the duration of time from a patient arriving at the HP until the patient is seen by medical staff (Konrad et al., 2013). The Door-to-Doctor time is affected by the availability of medical staff, whereas the waiting time is affected by the availability of healthcare resources such as emergency beds, laboratory rooms, and medical staff. *The length of stay* measures the total time that patient spent in the healthcare system and indicates the effectiveness of healthcare resource allocation (Chen & Wang, 2016). The length of stay includes waiting time for healthcare resources and times spent for treatments at all stations.

The time-based measures associated with the emergency medical response during disasters are illustrated in Figure 2.4. Patients are moved from shelters to HPs through a series of ordered medical services. The ordered services are defined in the boxes. In some disasters such as earthquakes or Tsunami, patients might go through all or part of the series of ordered medical services. In other types of disasters that are less severe it might be more common for patients to only go through patient transportation and patient treatment provision.

2.5.2 Based on number of patients

Several studies measured the *number of patients* rather than the waiting time. Ogawa et al. (2016) and Anderson et al. (2016) claimed that the goal of medical services during disasters is altered from providing the best medical services to each patient, to providing medical services to the maximum number of patients. Both number of treated patients and untreated patients were used in the literature. The *number of treated patients* (Bruneau & Reinhorn, 2007; Jerić & Figueira 2012) and the minimum service level (Lameris et al., 2008) were used to represent the effectiveness of healthcare resource allocation during disasters. The *minimum service level* is measured as a minimum percentage of patients who received allocated healthcare resources within an acceptable waiting time. In contrast, the number of untreated patients can indicate the shortage level of healthcare resources during disasters and can be used in the capacity planning of the emergency medical response. This measure was evaluated in terms of expected death rate (Arora et al., 2010; Xiang and Zhuang, 2016), unmet demand level (Crowe et al., 2014), and loss level (Cimellaro et al., 2010). The *expected death rate* is the estimated number of deaths when healthcare resources become stressed. The *unmet demand level* is measured as a number of patients who wait for a treatment due to a shortage of healthcare resources until the healthcare resources are available. The *loss level* is measured as the ratio of the number of untreated patients to treated patients.

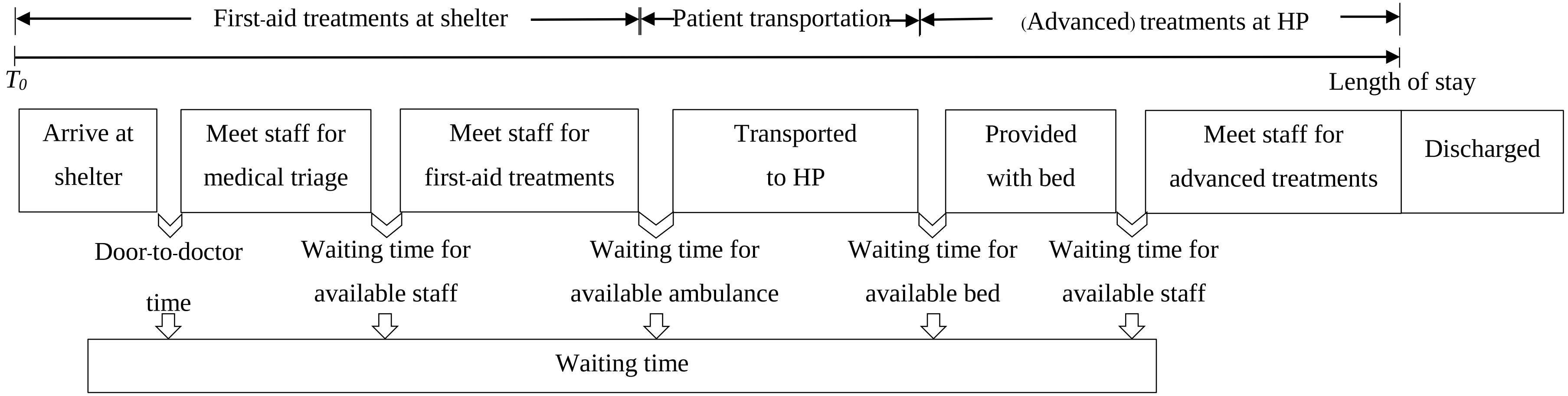


Figure 2.4 Time-based measures during disasters

2.5.3 Cost-based

Studies by Chen and Wang (2016), El-Rifai et al. (2016), and Lodree et al. (2017) measured resilience using costs. *Deprivation cost* represents the shortage level of healthcare resources during disasters. The deprivation cost can occur when the patient demands exceed the availability of healthcare resources. Patients need to wait until the resources are available, resulting in a delay in the treatments. The deprivation cost is thus measured as the total cost of delay for the treatments for untreated patients. The planning of resource allocation takes into account the deprivation cost when all resources are almost utilised (i.e., utilised up to a pre-determined level), especially in mass casualty incidents. The limited resources should be effectively allocated to patient categories in order to minimise the delay in treatments, so that the deprivation cost could be minimised. In addition, the deprivation cost and labour cost were sometimes simultaneously considered when staff were assigned to the shifts while trying to meet the expected patient demands.

2.5.4 Utilisation rate

A few studies have measured resilience in terms of the *utilisation rate*. These studies stated that the utilisation rate reflected the effective use of healthcare resources during disasters. The nurse utilisation was measured when additional nurses were allocated to the treatment activities while considering the total wage cost for nurses (Griffiths, 2005). The utilisation rate was also measured as the shortage level of healthcare resources during disasters. For instance, Harper and Shahani (2007) used the *refusal rate* to reflect the bed utilisation. The refusal occurred when no bed was available for an arriving patient. An increase in patient demand caused the higher refusal rate. This implied that the bed utilisation was higher because more beds were efficiently allocated to patients.

Table 2.4 presents a list of resilience measures proposed in the literature. The columns in the table show the characteristics of the resilience measures. These Characteristics are explained in Table 1.2.

We found that the time-based measures, measures based on number of patients, and costs are the comprehensive resilience measures since they can be used to evaluate the health conditions of population in the affected area, to reveal the quality of healthcare-network performance during disasters, and to compare the effectiveness of different strategies for emergency medical response. The information on the patients' health conditions at the network level reveals the effectiveness of current medical response, which is useful for the decisions on the required actions during disasters.

We note that the nurse utilisation rate can be used to evaluate the effectiveness of collaborative response when nurses are shared between HPs during disasters. However, this measure mainly assesses the efficient use of medical staff and is therefore of interest for staff allocation, but it does not reveal the patients' health conditions during disasters. In contrast, the refusal rate can reflect the population health when healthcare resources are in shortage. However, in the literature, the refusal rate refers only to the use of beds, although in practice the refusal occurs when other resource such as medical staff, medical equipment, and medical supplies is not available for an arriving patient.

Table 2.4 Resilience measures in healthcare context

Category	Quantitative measures found in literature	Characteristics of resilience measurement			
		Population health	Quality of healthcare-network performance	Benchmark	Information for decision maker
Time-based	Waiting time for different patient categories (Cimellaro & Piqué, 2016; Yang et al., 2016)	✓	✓	✓	✓
	Door-to-Doctor time (Konrad et al., 2013)	✓	✓	✓	✓
	Expected length of stay (Chen and Wang, 2016)	✓	✓	✓	✓
Based on number of patients	Number of treated patients (Bruneau & Reinhorn, 2007; Jerić & Figueira, 2012)	✓	✓	✓	✓
	Minimum service level (Lameris et al., 2008)	✓	✓	✓	✓
	Number of expected deaths (Arora et al., 2010; Xiang and Zhuang, 2016)	✓	✓	✓	✓
	Unmet demand level (Crowe et al., 2014)	✓	✓	✓	✓
	Loss level (Cimellaro et al., 2010)	✓	✓	✓	✓
Cost-based	Deprivation cost (Chen & Wang, 2016; El-Rifai et al., 2016; Lodree et al., 2017)	✓	✓	✓	✓
Utilisation rate	Nurse utilisation (Griffiths et al., 2005)	Ignores patient's health condition	✓	Limited to the medical staff allocation	Only concerns with the use of resources
	Refusal rate (Harper & Shahani, 2007)	✓	✓	✓	✓

2.6 Summary

This chapter provides a focused review of the literature on coordination in healthcare systems during disasters. Definitions of the terms in use in this field are provided. An overall descriptive statistic of the reviewed articles is given, followed by the review of the presented research problems, disaster types, and developed methodologies. The main characteristics of models for coordination in the healthcare system are described. The reviewed articles are categorised into two different types of coordination, namely integrative care and collaborative care. Integrative care mainly investigates resource allocation within a common governance, whereas collaborative care is mainly focused on the sharing of healthcare resources across governances. Both types of coordination aim to improve the emergency medical response by ensuring the continuity of medical services and improving healthcare capability during disasters.

In addition, measures of coordination effectiveness that denote resilience are discussed. Measures based on time and number of patients (treated or untreated) are commonly used. Resilience is often perceived at community level rather than at an individual institution when responding to disasters. Improving resilience at healthcare-network level requires collaboration between HPs, rather than an individual effort from a single HP.

Although the literature has made a substantial contribution in the area of collaborative care in response to disasters, the research about the effectiveness of collaborative care remains unclear. From the methodological perspective, the literature has not addressed collaborative care problems using a simulation approach. From an application perspective, the literature has not considered some real-world aspects of collaborative care that take place in an emergency medical response. These aspects include external resource sharing, and ambulance sharing for multiple patient transportation.

Chapter 3 Research methodology

This study employed sequential mixed methods to collect the relevant real-world data from HPs and gain understanding of the issues that arise in real-world activities of collaboration across a healthcare network in an emergency medical response to a disaster. The study commenced with interviews followed by the development of DES models and an MIP model.

3.1 Interviews

Semi-structured interviews were conducted to explore and explain the practice of collaboration across a healthcare network in an emergency medical response to a disaster. The interview questions covered areas such as the duties and practices of different healthcare facilities; flow of patients, sharing of internal and external healthcare resources; integrated ambulance system; staff assignment to ambulance trip; differences in clinical practices; and medical treatments. The list of interview questions is given in Appendix 1.

3.1.1 Sample selection

Our study utilised the data about the activities of emergency medical response in Thailand. These activities are elaborately planned by the Ministry of Public Health. Provincial Public Health Office in every province is informed about the plan of the activities. Thus, the selection of province does not matter since every province follows the same plan of the activities. However, we preferred to collect the data in Phuket because we had personal contact with some participants who could provide us with the data required.

To gain an understanding of how the activities of emergency medical response are implemented, the key participants were interviewed included head of emergency medical service (EMS) centres, emergency departments, nursing, and evacuation services from *all healthcare facilities* in Phuket, Thailand. We also selected a former and current director of Phuket Provincial Public Health who could provide the details of the past and current activities of emergency medical response, respectively. The past activities were implemented during the Tsunami in 2004, while the current ones were in place in response to boat capsizing in 2018 and will be implemented in response to future mass casualty incidents and disasters.

The interviews were conducted based on participant's experiences. The participants, who have the experience of providing medical services during Tsunami in 2004, were asked about the past activities of emergency medical response. On the other hand, participants who had experience during boat capsizing in 2018 were asked about the current activities.

3.1.2 Sampling technique

We employed the technique of snowball sampling for data collection because it was sometimes difficult to approach some participants. Known potential participants were invited first using our personal contact. Once these participants accepted to be involved in our study, they used their personal contacts to approach other potential participants. The snowball sampling technique helped us to include all participants required in our study.

3.1.3 Interview arrangement

The requesting letters for data collection were sent to the director of healthcare facilities in Phuket and Phuket Provincial Public Health Office. The letter stated the research aim, a list of potential participants, the areas of interview questions, the length of time required, as well as the request for conducting interview and the use of data. The permission letter for data collection and use of data needed to be signed before the interview appointments were made. The examples of these letters are given in Appendix 2 and Appendix 3, respectively.

3.1.4 Sample size

We acknowledged that the interviews always involve subjectivity. However, we aim to understand the "fact" of the activities of emergency medical response, not "opinion" relevant to the activities. Thus, the data quality depends on the information given by healthcare authorities who are responsible for the activities of emergency medical response.

All healthcare facilities in Phuket accepted to be involved in our study; the respondent rate is 100%, in total 8 HPs (2 EMS centres and 6 hospitals), 3 charity/municipal organisations (CMOs) and 1 Phuket Provincial Public Health

Office participated in our study. There were 2 participants from each HP, 1 participant from each CMO, and 2 participants from the Office. This allowed us to understand the sharing of healthcare resources between healthcare facilities as well as the flow of patients and resources during mass casualty incidents and disasters.

There are some potential limitations of interviews when the aim is to gain the "fact". Participants will be reporting their subjective view on what happened during the previous mass casualty incidents and disasters, which may be impaired by memory. Thus, the participants, who were in the same event (Tsunami and/or boat capsizing), were asked the same set of questions to ensure the credibility of data collected from the interviews. It aided to crosscheck the interview data. Data obtained from interviews were useful in providing insights into building a realistic simulation model.

3.1.5 Ethical review

Our study followed the University of Nottingham's Code of Practice on Ethical Standards. This included appropriate information sheets (see Appendix 4) and consent forms which ensured confidentiality in the storage and use of data (see Appendix 5). The ethics approval confirmation letter was given in Appendix 6.

Interviews were conducted on a one-to-one basis by meeting participants face-to-face at their workplaces. Before the interviews, the participants were given the information sheet, the consent form, and the ethics approval confirmation letter. Also, the participants were asked permission to audio record the interview. The interviews were anonymous and could be conducted when the consent form was voluntarily signed by both interviewer and interviewee. Different forms of bias were considered during the interviews. For example, the interviewer conveyed approval or disapproval of responses through facial expressions and/or nonverbal behaviour of interviewees. Interviewee's expressions may influence what they said or did not say during the interview.

3.2 Simulation method

Simulation methods have been developed in 1950s and usually employed to develop logical models imitating the real-world system's behaviour (Robinson, 2005). Also, simulation methods are commonly used to evaluate alternative policies, strategies, plans, or programmes without any disruption of the real-world system (Katsaliaki & Mustafee, 2011).

3.2.1 Application of simulation methods in healthcare problems

For several decades, simulation has been applied to address real-world problems in healthcare systems. Simulation methods are popular for healthcare studies in the areas of healthcare planning and resource management (Crowe et al., 2015; Uriarte et al., 2017). The most commonly used simulation methods are DES, MCS, system dynamics (SD), and agent-based simulation (ABS) (Katsaliaki & Mustafee, 2011; Gul & Guneri, 2015; Mishra et al., 2019; Brailsford et al., 2019). The following paragraphs present a brief description of these methods and examples of their applications in the healthcare context.

DES is a process-based simulation where state changes occur at discrete points of time and the logical activities of the real-world system can be simulated (Jun et al. 1999; Viana et al 2014). The focus of DES is on the detailed rules controlling the interaction of the individual entities through the defined processes in the system. A key aspect of DES is the system-state description. In the healthcare context, DES has lately been often applied in emergency departments with the aim to improve time- and efficiency-related metrics (Vázquez-Serrano et al. 2021). For example, DES models were developed to improve the bed capacity planning and the management of emergency and elective patient admissions in an emergency department (Landa et al. 2016). DES models were also used to reduce the overcrowding and patient waiting times (Bal et al. 2017; Maull et al. 2009), and to improve patient flow (Vile et al. 2017) in an emergency department.

MCS is a random-process modelling tool for an unknown-event decision making based on probabilistic distributions often derived from historical data (Rubinstein, 1981). MCS simulates a set of potential scenarios and provides the expected value of outputs associated with the scenarios. The applications of MCS in the healthcare context often evaluate the impact of health policy changes (Mielczarek, 2016). For example, MCS models were developed to determine the optimal vial size and the stock level in order to ensure adequate vaccine supply (Dhamodharan & Proano, 2012). MCS models were also used to determine the cost efficiency for combined vaccines for paediatric immunisation against six diseases including hepatitis B, diphtheria, tetanus, pertussis, haemophilus influenza type b, and polio (Jacobson et al. 2001)

SD is grounded in the theory of feedback control and takes a holistic approach to understand the cause-effect relationships among variables and the effects of system structure (referred to as stocks and flows) on system behaviour (Dangerfield, 1999; Sterman, 2001; Dong et al., 2012) The feedback loop mechanism is used to describe the relationships and effects. In the healthcare context, SD has been applied to support health policies related to prevention, health promotion, and healthcare delivery (Atkinson et al. 2015). For example, SD models were developed to investigate the strategic planning for cardiovascular disease prevention (Loyo et al. 2013), the long-term effects of smoking cessation interventions (Tobias et al. 2010), and the availability, accessibility and affordability of opioid (Chalmers et al. 2009).

ABS is a macro-scale simulation using bottom-up approach for modelling the actions of independent individuals (agents) in the system (Grimm et al. 2005). The agents can be individual entities such as customers or collective entities such as organisations. The system state (macro-scale) is changed by the interactions of these agents (micro-scale). ABS models are commonly used to gain insights into the collective behaviour constructed by the interactions among agents, and the effects of collective behaviour on the system state. In the healthcare context, ABS models were developed to examine the impact of several physician staffing configurations on time-related metrics in an emergency department (Jones & Evans, 2008; Cabrera et al., 2012). ABS models were also used to dynamically adjust the outpatient scheduling to the real-time situations in the orthopaedic department (Lu et al. 2014). They assumed that patients and medical staff were autonomous, and their behaviour changed according to the real-time situation which required the adjustment of patient scheduling in order to reduce patient waiting time and to improve hospital efficacy.

3.2.2 Use of discrete event simulation

For the research presented in this thesis we used DES for the following reasons. First, DES can be used to model the queuing system (Pidd, 2004). In our study, patients are perceived as customers and will be in a queue waiting to be served by available servers which are healthcare resources. Patients are served according to the priority scheme and First Come First Serve (FCFS) discipline within the triage category. The details of priority scheme and FCFS discipline will be described in Chapter 4. Second, DES is more concerned with process details than other simulation methods. Use of DES allows us to imitate sequential processes in the real-world activities of the emergency medical response. The ordered processes include medical triage, first-aid treatments at the sites (if provided), patient transportation, and treatments at the HPs. Also, the logical activities of the emergency medical response can be simulated using DES. Some activities can be undertaken only if the pre-defined conditions are met. For example, patients can be transported to HPs only when an ambulance is available. Third, DES allows us to track the behaviour of individual entities through a series of defined processes (Gul & Guneri, 2015). Individual patients need to be tracked in order to estimate the time when they are in a queue waiting for available resources. The data on patient waiting time are used in resilience metrics of different strategies for collaboration in the network. The resilience metrics will be described in Chapter 5.

3.3 Optimisation method

The problems of multiple patient allocation in collaborative care include patient assignment to ambulances for patient transportation and patient assignment to HPs for treatments. These problems can be modelled as a Flexible Job Shop Scheduling Problem (FJSP) with unrelated parallel machines that consists of a set of jobs and unrelated machines. Each job is assigned to an allowable machine for the duration of processing. The processing times of each job depends on the machine. For such FJSP problems, the order in which each machine processes its jobs should be considered (Rocha et al., 2008). In our context, patients can be perceived as a set of jobs, whereas ambulances and required resources for treatments in HPs are perceived as a set of machines. Each job consists of two sequential activities: *transportation to a HP* and *treatment at the HP*. In particular, each patient is loaded onto one of the available ambulances taking account of the ambulance capacities for multiple patient transportation, then transported to one of the HPs, and treated by appropriate available resources.

Please note that we define the roles of healthcare facilities and patient pathway addressed in the optimisation model based on the strategy for collaboration that has the biggest impact on resilience improvement observed in the simulation experiments.

The nature of the problems requires the development of MIP model, instead of IP model. Decisions involve the patient assignment to ambulances for patient transportation and the selection of HPs for patient treatments. A set of constraints addresses an assignment of multiple patients to one-trip ambulance considering ambulance capacities. The optimisation problem is to determine the sequence of patients to be assigned to each ambulance for patient transportation and to required resource for treatment at HPs. The objective is to minimise response times of all patients which is a common measure for the performance of emergency medical responses during disasters (Abir et al., 2013; Luscombe & Kozan, 2016; Repoussis et al., 2016). The definition of response time is presented in Chapter 7.

3.4 Summary

The interviews were conducted to understand the practice of collaboration in an emergency medical response in the healthcare network in Phuket, Thailand. These activities are developed by the Ministry of Public Health and implemented by Provincial Public Health Office. All healthcare facilities in Phuket were voluntarily involved in our study. The representatives of different healthcare facilities were asked about the sharing of healthcare resources and the allocation of patients in response to mass casualty incidents and disasters. We employed DES method to simulate the sequential processes in the real-world activities of emergency medical response. The behaviour of individual patients could be tracked which allowed us to investigate the resilience metrics of different strategies for collaboration in the network. An MIP model is then developed to address multiple patient allocation using ambulance sharing. The roles of healthcare facilities and patient pathway during disasters follow the strategy that the simulation suggest is superior in terms of resilience metrics.

Chapter 4 Strategies for collaboration in response to disasters

This chapter describes strategies for collaboration in the healthcare network in response to disasters. Based on the interviews, three strategies are defined including include a non-collaborative care strategy (Strategy 1), a semi-collaborative care strategy (Strategy 2), and a new collaborative care strategy (Strategy 3). Strategy 1 was in place in response to Tsunami in Phuket in 2004, while Strategy 2 is the current strategy in use which was implemented during the boat capsizing in Phuket in 2018. Strategy 3 is the strategy we propose which is defined by considering the disadvantages of the current strategy (Strategy 2). One of the pitfalls found in Strategy 2 is the improper TMU roles (details will be discussed in Chapter 6). Thus, the TMU roles are modified in Strategy 3. Strategy 3 also addresses a new collaboration in a healthcare network that enables information sharing and the classification of HPs. HPs share the information about their resource availability when allocating the remaining patients from TMUs to nearest available resource HPs. By proposing this strategy, we would like to highlight the impact of information sharing and how it might improve the overall performance of the healthcare system in response to a disaster. In addition, in Strategy 3, some HPs needs to allocate their staff to other HPs in order to enhance the healthcare capacity for severe injuries. Such sharing is not addressed in other strategies.

4.1 Common characteristics of strategies for collaboration in healthcare network

By analysing the interviews, we have established the common characteristics among two strategies that was also in place in the proposed one. The characteristics include duties and practices of healthcare facilities in response to disasters, patient flow, and vital healthcare resources relating specifically to disaster responses in Phuket, Thailand.

Duties and practices of healthcare facilities in response to disasters

According to the interviews conducted, with in the context of Phuket, Thailand, the vital healthcare facilities in disasters typically include patient assembly points (PAPs)/temporary medical units (TMUs), internal and external HPs, and charity/municipal organisations (CMOs). PAPs/TMUs are normally located in safe places and set for assembling affected patients for the transportation. The main difference between PAP and TMU lies in a first-aid treatment that is provided in the TMUs, but not in the PAPs. Internal HPs include emergency medical service (EMS) centres and hospitals offering ambulances, doctors, and nurses. EMS centres usually have larger healthcare resource capacity and capability to provide the emergency medical services than the hospitals. Some external HPs allocate some of their resources including ambulances, doctors, and nurses to the affected areas while being able to maintain their medical services. CMOs are humanitarian organisations offering ambulances and first responders (FRs) who are trained in the emergency rescue and emergency medical services. CMOs also provide an evacuation during disasters and a search of decrease after disasters.

Flow of patients

Patients enter the system at PAPs/TMUs and pass through the sequential processes including medical triage, first-aid treatments at the TMUs (if provided), patient transportation, and treatments at the HPs.

In the medical triage, FRs evaluate the medical condition of patients. Alive-patients are triaged into three categories, which are commonly used in the disaster response (Farahani et al., 2020): severe-, moderate-, and minor-injured patients. In the remaining part of the thesis, they will be referred to as Reds, Yellows, and Greens, respectively. Multiple patients, including potentially from different patient categories, are loaded onto ambulances considering the ambulance capacity, and are then transported to the assigned HP. In a provision of medical treatments, patients are served according to FCFS within patient categories and a priority scheme of Reds first, Yellows second, and Greens third.

Healthcare resources

There are three types of ambulances including patient transport ambulances, basic life support ambulances, and advanced life support ambulances. The difference lies in the resources on the ambulance and the main use of the ambulance, which is presented in Table 4.1.

Table 4.1 Different types of ambulance

Ambulance type	Resources on ambulance	Main purpose
Patient transport ambulance	- Need either one nurse or two FRs - Low equipped with first aid and medical equipment	- Transport patients who are not expected to become emergency patients
Basic life support ambulances	- Need either two nurses or three FRs - Fully equipped with first aid and standard medical equipment	- Transport and monitor patients who need basic treatments
Advanced life support ambulance	- Need one doctor and two nurses - Fully equipped with first aid and advanced medical equipment	- Transport and monitor patients who need advanced treatments

In non-disaster environment, the patient transport ambulances are used for transporting Greens only, while the basic life support ambulances are for either one Yellow or three Greens. The advanced life support ambulances can serve all patient categories but are commonly used just for one Red. Table 4.2 presents the number of patients that can be loaded onto a one-trip ambulance in a non-disaster environment. Please note that a one-trip ambulance is a trip that an ambulance traverses from one of PAPs/TMUs to one of any HPs.

Table 4.2 Number of patients in a one-trip ambulance in non-disaster environment

Ambulance type	Red	Yellow	Greens
Patient transport ambulance	0	0	3
Basic life support ambulances	0	1 or	3
Advanced life support ambulance	1 or	1 or	3

During disasters, these ambulances are used for staff and patient transportation. Ambulances transport staff to TMUs for the provision of first-aid treatments and transport patients to HPs for advanced treatment. Internal ambulances are used for multiple patient transportation in the internal network, whereas external ambulances are reserved only for transportation of one Red to the external HPs. All external ambulances are advanced life support ambulances. Table 4.3 presents the combination of different patient categories in a one-trip ambulance during disasters and applies only to the internal ambulances.

Table 4.3 Combination of different patient categories in one-trip ambulance in disaster events

Ambulance types	Red	Yellow(s)	Green(s)
Patient transport ambulance			4
Basic life support ambulances	1 and		1
		2	
		1 and	2
			4
Advanced life support ambulances	1 and	1	
	1 and		3
		2	
		1 and	3
			4

Please note that the basic life support ambulances need one doctor if they transport a Red to a HP.

Noticeably, a Red can be combined with a small number of other- category patients on the same ambulance. The medical services for a Red require more medical staff and medical equipment compared to other patient categories. As a result, there are not many resources are available for other patient categories.

Medical staff and ambulances are allocated to at most one of the following healthcare facilities including PAPs/TMUs, EMS centres, and internal hospitals. Staff includes doctors, nurses, and FRs who are key personnel providing medical treatments during disasters. Field beds and field mattresses are used in medical treatments at TMUs, whereas emergency beds and chairs are used in medical treatments at HPs. Field beds are reserved for Reds and Yellows, field mattresses are for Greens, emergency beds are for Reds, while chairs are for Yellows and Greens. The resource allocation is implemented according to the First In First Out (FIFO) policy.

4.2 Activities undertaken under different strategies

The characetristics of colloaboration under different strategies are presented in Table 4.4. The strategies differ with respect to the first treatment provision, sharing of staff and ambulances, and patient transportation. The first treatment provision is the first treatment a patient receives. The patient pathways in a disaster event in the context of disaster responses in Phuket Thailand are illustrated in Figure 4.1. The red, yellow, and green lines represent the flow of Reds, Yellows, and Greens, respectively. The relationship between different HPs in Strategy 1, 2, and 3 are illustrated in Figure 4.2, Figure 4.3, and Figure 4.4 respectively. In these figures, the black solid lines denote the initial patient transportation/staff allocation, whereas the dash lines show (1) the re-transportation of Reds when the first assigned HPs are short on resources for severe injuries, or (2) the reallocation of external staff when other healthcare facilities need additional staff. The grey solid lines show the alternative patient transportation.

Table 4.4 Strategies for collaboration in the healthcare network

Issues	**Non-collaborative care strategy (Strategy 1)**	**Semi-collaborative care strategy (Strategy 2)**	**Collaborative care strategy (Strategy 3)**
PAP/TMU setting and their roles	- PAP; No TMU	- No PAP; Relief supplies are prepared for TMU setting	- Same as Strategy 2
	- Medical triage is implemented at the PAPs.	- Medical triage is implemented at the TMUs.	- Same as Strategy 2
	- No first aid provided. All patients must be treated at the HPs.	- Reds and Yellows *receive first aid* before being transported to the HPs. - Greens can receive first aid at one of facilties (TMUs/HPs). They are discharged at the facility where they recive first aid.	- Reds and Yellows *do not receive first aid* before being transported to the HPs. - *All Greens* must receive first aid and be discharged at the TMUs.
Sharing of staff	- Internal doctors and nurses are required to work at their facilities.	- Same as Strategy 1	- HL2 need to allocate at least one doctor and one nurse to HL1 in order to enhance the healthcare capacity for severe injuries.
	- CMOs need to allocate FRs to *the nearest PAP* for a medical triage.	- EMS centres and internal hospitals need to allocate at least one doctor and one nurse, and CMOs need to allocate at least one FR *to the nearest TMU* for providing the first- aid treatments.	- HL1 and HL2 need to allocate at least one doctor and one nurse, and CMOs need to allocate at least one FR *to the nearest TMU* for providing the Green treatments.
	- External staff are allocated to EMS centres first, then are reallocated to internal hospitals based on their capabilities to handle severe and moderate injuries.	- External staff are allocated to EMS centres first, then reallocated to internal hospitals and TMUs *respectively* based on their capabilities to handle severe and moderate injuries.	- External staff are allocated to HL1, HL2, and TMUs by *simultaneously* considering their capabilities to handle severe and moderate injuries. - HL1 is the highest priority; and TMU is the relative lowest - No further reallocation of external staff
Sharing of ambulances	- Internal ambulances are responsible for patient transportation from PAPs to the assigned internal HPs.	- Internal ambulances are responsible for staff transportation to TMUs for first-aid treatments and patient transportation from TMUs to the assigned internal HPs.	- Same as Strategy 2
	- External ambulances are allocated to EMS centres equally and are responsible for re-transporting Reds from EMS centres to the external HPs.	- Same as Strategy 1	- External ambulances are allocated to TMUs equally and are responsible for transporting Reds from TMUs to the external HPs.

Issues	Non-collaborative care strategy (Strategy 1)	Semi-collaborative care strategy (Strategy 2)	Collaborative care strategy (Strategy 3)
Patient transportation	- *Multiple patients* are loaded onto ambulances considering the ambulance capacity.	- Same as Strategy 1	- Same as Strategy 1
	Case 1: A Red is on ambulance.	Case 1: A Red is on ambulance.	Case 1: A Red is on ambulance.
	- All patients on the ambulance are transported to the *nearest* internal HP.	- Same as Strategy 1.	- *Initially*, all patients on the ambulance are transported to the nearest HL1 where the capacity for severe injuries is available. - *Alternatively*, when no HL1 has capacity to admit Reds, all patients on the ambulance are transported to the nearest HL2 where the capacity for severe injuries is available.
	- When the first assigned HP (not EMS centre) is short on resources for severe injuries, Red is re-transported to the *nearest* EMS centre.	- Same as Strategy 1.	- No re-transportation of Red
	Case 2: Red is not on ambulance.	Case 2: Red is not on ambulance.	Case 2: Red is not on ambulance.
	- All patients on the ambulance are transported to the *nearest* internal HP except EMS centres.	- All patients on the ambulance are transported to *any* internal HPs except EMS centres.	- *Initially*, all patients on the ambulance are transported to the nearest HL2 where the upper-bound capacity is available. - *Alternatively*, when the upper-bound capacity is fully utilised, all patients on the ambulance are transported to the nearest HL1.
	Case 3: No internal HP has capacity to admit Reds	Case 3: No internal HP has capacity to admit Reds	Case 3: No internal HP has capacity to admit Reds
	- Reds are re-transported from *EMS centre* to the *nearest* external HP where capacity for severe injuries is available.	- Same as Strategy 1.	- Reds are transported from *TMU* to the *nearest* external HP where the capacity for severe injuries is available.

Note: Multiple patients are loaded onto one ambulance considering the ambulance capacity. The combination of different patient categories in a one-trip ambulance, as given in Table 4.3, can be classified into two cases including a Red and no Red on the ambulance.

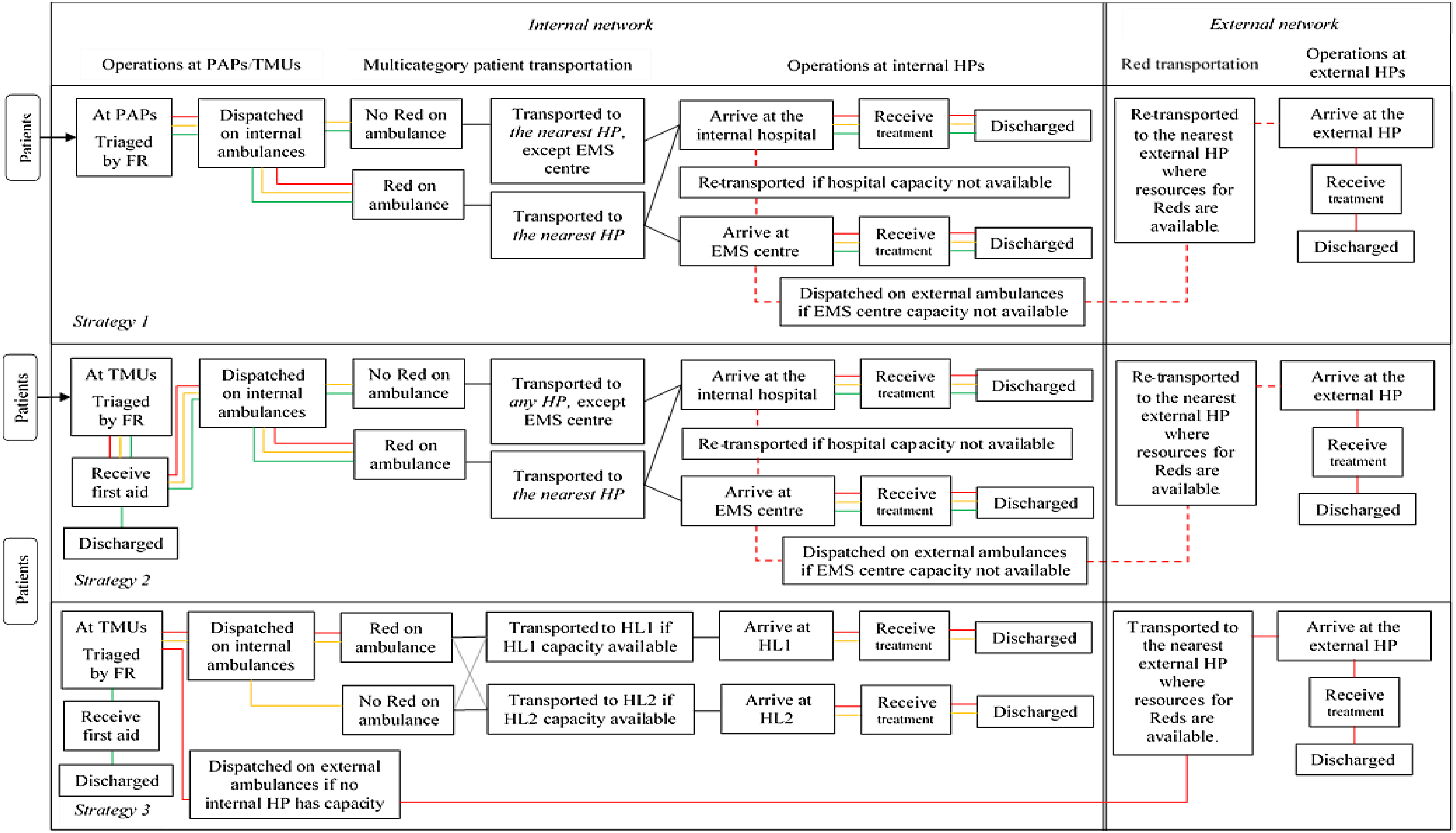


Figure 4.1 Patient pathways through the healthcare system during disasters

In Strategy 1, there is no preparedness for collaboration across a healthcare network in emergency medical response to a disaster. Alive patients are evacuated to PAPs which do not provide first- aid treatments. Patients are transported from PAPs to the HP that requires minimal travel time. All internal HPs work completely independently with no sharing of internal staff. They are required to provide medical services at their own facilities. Only CMOs need to allocate their FRs to PAPs for a medical triage. The external staff are allocated to EMS centres first, then reallocated to internal hospitals to increase their capabilities. The external ambulances are allocated to EMS centres and responsible for re-transporting Reds from EMS centres to the external HPs when the internal network is short on resources for severe injuries.

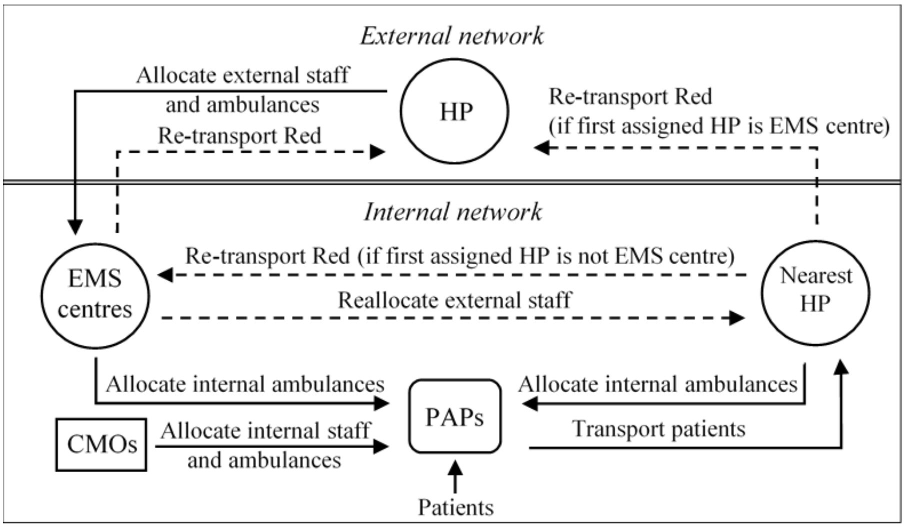


Figure 4.2 Non-collaborative care strategy (Strategy 1)

The main difference between Strategy 1 and 2 is that Strategy 2 introduces TMUs. In Strategy 2, all internal HPs need to allocate some of their doctors and nurses to the TMUs. Both Reds and Yellows must receive the first-aid treatments at the TMUs before being transported to the internal HPs. When no Red and Yellow are in the queue, Greens can receive the treatments and be discharged at the TMUs. Some Greens, who do not receive the treatments at the TMUs, can receive the treatments at the internal HPs.

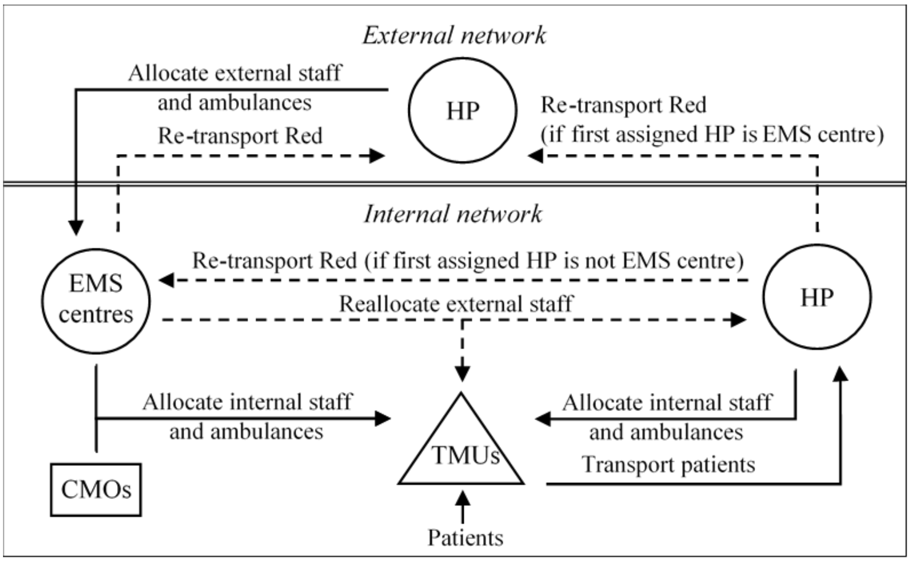


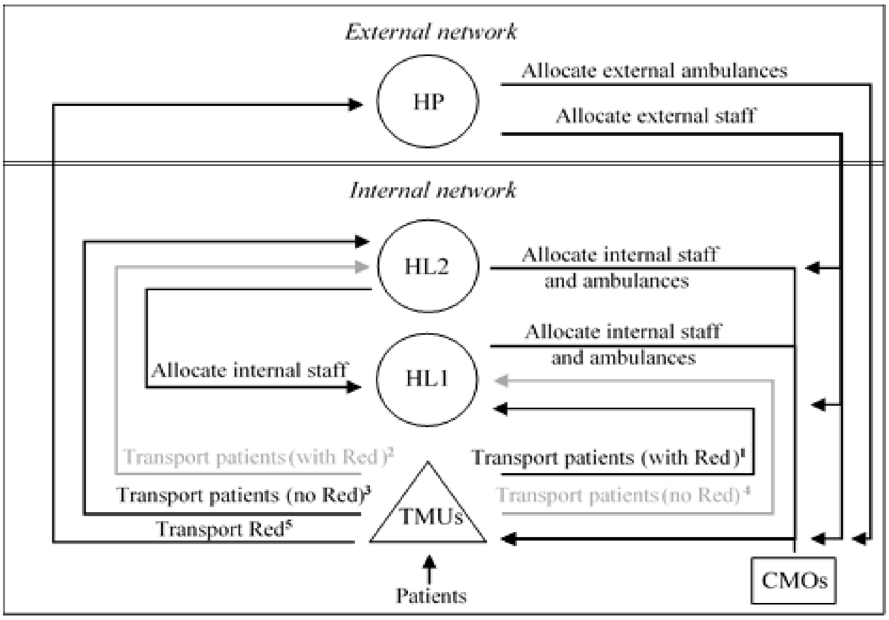
Figure 4.3 Semi-collaborative care strategy (Strategy 2)

In Strategy 3, Greens receive the treatments at the TMUs only. Reds and Yellows are immediately transported to *the nearest HPs with available capacity*. They are transported from the TMUs to the closest HPs with available capacity. Strategy 3 introduces *a new network structure*. Internal HPs are categorised into two groups, namely layer 1 and 2, by considering their healthcare capacities. These capacities can be measured by availability of healthcare resources and capability to provide emergency medical services. HPs in layer 1 (HL1) have high capacity due to the high availability of staff, emergency beds, and high-technologically advanced medical equipment for severe injuries. These HPs also have high capability to provide the emergency medical services and are initially responsible for Reds. EMS centres normally fall into this category. In contrast, HPs in layer 2 (HL2) have lower availability of healthcare resources and lower capability to respond to demand for emergency medical services. The HL2 are initially responsible for Yellows during disasters. In addition, HL2 create surge capacity by using their free areas to admit Yellows who do not need either emergency beds or urgent treatments. In this sense, these areas have the upper-bound capacity which can be measured by the maximum number of chairs for Yellows waiting for medical services. The characteristics of HPs in different layers are summarised in Table 4.5.

Table 4.5 Characteristics of HPs in different layers

Characteristics	HL1	HL2
Healthcare resource availability	- High availability of staff - High availability of beds - Lower availability of chairs - High-technologically advanced medical equipment	- Lower availability of staff - Lower availability of beds - High availability of chairs - Standard-quality medical equipment
Capability to respond to disasters	- High capability to provide emergency medical services for severe injuries	- High capability to provide emergency medical services for moderate injuries

The external staff are allocated to HL1, HL2, and TMUs by simultaneously considering their capabilities to handle severe and moderate injuries. The external ambulances are allocated to the TMUs and responsible for transporting Red from the TMUs to the external HPs when the internal network is short on resources for severe injuries.



1 – if HL1 capacity available; 2 – if HL1 capacity not available; 3 – if upper-bound capacity available; 4 – if upper-bound capacity not available; 5 – if no internal HP has capacity

Figure 4.4 Collaborative care strategy (Strategy 3)

4.3 Summary

Strategies for collaboration in the healthcare network are defined based on interviews and defined for investigating real-world options in emergency medical response during disasters. These strategies are non-collaborative (Strategy 1), semi-collaborative (Strategy 2), and collaborative care (Strategy 3). All strategies include PAPs/TMUs, internal and external HPs, and CMOs; follow the same sequence of processes in the activities of emergency medical response; and provide medical treatments to patients according to the priority scheme and FCFS within the patient category. In the context of Phuket and as modelled in the work in this thesis, ambulances, staff, and beds/mattresses/chairs are the vital healthcare resources in emergency medical services. All strategies allocate these resources according to FIFO policy. However, the strategies differ with respect to the provision of first treatments, patient transportation, and resource sharing. Strategy 1 provides first treatments to all patients at the nearest HPs, and requires internal staff to work at their facilities. Strategy 2 introduces TMUs where Reds and Yellows must receive the first-aid treatments before being transported to HPs, discharges some Greens who receive treatment at the TMUs, and implements sharing of internal staff for providing the treatments at the TMUs. On the other hand, Strategy 3 transports Reds and Yellows to the nearest HPs with available capacity for their first treatments, requires all Greens to be treated at the TMUs, and shares internal staff according to the defined network structure.

Chapter 5 Development of simulation models

Our DES models simulate the strategies for collaboration in healthcare network in response to disasters. This chapter presents model development including the assumptions that were made, the system objects that were defined, flowchart diagrams of strategies, input parameters, computation setup, validation and verification of the models, and definitions of the resilience metrics used.

5.1 Assumptions

In order to specify the model scope and to manage the inherent system complexity without compromising the applicability of the models, some assumptions have been defined and set with the healthcare professionals and the director of Phuket Provincial Public Health.

- PAPs/TMUs are in a safe and known locations. FRs are at PAPs/TMUs for implementing medical triage. The opened TMUs are equipped with the relief supplies. Thus, the PAPs/TMUs are ready to accept patients.
- Patients are evacuated to the nearest PAPs/TMUs. The number of patients is known. Only alive patients are included in the models. The patient category remains static through the simulation run time.
- There is no patient transportation between PAPs/TMUs as ambulances are limited and solely used for patient transportation from PAPs/TMUs to HPs.
- There is no pandemic during a disaster.
- Both HPs and CMOs have limited capacity of resources in response to disasters. Resources at HPs include doctors, nurses, basic life support ambulances, advanced life support ambulances, emergency beds, and chairs. CMOs have FRs and basic life support ambulances. They are identical in the corresponding category. These resources are not affected by the disaster and are available at their facilities before the simulation starts. These assumptions are based on the fact that when disaster/mass casualty incident occurs, staff and ambulances are at their facilities before patient arrivals at PAPs/TMUs. We do not include in the study staff who are allocated to existing patients admitted before the events, in which they are approximately 20% of total

staff. The staff availability for taking care of the causalities of the disaster is set to 80% of staff in each HP as advised by the healthcare professionals.

- Staff are always present on their ambulances for monitoring patients and providing medical treatments during the patient transportation. In each trip, ambulances carry patients and visit one HP. Ambulances are not required to transport patients to the HPs where the ambulances belong to.
- Roads are not affected by the disaster; thus, the travel time between PAPs/TMUs and HPs and between the HPs are known and fixed.

5.2 Queuing structure and system objects

The queuing structure and system objects used in the DES models in our study are presented in Table 5.1. Customers are patients affected by disasters and categorised into Reds, Yellows, and Greens, while servers include ambulances, staff, and beds/mattresses/chairs. We define patients, ambulances, and staff as *entities*, while beds/mattresses/chairs are defined as *resources* in the models.

In the literature, staff are grouped and assigned to one of three zones in the healthcare facilities including red, yellow, and green zone, so that staff are commonly defined as *resources* for different zones (Konrad et al., 2013; Yang et al., 2016; Niessner et al., 2018). Different groups of staff are responsible for different patient category, which is against the collaboration in the healthcare network during disasters. For the collaboration, staff are shared between HPs and perceived as the network resources to ensure the continued provision of medical services in the network during disasters. Staff are assigned to any patients awaiting available staff (not a particular patient category) and allocated to any healthcare facilities that need additional staff. These can be done by treating staff as *entity*, rather than *resources.*

Table 5.1 Queuing structure and system objects

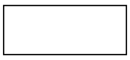
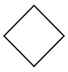
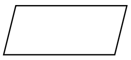
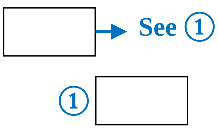
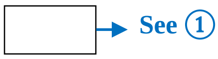
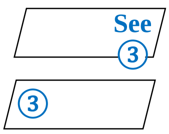
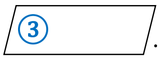
Queuing structure	**Objects of the system**	**Queuing discipline**
Customer	Patient *(defined as entities)* - Reds - Yellows - Greens	- Priority scheme based on patient category - FCFS in the patient category
Server	Ambulance *(defined as entities)* - Internal ambulances: patient transport, basic life support, and advanced life support ambulances	- FIFO policy

Queuing structure	Objects of the system	Queuing discipline
	- External ambulances: advanced life support ambulances	
	Staff *(defined as entities)* - Internal staff: doctors, nurses, and FRs - External staff: doctors, and nurses	- FIFO policy
	At TMUs *(defined as resources)* - Field beds for Reds and Yellows - Field mattresses for Greens At HPs - Emergency beds for Reds - Chairs for Yellows and Greens	- FIFO policy

5.3 Flowchart diagrams

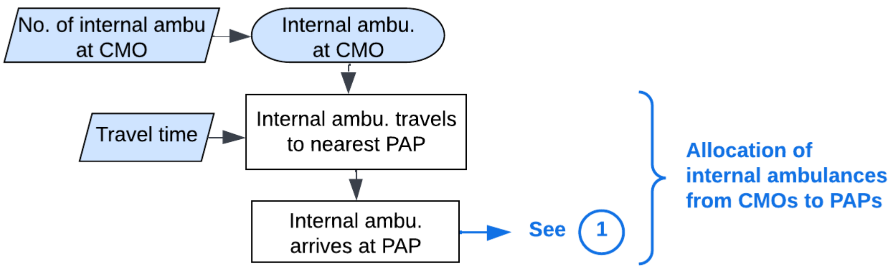
The flowchart diagrams of strategies are divided into four parts including the activities of collaboration in an emergency medical response to a disaster at CMOs, PAPs/ TMUs, internal HPs, and external HPs. Table 5.2 shows the symbols used in the flowchart diagrams.

Table 5.2 Flowchart symbols

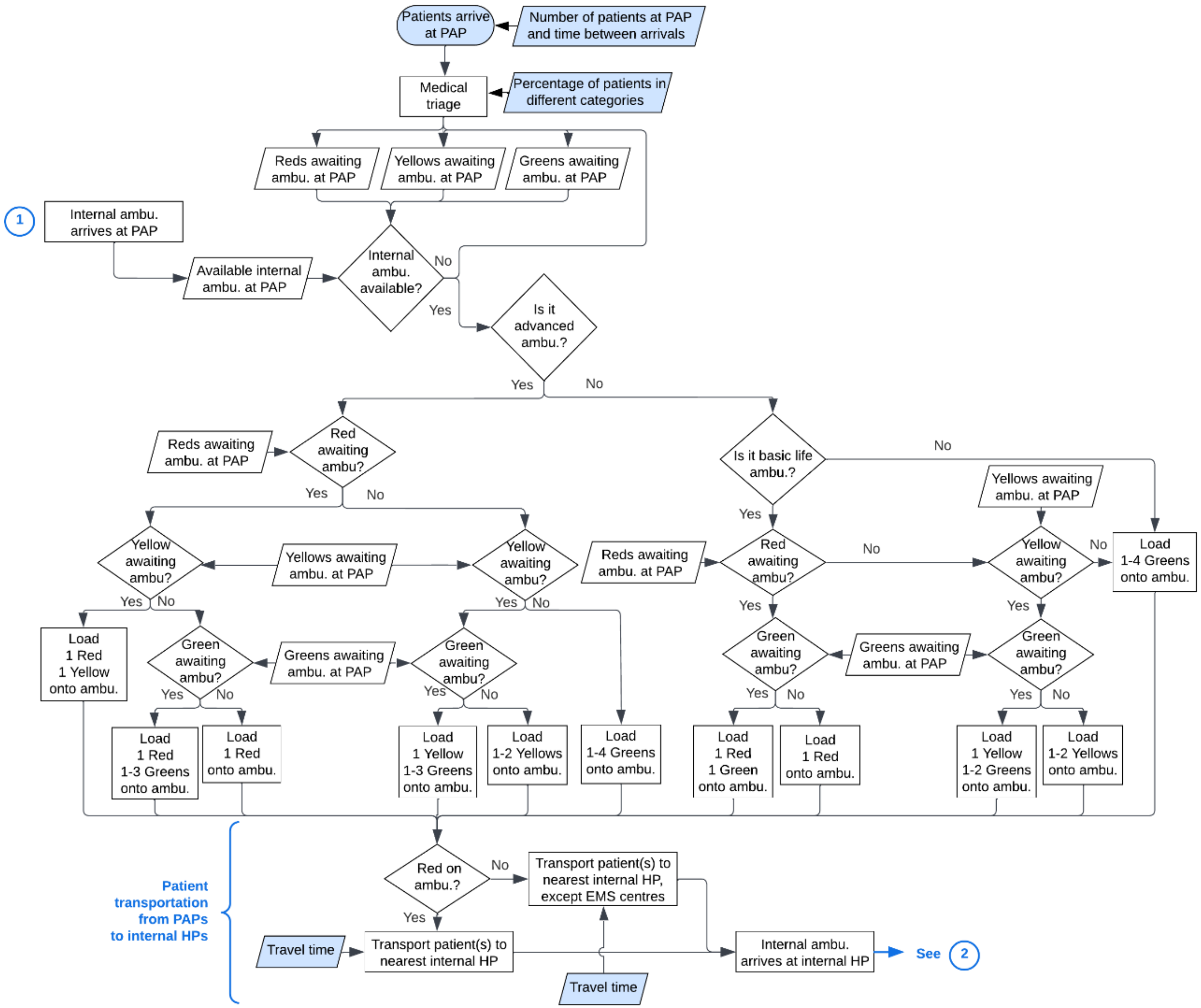
Symbols	Description
	A start symbol represents "creating entities" to the models.
	An end symbol represents "terminating entities" from the models.
	A process symbol represents a process or an action.
	A decision symbol indicates a question to be answered (Yes/No). The flowchart path is then spilt into two branches depending on the answer.
	A data symbol represents the input parameters of the simulation models.
	A data symbol represents the data occurred through simulation time. These data are always changed depending on the system state.
	Some sequential processes are spilt into different flowchart diagrams. These symbols represent the next processes. The process after  is  .
	These symbols represent the data flow between different flowchart diagrams. The data occurred in  is the input data of  .

5.3.1 Flowchart diagrams of non-collaborative care strategy (Strategy 1)

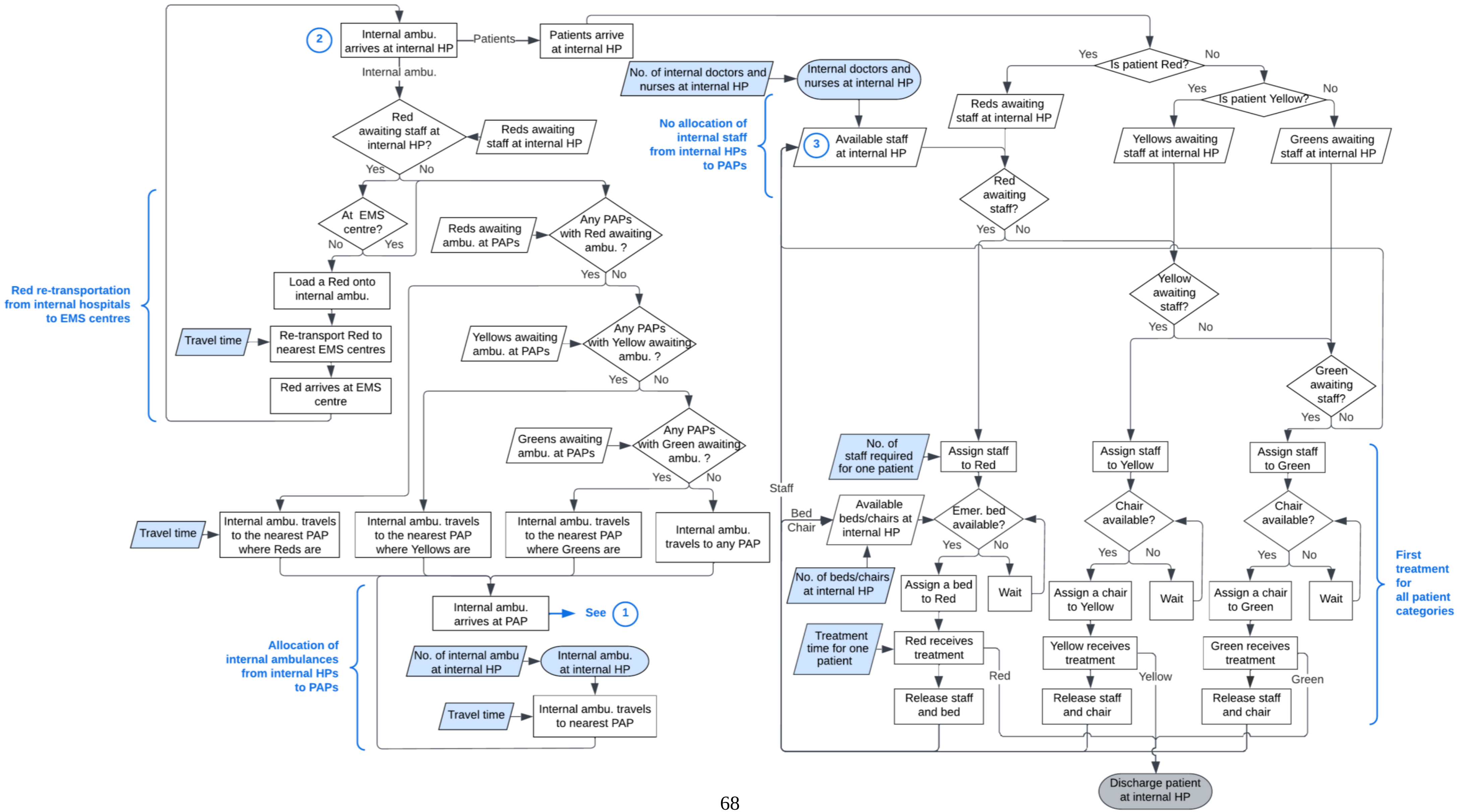
Activities of collaboration in an emergency medical response at CMOs

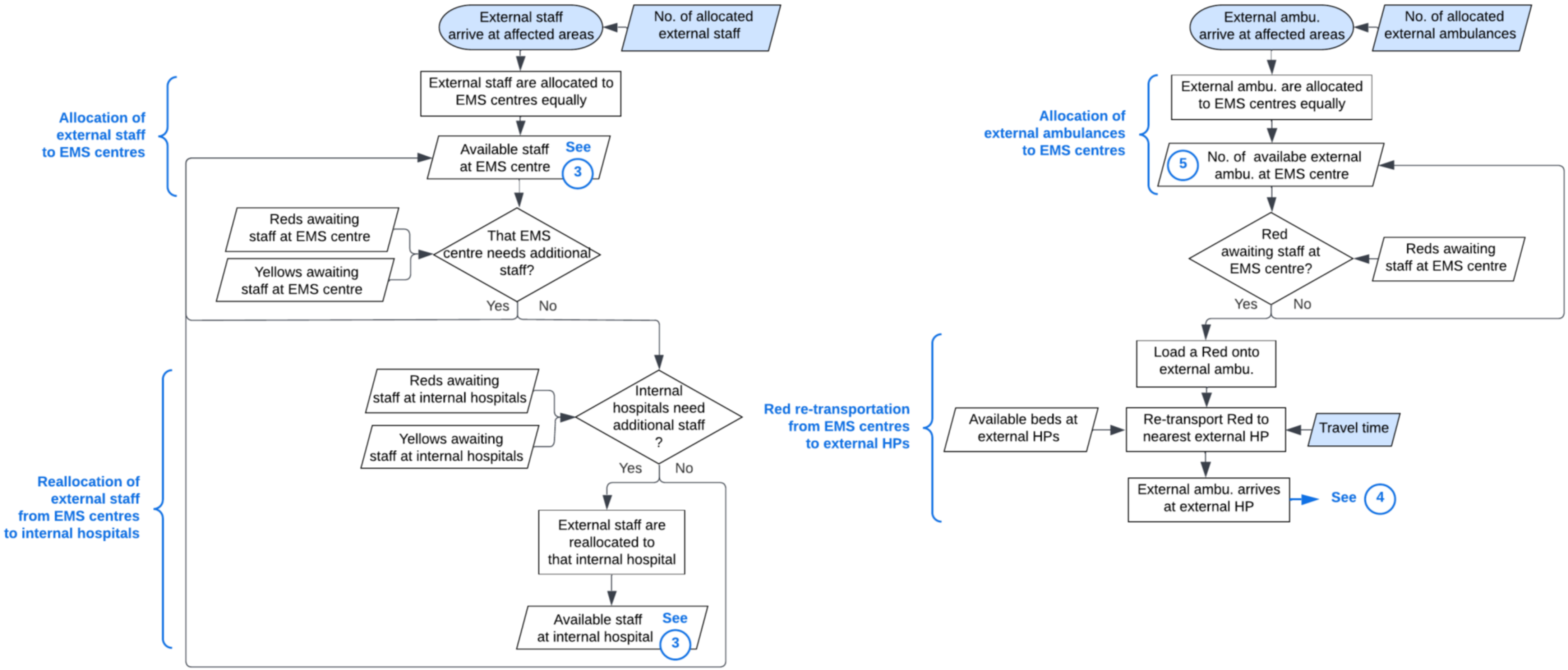


Activities of collaboration in an emergency medical response at PAPs



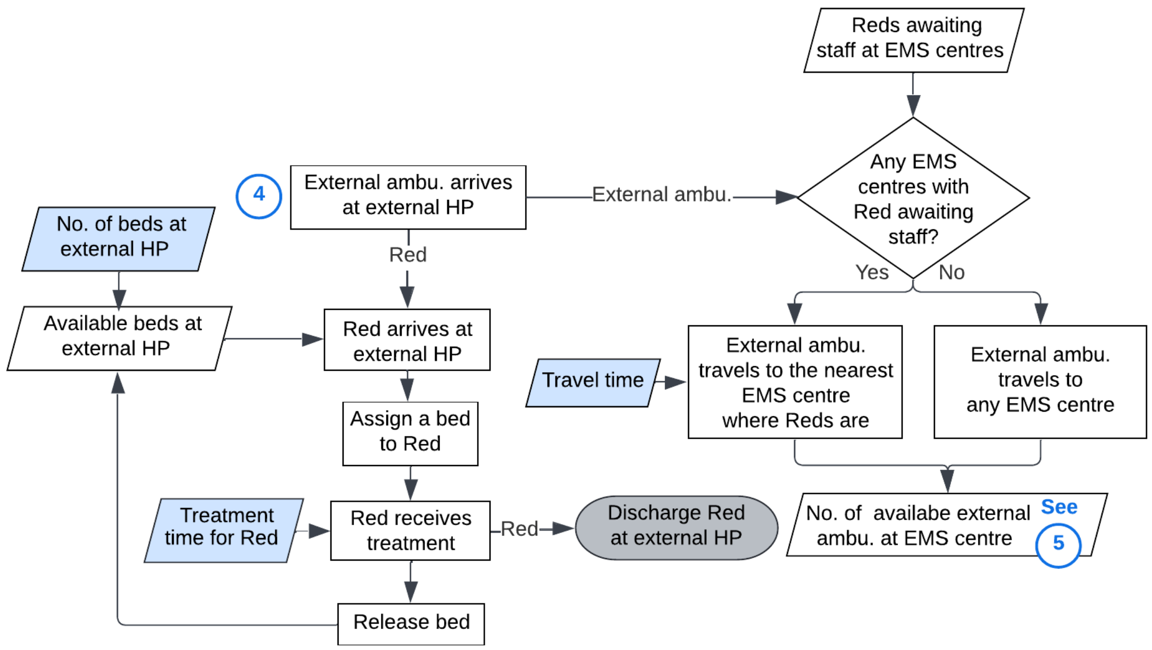
Activities of collaboration in an emergency medical response at internal HPs





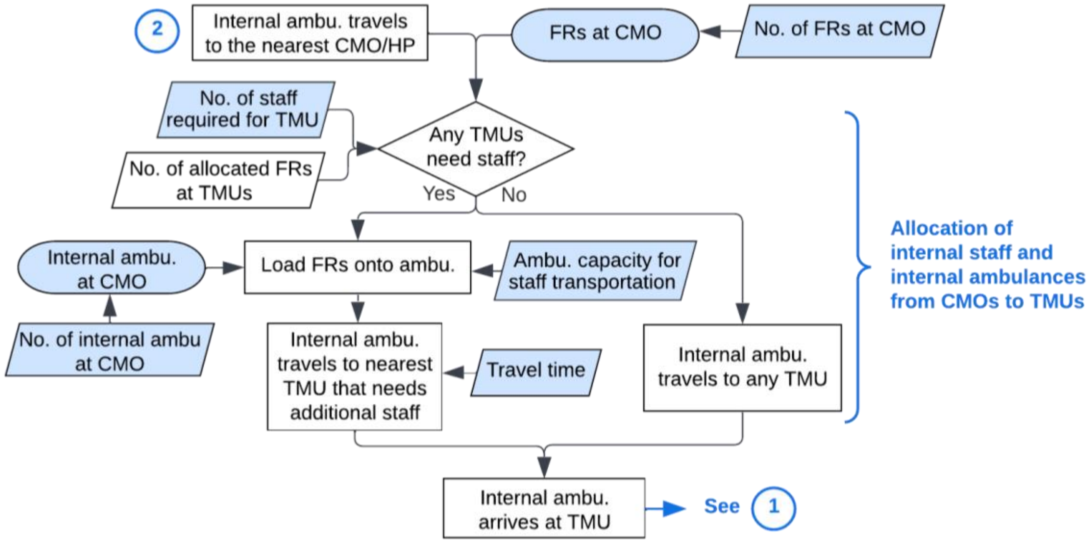
External staff arrive at affected areas
No. of allocated external staff
External staff are allocated to EMS centres equally
Allocation of external staff to EMS centres
Available staff at EMS centre
See 3
Reds awaiting staff at EMS centre
Yellows awaiting staff at EMS centre
That EMS centre needs additional staff?
Yes
No
Reds awaiting staff at internal hospitals
Yellows awaiting staff at internal hospitals
Internal hospitals need additional staff ?
Yes
No
External staff are reallocated to that internal hospital
Available staff at internal hospital
See 3
Reallocation of external staff from EMS centres to internal hospitals
External ambu. arrive at affected areas
No. of allocated external ambulances
External ambu. are allocated to EMS centres equally
Allocation of external ambulances to EMS centres
5
No. of availabe external ambu. at EMS centre
Red awaiting staff at EMS centre?
Reds awaiting staff at EMS centre
Yes
No
Load a Red onto external ambu.
Red re-transportation from EMS centres to external HPs
Available beds at external HPs
Re-transport Red to nearest external HP
Travel time
External ambu. arrives at external HP
See 4

Activities of collaboration in an emergency medical response at external HPs

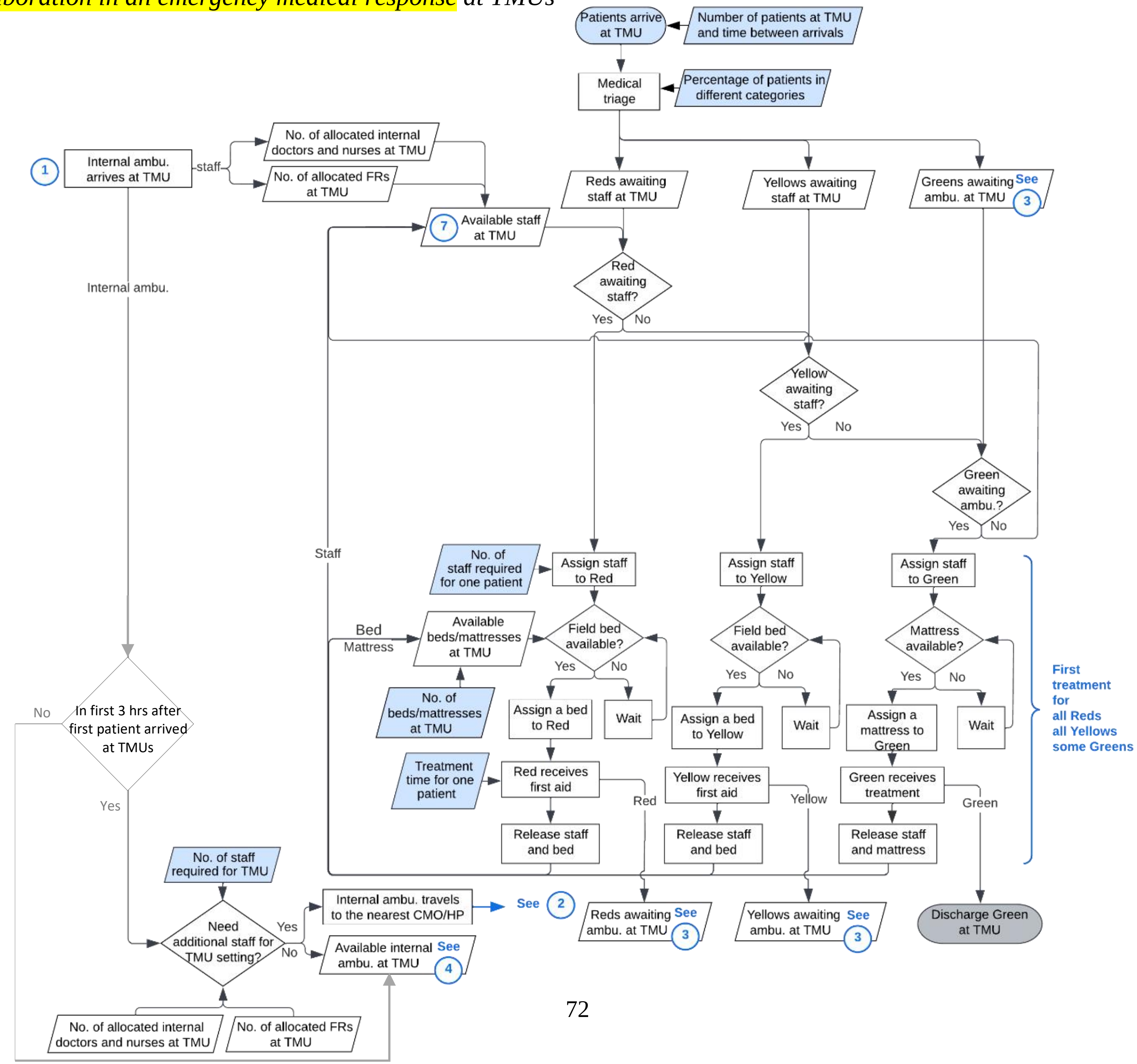


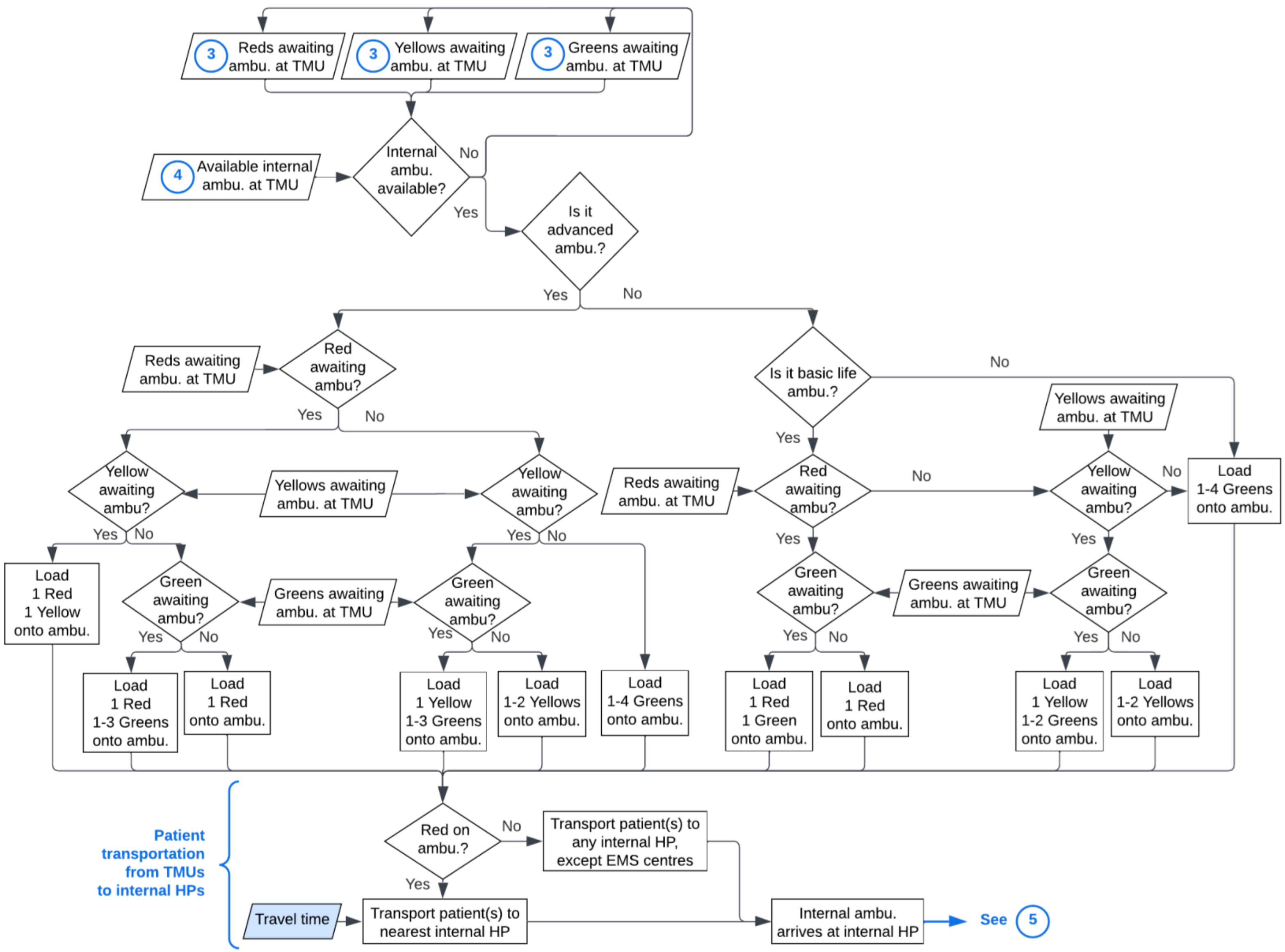
5.3.2 Flowchart diagrams of semi-collaborative care strategy (Strategy 2)

Activities of collaboration in an emergency medical response at CMOs



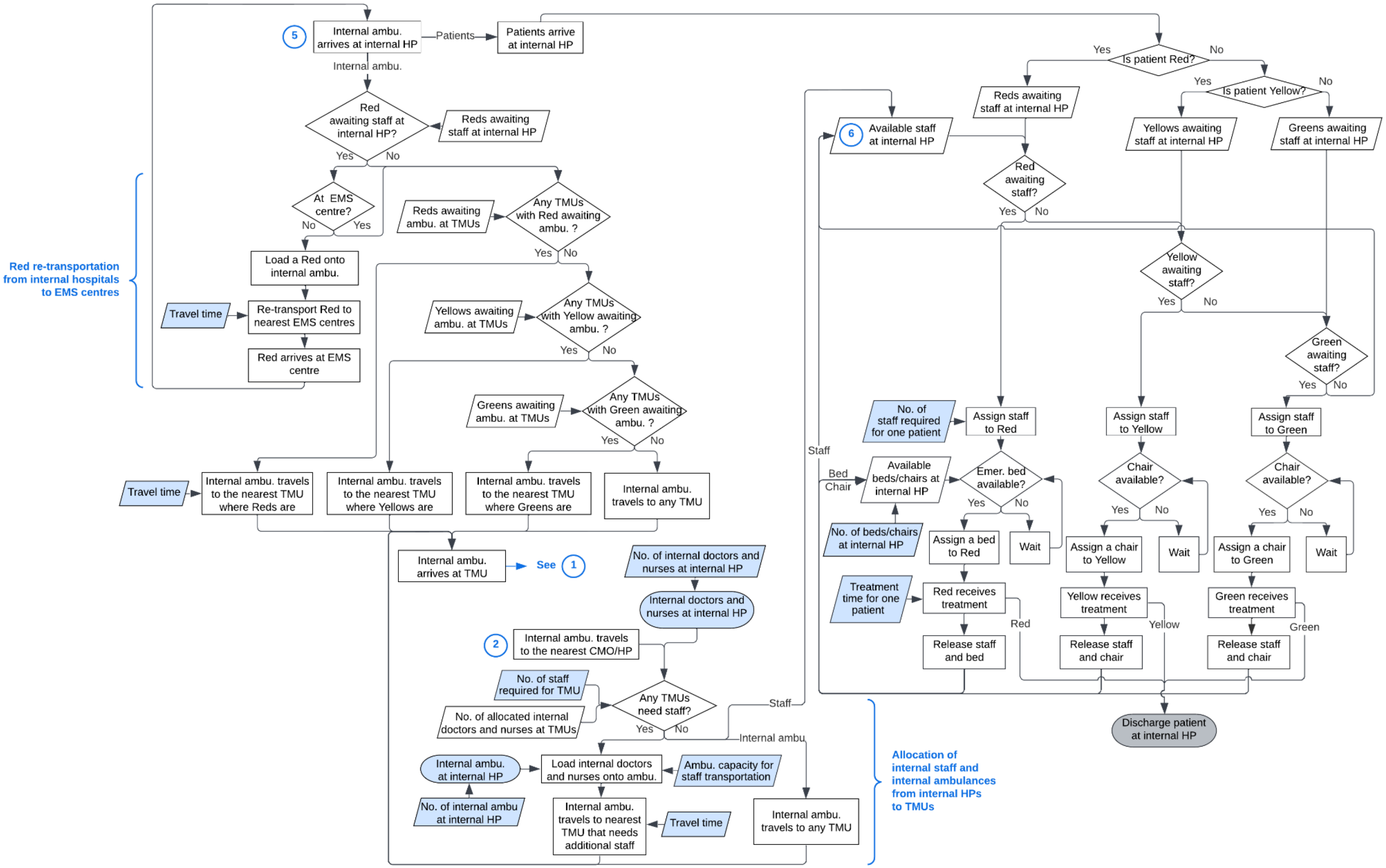
Activities of collaboration in an emergency medical response *at TMUs*

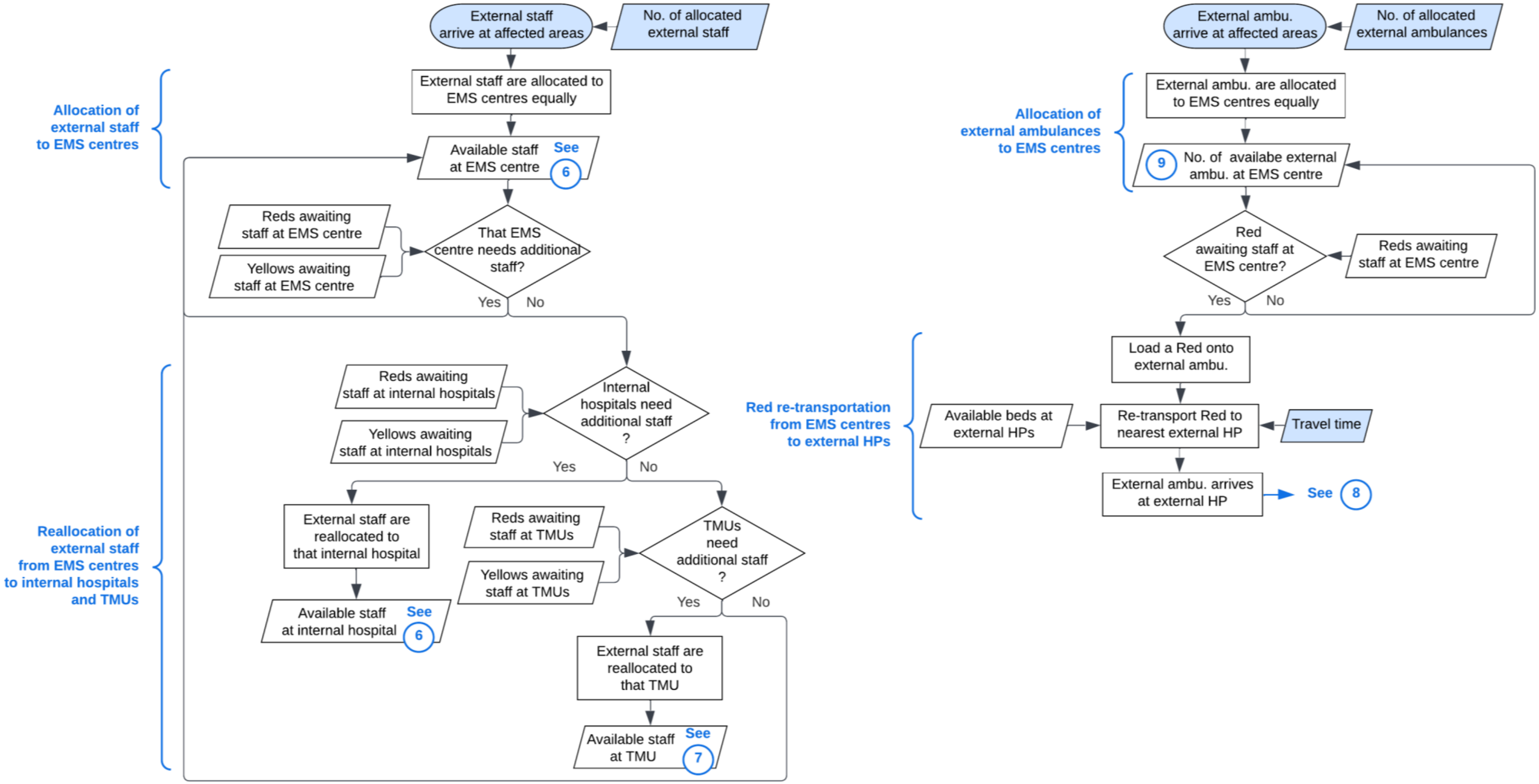




3 Reds awaiting ambu. at TMU
3 Yellows awaiting ambu. at TMU
3 Greens awaiting ambu. at TMU
4 Available internal ambu. at TMU
Internal ambu. available?
No
Yes
Is it advanced ambu.?
Yes
No
Reds awaiting ambu. at TMU
Red awaiting ambu?
Yes
No
Is it basic life ambu.?
No
Yes
Yellows awaiting ambu. at TMU
Yellow awaiting ambu?
Yellows awaiting ambu. at TMU
Yellow awaiting ambu?
Reds awaiting ambu. at TMU
Red awaiting ambu?
No
Yellow awaiting ambu?
No
Load 1-4 Greens onto ambu.
Load 1 Red 1 Yellow onto ambu.
Green awaiting ambu?
Greens awaiting ambu. at TMU
Green awaiting ambu?
Green awaiting ambu?
Greens awaiting ambu. at TMU
Green awaiting ambu?
Load 1 Red 1-3 Greens onto ambu.
Load 1 Red onto ambu.
Load 1 Yellow 1-3 Greens onto ambu.
Load 1-2 Yellows onto ambu.
Load 1-4 Greens onto ambu.
Load 1 Red 1 Green onto ambu.
Load 1 Red onto ambu.
Load 1 Yellow 1-2 Greens onto ambu.
Load 1-2 Yellows onto ambu.
Patient transportation from TMUs to internal HPs
Red on ambu.?
No
Transport patient(s) to any internal HP, except EMS centres
Yes
Travel time
Transport patient(s) to nearest internal HP
Internal ambu. arrives at internal HP
See 5

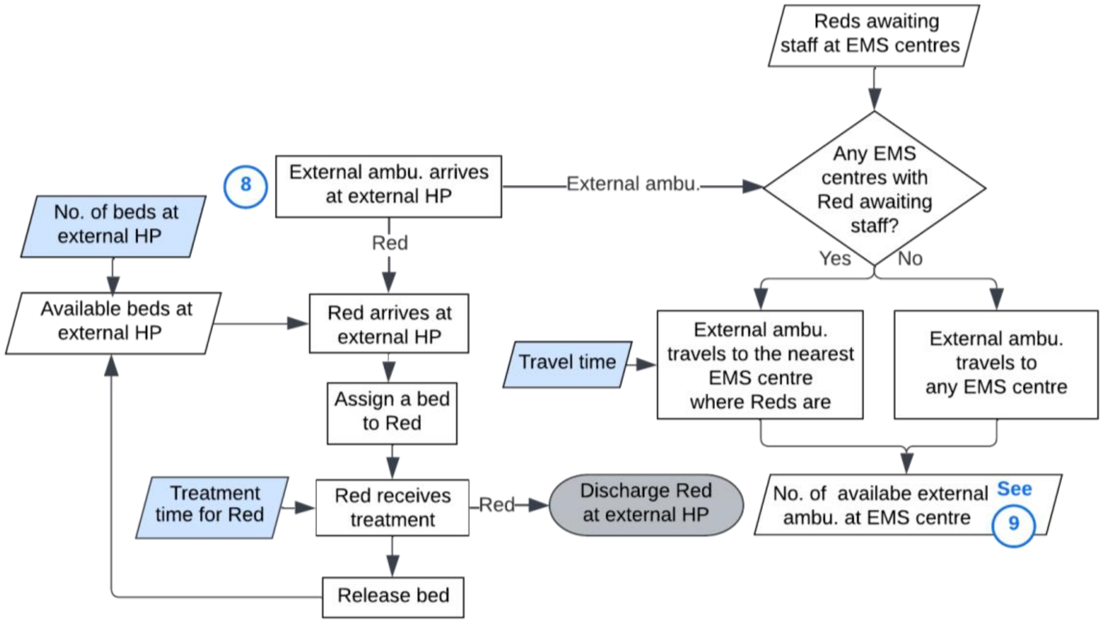
Activities of collaboration in an emergency medical response at internal HPs





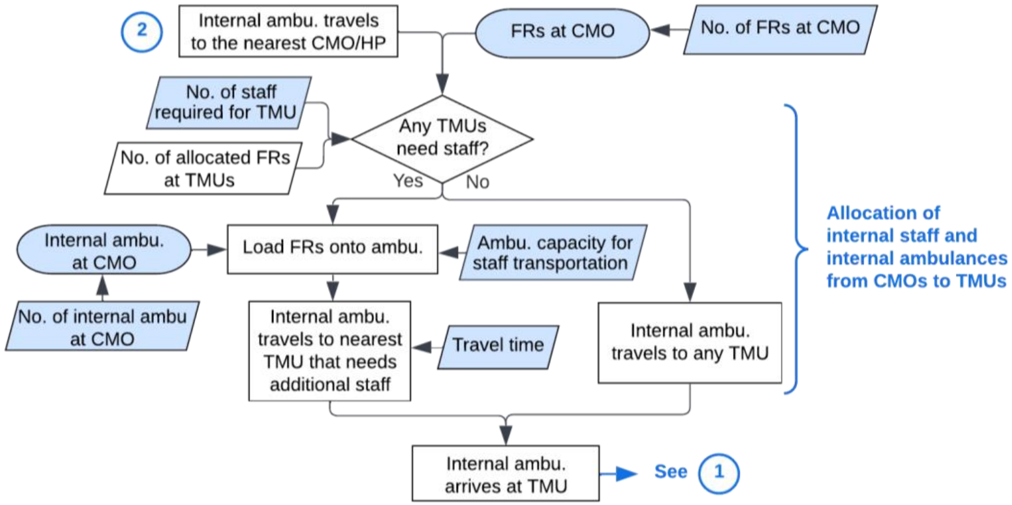
External staff arrive at affected areas
No. of allocated external staff
Allocation of external staff to EMS centres
External staff are allocated to EMS centres equally
Available staff at EMS centre
See 6
Reds awaiting staff at EMS centre
Yellows awaiting staff at EMS centre
That EMS centre needs additional staff?
Yes
No
Reallocation of external staff from EMS centres to internal hospitals and TMUs
Reds awaiting staff at internal hospitals
Yellows awaiting staff at internal hospitals
Internal hospitals need additional staff ?
Yes
No
External staff are reallocated to that internal hospital
Available staff at internal hospital
See 6
Reds awaiting staff at TMUs
Yellows awaiting staff at TMUs
TMUs need additional staff ?
Yes
No
External staff are reallocated to that TMU
Available staff at TMU
See 7
External ambu. arrive at affected areas
No. of allocated external ambulances
Allocation of external ambulances to EMS centres
External ambu. are allocated to EMS centres equally
9
No. of availabe external ambu. at EMS centre
Red awaiting staff at EMS centre?
Reds awaiting staff at EMS centre
Yes
No
Red re-transportation from EMS centres to external HPs
Load a Red onto external ambu.
Available beds at external HPs
Re-transport Red to nearest external HP
Travel time
External ambu. arrives at external HP
See 8

Activities of collaboration in an emergency medical response at external HPs

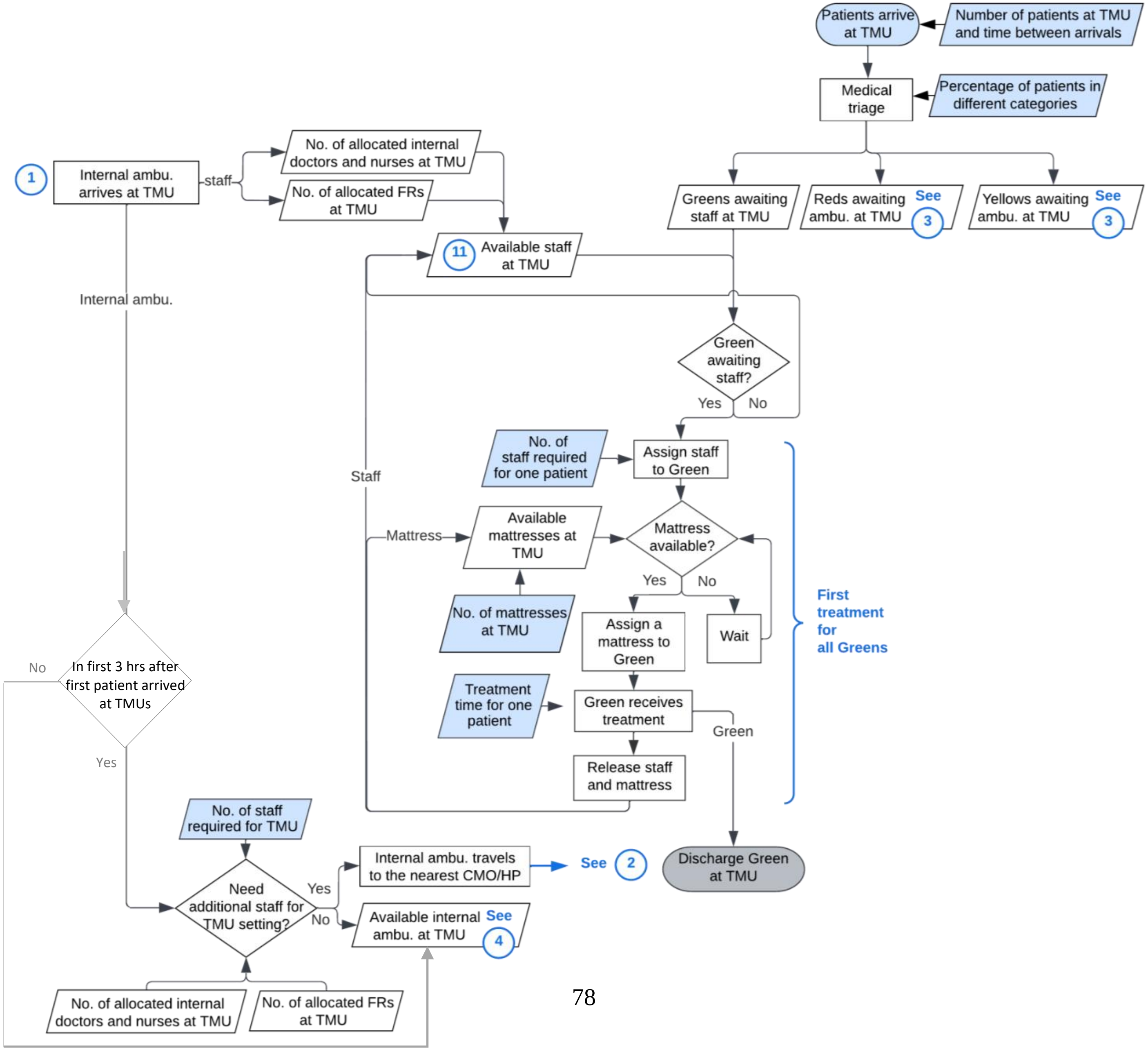


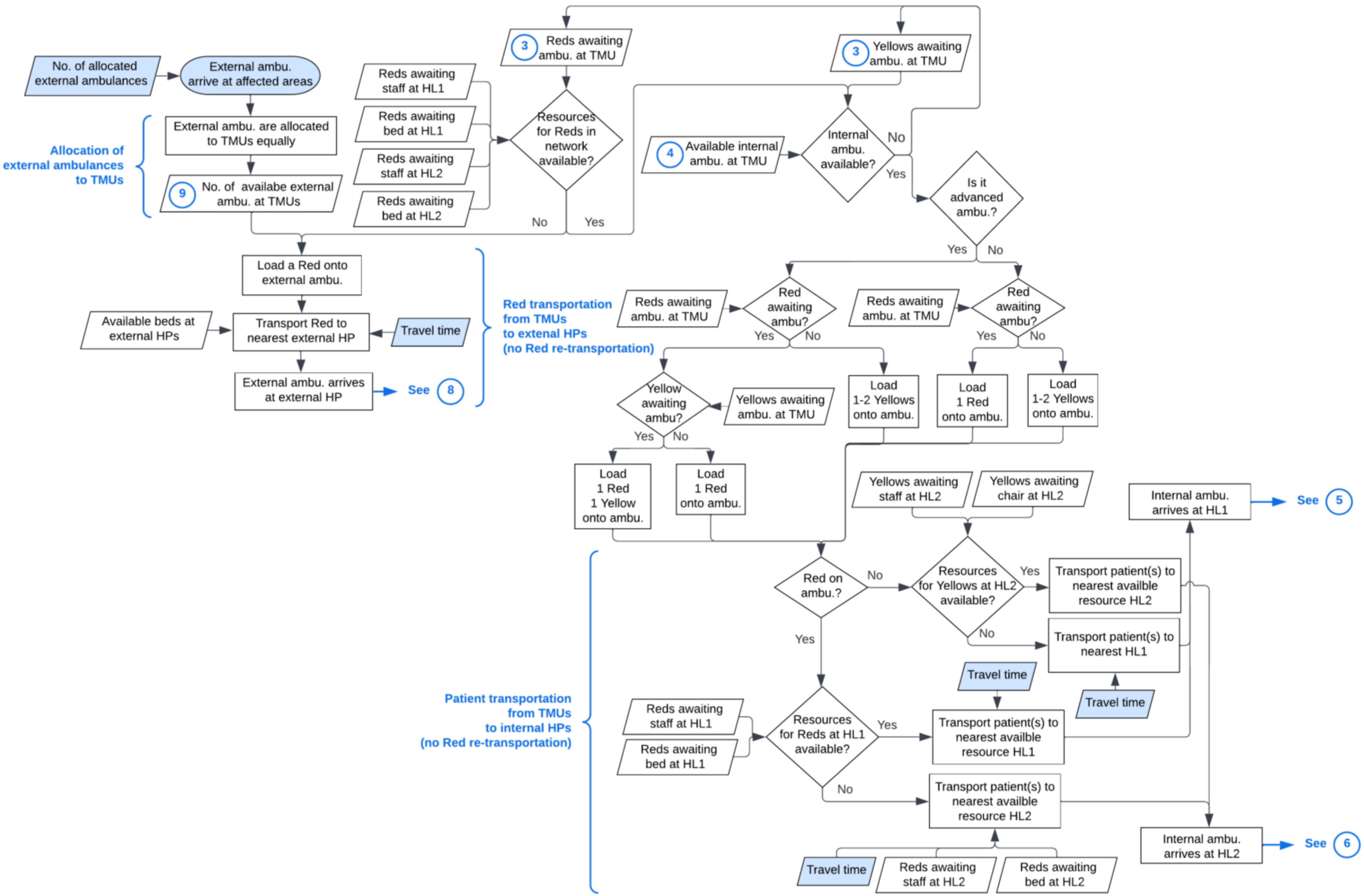
5.3.3 Flowchart diagrams of collaborative care strategy (Strategy 3)

Activities of collaboration in an emergency medical response at CMOs

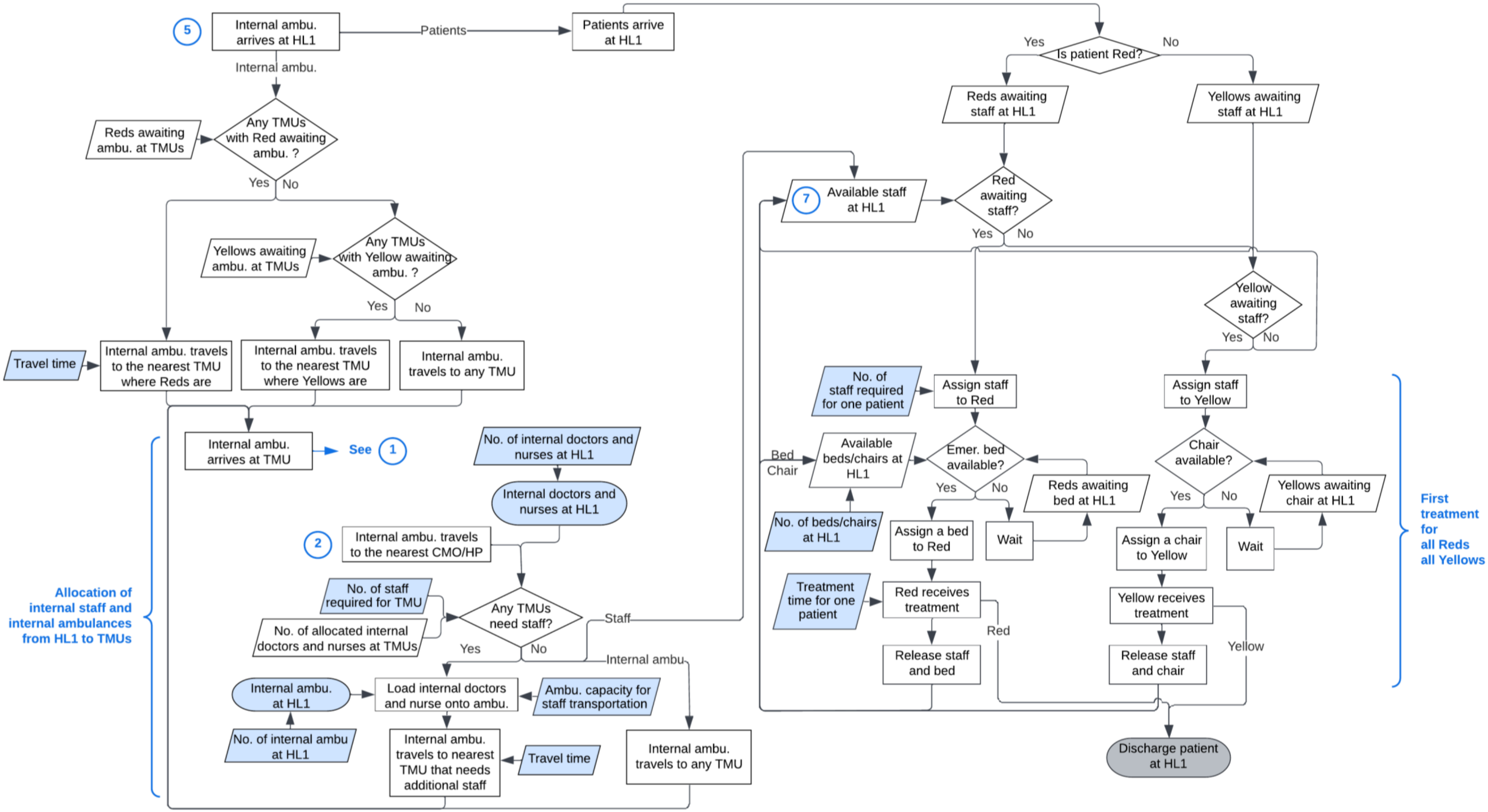


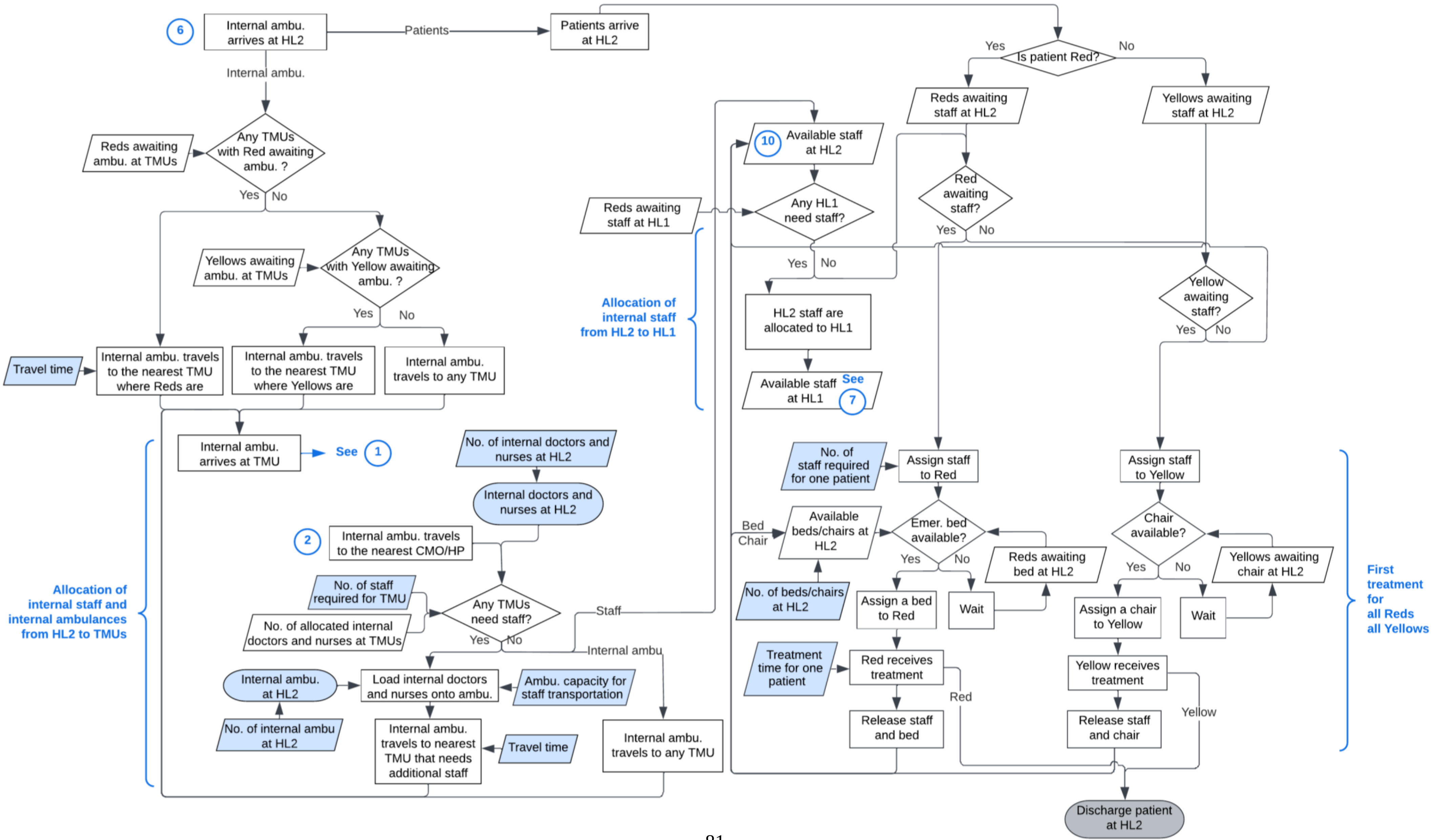
Activities of collaboration in an emergency medical response at TMUs

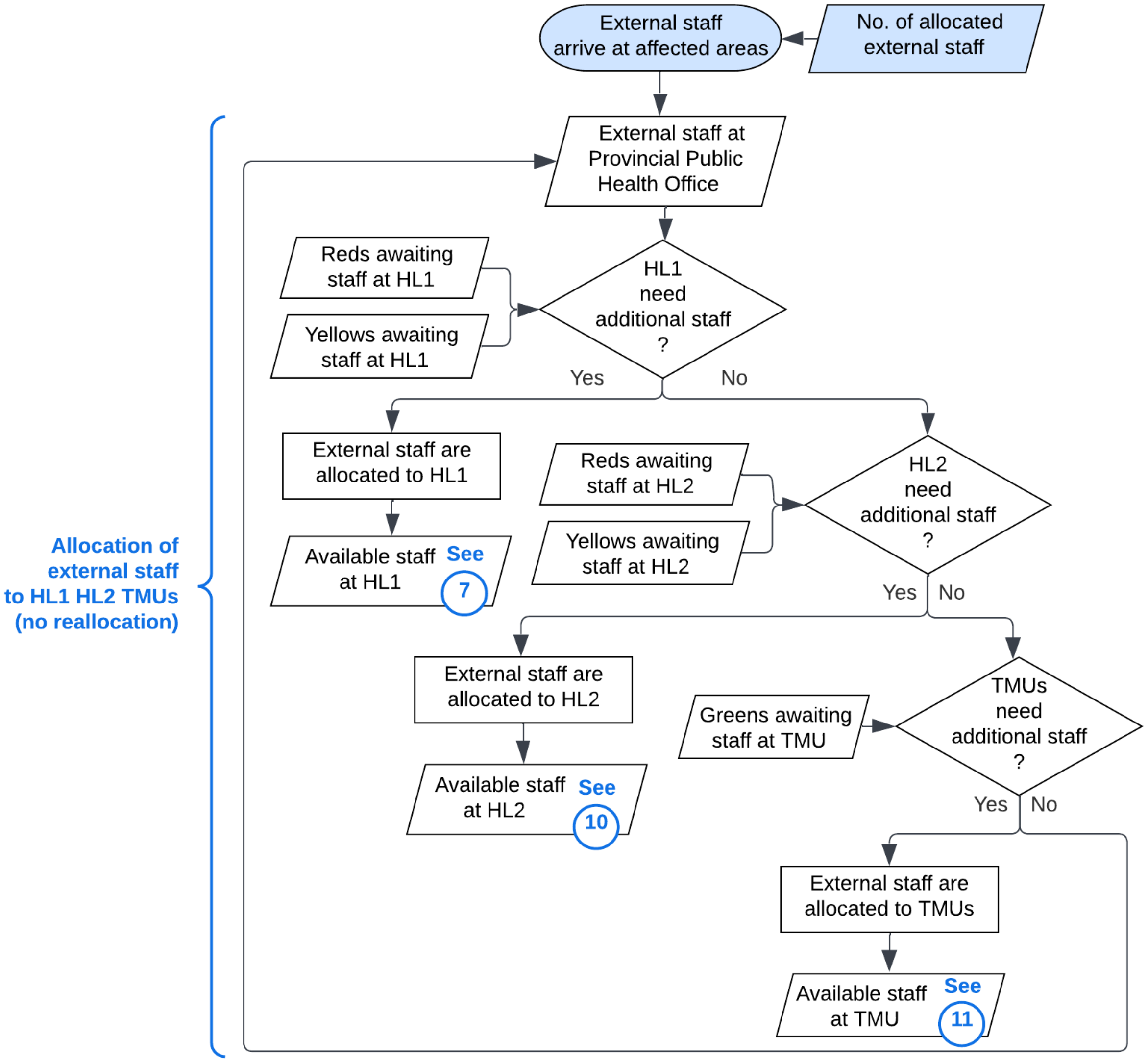



No. of allocated external ambulances
External ambu. arrive at affected areas
Allocation of external ambulances to TMUs
External ambu. are allocated to TMUs equally
9 No. of availabe external ambu. at TMUs
Reds awaiting staff at HL1
Reds awaiting bed at HL1
Reds awaiting staff at HL2
Reds awaiting bed at HL2
3 Reds awaiting ambu. at TMU
Resources for Reds in network available?
No
Yes
3 Yellows awaiting ambu. at TMU
4 Available internal ambu. at TMU
Internal ambu. available?
No
Yes
Is it advanced ambu.?
Yes
No
Load a Red onto external ambu.
Available beds at external HPs
Transport Red to nearest external HP
Travel time
External ambu. arrives at external HP
See 8
Red transportation from TMUs to extenal HPs (no Red re-transportation)
Reds awaiting ambu. at TMU
Red awaiting ambu?
Yes
No
Reds awaiting ambu. at TMU
Red awaiting ambu?
Yes
No
Yellow awaiting ambu?
Yellows awaiting ambu. at TMU
Yes
No
Load 1-2 Yellows onto ambu.
Load 1 Red onto ambu.
Load 1-2 Yellows onto ambu.
Load 1 Red 1 Yellow onto ambu.
Load 1 Red onto ambu.
Yellows awaiting staff at HL2
Yellows awaiting chair at HL2
Internal ambu. arrives at HL1
See 5
Red on ambu.?
No
Resources for Yellows at HL2 available?
Yes
No
Transport patient(s) to nearest availble resource HL2
Transport patient(s) to nearest HL1
Yes
Travel time
Travel time
Patient transportation from TMUs to internal HPs (no Red re-transportation)
Reds awaiting staff at HL1
Reds awaiting bed at HL1
Resources for Reds at HL1 available?
Yes
No
Transport patient(s) to nearest availble resource HL1
Transport patient(s) to nearest availble resource HL2
Internal ambu. arrives at HL2
See 6
Travel time
Reds awaiting staff at HL2
Reds awaiting bed at HL2

Activities of collaboration in an emergency medical response at internal HPs

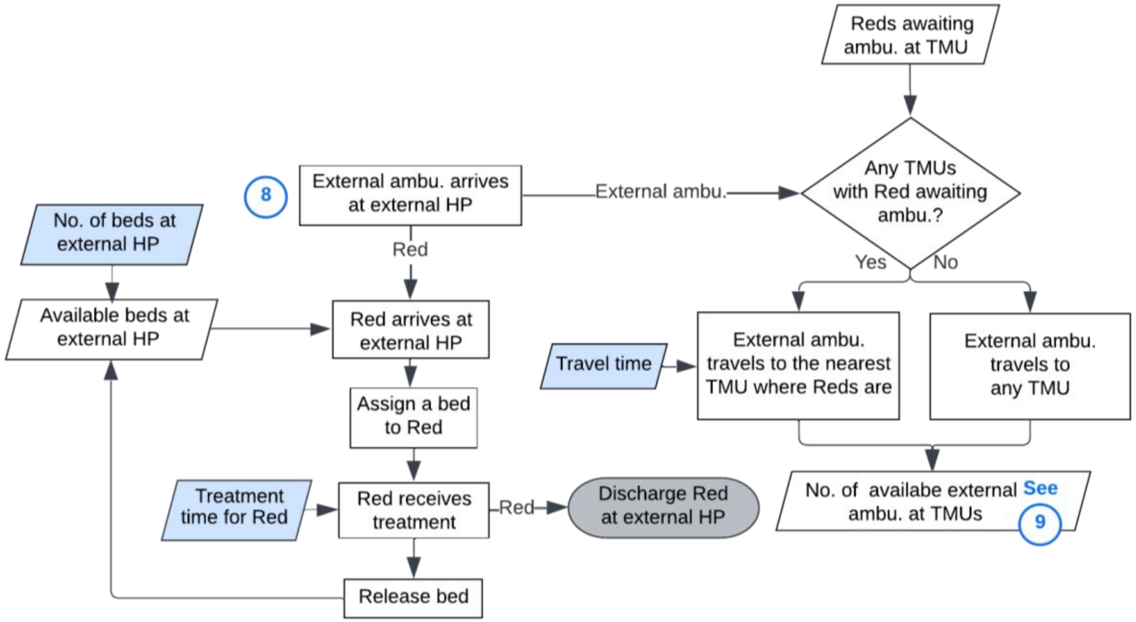



6
Internal ambu. arrives at HL2
Patients
Patients arrive at HL2
Internal ambu.
Reds awaiting ambu. at TMUs
Any TMUs with Red awaiting ambu. ?
Yes
No
Yellows awaiting ambu. at TMUs
Any TMUs with Yellow awaiting ambu. ?
Yes
No
Travel time
Internal ambu. travels to the nearest TMU where Reds are
Internal ambu. travels to the nearest TMU where Yellows are
Internal ambu. travels to any TMU
Internal ambu. arrives at TMU
See 1
No. of internal doctors and nurses at HL2
Internal doctors and nurses at HL2
2
Internal ambu. travels to the nearest CMO/HP
No. of staff required for TMU
No. of allocated internal doctors and nurses at TMUs
Any TMUs need staff?
Yes
No
Staff
Internal ambu
Allocation of internal staff and internal ambulances from HL2 to TMUs
Internal ambu. at HL2
Load internal doctors and nurses onto ambu.
Ambu. capacity for staff transportation
No. of internal ambu at HL2
Internal ambu. travels to nearest TMU that needs additional staff
Travel time
Internal ambu. travels to any TMU
Is patient Red?
Yes
No
Reds awaiting staff at HL2
Yellows awaiting staff at HL2
10
Available staff at HL2
Reds awaiting staff at HL1
Any HL1 need staff?
Yes
No
Red awaiting staff?
Yes
No
Allocation of internal staff from HL2 to HL1
HL2 staff are allocated to HL1
Available staff at HL1
See 7
Yellow awaiting staff?
Yes
No
No. of staff required for one patient
Assign staff to Red
Assign staff to Yellow
Bed
Chair
Available beds/chairs at HL2
Emer. bed available?
Yes
No
Reds awaiting bed at HL2
Chair available?
Yes
No
Yellows awaiting chair at HL2
No. of beds/chairs at HL2
Assign a bed to Red
Wait
Assign a chair to Yellow
Wait
Treatment time for one patient
Red receives treatment
Yellow receives treatment
Red
Yellow
Release staff and bed
Release staff and chair
First treatment for all Reds all Yellows
Discharge patient at HL2



External staff arrive at affected areas
No. of allocated external staff
Allocation of external staff to HL1 HL2 TMUs (no reallocation)
External staff at Provincial Public Health Office
Reds awaiting staff at HL1
Yellows awaiting staff at HL1
HL1 need additional staff ?
Yes
No
External staff are allocated to HL1
Available staff at HL1
See 7
Reds awaiting staff at HL2
Yellows awaiting staff at HL2
HL2 need additional staff ?
Yes
No
External staff are allocated to HL2
Available staff at HL2
See 10
Greens awaiting staff at TMU
TMUs need additional staff ?
Yes
No
External staff are allocated to TMUs
Available staff at TMU
See 11

Activities of collaboration in an emergency medical response at external HPs



5.4 Input parameters

The values of input parameters in our models are set using the two real-world disaster events in Thailand. We use a case study of *boat capsizing* on 5th of July 2018, which is a recent mass casualty incident that has occurred in Phuket, for the model validation and verification. Strategy 2 was in place in response to that incident. During the event, there were no external resources because the internal HPs could handle the affected patients.

The case of *Tsunami in Phuket in 2004* is used to investigate the effectiveness of strategies for collaboration in terms of resilience. Tsunami 2004 disaster was not used for the validation and verification because none of measures were recorded in that event. During the event, external HPs allocated their resources to Phuket, while keeping the required resources to maintain their day-to-day services. Unfortunately, the data on their original facilities were not available. For the provision of medical treatments at the external HPs, we only include beds in our models because the data on staff capacity at the external HPs are not available.

Table 5.3 and Table 5.4 present a list of input parameters and their values in two case studies. Overall, there are at most three TMUs/PAPs, two EMS centres in layer 1 (HL1), six internal hospitals in layer 2 (HL2) and three CMOs. The internal HPs and CMOs are located in Phuket, while the external HPs are located in Phang-nga, Krabi, and Surat Thani. The healthcare authorities provided the average time between patient arrivals, the average number of affected patients, the average treatment time, the number of healthcare resources at TMUs, the number of resources required for treatments, and the ambulance capacity for multiple patient transportation and for staff transportation. Normal distribution is commonly used to incorporate the uncertainties associated with patient demands and activity durations in healthcare and disaster management; (see for example Brailsford et al., 2007; Viana et al., 2014; Farahani et al., 2020; Lin et al., 2022; Ridler et al., 2022). We have the average values that were provided by the stakeholders. However, we do not have sample data, so variances have to be set arbitrarily. The normal distribution is in the form of $N(\mu,\sigma^2)$. The percentage of patients in different categories and the number of allocated external resources follow historical data recorded during the event. The travel times are asymmetric based on the shortest route obtained by the Google map.

Table 5.3 Input values for simulation parameters (Boat capsizing for validation and verification)

Input parameters	**Input values**
Demand	
Time between patient arrivals	Exponential distribution: λ = 5 minutes
Total number of patients	$N(46, 3.25)$
Total number of patients at TMU A	$N(10, 1)$
Total number of patients at TMU B	$N(36, 2.25)$
Patient category	For TMU A, R - 0%; Y - 30%; G - 70% For TMU B, R - 9%; Y - 12%; G - 79%
Internal resources	
Healthcare resources at each TMU	10 fb, 30 fm
Resource requirement for running all TMUs	≥ 10 dr, ≥ 30 nr, ≥ 15 fr, ≥ 1 ba, ≥ 1 ad
Healthcare resources at EMS 1	110 dr, 395 nr, 2 ba, 7 ad, 20 eb, 150 ch,
Healthcare resources at EMS 2	96 dr, 312 nr, 4 ba, 7 ad, 14 eb, 130 ch,
Healthcare resources at H 1	17 dr, 74 nr, 6 ad, 10 eb, 85 ch
Healthcare resources at H 2	23 dr, 68 nr, 1 ba, 2 ad, 7 eb, 110 ch
Healthcare resources at H 3	51 dr, 157 nr, 3 ba, 2 ad, 8 eb, 55 ch
Healthcare resources at H 4	16 dr, 27 nr, 1 ad, 3 eb, 40 ch
Healthcare resources at H 5	19 dr, 86 nr, 3 ba, 3 ad, 5 eb, 45 ch
Healthcare resources at H 6	19 dr, 64 nr, 2 ba, 3 ad, 7 eb, 50 ch
Healthcare resources at CMO 1	50 fr, 2 ba
Healthcare resources at CMO 2	138 fr, 18 ba
Healthcare resources at CMO 3	51 fr, 17 ba
External resources	
Number of allocated external resources	N/A
Healthcare resources at external HPs	N/A
Medical services	
Resources required for treatments at TMUs	R - 1 fb, 1 dr, 4 nr, 2 fr; Y - 1fb, 1 dr, 2 nr, 1 fr; G - 1 fm, 1 dr, 1 nr, 1 fr
Resources required for treatments at HPs	R - 1 eb, 1 dr, 4 nr; Y - 1 ch, 1 dr, 2 nr; G - 1 ch, 1 dr, 1 nr
Treatment time at TMUs (minutes)	R - $N(32.5, 6.25)$; Y - $N(22.5, 6.25)$; G - $N(12.5, 6.25)$
Treatment time at HPs (minutes)	R - $N(65, 6.25)$; Y - $N(30, 6.25)$; G - $N(12.5, 6.25)$
Transportation	
Ambulance capacity for multiple patient transportation	pa/pc - 4 G ba - 1 R & 1 G / 2 Y / 1 Y & 2 G / 4 G ad - 1 R & 1 Y / 1 R & 3 G / 2 Y / 1 Y & 3 G / 4 G
Ambulance capacity for staff transportation	1 dr & 3 nr / 3 fr
Travel time	Asymmetric travel time

Note: TMU - temporary medical unit, EMS - emergency medical service centre, H - internal hospital, CMO - charity/municipal organisation, R - Reds, Y - Yellows, G - Greens, dr - doctor, nr - nurse, fr - first responder, fb - field bed, fm – field mattress, eb - emergency bed, ch - chair, pa - patient transport ambulance, ba - basic life support ambulance, ad - advanced life support ambulance, pc - private car, N/A - Not applicable, / - or, Normal distribution is in the form of $N(\mu, \sigma^2)$

Table 5.4 Input values for simulation parameters (Tsunami for experiments)

Input parameters	**Input values**
Demand	
Time between patient arrivals	Exponential distribution: λ = 5 minutes
Total number of patients	$N(2000, 3600)$
Total number of patients at PAP/TMU A	$N(900, 2025)$
Total number of patients at PAP/TMU B	$N(700, 1225)$
Total number of patients at PAP/TMU C	$N(400, 400)$
Patient category	For all PAPs/TMUs, R - 55%; Y - 14%; G - 31%
Internal resources	
Healthcare resources at each TMU	10 fb, 30 fm
Resource requirement for running all TMUs	≥ 10 dr, ≥ 30 nr, ≥ 15 fr, ≥ 1 ba, ≥ 1 ad
Healthcare resources at EMS 1 (HL1)	110 dr, 395 nr, 2 ba, 7 ad, 20 eb, 150 ch,
Healthcare resources at EMS 2 (HL1)	96 dr, 312 nr, 4 ba, 7 ad, 14 eb, 130 ch,
Healthcare resources at H 1 (HL2)	17 dr, 74 nr, 6 ad, 10 eb, 85 ch, 30 ach
Healthcare resources at H 2 (HL2)	23 dr, 68 nr, 1 ba, 2 ad, 7 eb, 110 ch, 60 ach
Healthcare resources at H 3 (HL2)	51 dr, 157 nr, 3 ba, 2 ad, 8 eb, 55 ch, 105 ach
Healthcare resources at H 4 (HL2)	16 dr, 27 nr, 1 ad, 3 eb, 40 ch, 30 ach
Healthcare resources at H 5 (HL2)	19 dr, 86 nr, 3 ba, 3 ad, 5 eb, 45 ch, 60 ach
Healthcare resources at H 6 (HL2)	19 dr, 64 nr, 2 ba, 3 ad, 7 eb, 50 ch, 60 ach
Healthcare resources at CMO 1	50 fr, 2 ba
Healthcare resources at CMO 2	138 fr, 18 ba
Healthcare resources at CMO 3	51 fr, 17 ba
External resources	
Number of allocated external resources	129 dr, 176 nr, 15 ad
Healthcare resources at external HPs	EH 1 - 6 eb, EH 2 - 5 eb, EH 3 - 6 eb, EH 4 - 4 eb, EH 5 - 8 eb, EH 6 - 8 eb, EH 7 - 8 eb, EH 9 - 8 eb, EH 9 - 6 eb, EH 10 - 12 eb, EH 11 - 10 eb, EH 12 - 6 eb
Medical services	
Resources required for treatments at TMUs	R - 1 fb, 1 dr, 4 nr, 2 fr; Y - 1fb, 1 dr, 2 nr, 1 fr; G - 1 fm, 1 dr, 1 nr, 1 fr
Resources required for treatments at HPs	R - 1 eb, 1 dr, 4 nr; Y - 1 ch, 1 dr, 2 nr; G - 1 ch, 1 dr, 1 nr
Treatment time at TMUs (minutes)	R - $N(32.5, 6.25)$; Y - $N(22.5, 6.25)$; G - $N(12.5, 6.25)$
Treatment time at HPs (minutes)	R - $N(65, 6.25)$; Y - $N(30, 6.25)$; G - $N(12.5, 6.25)$
Transportation	
Ambulance capacity for multiple patient transportation	pa/pc - 4 G ba - 1 R & 1 G / 2 Y / 1 Y & 2 G / 4 G ad - 1 R & 1 Y / 1 R & 3 G / 2 Y / 1 Y & 3 G / 4 G
Ambulance capacity for staff transportation	1 dr & 3 nr / 3 fr
Travel time	Asymmetric travel time

Note: PAP - patient assembling point, TMU - temporary medical unit, EMS - emergency medical service centre, H - internal hospital, HL1 – healthcare provider in layer 1, HL2 – healthcare provider in layer 2, EH - external HP, CMO - charity/ municipal organisation, R - Reds, Y - Yellows, G - Greens, dr - doctor, nr - nurse, fr - first responder, fb - field bed, fm – field mattress, eb - emergency bed, ch - chair, ach - additional chair for the upper-bound capacity, pa - patient transport ambulance, ba - basic life support ambulance, ad - advanced life support ambulance, pc - private car, N/A - Not applicable, / - or, Normal distribution is in the form of $N(\mu, \sigma^2)$

5.5 Computation setup

The simulation models were developed in Arena Simulation Enterprise Suite version 14.0. All experiments were conducted on a computer with a 3GHz processor, Intel Core i5-9500E, 8 GB RAM, and 64-bit Windows 10 Professional operating system. The number of replications performed per experimental condition was 1,000 with 95% confidence intervals following the suggestions by Robinson (2005) and Karnon et al. (2012) that at least 100 replications are required to provide performance accuracy of the models. In each replication, the models were run until all patients were treated. There was no warm-up period included because the real-world activities of collaboration in an emergency medical response start from an empty and idle state. Before the disasters, there is no affected patients, and also none of resources is allocated to the PAPs/TMUs.

5.6 Validation and verification

The model validation and verification are essential to demonstrate the model's credibility and require the data from the real-world system. So far, there have been two events in Phuket that affect many victims and need emergency medical response. These events are Tsunami in 2004 and boat capsizing in 2018. We cannot use Tsunami 2004 disaster for the model validation and verification because none of measures were recorded in that event. Thus, the event of boat capsizing in 2018 was used to validate and verify the models. Strategy 2 was in place in response to that event. The allocation of resources and patients were carried out as presented in Figure 4.3.

Unfortunately, we cannot validate and verify the models of Strategy 1 and 3 as the required data were not available. Specifically, Strategy 1 was implemented in response to Tsunami in Phuket, while Strategy 3 is a collaborative care strategy that we propose and that has not been implemented yet. However, validating Strategy 2 allows us to validate some activities of Strategy 1 and 3 including resource assignment and treatment provision of patients. The resources are assigned to patients according to priority scheme and FCFS within the category.

We use two techniques for validating the models including expert intuition and a statistical approach, which are widely used in simulation studies (Kleindorfer et al., 1998; Brailsford et al., 2019).

During the model development, the healthcare authorities who were interviewed in the stage of data collection validated the components and input parameters which are listed in Table 5.1, Table 5.3, and Table 5.4 in the computerised models for accuracy. They were checked against the data collected in interviews. The model is further validated by using the paired t-test analysis. This method involves comparing the model outputs of selected measures with the system outputs.

Several measures can be used for the model validation such as the average waiting time at the TMUs, length of stay, transportation and treatment time. Unfortunately, such data were not recorded during the event. We thus validate four available measures including the number of patients in different categories at TMUs, resource allocation, patient allocation, and average waiting time at HPs. Table 5.5, Table 5.6, Table 5.7, and Table 5.8 present the observed historical data and results from the simulation model and the results of statistical analysis.

Table 5.5 Comparative analysis of number of patients in different categories at TMU

Measures	**Observed**	**Simulated**	**Half width**
Number of Yellows at TMU A	3	2.80	0.09
Number of Greens at TMU A	7	6.69	0.09
Number of Reds at TMU B	3	3.23	0.11
Number of Yellows at TMU B	4	4.29	0.13
Number of Greens at TMU B	29	27.95	0.15
P-value ($\alpha = 0.05$)	0.42		

Table 5.6 Comparative analysis of resource allocation

Measures	**Observed**	**Simulated**	**Half width**
Number of doctors allocated to TMU A	5	5.00	0.00
Number of nurses allocated to TMU A	15	15.00	0.00
Number of FRs allocated to TMU A	12	12.00	0.00
Number of basic ambulances allocated to TMU A	6	6.00	0.00
Number of advanced ambulances allocated to TMU A	3	3.00	0.00
Number of doctors allocated to TMU B	5	5.61	0.03
Number of nurses allocated to TMU B	15	16.82	0.09
Number of FRs allocated to TMU B	12	12.00	0.00

Measures	Observed	Simulated	Half width
Number of basic ambulances allocated to TMU B	6	6.00	0.00
Number of advanced ambulances allocated to TMU B	3	3.00	0.00
P-value (α = 0.05)	0.22		

Table 5.7 Comparative analysis of patient allocation

Measures	Observed	Simulated	Half width
Number of Reds transported to EMS 2	0	0.01	0.00
Number of Yellows transported to H 2	3	2.29	0.09
Number of Greens transported to H 2	3	2.64	0.19
Number of Yellows transported to H 3	2	2.29	0.09
Number of Greens transported to H 3	3	2.59	0.19
Number of Reds transported to H 6	3	3.23	0.11
Number of Yellows transported to H 6	2	2.34	0.09
Number of Greens transported to H 6	8	5.58	0.20
Number of Reds re-transported to EMS	0	0.01	0.00
P-value (α = 0.05)	0.27		

Table 5.8 Comparative analysis of average waiting time at HPs

Measures	Observed	Simulated	Half width
Average waiting time of Reds (hours)	0.53	0.54	0.03
Average waiting time of Yellows (hours)	0.35	0.37	0.02
Average waiting time of Greens (hours)	0.90	0.83	0.03
P-value (α = 0.05)	0.74		

In all cases, the statistical results show that the simulated outputs fall within the 95% confidence interval. These is no significant difference between the simulated and observed data. Therefore, from the statistical perspective, the baseline simulation model is considered to adequately represent the real-world system under the assumptions which were made.

In addition, the model logic is verified to ensure that the allocation of resources and patients follows the real-world activities of emergency medical response. The model verification is achieved by using both visual confirmation of the model through Arena's interactive animation environment, as well as inspection of the source code of the simulation. These techniques are widely used in simulation studies (Abo-Hamad & Arisha, 2013; Glasgow et al., 2018; Gul et al., 2020). The healthcare authorities also verified the visual inspection of the model, which ensures the accuracy of the flow of patients, staff, and ambulances.

Figure 5.1, Figure 5.2, and Figure 5.3 illustrate the screenshots of simulation animation developed in Arena's interactive animation environment. In these figures, the flow of patients is from left-to-right. The doctors, nurse, and FRs at the top of the figures are the available staff waiting for upcoming patients. The circles represent the queue of the corresponding patient categories waiting to be allocated to resources. The white boxes represent the idle state of bed/mattress/chair which turn to green when such resources are busy.

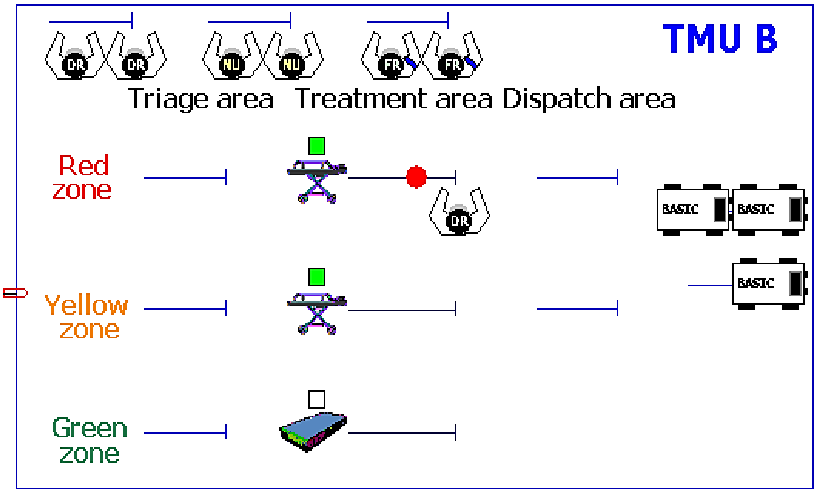


Figure 5.1 The screenshot of TMU activities

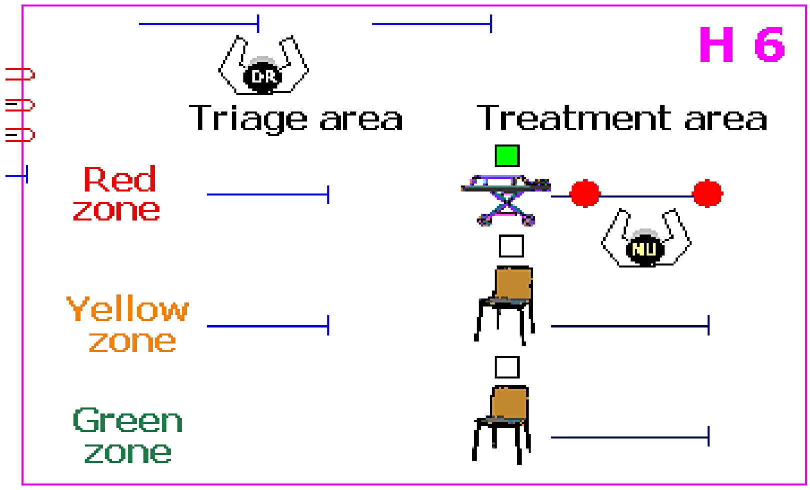


Figure 5.2 The screenshot of HP activities

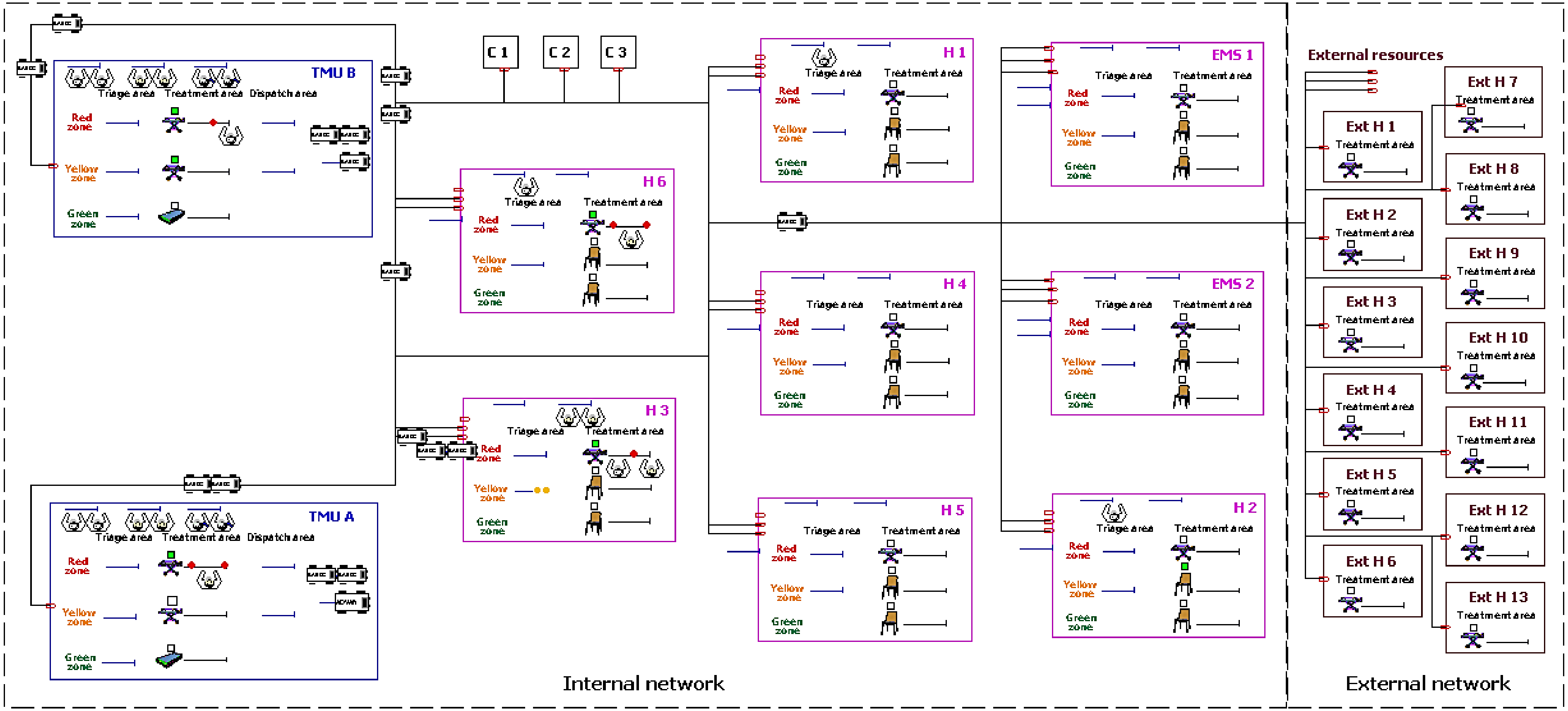


Figure 5.3 The screenshot of network-level activities

5.7 Resilience metrics

The studies by Bruneau & Reinhorn (2007), Cimellaro et al. (2010), and Henry & Ramirez-Marquez (2012) provide different resilience metrics developed for disasters. The consensus among them is that resilience metrics should incorporate two components: an estimation of the loss and an estimation of the recovery. In the field of medical management, the loss estimation includes the deterioration of healthcare performance, and counts of deaths and untreated patients. These measures are based on the fact that the healthcare resources are often short during disasters even if some emergency medical plans have been developed in advance. The recovery estimation includes the recovery rate and recovery time. These measures are in agreement with the classic definition of resilience (Bruneau et al., 2003) as the ability of a system to recover to the normal condition or the acceptable levels as quickly as possible.

Although Section 2.5 presents the metrics of resilience used in healthcare disaster context, these metrics only show the state of healthcare network during disasters without comparison to the non-disaster state of healthcare network. As such, these metrics cannot be used to show the restoration of resilience. In this regard, we adapt the generic metric of resilience proposed by Henry & Ramirez-Marquez (2012) to suit the healthcare context, whereas Bruneau & Reinhorn (2007) and Cimellaro et al. (2010) provide metrics for infrastructure and facilities. The metric by Henry & Ramirez-Marquez (2012) is formulated as time dependent function and is in agreement with the concept of resilience that is the ability of a system to "bounce back" (Bruneau et al., 2003). The adapted metric describes the ratio of recovery rate at time t to maximum loss rate most by the system and incorporates the state of healthcare network during the disaster event and the non-disaster environment. In such a way, the adapted metric can be used to show the resilience curve through the simulated time period. Furthermore, Henry & Ramirez-Marquez (2012) demonstrated the applicability of the proposed metric of resilience in the road network during the defined disruptive events causing the blockage of roads. They illustrated the impact of different strategies on the restoration of resilience in the events.

Let us denote the resilience at time t by $R(t)$, which is measured by the ratio of recovery rate at time t to maximum loss rate at $t > 0$ suffered by the system and is calculated using the following formula.

$$R(t) = \frac{Recovery\ rate\ (t)}{Loss\ rate} = \frac{h(t) - h^{-}}{h(0) - h^{-}} \tag{5.1}$$

In this formula, $h(t)$ is the state of the healthcare network at time t, where $t = 0$ is the time before a disaster occurs, and $t \geq 1$ is the time in a disaster event; h^{-} is the worst possible state of the healthcare network in a disaster event.

Based on formula (5.1), $R(t) \in [0,1]$, and $R(t) = 1$ implies that the healthcare network has been fully recovered from the disrupted state to the normal state i.e., $h(t) = h(0)$.

According to formula (5.1), we define two resilience metrics based on the average weighted patient waiting time at time t $\left(W(t)\right)$, denoted by $RW(t)$, and the weighted number of patients at time t whose waiting time exceeds the clinically appropriate timeframe $(Q(t))$ denoted by $RQ(t)$. The timeframe is the target waiting time which is defined in the Australasian Triage Scale and is widely used to ensure that patients presenting to an emergency department are treated within their threshold (Acem.org.au, 2000). These two metrics are then calculated using the following formulas, which are adopted from (5.1).

$$RW(t) = \frac{W(t) - W^{-}}{W(0) - W^{-}} \tag{5.2}$$

$$RQ(t) = \frac{Q(t) - Q^{-}}{Q(0) - Q^{-}} \tag{5.3}$$

We calculate $W(t)$ and $Q(t)$ using the following formulas.

$$W(t) = \sum_{p=1}^{P} \beta_p \overline{w}_p(t)\,, where\ \overline{w}_p(t) = \frac{\sum_{n=1}^{N_P(t)} w_p^n(t)}{N_P(t)}\ and \sum_{p=1}^{P} \beta_p = 1 \tag{5.4}$$

$$Q(t) = \sum_{p=1}^{P} \sum_{n=1}^{N_p(t)} \beta_p q_p^n(t)\,, where\ q_p^n(t) = \begin{cases} 1\ if\ \ w_p^n(t) > w_p^{'} \\ 0, otherwise \end{cases}\ and \sum_{p=1}^{P} \beta_p = 1 \tag{5.5}$$

In formula (5.4) and (5.5), β_p and $\overline{w}_p(t)$ are the priority level and the average waiting time at time t of the patients with triage level p, respectively. We indicate the Reds, Yellows and Greens, by p values of 1, 2 and 3, respectively.

Throughout the thesis, we use the priority levels as follws; a $\beta_1 = 0.8, \beta_2 = 0.15$ and $\beta_3 = 0.05$. Please note that the values of β_p are defined based on the fact that Reds are the first priority, Yellows are the second priority, and Greens are the third priority. Thus, the highest value is given to β_1, whereas the lowest value is given to β_3. To the best of my knowledge, no literature investigates the appropriateness of defining these values. It is difficult to justify these values. Thus, these values are subjective and estimated based on intuition. A measure of $\overline{w}_p(t)$ incorporates a waiting time of patient n from triage level p at time t ($w_p^n(t)$) and the total number of patients in triage level p at time ($N_p(t)$). A binary parameter $q_p^n(t)$ equals to 1 if patient n from triage level p at time t has a waiting time that exceed the defined threshold $w_p^{'}$, which denotes the target waiting time for the medical treatments of patients in triage level p. The values of $w_1^{'}$, $w_2^{'}$ and $w_3^{'}$ are 0, 30, and 60 minutes, respectively, which are defined in the Australasian Triage Scale.

To estimate the state of the healthcare network at time t in a disaster event ($h(t), t \geq 1)$) in the simulation models, we measure both $W(t)$ and $Q(t)$ when patients are in the queue waiting for available staff and bed/mattress/chair at TMUs, and internal and external HPs. In each scenario to be defined in our experiments, we consider all values of $W(t)$ and $Q(t)$ from three strategies in order to estimate the worst possible state of healthcare network in a disaster event (h^{-}). The highest values of $W(t)$ and $Q(t)$, denoted by W^{-} and Q^{-} respectively, show the worst $W(t)$ and $Q(t)$ in that scenario.

The state of healthcare network in a pre-disaster event ($h(0)$) is determined by the average weighted patient waiting time in no-disaster environment ($W(0)$) and the weighted number of patients in no-disaster environment whose waiting time exceeds their threshold ($Q(0)$). We use the data in the real-world emergency departments in Phuket, Thailand to calculate the values for $W(0)$ and $Q(0)$. All emergency departments in Phuket, which are located in 2 EMS centres and 6 hospitals, are included. The data on waiting time for medical treatments in a one-year period, between 1st of January and 31st of December 2019, were collected to cover all seasons. There was no mass casualty incident, and it was before the SARS-CoV-2 pandemic started in Thailand. The waiting time for medical treatments included the time when a patient was in the queue waiting for available staff and bed. The data which represent the state of healthcare network in no-disaster environment are given in Table 5.9. We indicate the Reds, Yellows and Greens, by p values of 1, 2 and 3, respectively.

Table 5.9 State of healthcare network in the pre-disaster condition ($h(0)$)

Measures	$p = 1$	$p = 2$	$p = 3$	Value
$\overline{w}_p(0)$ (hours)	0	0.56	1.11	$W(0) = 0.14$
$\sum_{n=1}^{N_p(0)} q_p^n(0)$ (patients)	0	116	280	$Q(0) = 31.4$

5.8 Summary

This chapter presents the development of DES models of strategies for collaboration in healthcare network. A list of modelling assumptions is defined, which were agreed in discussions with the healthcare authorities in Phuket. In the models, patients, ambulances, and staff are defined as entities, while beds, mattresses, and chairs are resources at TMUs and HPs. The flowchart diagrams of different strategies are presented. These diagrams show how initial treatment is provided to patients, how internal and external resources are allocated, and how patient transportation operates in each of the strategies for collaboration in healthcare network. Some input parameters are set by the healthcare authorities, while some of them are based on the historical data recorded during the disaster events. For computation setup, the models are run for 1,000 replications with 95% confidence intervals per experimental condition. No warm-up period is included as the practice of collaboration in an emergency medical response starts from an idle state. We utilise the data in the boat capsizing in Phuket in 2018 for model validation and verification and use the case of the Tsunami in Phuket in 2004 for the experiments on the effectiveness of strategies in response to a disaster. Both expert opinion and a statistical approach are used to validate the model. Model verification is achieved by using the visual inspection of the model which ensures the accuracy of the flow of patients, staff, and ambulances, and by using the inspection of the source code of the simulation. For the simulation experiments, the focus was understanding the impact on resilience of using different strategies for collaboration in healthcare network. We adapt a generic resilience metric proposed in the literature to suit the healthcare context. The resilience metric is a function of time and incorporates the recovery and loss rate.

The resilience metric is a function of time and incorporates the recovery and loss rate, which are estimated by determining the state of the healthcare network during and before a disaster. We measure resilience based on the average weighted patient waiting time at time t and the weighted number of patients at time t whose waiting time exceeds the target waiting time. The waiting time includes the time when a patient is in the queue waiting for available resources.

Chapter 6 Simulation experiments

Data on the 2004 Tsunami are used to investigate the impacts of non-collaborative and two collaborative care strategies on resilience metrics. We then compare resilience across different defined disaster scenarios.

6.1 Resilience in base case

The base case refers to the model setting with the input parameters given in Table 5.4.

Figure 6.1 illustrates $RW(t)$ and $RQ(t)$ of different strategies in the base case. The vertical axis shows resilience level, while the horizontal axis is time t, where $t = 0$ is the time in a pre-disaster event, and $t \geq 1$ is the time since a disaster event has occurred. The discretisation step is 1 day; S1, S2, S3 refer to Strategy 1 (non-collaborative care), 2 (semi-collaborative care) and 3 (new collaborative care), respectively; the values of W^{-} and Q^{-} are positioned next to the strategy that yields the worst $W(t)$ and $Q(t)$, respectively in the base case.

It is evident that Strategy 3 is superior in both metrics, followed by Strategy 1 and 2. Particularly, $RW(t)$ and $RQ(t)$ of Strategy 3 drop to 0.92 and 0.63, respectively on day 1, then reach 1 on day 2. The base case causes the lowest resilience in Strategy 2 for both metrics. Both $RW(t)$ and $RQ(t)$ of Strategy 2 decrease considerably to 0 on day 1 and take 7 days to reach the pre-disaster condition. Similarly, these metrics of Strategy 1 fall sharply on day 1, then rise gradually to 1 by day 5. However, Strategy 1 seems to provide better resilience compared to Strategy 2. Strategy 1 spends fewer days to recover from the disruptive condition and provides higher resilience level in both metrics.

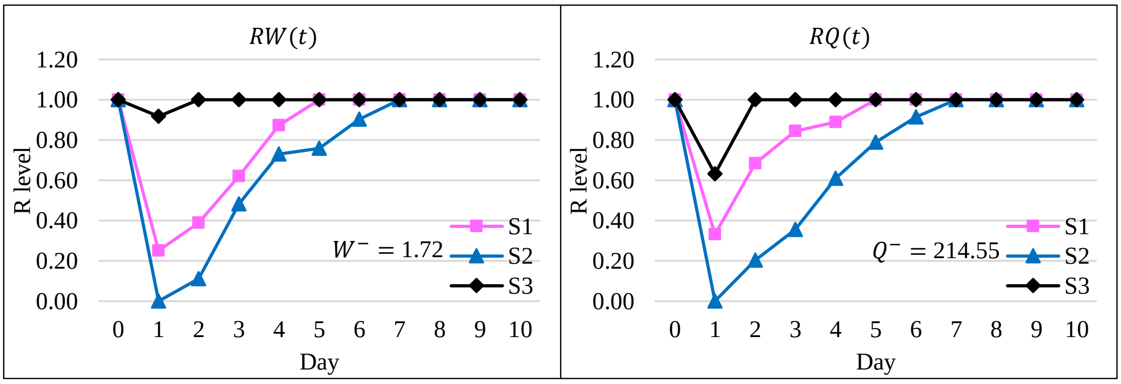


Figure 6.1 Resilience metrics in base case

To gain insights into the impact of strategies on resilience improvement, we also investigate how $RW(t)$ and $RQ(t)$ of different strategies change in the first 24 hours (see Figure 6.2).

In the first hour of the disaster event, some patients are evacuated to the nearest PAPs/TMUs, while the internal resources including staff and ambulances are still on the way to the opened PAPs/TMUs. These patients need to wait for the medical services at the PAPs/TMUs. Consequently, in the first hour, both $RW(t)$ and $RQ(t)$ sharply drop to 0.46 and 0.35, respectively.

After 1 hour, the allocated resources arrive at the PAPs/TMUs. Different strategies yield resilience differently. In the first 10 hours, Strategy 2 performs well. Both $RW(t)$ and $RQ(t)$ of Strategy 2 are higher than the ones of other strategies. One reason is that Strategy 2 provides the treatments to Reds and Yellows at the TMUs, whereas Strategy 1 and 3 need to transport them to the HPs for treatment. In addition, Strategy 1 outperforms Strategy 3 in both $RW(t)$ and $RQ(t)$ because Strategy 1 transports patients to the HPs with the shortest travel time, while Strategy 3 transports them to the HPs considering both resource availability and shortest travel time. It is possible that the assigned HP is not the nearest HP one. For example, it may happen that Reds are transported to the second nearest HL1 where the resources to treat severe injuries are available. Thus, in the first 10 hours, patients can be treated within a shorter time when they are transported to the nearest HPs.

However, after 10 hours, both $RW(t)$ and $RQ(t)$ of Strategy 1 and 2 continually drop, while they gradually rise in Strategy 3. For Strategy 1, we found that the patient transportation to the nearest HPs, regardless of the resource availability, causes the congestion at that HPs later. Patients experience a high waiting time, as presented in Table 6.1, because they are stuck in the queue waiting for available resources. In Strategy 1, $\bar{w}_1(7)$ is 3.39 hours, $\bar{w}_2(7)$ is 1.91 hours, while $\bar{w}_3(7)$ is 10.13 hours, where $\bar{w}_1(t), \bar{w}_2(t), \bar{w}_3(t)$ are the average waiting time at time t of Reds, Yellows, and Greens, respectively. These waiting times are measured until all patients are treated and that is on day 7. For Strategy 2, we found that the TMU role defined in the current emergency medical response, that is a provision of treatments to Reds and Yellows, causes the congestion at the TMUs. Reds and Yellows are in the queue for available staff at the TMUs. The number of staff at the TMUs is much lower than at the HPs. Approximately 10 doctors and 30 nurses are allocated to the TMUs, whereas the number of these resources at the HPs is at least doubled as shown in Table 5.4. Consequently, Reds and Yellows encounter the highest waiting time if they are required to be treated at the TMUs. In Strategy 2, $\bar{w}_1(7)$ and $\bar{w}_2(7)$ is 5.17 and 8.43 hours, respectively, which are higher values compared to Strategy 1. However, $\bar{w}_3(7)$ of Strategy 2 is 4.86 hours which is lower than the one of Strategy 1. The reason is that Strategy 2 provides the treatments to Greens at either TMUs or HPs and discharges them, whereas Strategy 1 requires all Greens to be treated at the HPs only. In Strategy 3, TMUs are used to provide the treatments to Greens only, thereby improving both $RW(t)$ and $RQ(t)$ in long term. Particularly, when Reds and Yellows arrive at the TMUs, they are transported to the HPs immediately, they do not need to wait to receive the treatments. The decision on patient transportation is made considering both resource availability and shortest travel time. Thus, they are treated at the first assigned HP (with no re-transportation of Red). In Strategy 3, $\bar{w}_1(7)$, $\bar{w}_2(7)$, $\bar{w}_3(7)$ are 0.32, 0.11, and 1.31 hours, respectively, and these are the smallest values across the strategies.

Table 6.1 $\bar{w}_p(t)$ of strategies

Strategy		*(hours)*	
	$\bar{\boldsymbol{w}}_{\mathbf{1}}(\mathbf{7})$	$\bar{\boldsymbol{w}}_{\mathbf{2}}(\mathbf{7})$	$\bar{\boldsymbol{w}}_{\mathbf{3}}(\mathbf{7})$
1	3.39	1.91	10.13
2	5.17	8.43	4.86
3	0.32	0.11	1.31

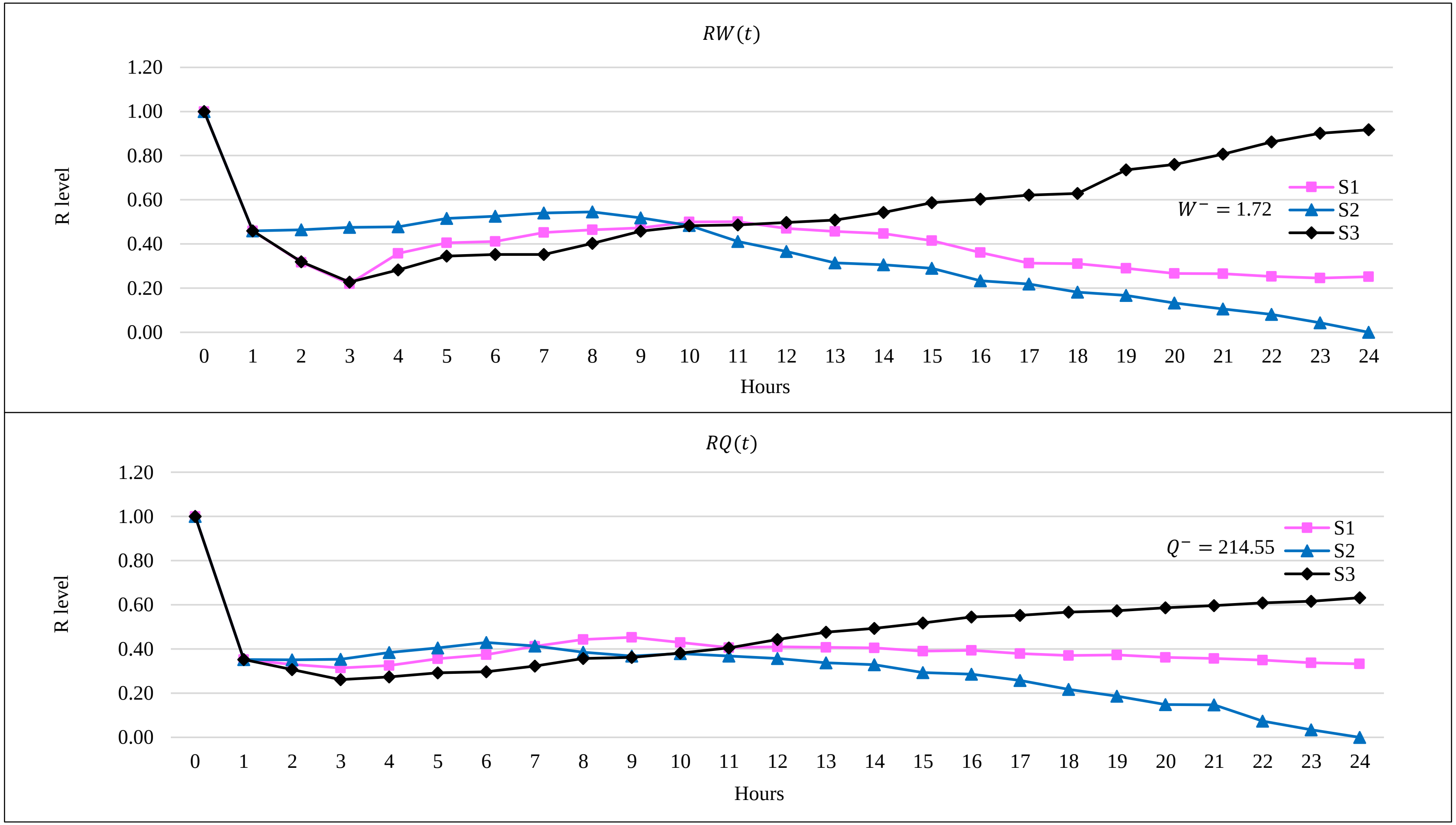


Figure 6.2 Resilience metrics in base case in the first 24 hours

6.2 Disaster scenarios

We have discussed with the healthcare authorities how to define the simulation scenarios. These scenaios reflect the possible characteristics of real-world disasters. We consider the definitions of disruption levels adopted from the study by Crowe et al. (2014) including mild, moderate and severe disruption. Simulation scenarios are defined to examine the impact of variation in demand, healthcare capacity, and patient transportation on the strategy performance in the perspective of resilience. The scenarios to be simulated are given in Table 6.2.

Table 6.2 Simulation scenarios

Scenarios	**Mild**	**Moderate**	**Severe**
1. Time between patient arrivals	30 minutes	15 minutes	5 minutes
2. Probability of patient category[1]	40 : 30 : 30	60 : 30 : 10	80 : 15 : 5
3. Total number of patients[2]	$N(500, 625)$	$N(2000, 3600)$	$N(3500, 9025)$
4. Percentage of resource availability	80	70	60
5. Probability of Greens transported using cars	40	50	60

Note: 1 - Reds : Yellows : Greens, 2 - Normal distribution is in the form of $N(\mu, \sigma^2)$

In each scenario, one of the input parameters is changed with a value given in Table 6.2, while the remaining ones have the values given in Table 5.4. For example, in Scenario 1, the time between patient arrivals is changed to 30, 15, and 5 minutes, while other input parameters remain the same as given in Table 5.4. The values given in Table 6.2 are used in the simulation experiments to compare the performance of different strategies for collaboration in a healthcare network, not to compare them with the base case.

The following subsections present the effects of disaster scenarios on resilience. The chart titles denote the resilience metric in different disruption levels. For example, the chart entitled "$RW(t)$ – mild" shows the $RW(t)$ in the mild disruption. The vertical axis shows the resilience level, while the horizontal axis shows time t, where $t = 0$ is the time before the disaster event, and $t \geq 1$ is the time since the event has occurred. The discretisation step is 1 day; and S1, S2, S3 refer to Strategy 1, 2, 3, respectively. The values of W^- and Q^- are positioned next to the strategy that yields the worst $W(t)$ and $Q(t)$, respectively in each scenario.

Scenario 1: *Time between patient arrivals*

Disasters creat a surge of demand for emergency medical services. Using simulation allows us to model the surge of demand in several aspects. One of them is changes in the time between patient arrivals. We set 30, 15, and 5 minutes of time between patient arrivals in mild, moderate, and severe disruptions, respectively. The effects are illustrated in Figure 6.3.

As expected, when the disruption is more severe, resilience of all strategies decreases. Strategy 3 is superior in both $RW(t)$ and $RQ(t)$, followed by Strategy 1 and 2. These metrics in Strategy 3 are not only superior to other strategies, but they also regain 1 in a shorter time. These effects can be found in all scenarios. For instance, in Figure 6.3, $RW(1)$ of Strategy 3 slightly decreases to 0.98, 0.96, and 0.92 when the disaster disruption is mild, moderate, and severe, respectively. Then, this measure reaches the pre-disaster condition on day 2 in all disruption levels. In contrast, $RW(1)$ of other strategies fall sharply to below 0.7 and take at least 3 days to reach the pre-disaster conditions, i.e., 1.

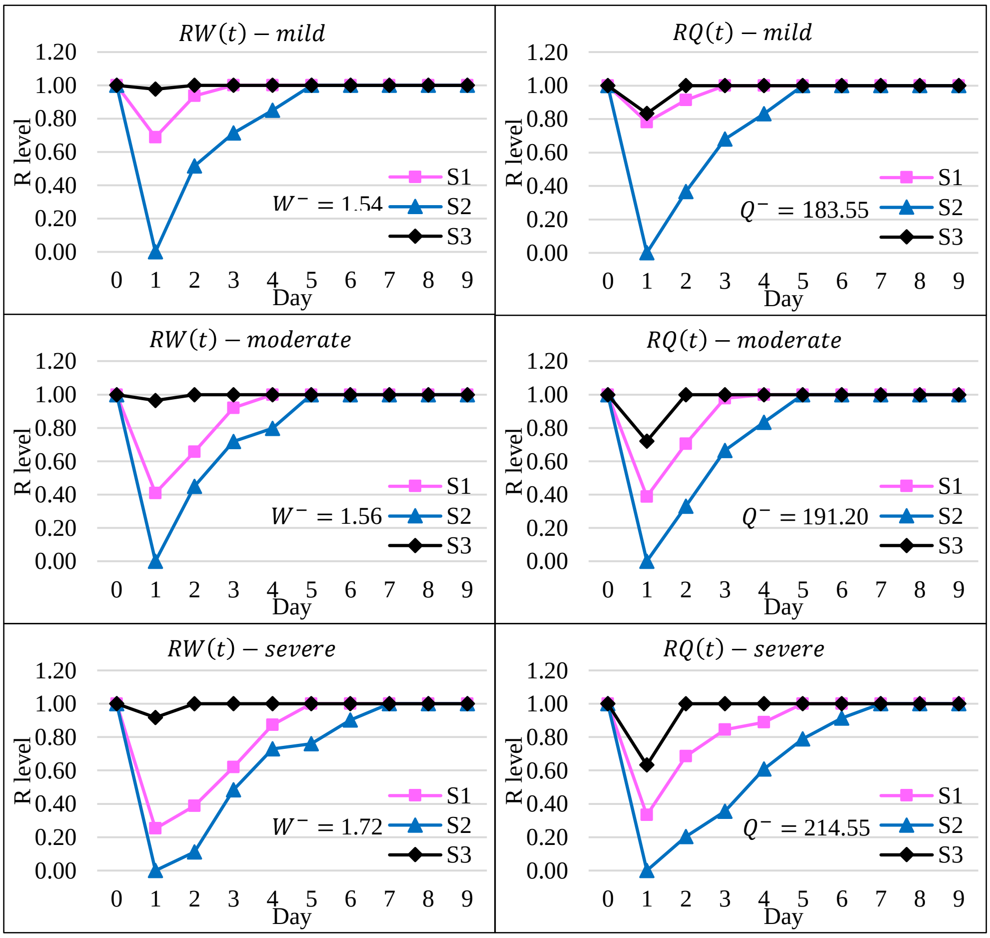


Figure 6.3 Effect of different time between patient arrivals on resilience metrics

Scenario 2: *Probability of patient category*

Another aspect of the surge of demand is changes in the probability of patient category. We simulate different probabilities of patient category as listed in Table 6.2. Figure 6.4 illustrates their effects on $RW(t)$ and $RQ(t)$.

This form of demand surge also adversely affects the resilience. Especially, $RW(1)$ and $RQ(1)$ of Strategy 1 suddenly fall to 0.13 and 0.38, respectively, even if the disruption is mild. These metrics of Strategy 1 are getting worse when the disruption is severe, in which $RW(1)$ and $RQ(1)$ drop to 0.05 and 0.34, respectively. On the other hand, $RW(1)$ and $RQ(1)$ of Strategy 2 drop to 0 in all disruption level.

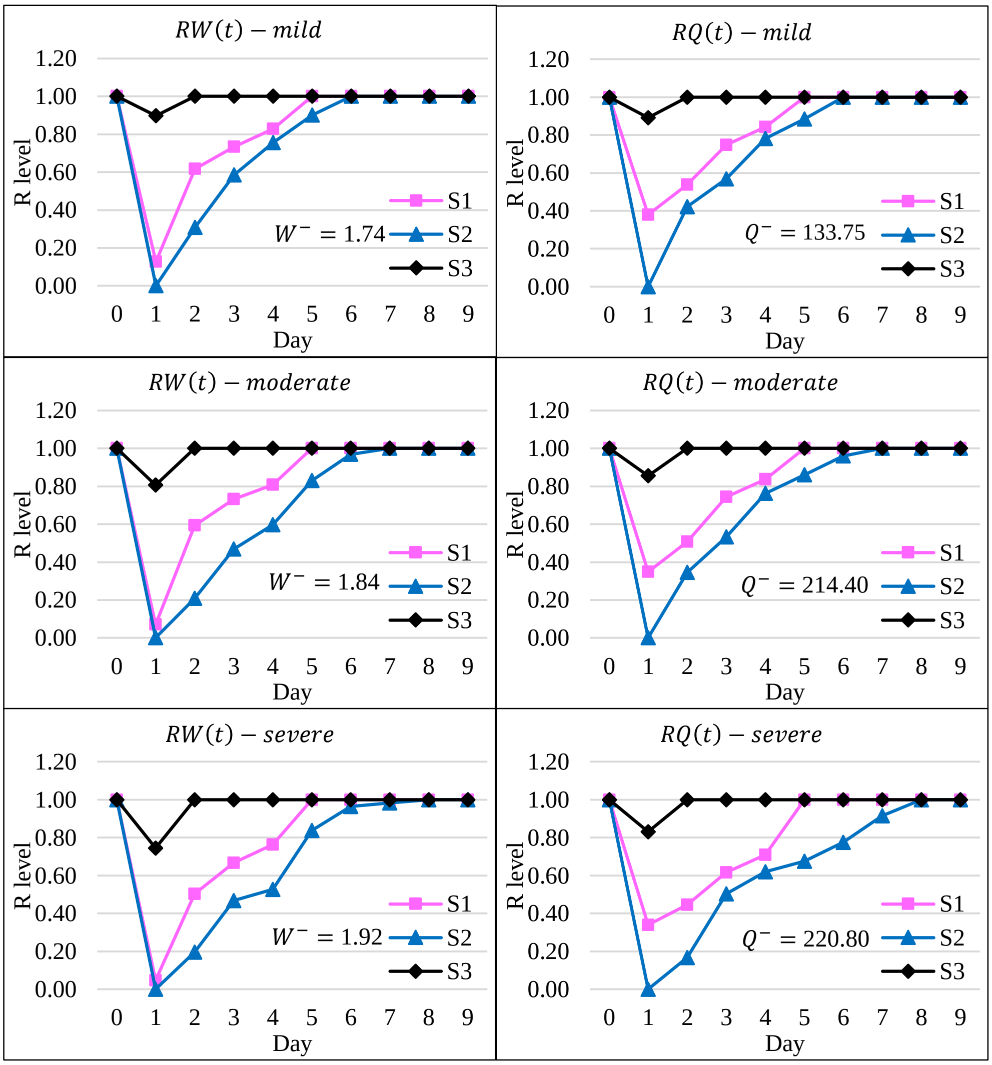


Figure 6.4 Effect of different probability of patient category on resilience metrics

Scenario 3: *Total number of patients*

In this scenario, we investigate the impact of different number of patients, including 500, 2,000, and 3,500 patients, on the strategy performance (see Figure 6.5).

Compared to other scenarios, the high number of patients in severe disruption causes the highest values of the worst average patient waiting time (W^{-}) and of the worst number of patients whose waiting time exceeds their threshold (Q^{-}), which are 2.59 and 305.85, respectively. The severe disruption also causes the lowest $RQ(1)$ in Strategy 3, which equals 0.47. Interestingly, when the total number of patients is small as in mild disruption, $RW(t)$ and $RQ(t)$ of Strategy 2 are better than the ones of Strategy 1. These metrics of Strategy 1 equal to 0 as shown in Figure 6.5. One reason is that the TMU capacities in Strategy 2 are enough to provide the medical services to the small number of patients.

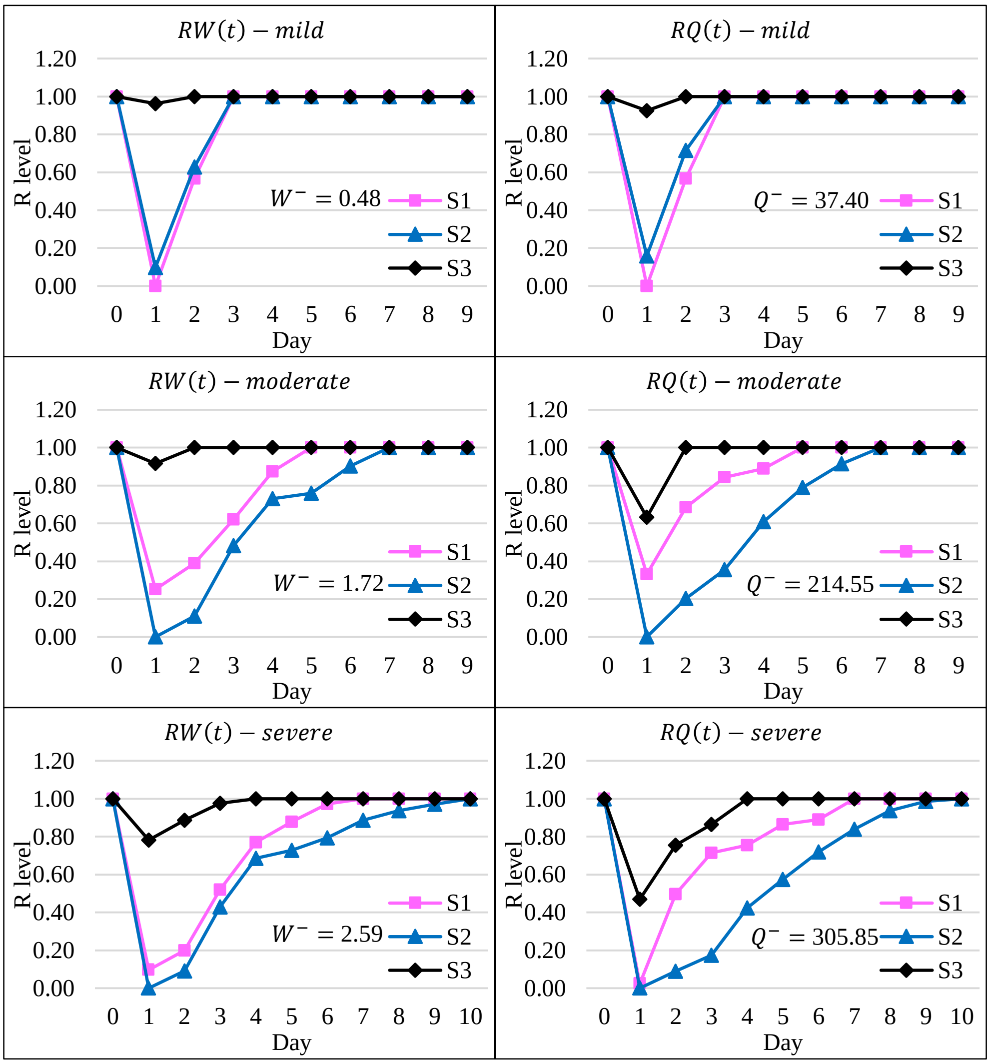


Figure 6.5 Effect of different number of patients on resilience metrics

To highlight the effectiveness of Strategy 2, we further investigate the impact of small number of patients on resilience, when there are 200 patients. This number is smaller than the number defined in the mild disruption described by $N(500, 625)$ and is still considered as a disaster (Ritchie & Roser, 2021). As Figure 6.6 shown, Strategy 2 yields more resilience than Strategy 1. Particularly, $RW(1)$ and $RQ(1)$ of Strategy 2 is 0.42 and 0.41, respectively, while these metrics drop to 0 in Strategy 1. However, Strategy 3 still performs well in this case.

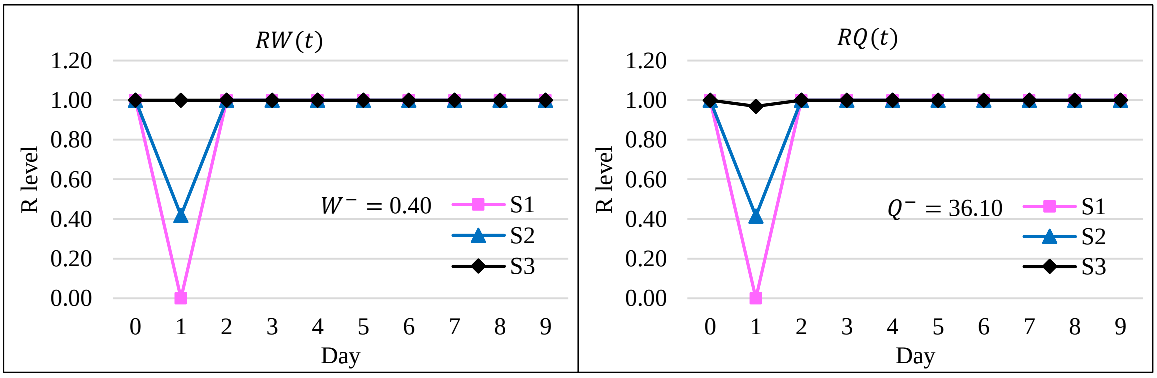


Figure 6.6 Effect of small number of patients on resilience metrics

Scenario 4: *Percentage of resource availability*

In real-world, the HPs cannot discharge all existing patients admitted before disasters. The HPs need to assign some staff and beds to existing patients. Such circumstance affects the availability of staff and beds for new patients affected by disasters. Thus, in this scenario, we simulate different levels of resource availability in the HPs, which is between $60 - 80\%$ of the full capacity of staff and beds.

As shown in Figure 6.7, the resource availability adversely affects resilience in all strategies. The lower availability of resources, the lower resilience, and the longer time is required to regain the state of the network before the disaster. Especially, $RW(1)$ and $RQ(1)$ of Strategy 2 suddenly drop to 0 and take at least a week to regain 1.

Compared to other scenarios, the severe disruption in the resource availability causes the second highest W^- and Q^- which are 2.25 and 262.70, respectively. This scenario also causes the lowest $RW(1)$ in Strategy 3, which is 0.64 and takes 3 days to regain 1. One reason is that Strategy 3 benefits from the resource availability for collaborative responses.

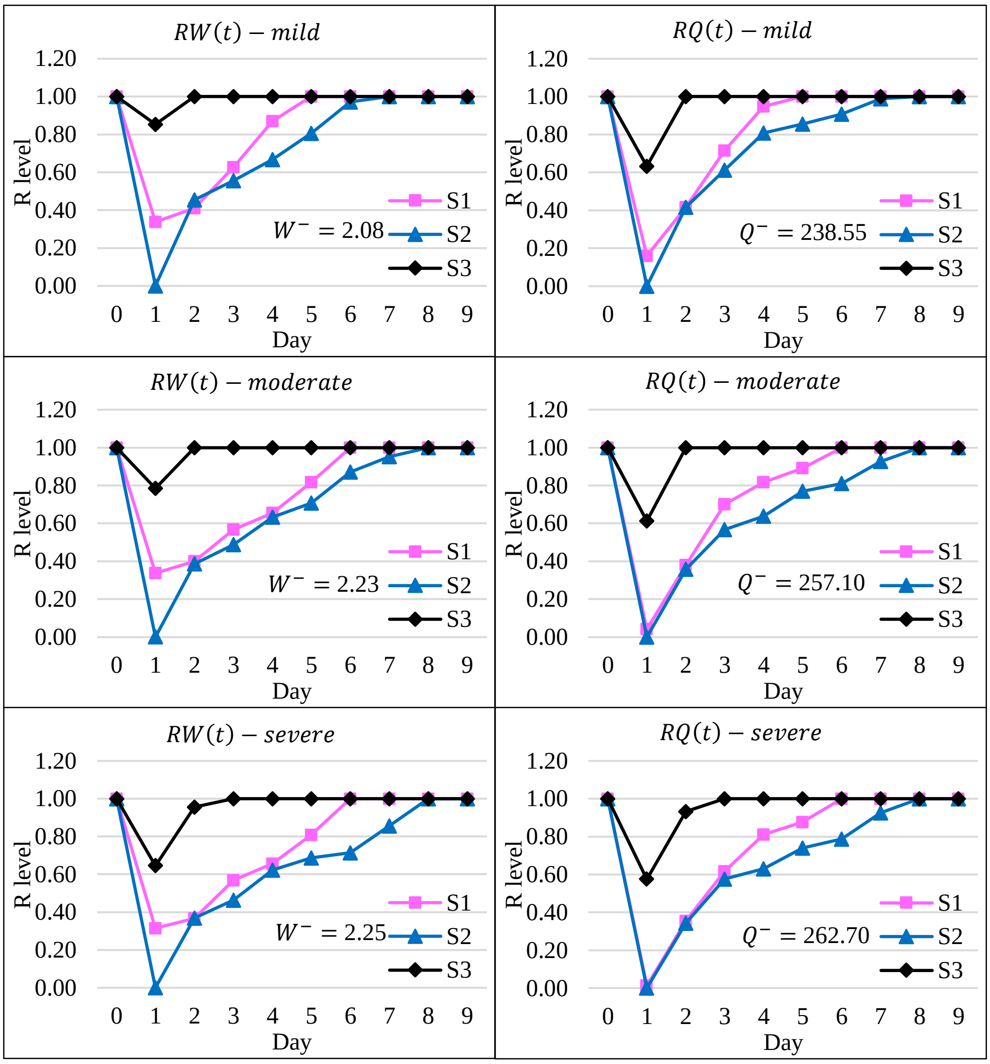


Figure 6.7 Effect of different percentage of resource availability on resilience metrics

Scenario 5: Probability of Greens transported using private cars

In the base case, private cars are not included in the model because Greens are transported to HPs by ambulances only. As such, the probability of Greens transported using cars is not in Table 5.4. According to the interviews, apart from ambulances, patients can be transported by taxi, private car, police car, helicopter, or even walk. Volunteers who lived nearby the affected areas offered their private cars for patient transportation during Tsunami in 2004. Approximately 50% of the Greens were transported to the HPs by private cars. Thus, we investigate the impact of different percentage of Greens, 40 – 60%, being transported to the HPs by private cars on resilience. However, only Greens can be transported to the HPs by private cars. Both Reds and Yellows need medical staff during the transportation since their health condition may change.

In Figure 6.8, we observe that an increase in the number of Greens being transported to the HPs causes a decrease in resilience in all strategies. For example, $RW(1)$ of Strategy 1 falls to 0.23, 0.20, and 0.15 in the mild, moderate, and severe disruption, respectively. One reason is that the healthcare resources are limited in response to a disaster. These resources are usually allocated to patients regarding the patient priority and patient arrival time. Greens may arrive at the HPs before patients in other categories. At the time of Green arrivals, the limited resources may be allocated to Greens immediately if no higher-category patient is waiting in the queue. However, this can cause a longer waiting time of higher- category patients when no resource is available at the time of their arrivals.

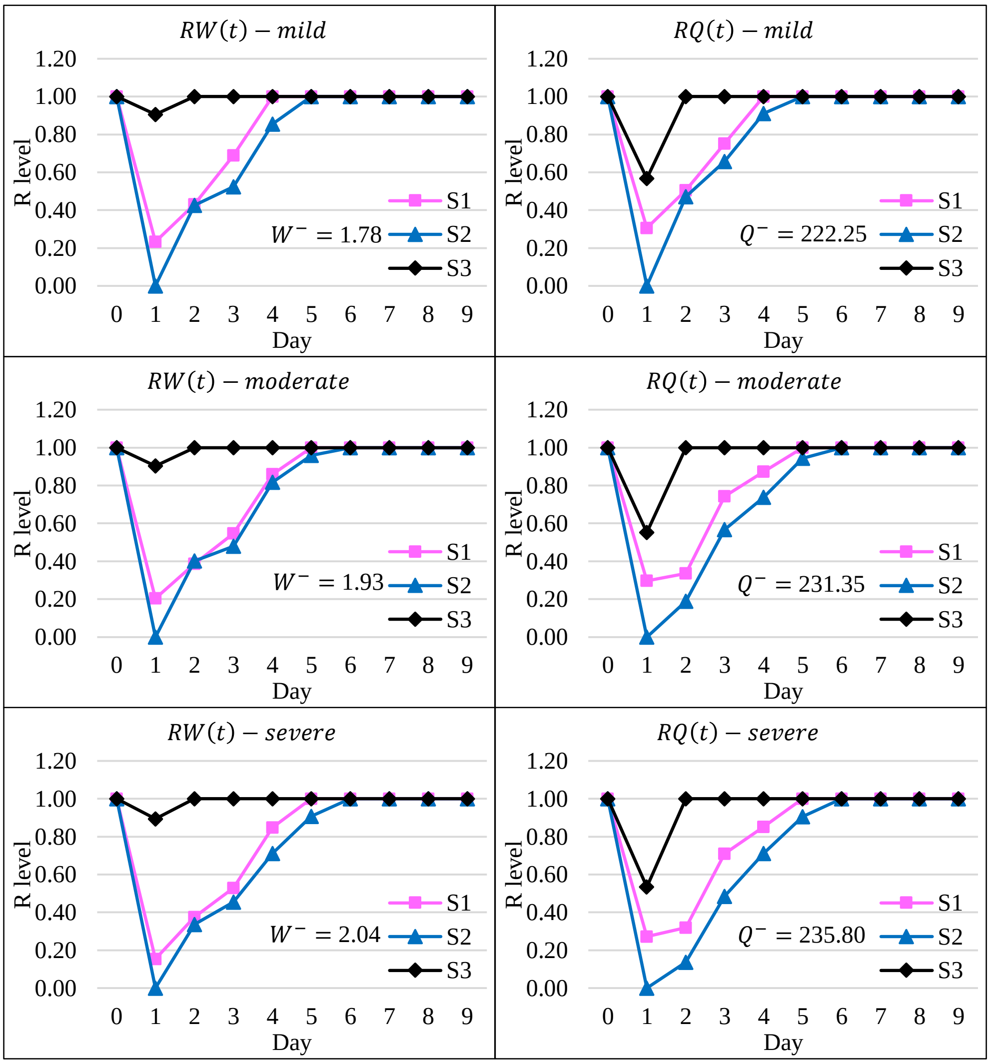


Figure 6.8 Effect of different probability of Greens transported using cars on resilience metrics

In real-world, several scenarios can happen simultaneously. Disasters affect a large number of patients in which the majority of them are Reds. Some Greens are transported to the HPs by private cars. The roles of HPs in providing treatments become even more critical during disasters because their resources need to be allocated to both existing and new patients affected by a disaster. In this regard, we investigate the impact of *extremely severe disruption* on resilience of different strategies. Input parameters as given in Table 5.4 are changed as follows. There are 3,500 affected patients in which 80% of them are Reds, 15% of them are Yellows, and 5% of them are Greens. Also, 60% of Greens are transported to the HPs by volunteers using their own cars; 60% of healthcare resources are available for the affected patients because the HPs need to allocate the rest of resources to the existing patients admitted before disasters.

The extremely severe disruption causes the worse resilience in all strategies as shown in Figure 6.9. Both W^- and Q^- are much higher than the ones in the previous scenarios. The former metric rises to 10.33 and the latter rises to 1,343.80. Strategy 1, 2, and 3 experience a plunge in $RW(1)$ which rapidly drops to 0.03, 0, and 0.59, respectively. Also, this effect can be found in $RQ(t)$. Especially, $RQ(1)$ of Strategy 3 sharply falls to 0.42. All strategies take longer time to reach the pre-disaster conditions, i.e., a resilience value of 1. Strategy 1, 2, and 3 take 9, 12, and 7 days, respectively.

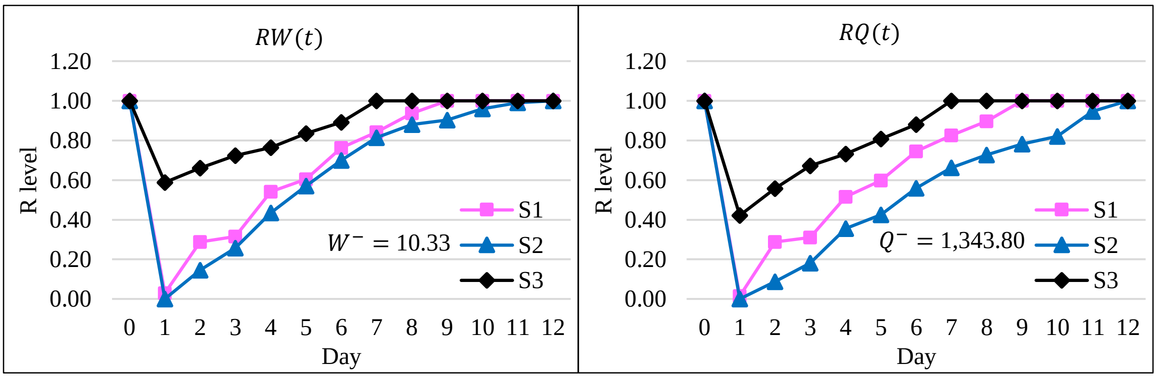


Figure 6.9 Effect of extremely severe disruption on resilience metrics

6.3 Managerial insights

The proposed Strategy 3 with collaborative care has a greater impact on the resilience improvement than Strategy 1 with non-collaborative care and Strategy 2 with semi-collaborative care. Strategy 3 can regain the pre-disaster state of healthcare network in a shorter time in all defined scenarios. Especially, it can regain the pre-disaster state of the network within 3 days in almost all scenarios, except in the severe level of disruption caused by the high number of affected patients and the low availability of healthcare resources; and in the extremely severe level of disruption described by mixed disaster scenarios. In contrast, Strategy 1 and 2 often yield a low resilience even in the case of mild disaster. Strategy 2 is more sensitive to disruption scenarios compared to Strategy 1. Strategy 1 generally takes between 2 and 9 days to reach the pre-disaster state, whereas Strategy 2 needs 4 - 12 days. However, when there are small number of affected patients, the resilience of Strategy 2 is better than the one of Strategy 1.

The simulation experiments in this study show how different strategies for the collaboration in a healthcare network can impact on resilience in the context of Phuket, Thailand. Strategy 3 includes the concept of collaboration which are HP categorisation, patient transportation considering resource availability and the shortest travel time, staff sharing across HPs, and TMU roles for minor treatment yield the highest resilience compared to other strategies in long term. Strategy 3 yields the highest resilience compared to other strategies in long term, but not always in the short term (first 10 hours). Therefore, we can conclude that improving the resilience during disasters requires collaborative response in the healthcare network. The response strategies should consider the following points:

(1) HPs should be categorised into groups by considering their availability of healthcare resources and their capabilities to provide emergency medical services. The HPs with higher capacity should be mainly responsible for high severe injuries, whereas the less severe-injured patients should be transported to the lower-capacity HPs. However, this can be only implemented in an urban area, e.g. Phuket, where HPs are not far apart.

(2) The information sharing is essential for patient allocation. The information on the resource availability should be shared between HPs in order to allocate the remaining affected patients effectively. By doing these, patients are transported to the HP that is the closest but also has the resources available.

(3) The decision on staff sharing should be made by taking into consideration the HP capabilities to handle severe and moderate injuries. Based on the performance of Strategy 3, we observe that the lower-capacity HPs should allocate their staff to the higher-capacity HPs in order to enhance the healthcare capacity for severe injuries in the network. However, this finding is based on the specific simulated scenarios in the context of Phuket, Thailand.

(4) Given the set of scenarios explored in this thesis and within the specific context of the health network in Phuket, the simulation experiments suggest that the design of TMU roles has an impact on the resilience improvement. The healthcare authorities state that the TMUs are set with the aim to provide the medical services to patients in a timely manner. To achieve the aim, Greens should be treated and discharged at the TMUs in order to reduce the overcrowding in the HPs. This has been observed in *Scenario 5: Probability of Greens transported using private cars* The resilience levels of all strategies are getting worse when more Greens are at the HPs. In addition, Reds and Yellows should be transported to the HPs as soon as possible in order to avoid a crowd of patients at the TMUs. Treating Reds and Yellows at the TMUs causes very high waiting time and ultimately causes the low level of resilience. This effect can be found in Strategy 2 in which these patients need to be treated at the TMUs before the patient transportation. Consequently, Strategy 2 provides the highest waiting time of Reds and Yellows as shown in Table 6.1 and the worst resilience level as shown in the defined scenarios.

We notice that even for the same disruption levels the resilience with respect to the average waiting time, $RW(t)$, and the number of patients with late treatments, $RQ(t)$, can behave differently. For example, in Figure 6.8, $RW(1)$ of Strategy 3 slightly decreases to 0.89, whereas its $RQ(1)$ sharply falls to 0.53 in the severe disruption. This phenomenon can also be found in other strategies. One reason can be that $Q(t)$ considers the number of patients whose waiting time exceed the threshold, while $W(t)$ considers the total waiting time. Even a small delay in providing treatment (0.00001 hour) exceeds the target waiting time causes an increase in $Q(t)$. On the other hand, such exceeding hour have a very low impact on the total waiting time which is one of components in $W(t)$. Thus, $RQ(t)$ is likely to be lower than or equal to $RW(t)$ in the same scenario.

To support this assumption, we found that the relation ($RQ(t) \leq RW(t)$) holds in 375 out of 450 cases (3 strategies × 5 scenarios × 3 disruption levels for each scenario × 10 days), which is 83% of the total number of cases. Please note that, 10 days are the longest period that the resilience takes to regain 1 in 5 scenarios. However, both $RW(t)$ and $RQ(t)$ reach 1 on the same day in all cases.

6.4 Discussion

Although the simulation experiments suggest that a new collaborative care strategy that we propose provide better resilience of the healthcare network during disasters, in practice it might take time to implement it and a trade-off between collaboration and how a quick response is may be required. We presented the findings to the executive board of Phuket Provincial Public Health and EMS centres in Phuket, Thailand. They acknowledged that the findings provided an important opportunity to advance the understanding of collaborative response and could directly contribute to the plan for the collaboration in an emergency medical response across a healthcare network. So far, the healthcare authorities categorised HPs in Phuket into two groups by considering their healthcare capacity. The categorisation of HPs was done in the annual meeting for the emergency medical response plan, which is regularly held in Phuket to revise the current strategy in response to future disasters. However, the allocation of staff and patients for collective response during disasters is still under discussion.

The study sets a basis of the simulation models for collaboration in an emergency medical response across a healthcare network duing disasters. The study has investigated the collaboration in an emergency medical response in a healthcare network during the Tsunami and the mass casualty incident in the context of Thailand. However, the models remain applicable in other countries and other types of disaster. Even if the activities of collaboration in an emergency medical response may be slightly different between countries, the focus of the collaboration in an emergency medial response in a healthcare network is still on the sharing of resources and information. Some of resource sharing can be adapted to countries that are frequently affected by disasters. The models may be adjusted to suit the characteristics of disasters and the severity of disaster impact. For example, the drug/vaccine sharing is essential for pandemic response in order to reduce the number of infected patients, or the ambulance sharing is required in response to earthquakes in order to transport multiple patients to hospitals as soon as possible, etc.

In addition, the resilience metrics adopted in this thesis are primarily defined to assess the ability of a system to "bounce back". We demonstrate the applicability of the adopted metrics of resilience during Tsunami and illustrate the impact of different strategies on the restoration of resilience in the event. However, the resilience metrics are not specifically designed for the Tsunami. These metrics can be applicable to other types of disasters that cause the deterioration of healthcare performance. However, the resilience metrics adopted in this thesis are the ratio of the recovery rate to the maximum loss rate of the system. An estimation of the loss rate requires the real-world data, which may be challenging.

6.5 Summary

This chapter presents the impacts of strategies on resilience metrics in the case study of Tsunami in Phuket in 2004. The simulation results show that in the first hours of the disaster event, Strategy 2 is more effective in response to disasters, followed by Strategy 1 and 3. After 10 hours, the resilience metrics of Strategy 1 and 2 gradually decrease, while they steadily increase in Strategy 3. However, we do not advocate for a mixed strategy, i.e. starting with Strategy 2 and then switch to Strategy 3, because this is out of the study scope.

In addition, the simulation results reveal the impacts of variation in patient demands, healthcare resource availability, and patient transportation on resilience metrics of strategies. Overall, Strategy 3 yields a higher resilience and reaches the pre-disaster state of healthcare network in a shorter time than other strategies.

Chapter 7 A Mixed Integer Programming model for allocation of multiple patients in collaborative care

This chapter deals with the optimal allocation of patients in the collaborative care strategy. It presents a first step in the research that follows the development of the simulation models for strategies for collaboration in a healthcare network. The focus of the simulation models was on investigating of the impact of different strategies on the resilience. However, the simulation models were not developed with the aim to obtain the optimal allocation of patients. In addition, the problems of patient allocation in collaborative care include patient assignment to ambulances for multiple patient transportation and patient assignment to HPs for treatments. The nature of the problems requires the development of a mixed integer programming (MIP) model, instead of integer programming (IP) model. A set of binary decision variables involve the patient assignment to ambulances for multiple patient transportation, the selection of HPs, and the patient assignment to the required healthcare resources for patient treatments. Time-based decision variables including travel time and waiting time have fractional values. Thus, the MIP model for patient allocation under collaborative care strategy in response to disasters is presented. The model addresses the ambulance sharing for multiple patient transportation in one trip. The literature in patient allocation for disaster response is reviewed. The research problems and the MIP model are presented accordingly.

7.1 Introduction

During disasters, HPs in the networks are required to work together in order to provide emergency medical responses which mainly deal with patient allocation in the network (Tippong et al., 2022). Patients who are affected by disasters are evacuated to the nearest opened TMUs. HPs in the network share their ambulances for transporting these patients from the TMUs to the assigned HPs for treatments. Due to a limited number of available ambulances, they need to make multiple trips during the events (Repoussis et al., 2016). In addition, according to the interviews with the healthcare authorities, multiple patients can be loaded onto the same ambulance when responding to disasters which has been presented in Table 4.3.

Performance of the emergency medical responses during disasters is often measured through time-based targets such as response time, defined as the time between a patient's arrival and the beginning of treatment provision (Abir et al., 2013; Luscombe & Kozan, 2016; Repoussis et al., 2016). The ultimate goal of the emergency medical responses is to treat all patients as early as possible in order to reduce the mortality rate (Holguín-Veras et al., 2013). The patients' chance of survival could be changed over time until patients receive medical treatments. Thus, the aim of emergency medical responses is often to minimise the response time.

We present an MIP model in which the focus is on the allocation of multiple patients to HPs in collaborative response. The goal is to transport multiple patients in one-trip ambulance so as to improve patient outcomes. The objective is to minimise the overall response time.

7.2 Relevant literature

Problems of patient allocation in response to disasters have been widely studied in the literature. Several models considered patient allocation/transportation in disasters. The focus was on allocating/transporting all affected patients to healthcare facilities. For example, Christie & Levary (1998) developed a DES model for patient allocation to HPs in mass casualty incidents. The HPs were perceived as multiple servers. Na & Banerjee (2015) proposed an MIP model for allocating patients to healthcare facilities located in nearby area in which these facilities could be HPs or shelters. The model aimed to simultaneously optimise the number of survivors and the transportation cost with respect to ambulance and facility capacities. Apart from allocating patients, the model was also developed to determine the number of ambulances and resources at healthcare facilities that were required for a large-scale disaster response. Kamali et al. (2017) studied a problem of resource-based triage for patient transportation. They developed an MIP model to transport patients to the HPs. The model took into account the ambulance availability, the disaster scale, and the change in the patients' chance of survival in the triage process. They aimed to maximise the number of expected survivals. Wilson et al., (2013) presented a response model for the entire activities of emergency medical services in the aftermath of a mass casualty incident. They developed an MIP model for the combined patient allocation in the network and treatment ordering problem. They modelled the entire activities as Flexible Job Shop Scheduling Problem (FJSP). Each patient was considered as a job and each medical staff as a machine. The processing of jobs was represented by a sequence of activities including transportation to the HP, and treatment. Each patient was assigned to a HP, and each staff was assigned to the activities. The objectives were to minimise the overall response time and the length of stay.

Some studies considered the problems of dispatching ambulances to clusters of patients and transporting some affected patients to the HPs. Patient assembly points were grouped into clusters. The focus was on dispatching ambulances to clusters in order to perform patient pickup and/or to provide medical treatments. The information on patient demands, road and traffic conditions, and distance were used to dispatch ambulances to clusters. These studies assumed that high-severe injured patients must be treated at the HPs. Low-severe injured patients could be treated at the assembly points. An ambulance could visit the next patient after having served a low-severe injured patient. Each ambulance could carry one high-severe injured patient at a time and that patient was directly transported to a HP after having been picked up. For example, Gong & Batta (2007) proposed two models for ambulance allocation and reallocation to clusters in an earthquake. The first model attempted to allocate ambulances to clusters and to determine the initial completion time for each cluster. The second model considered the reallocation of ambulances with the aim to enhance the ambulance utilisation. The distance between clusters was taken into account when making an ambulance reallocation decision. The objective was to minimise the makespan and weighted total flow time in which the weights were assigned to clusters. Talarico et al. (2015) developed a model for ambulance routing in which a route started from a HP, visited one or more patients in a specified sequence, and ended at either the starting HP or other HP. The optimisation problem was to determine the ambulance routes to serve different patient categories with the aim to minimise the latest service completion time.

Some literature investigated relief supply distribution and patient transportation using the same vehicles. In these studies, the focus was on the transportation of relief supplies to affected areas and of patients to HPs. The main effort was to determine the vehicle routing and the flows of relief supplies and patients in the network. For example, Yi & Kumar (2007) presented an ant colony optimisation model for transporting relief supplies to distribution centres and patients to HPs during disasters. The objective aimed at minimising the service delay which was measured in perspective of the unmet demands for relief supplies and the number of untreated patients. Najafi et al. (2013, 2014) developed multi-objective dynamic models for dispatching and routing vehicles in response to earthquakes. The aims were to minimise the total lead time to fulfil the needs of relief supplies and the total times until patient arrival at the HP. The proposed models were capable of adjusting the vehicle routing plans according to the updated information.

On the other hand, some literature simultaneously examined facility location and patient transportation. For example, Salman & Gül (2014) and Caunhye & Nie (2018) assumed that patient demands affected by disasters always overwhelm the capacities of existing healthcare facilities. The response plan for such circumstances requires a surge capacity to be established. They developed an MIP model to determine the location and capacity of new healthcare facilities to be established together with the patient transportation to the existing and newly-located healthcare facilities after an earthquake. The objective aimed at minimising the total travel and waiting times of patients and the total cost of establishing new facilities.

The current literature has proposed several models to solve the problems of patient allocation in the network with the aim to minimise response time. However, the literature has not addressed the ambulance sharing for multiple patient transportation. The models always assume that one ambulance carry one patient in one trip. One main difference of our study compared to the existing works is that a group of patients is assigned to one-trip ambulance considering ambulance capacities and allocated to one of the HPs in the network under the collaborative care strategy.

7.3 Problem description and mathematical model

This section presents the problem of the allocation of multiple patients in collaborative response and an MIP model developed for the problem.

7.3.1 Problem description

In the simulation experiments, the results show that the collaborative care strategy (Strategy 3) has a greater impact on the resilience improvement than other strategies. It can regain the pre-disaster state of healthcare network in a shorter time in all defined scenarios. Thus, in the optimisation model, we adopt the roles of TMUs and HPs as well as patient pathways defined in Strategy 3. Please note that we do not classify HPs into groups, i.e. HL1 and HL2. Although the classification of HPs is a part of Strategy 3, such classification is for defining the patient flow in simulation model when allocating patients to HPs. DES requires the detailed rules for controlling the individual entities (patients) through the defined activities in the system. In the optimisation model, the decision making on patient allocation can be defined as an optimisation problem for which a mathematical model can be developed.

Specifically, patients are evacuated to the TMUs over time. They are triaged into three categories including Reds, Yellows, and Greens. A fixed-priority ordering scheme is adopted among different patient categories, so that the patient category is static, i.e. does not change over time. The number of patients in different categories are known which are based on historical data. TMUs are set for assembling Reds and Yellows for transportations to HPs and providing treatments for Greens. Reds and Yellows receive the treatments at one of the HPs, while Greens are treated at the TMUs and discharged. In this regard, Greens are not included in the model because the focus of the study is on patient allocation to HPs.

The TMU locations are known. The humanitarian activities including patient evacuation and facility location are fixed in advance and thus are not covered in the model. In addition, the resources required at the TMUs including staff, first aid equipment, field beds, field mattresses, and ambulances are assumed to be present at the opened TMUs in the immediate aftermath of a disaster. The resource assignment to the opened TMUs is out of the scope of this model.

On arrival of Reds and Yellows at TMUs, they are immediately loaded onto ambulances and transported to HPs. The number of available ambulances is usually limited during disasters. Therefore, they need to carry multiple patients in one trip and need to make multiple trips from the TMUs to the HPs. Different types of ambulances have different capacity for patient transportation. Basic life support ambulances are equipped with first aid and standard medical equipment, while advanced life support ambulances are equipped with first aid and advanced medical equipment (Reuter-Oppermann et al., 2017). The former can carry at most one Red, or two Yellows in one trip. The latter can carry at most one Red and one Yellow, or two Yellows in one trip. These possible combinations of patients in a one-trip ambulance are defined by the healthcare authorities who have experience of providing medical services during mass casualty incidents and/or disasters. However, these combinations are only implemented when there is a surge of emergency medical service demands.

Healthcare authorities state that it may increase overall response time when ambulances need to visit multiple HPs for dropping patients off. Thus, we assume that ambulances visit one HP in one trip, then travel to the TMU for the next trip. The assumption is that the roads are not affected by disasters. The travel time between the TMUs and the HPs are known and fixed. Travel time is asymmetric based on the shortest route obtained by Google map.

Due to limited resources in the network in reality, some Reds may be transported to the external HPs that are located outside the affected network. However, the healthcare authorities state that majority of patients were generally treated in the network during Tsunami in 2004. Less than 1% of patients were transported to the external HPs. In addition, the simple model should be built in the first instance to reduce the computational burden. We thus exclude the external network in order to reduce the complexity of the model. We assume that all patients must be treated in the network.

In a provision of treatment, each patient category needs different medical treatment. Reds require highly specialised equipment, more medical staff, and advanced life support for their treatments, while Yellows need fewer medical staff and lower complexity care. For simplicity, resources including medical equipment, staff, beds/chairs are organised into *resource groups* with respect to the medical treatment required for each patient category (Luscombe & Kozan, 2016). We assume that these resources are not affected by disasters and are available at their facilities immediately after disasters. We do not include in the model the resources that are allocated to existing patients admitted before the events, in which they are approximately 20% of total resources. The resource availability for taking care of the causalities of the disaster is set to 80% of total staff in each HP as advised by the healthcare professionals. The data about the number of resource groups and ambulances are known in advance.

Each patient that arrives at the HPs is assigned immediately to a resource group if one is available. One resource group can be occupied by a patient at a time. The resource group becomes available for the next patient when the treatment for the assigned patient are completed. The treatment times for different patient categories are known which are based on historical data.

We model the problems of multiple patient allocation in collaborative response as a FJSP with unrelated parallel machines. Reds and Yellows are perceived as job sets, whereas ambulances and resource groups in HPs are perceived as machine sets. Each job consists of a sequence of activities: *transportation to a HP* and *treatment at the HP*. The optimisation problem is to determine the sequence of Reds and Yellows to be assigned to ambulances and resource groups at the HPs. The objective is to minimise the sum of weighted response times of all the jobs (patients) because the long delays lead to a higher mortality rate. The higher weight is given to Reds.

7.3.2 An MIP model for optimal patient allocation

In this section we introduce the notation required to describe the MIP model, and then present the MIP model for the multiple patient allocation in collaborative care. Our MIP model is based on the model suggested by Repoussis et al. (2016) who studied the patient allocation to HPs and assumed that an ambulance carries one patient in one trip. They considered one ambulance type and one patient category in the model. However, the information about what ambulance type was used and what patient catogory was addressed was not provided.

Sets:

H Set of HP locations, $H = \{1, \ldots, |H|\}$, indexed by h

I Set of TMU locations, $I = \{1, \ldots, |I|\}$, indexed by i and j

R Set of Reds, $R = \{1, \ldots, |R|\}$, indexed by r

Y Set of Yellows, $Y = \{1, \ldots, |Y|\}$, indexed by y

M Set of basic life support ambulances, $M = \{1, \ldots, |M|\}$, indexed by m

N Set of advanced life support ambulances, $N = \{1, \ldots, |N|\}$, indexed by n

P Set of resource groups for Reds, $P = \{1, \ldots, |P|\}$, indexed by p

Q Set of resource groups for Yellows, $Q = \{1, \ldots, |Q|\}$, indexed by q

Parameters:

a'_{ri} Arrival time of patient $r \in R$ at TMU $i \in I$

a''_{yi} Arrival time of patient $y \in Y$ at TMU $i \in I$

t'_{r} Treatment time for patient $r \in R$

t''_{y} Treatment time for patient $y \in Y$

α Weight assigned to Reds, $0 \leq \alpha \leq 1$

$1 - \alpha$ Weight assigned to Yellows, $0 \leq \alpha \leq 1$

Binary decision variables:

A solution of the examined problem is a schedule of patient transportation by an ambulance and treatment provision by a resource group at the HP. For the patient transportation, ambulance $m \in M$ provides transportation on trip $f = (i, h, j)$, where $i, j \in I$, $h \in H$; whereas ambulance $n \in N$ provides services on trip $g = (i, h, j)$, where $i, j \in I$, $h \in H$. Let $f \in F_m$ and $g \in G_n$, where F_m and G_n are the total maximum trips performed by ambulance $m \in M$ and $n \in N$, respectively. For the treatment provision at the HP, resource group $p \in P$ serves one Red in treatment k, while resource group $q \in Q$ treats one Yellow in treatment l. We let $k \in K_p$ and $l \in L_q$, where K_p and L_q are the total maximum treatments served by resource group $p \in P$ and $q \in Q$, respectively. The following binary decision variables are defined to identify the positions of patients in the processing sequence for each ambulance and resource group.

u'_{rmf} equal to 1 if patient $r \in R$ is assigned to ambulance $m \in M$ on trip f; 0 otherwise

u''_{ymf} equal to 1 if patient $y \in Y$ is assigned to ambulance $m \in M$ on trip f; 0 otherwise

v'_{rng} equal to 1 if patient $r \in R$ is assigned to ambulance $n \in N$ on trip g; 0 otherwise

v''_{yng} equal to 1 if patient $y \in Y$ is assigned to ambulance $n \in N$ on trip g; 0 otherwise

$u^{(f)}_{mih}$ equal to 1 if ambulance $m \in M$ travels from TMU $i \in I$ to HP $h \in H$ on trip f; 0 otherwise

$v^{(g)}_{nih}$ equal to 1 if ambulance $n \in N$ travels from TMU $i \in I$ to HP $h \in H$ on trip g; 0 otherwise

$x^{(k)}_{rph}$ equal to 1 if patient $r \in R$ is assigned to resource group $p \in P$ and treated in treatment k at HP $h \in H$; 0 otherwise

$z^{(l)}_{yqh}$ equal to 1 if patient $y \in Y$ is assigned to resource group $q \in Q$ and treated in treatment l at HP $h \in H$; 0 otherwise

Non-negative decision variables:

a_{mf} Travel time of ambulance $m \in M$ on trip f

b_{ng} Travel time of ambulance $n \in N$ on trip g

c_{mf} Arrival time of ambulance $m \in M$ at the TMU for doing trip f

d_{ng} Arrival time of ambulance $n \in N$ at the TMU for doing trip g

w_{mf} Waiting time of ambulance $m \in M$ at the TMU for doing trip f

x_{ng} Waiting time of ambulance $n \in N$ at the TMU for doing trip g

e'_{rh} Arrival time of patient $r \in R$ at HP $h \in H$

e''_{yh} Arrival time of patient $y \in Y$ at HP $h \in H$

t'_{pkh} Treatment start time of the patient assigned to resource group $p \in P$ and treated in treatment k at HP $h \in H$

t''_{qlh} Treatment start time of the patient assigned to resource group $q \in Q$ and treated in treatment l at HP $h \in H$

s'_{ri} Response time of patient $r \in R$ who is evacuated to TMU $i \in I$

s''_{yi} Response time of patient $y \in Y$ who is evacuated to TMU $i \in I$

These decision variables are defined to capture the time stamps for the model during the transportation and treatment. The objective is to minimise the total weighted response time of all patients in Eq. (7.1).

$$Minimise \sum_{r \in R} \sum_{i \in I} \alpha s'_{ri} + \sum_{y \in Y} \sum_{i \in I} (1-\alpha) s''_{yi} \tag{7.1}$$

The following constraints are defined:

Patient assignment to ambulance and multiple patient transportation

$$\sum_{m \in M} \sum_{f \in F_m} u'_{rmf} + \sum_{n \in N} \sum_{g \in G_n} v'_{rng} = 1 \qquad \forall r \in R \tag{7.2}$$

$$\sum_{m \in M} \sum_{f \in F_m} u''_{ymf} + \sum_{n \in N} \sum_{g \in G_n} v''_{yng} = 1 \qquad \forall y \in Y \tag{7.3}$$

$$\sum_{h \in H} u^{(f)}_{mih} \leq \sum_{r \in R} u'_{rmf} + \sum_{y \in Y} u''_{ymf} \qquad \forall m \in M, f \in F_m, i \in I \tag{7.4}$$

$$\sum_{r \in R} u'_{rmf} \leq 1 \qquad \forall m \in M, f \in F_m \tag{7.5}$$

$$\sum_{y \in Y} u''_{ymf} \leq 2 \qquad \forall m \in M, f \in F_m \tag{7.6}$$

$$\sum_{r \in R} u'_{rmf} + \sum_{y \in Y} u''_{ymf} \leq 2 \qquad \forall m \in M, f \in F_m \tag{7.7}$$

$$\sum_{r \in R} u'_{rmf} - \sum_{y \in Y} u''_{ymf} \neq 0 \qquad \forall m \in M, f \in F_m \tag{7.8}$$

$$\sum_{h \in H} v^{(g)}_{nih} \leq \sum_{r \in R} v'_{rng} + \sum_{y \in Y} v''_{yng} \qquad \forall n \in N, g \in G_n, i \in I \tag{7.9}$$

$$\sum_{r \in R} v'_{rng} \leq 1 \qquad \forall n \in N, g \in G_n \tag{7.10}$$

$$\sum_{y \in Y} v''_{yng} \leq 2 \qquad \forall n \in N, g \in G_n \tag{7.11}$$

$$\sum_{r \in R} v'_{rng} + \sum_{y \in Y} v''_{yng} \leq 2 \qquad \forall n \in N, g \in G_n \tag{7.12}$$

$$\sum_{h\in H} u_{mih}^{(f)} = 1 \qquad \forall m \in M, f \in F_m, i \in I \tag{7.13}$$

$$\sum_{h\in H} v_{nih}^{(g)} = 1 \qquad \forall n \in N, g \in G_n, i \in I \tag{7.14}$$

Constraint (7.2) and (7.3) ensure that each patient is assigned to one ambulance only. Constraint (7.4) – (7.8) dictate basic life support ambulance sharing for multiple patient transportation. Constraint (7.4) links the basic life support ambulance dispatching with the patient assignment to the ambulance. Patients can be assigned to the ambulance that is used for the trip. The basic one can carry at most one Red (constraint 7.5) or two Yellows (constraint 7.6) in one trip. At most two patients can be loaded onto the same ambulance (constraint 7.7). However, they must be from the same categories (constraint 7.8).

Constraint (7.9) – (7.12) are multiple patient transportation for advanced life support ambulances. Constraint (7.9) links the advanced life support ambulance dispatching with the patient assignment to the ambulance. At most one Red (constraint 7.10) or two Yellows (constraint 7.11) can be assigned to the advanced one. At most two patients can be loaded onto the same ambulance (constraint 7.12). Constraint (7.13) and (7.14) ensure that the ambulance visits exactly one HP in one trip.

Time stamps for ambulance

$$\sum_{h\in H} u_{mih}^{(1)} c_{m1} = \min_{r\in R, y\in Y}\left(u'_{rm1} a'_{ri}, u''_{ym1} a''_{yi}\right) \qquad \forall m \in M, i \in I \tag{7.15}$$

$$\sum_{h\in H} v_{nih}^{(1)} d_{n1} = \min_{r\in R, y\in Y}\left(v'_{rn1} a'_{ri}, v''_{yn1} a''_{yi}\right) \qquad \forall n \in N, i \in I \tag{7.16}$$

$$\sum_{h\in H} u_{mih}^{(f)} c_{mf} \geq \sum_{h\in H} u_{mih}^{(f-1)} \left(c_{m(f-1)} + a_{m(f-1)}\right) \ \forall m \in M, i \in I, f \in F_m \setminus \{1\} \tag{7.17}$$

$$\sum_{h\in H} v_{nih}^{(g)} d_{ng} \geq \sum_{h\in H} v_{nih}^{(g-1)} \left(d_{n(g-1)} + b_{n(g-1)}\right) \quad \forall n \in N, i \in I, g \in G_n \setminus \{1\} \tag{7.18}$$

$$w_{mf} = \max_{r\in R, y\in Y, m\in M, i\in I, h\in H} \left(u'_{rmf} a'_{ri} - u_{mih}^{(f)} c_{mf}, u''_{ymf} a''_{yi} - u_{mih}^{(f)} c_{mf}\right) \tag{7.19}$$

$$x_{ng} = \max_{r\in R, y\in Y, n\in N, i\in I, h\in H} \left(v'_{rng} a'_{ri} - v_{nih}^{(g)} d_{ng}, v''_{yng} a''_{yi} - v_{nih}^{(g)} d_{ng}\right) \tag{7.20}$$

Constraint (7.15) and (7.16) initialise the arrival time of ambulance at TMU for its first trip. These constraints are based on the assumption in which the ambulances are already at the opened TMUs, so that the arrival time of the ambulance for its first trip ($f = 1$ or $g = 1$) equals to the arrival time of the patient at TMU who is assigned to that ambulance. Constraint (7.17) and (7.18) dictate the arrival time of ambulance at TMU for doing the next trips. Its arrival time equals to the arrival time of the previous trip adding the travel time on the trip. Constraint (7.19) and (7.20) dictate the ambulance waiting time for arriving patients at TMU.

Patient assignment to treatment

$$\sum_{h \in H} \sum_{p \in P} \sum_{k \in K_p} x_{rph}^{(k)} = 1 \qquad \forall r \in R \tag{7.21}$$

$$\sum_{h \in H} \sum_{q \in Q} \sum_{l \in L_q} z_{yqh}^{(l)} = 1 \qquad \forall y \in Y \tag{7.22}$$

$$\sum_{r \in R} x_{rph}^{(k)} \leq 1 \qquad \forall p \in P, k \in K_p, h \in H \tag{7.23}$$

$$\sum_{y \in Y} z_{yqh}^{(l)} \leq 1 \qquad \forall q \in Q, l \in L_q, h \in H \tag{7.24}$$

Constraint (7.21) and (7.22) ensure that each patient is treated at exactly one HP. Constraint (7.23) and (7.24) dictate at most one patient can occupy one treatment which is served by one resource group.

Time stamps for patient and patient waiting times

$$\sum_{r \in R} x_{rph}^{(1)} t'_{p1h} = \sum_{r \in R} x_{rph}^{(1)} e'_{rh} \qquad \forall p \in P, h \in H \tag{7.25}$$

$$\sum_{y \in Y} z_{yqh}^{(1)} t''_{q1h} = \sum_{y \in Y} z_{yqh}^{(1)} e''_{yh} \qquad \forall q \in Q, h \in H \tag{7.26}$$

$$e'_{rh} \geq u'_{rmf} u_{mih}^{(f)} (c_{mf} + a_{mf} + w_{mf}) + v'_{rng} v_{nih}^{(g)} (d_{ng} + b_{ng} + x_{ng})$$

$$\forall r \in R, m \in M, n \in N, i \in I, h \in H, f \in F_m, g \in G_n \tag{7.27}$$

$$e''_{yh} \geq u''_{ymf} u_{mih}^{(f)} (c_{mf} + a_{mf} + w_{mf}) + v''_{yng} v_{nih}^{(g)} (d_{ng} + b_{ng} + x_{ng})$$

$$\forall y \in Y, m \in M, n \in N, i \in I, f \in F_m, g \in G_n \tag{7.28}$$

$$t'_{p(k+1)h} \geq t'_{pkh} + \sum_{r \in R} x_{rph}^{(k)} t'_r \qquad \forall p \in P, h \in H, k \in K_p \setminus \{|K_p|\} \tag{7.29}$$

$$t''_{q(l+1)h} \geq t''_{qlh} + \sum_{y \in Y} z^{(l)}_{yqh} t''_{y} \qquad \forall q \in Q, h \in H, L \in L_q \setminus \{|L_q|\} \tag{7.30}$$

$$s'_{ri} \geq \sum_{h \in H} \sum_{p \in P} \sum_{k \in K_P} x^{(k)}_{rph} t'_{pkh} - a'_{ri} \qquad \forall r \in R, i \in I \tag{7.31}$$

$$s''_{yi} \geq \sum_{h \in H} \sum_{q \in Q} \sum_{l \in L_q} z^{(l)}_{yqh} t''_{qlh} - a''_{yi} \qquad \forall y \in Y, i \in I \tag{7.32}$$

Constraint (7.25) and (7.26) initialise the treatment start time of the patients of the first treatment in the sequence. The patients being first in the treatment sequence can be treated immediately as no patient is in the queue. This is based on the assumption in which the healthcare resources are available at their facilities immediately after disasters. So, the start time of the first treatment in the sequence ($k = 1$ or $l = 1$) equals to the arrival time of patients at HPs who are assigned to the first treatment in the sequence. Constraint (7.27) and (7.28) indicate the arrival time of patient at the assigned HP. It is estimated by the arrival time of the ambulance at TMU that carries the patient adding the travel time on the trip. Constraint (7.29) and (7.30) indicate the treatment start time of each patient according to the treatment time of the previous treatment sequence. Constraint (7.31) and (7.32) carry the information about the patient's response time. These constraints incorporate the patient's treatment start time at HP and the patient's arrival time at TMU.

Value range of decision variables

$$a_{mf}, c_{mf} \geq 0 \qquad \forall m \in M, f \in F_m \tag{7.33}$$

$$b_{ng}, d_{ng} \geq 0 \qquad \forall n \in N, g \in N_g \tag{7.34}$$

$$e'_{rh}, e''_{yh} \geq 0 \qquad \forall r \in R, y \in Y, h \in H \tag{7.35}$$

$$s'_{ri}, s''_{yi} \geq 0 \qquad \forall r \in R, y \in Y, i \in I \tag{7.36}$$

$$t'_{pkh}, t''_{qlh} \geq 0 \qquad \forall p \in P, q \in Q, k \in K_p, l \in L_q, h \in H \tag{7.37}$$

$$u'_{rmf}, u''_{ymf}, v'_{rng}, v''_{yng}, u^{(f)}_{mih}, v^{(g)}_{nih}, x^{(k)}_{rph}, z^{(l)}_{yqh} \in \{0,1\}$$
$$\forall r \in R, y \in Y, m \in M, n \in N, h \in H, f \in F_m, g \in G_n, k \in K_p, l \in L_q \tag{7.38}$$

Constraint (7.33) - (7.38) impose the binary restrictions and non-negative bounds.

7.4 Summary

The MIP model is developed to allocate patients to HPs under the collaborative care strategy. The optimisation problem is to determine the sequence of Reds and Yellows to be assigned to ambulances and resource groups at HPs with the aim to minimise the response time. The model incorporates different ambulance types and different patient categories and introduces some constraints for an assignment of patient groups to one-trip ambulance, which is missing in the literature. A set of decision variables are defined to identify the patient positions in the sequentially processing activities and to determine the times related to transportation and treatment services.

However, the presented MIP model can serve as a basis and the next steps would be to implement it using a software package for Linear programming e.g. Gurobi. The model parameters may be adopted from the literature that are most relevant for the defined problem. The potential challenges might be the time consuming when solving the defined problem as two ambulance types and two patient categories are included in the model. The obtained results in the optimisation model can be added in the simulation models and can provide additional insights into the resilience improvement during disasters.

Chapter 8 Conclusions and implications

This chapter is dedicated to addressing the responses to the research questions and suggesting the future research works in the coordination in the healthcare systems in response to disasters.

8.1 Conclusions

DES models have been developed to simulate strategies for collaboration in a healthcare network following the real-world activities of emergency medical response. The models include treatment provision of patients, internal and external resource sharing and allocation, and multiple patient transportation. Patients, ambulances, and staff are treated as entities, while beds/mattresses/chairs are defined as resources in the models. The computerised models are developed in Arena Simulation Enterprise Suite version 14.0 based on the presented flowchart diagrams. We utilise the data from the two real-world events in Thailand. We use a case study of boat capsizing in 2018 for the model validation and verification. Expert opinion and a statistical approach are used for validating the models, while a visual confirmation of the models and an inspection of source code of the simulation are used for the model verification. The case of the Tsunami in 2004 is used to investigate the impact of the strategies on resilience. The majority of input parameters in both case studies were provided by the healthcare authorities in Thailand. These parameters include average time between patient arrivals, the average number of affected patients, the average treatment time, the number of healthcare resources at TMUs, the number of resources required for treatments, and the ambulance capacity for multiple patient transportation and for staff transportation. Both percentage of patients in different categories and the number of allocated external resources follow historical data recorded during the event.

We adapt a generic resilience metric proposed in the literature to suit the healthcare context. The resilience is measured by the ratio of recovery rate during a disaster to maximum loss rate suffered by the system. The ratio incorporates the state of the healthcare network before a disaster occurs and during a disaster, and the worst state of the healthcare network over the course of the disaster event. A higher ratio implies that the healthcare network recovered better from the disrupted state to the normal state.

We define two resilience metrics based on defining the system state either as the average weighted patient waiting time, or the weighted number of patients whose waiting time exceeds the clinically appropriate time frame.

- *To estimate the state of the healthcare network before a disaster event*, we measure the average weighted patient waiting time in the no-disaster environment and the weighted number of patients in the no-disaster environment whose waiting time exceeds their threshold. The data on waiting time is between 1st of January and 31st of December 2019 which cover all seasons and is before the SARS-CoV-2 pandemic started in Thailand. These data are from all emergency departments in Phuket, Thailand.
- *The state of the healthcare network in a disaster event* is obtained using the simulation. The waiting time is measured when patients are in the queue waiting for available staff and bed/mattress/chair at TMUs, and internal and external HPs.
- *The worst state of the healthcare network during the event* is estimated by comparing all values of average weighted patient waiting time and of the weighted number of patients with a treatment delay from three strategies for collaboration. The highest values denote the worst state of the healthcare network in that scenario.

The simulation experiments conducted in this thesis show how different strategies for the collaboration in a healthcare network can impact on resilience in a particular disaster in Phuket, Thailand. The 'new collaborative care' strategy we proposed improves resilience more than the 'non-collaborative care' and 'semi-collaborative care' strategies. Based on the performance of the new collaborative care strategy, authorities considering how to incorporate collaboration in their response strategies should consider the following points:

(1) The categorisation of HPs. The HPs should be categorised into the groups by considering their capacities which are measured by their availability of healthcare resources and their capabilities to provide emergency medical

services. The HPs with higher capacity should be likely responsible for high severe injuries, whereas the less severe-injured patients should be likely transported to the lower-capacity HPs. However, this can be only implemented in the urban area, e.g. Phuket, where HPs are not far apart.

(2) Patients can be allocated to HPs more effectively if the resource availability in the network, i.e. at different HPs, is known at the point of deciding which HP to take the patient to.

(3) The lower-capacity HPs should allocate their staff to the higher-capacity HPs in order to enhance the healthcare capacity for severe injuries in the network. However, this finding is based on the specific experimented scenarios in the context of Phuket, Thailand.

(4) Given the set of scenarios explored in this thesis and within the specific context of the health network in Phuket, the simulation experiments suggest that greater resilience could be achieved if TMUs assemble Reds and Yellows for transportation to HPs (without administering treatments) and providing treatments only for Greens. Please note that this finding is based on the model assumption in which patient category remains static through the simulation run time. Change in triage level is out of the study scope.

We have faced a number of challenges during the process of gathering the data in the development of the simulation models. The unwillingness of healthcare provider authorities to provide the data on staff capacity at the external HPs (outside the network) may affect the quality of simulation results. However, the healthcare authorities stated that during Tsunami in 2004 the capacity of the external HPs did not matter to the overall provision of medical services because most of the patients were treated within the network, while less than 1% of patients were transported to the external network. Additionally, the lack of real-world data on medical services during disasters such as average waiting time at the TMUs, length of stay, transportation time, and treatment time limited, to some extent, the validation of simulation models.

While simulation allows us to investigate the impact of the strategies on the resilience, the optimisation allows us to addresses problems of patient allocation including patient assignment to ambulances for patient transportation given ambulance sharing of multiple patients, and patient assignment to HPs for treatments. These problems are modelled as a Flexible Job Shop Scheduling Problem with unrelated parallel machines. Patients are perceived as a set of jobs, while ambulances and resource groups in HPs are perceived as a set of machines.

In the MIP model, deterministic parameters include patient arrival time and treatment time. A set of binary decision variables involve the patient assignment to ambulances, the HP selection, and the patient assignment to resource groups. The optimisation problem is to determine the sequence of Reds (severe-injured patients) and Yellows (moderate-injured pateints) to be assigned to each ambulance and resource group at the assigned HPs. The objective is to minimise overall response times of all patients. The model incorporates different ambulance types and introduces constraints that incorporate the possibility of multiple patients sharing an ambulance in their transportation to a HP, depending on their severity category and ambulance capacities. In these constraints, at most one Red, or two Yellows can be assigned to a basic life support ambulance, whereas an advanced life support ambulance can carry at most one Red and one Yellow, or two Yellows in one trip.

8.2 Future research

8.2.1 Extensions of the current models

There are still some research avenues to be explored by the OR community to increase the applicability of OR methodologies and methods to exploring how healthcare systems can best coordinate to enhance resilience within real-world disaster management.

Integrative care across HP setting

According to the focused literature review presented in Chapter 2, studies that have used models for 'integrative care' have tended to focus on only one hospital, and so there is scope to extend the literature to explore integrative care acting over a healthcare network. For instance, models for integrative care between different hospital branches operating under a common governance structure could be developed to investigate the impact of integrative care on the response to the surge of patient demands during disasters. Please note that if the current integrative care studies that focus on a single hospital setting are extended to cover multiple hospital branches operating under the common governance structure, they would still fall into the category of integrative care by the definition given in Table 1.1. Whilst, the extended models may cause a considerably heavier computational burden, but would be very beneficial to the real-world disaster management. Studies on the integrative care across HP setting may offer the knowledge of how a group of hospitals under common governance structure can better coordinate to enhance resilience during disasters.

Extensions of the application of the models presented in thesis to other health system

Although the simulation study demonstrates the advantages of collaborative care strategy compared to other strategies under the circumstances considered in the Tsunami in the context of Phuket, Thailand, there is still room for future work. For example, this study has incorporated EMS centres and hospitals into the models. The extensions of the collaborative care response to other agencies in the healthcare system are possible, such as the skilled nursing facilities and health promoting hospitals. Their roles and responsibilities in the collaborative care response would need to be specified. The engagement of these agencies may provide further insights into the advantages of collaborative care in response to disasters.

Improvement of the models of the proposed strategy for collaboration

The models of the proposed strategy for collaboration (Strategy 3) in an emergency medical response across a healthcare network works best in the context of Phuket where HPs are not far apart. The future study may look at how effective proposed strategy is when there is longer travel time, especially in the rural setting where HPs are very far apart.

In addition, there are the events that can occur during disasters which are not included in the models. For example, patient category can change over time, and there can be pandemics. Consequently, the further study may incorporate a probability of patient survival as a function of time

According to the interviews, collaborative care in response to biological disasters (e.g., pandemics) is not the same as the one in response to geophysical disasters (e.g., Tsunami). The main difference lies in the re-transportation of patients and the decisions on medical staff sharing. Specifically, although the medical services remain insufficient, patients are not re-transported to other healthcare networks in order to control the spread of disease. The medical staff are the key resources providing medical treatments during pandemics. They are required to work at their facilities in order to reduce the potential infection that may happen during the transportation and from other areas. The infected medical staff can cause an adverse impact on the healthcare resource availability. However, the sharing of medical staff can be implemented once the pandemics are under control in their areas. This can be found in the SARS-CoV-2 pandemic. When China managed to reduce the daily number of newly infected patients, they allocated some medical staff to other countries to respond to a surge of patient demands (TheGuardian.com, 2020). In this respect, it would be of value to adapt the proposed collaborative care strategies in response to pandemics.

Responses to pandemic may not succeed without pandemic preparedness. Plans for resource sharing during pandemic should be developed in advance and revised annually. These plans should be adjusted before being implemented in response to pandemic. Some characteristics of collaboration presented in this thesis can be applied to pandemic preparedness and response. These characteristics include sharing of medical equipment, vaccines, drugs, and staff. The future research may investigate a collaboration in a healthcare network for pandemic preparedness and response, for example, the prepositioning and allocations of vaccines and drugs.

The focus of simulation study was on the activities of collaboration in an emergency medical response and therefore excluded the decisions on facility location planning, relief supplies distribution, and evacuation routing. It is to be expected that a holistic model that also included these aspects would improve the network resilience.

Implementation of the proposed MIP model and analysis of the results

The focus of this thesis was on simulation models. However, we understood that allocating patients using simulation method might not be optimal. So, the final stage of this PhD research study was to develop a mathematical model for optimal allocation of patients in collaborative care. The next step is to implement this model using available software package for Linear programming such as Gurobi and analyse results. This can be another piece of the research.

8.2.2 Methodologies and models

Although many OR methods have been applied to address the coordination of healthcare resources in disaster management, there are still methodologies and models to be investigated. Particularly, we identify mixed models/methods, data-driven optimisation, and online optimisation to be of great interest.

Mixed models/methods

In many complex real-world problems, decisions at the strategic level have an impact on the decisions at the operational level, and vice versa. Modelling approaches traditionally cover only some aspects of decision making at a certain level. The benefits of combining different modelling approaches and consequently different methods have been discussed in the OR community for more than a decade (Morgan et al., 2017). Particularly, the mixing of DES, which is often employed in healthcare, and SD has attracted the most interest in the healthcare simulation community, because these two modelling approaches offer complementary views of the system. SD methodology provides a macro perspective of the system, aiming at capturing dynamic (causal) relationships between entities in a system. On the other hand, DES provides a picture of the system at a micro level, usually sampling arrivals of entities in the system and their required service time from probability distributions. Changes of the state of the system occur at discrete points of time. There have been studies of combining SD and DES in healthcare in different healthcare settings (Brailsford et al., 2010; Ahmad et al., 2012; Viana et al., 2014). However, in spite of the growing number of publications, it seems that this approach to modelling has still not reach its momentum. As pointed out by Brailsford et al. (2019) there is a need for the development of a new rigorous methodology, which should focus on the modelling of links between different models. So far, the research into the healthcare coordination in disaster management has resorted mostly to DES but not to SD. We argue that the combination of these two complementary approaches would considerably strengthen the healthcare coordination in disaster management. DES would provide insights into detailed interactions of individual entities (such as patients, ambulance, staff, etc.), which affect the overall behaviour of the system and determines its performance. SD would interact with DES and would be particularly useful in the investigation of relations between separate components in the healthcare network and how they affect each other. It would enable the identification of potential bottlenecks in the network. Ultimately, it would give a tool to the policy makers to evaluate different policies and choose appropriate one to implement in disaster management. We recommend that future research combining DES and SD in the context of disaster management would benefit from using the framework for assisting in the design of mixed methods by Morgan et al. (2017). Based on the insights from practice, the authors introduced a framework consisting of a series of questions to assist in OR modelling in choosing suitable methods and suggesting the design of mixed methods.

Data-driven optimisation

It is very difficult to define uncertain parameters and variables in OR models because their accurate probabilistic descriptions of randomness is often unavailable in practice (Mandelbaum et al., 2020). Recent years have seen an increased interest in application of data- driven optimisation to resource allocation problems in healthcare, especially to real-time epidemic control (Han et al., 2015; Du et al., 2020). In these applications, data-driven optimisation aims to use analysis of data collected periodically (progressively) in order to refine the decisions over time. This is opposite to classical approaches to dealing with uncertainty, which assume that all probability distributions are known at the beginning of the planning horizon. There has been a study by Sarkar et al. (2021) into data-driven optimisation in healthcare coordination. We strongly believe that data-driven optimisation could serve as an excellent tool for handling uncertainties that arise in the context of healthcare coordination during disasters such as the routing of ambulances for patient transportation with uncertain travel times, the calculation of healthcare resources capacity with uncertain time of treatment durations, etc. As more and more data about the type and scale of disaster gradually become available, decision making process could be improved over time leading to better i.e. often called fact-based decisions.

Online optimisation

Online optimisation is a rather overlooked method to address real-world uncertainties in healthcare coordination in disaster management. Online algorithms receive their input piece by piece upon making certain actions and must react with respect to each piece of input. The goal of online algorithms is to guarantee a performance which is as close as possible to the optimal performance achievable if the entire input is known in advance. Different from stochastic optimisation, in online optimisation, no prior probabilistic knowledge is required. In a real-world disaster setting, some information might be revealed over time and upon taking particular actions. Online optimisation has been successfully used in some post-disaster DOM problems. Shiri et al. (2020) is one of these studies in which routing and allocation of search-and-rescue teams to areas with trapped victims was addressed. In that study, the number of casualties in a post-disaster emergency assembly location and the status of the roads that were damaged after a disaster could only be revealed by close observation of the search-and-rescue teams on the scene. In another recent study, Akbari and Shiri (2021), addressed the post-disaster relief distribution problem in which some of the road segments were blocked. The blockage of these roads was not known in advance and had an online nature. It could only be revealed when the relief distribution team observed them. Online optimisation would provide a robust tool for handling uncertainties and providing algorithms that can address real aspects of coordination in healthcare systems of disaster management. An example of online parameters in our context is the triage categories for each patient. While in most of the studies, the triage category of each patient is determined by either a stochastic or deterministic approach, it is plausible to identify it after a nurse or doctor observes the conditions of a patient for the first time. Another example of online information is the required time for emergency treatment of a patient. This time can only be assessed after an initial monitoring of the patient by the medical staff on the scene. These online parameters have a direct impact on the obtained input information and hence can have a direct influence on the performance of a solution approach.

8.2.3 Resilience measures

In this section, we propose the future research directions related to resilience measures including standardisation of measures and additional cost-based measures.

Standardisation of measures

Different resilience measures have been proposed in the OR literature. It has to be further investigated which of these can best reflect resilience in the healthcare system during disasters under different circumstances, and whether it is feasible and desirable to standardise resilience measures. One benefit of doing so would be to enable OR researchers to compare and evaluate their models and algorithms.

Additional cost-based measures

In disaster management the aim is usually to minimise the response time, rather than to minimise costs (Rolland et al., 2010). Considering only the cost minimisation may be a threat to resilience because the resilient healthcare system requires the redundant capacity of healthcare resources to respond to a surge of demand during disasters (Fairbanks et al., 2014). The redundant capacity can be perceived as unnecessary healthcare resources when the total cost has to be minimised. However, we argue that costs, e.g. deprivation cost, could be measured in terms of a probability of deaths and social disturbances due to the time delay which is caused by the shortage of healthcare resources. Future research may investigate how to quantify deprivation costs in resilience metrics. Also, instead of using only cost-based measures a trade-off between cost and other healthcare performances must be made, such as the number of treated patients. Multi-objective decision making methods could be a useful tool to provide insights into such a trade-off that reflect the effectiveness of the healthcare network.

References

Abir, M., Davis, M. M., Sankar, P., Wong, A. C., & Wang, S. C. (2013). Design of a model to predict surge capacity bottlenecks for burn mass casualties at a large academic medical center. *Prehospital and Disaster Medicine*, *28*(1), 23–32.

Abo-Hamad, W., & Arisha, A. (2013). Simulation-based framework to improve patient experience in an emergency department. *European Journal of Operational Research*, *224*, 154–166.

Acem.org.au (2000) *Triage.* Retrived from https://acem.org.au/Content-Sources/Advancing-Emergency-Medicine/Better-Outcomes-for-Patients/Triage. Accessed September 15, 2021.

Achour, N., Miyajima, M., Pascale, F., & Price, A. D. F. (2014). Hospital resilience to natural hazards: Classification and performance of utilities. *Disaster Prevention and Management*, *23*(1), 40–52.

Achour, N., & Price, A. D. F. (2010). Resilience strategies of healthcare facilities: present and future. *International Journal of Disaster Resilience in the Built Environment*, *1*(3), 264–276.

Ahmad, N., Ghani, N. A., Kamil, A. A., & Tahar, R. M. (2012). Emergency department problems: A call for hybrid simulation. In S. I. Ao, L. Gelman, D. W. L. Hukins, A.Hunter, & A. M. Korsunsky, (Eds.), *Proceedings of the world congress on engineering*, 4–6 July 2012, Vol. III, pp. 1470–1474). London, UK: Imperial College London.

Ahmadi-Javid, A., Seyedi, P., & Syam, S. S. (2017). A survey of healthcare facility location. *Computers and Operations Research*, *79*, 223–263.

Akbari, V., & Shiri, D. (2021). Weighted online minimum latency problem with edge uncertainty. *European Journal of Operational Research*. 295(1), 51–65.

Altay, N., & Green, W. G. (2006). OR/MS research in disaster operations management. *European Journal of Operational Research*, *175*(1), 475–493.

Anaya-Arenas, A. M., Renaud, J., & Ruiz, A. (2014). Relief distribution networks: a systematic review. *Annals of Operations Research*, *223*(1), 53–79.

Anderson, J. E., Ross, A. J., Back, J., Duncan, M., Snell, P., Walsh, K., & Jaye, P. (2016). Implementing resilience engineering for healthcare quality improvement using the CARE model: A feasibility study protocol. *Pilot and Feasibility Studies*, *2*(1), 1–9.

Arora, H., Raghu, T. S., & Vinze, A. (2010). Resource allocation for demand surge mitigation during disaster response. *Decision Support Systems*, *50*(1), 304–315.

Atkinson, J. A., Wells, R., Page, A., Dominello, A., Haines, M., & Wilson, A. (2015). Applications of system dynamics modelling to support health policy. *Public Health Research and Practice*, *25*(3), 1–8.

Bal, A., Ceylan, C., & Taçoğlu, C. (2017). Using value stream mapping and discrete event simulation to improve efficiency of emergency departments. *International Journal of Healthcare Management*, *10*(3), 196–206.

BBC.com (2018). *Ambulances to stop for additional emergency patients.* Retrieved from https://www.bbc.co.uk/news/uk-england-norfolk-45550841. Accessed February 2, 2021

BBC.com (2021). *Covax: How many Covid vaccines have the US and the other G7 countries pledged?.* Retrieved from https://www.bbc.co.uk/news/world-55795297. Accessed December 5, 2021.

Becker, T., Steenweg, P. M., & Werners, B. (2018). Cyclic shift scheduling with on-call duties for emergency medical services. *Health Care Management Science*, *22*(4), 676–690.

Bender, M., Connelly, C. D., & Brown, C. (2013). Interdisciplinary collaboration: The role of the clinical nurse leader. *Journal of Nursing Management*, *21*(1), 165–174.

Berg, S. H., Akerjordet, K., Ekstedt, M., & Aase, K. (2018). Methodological strategies in resilient health care studies: An integrative review. *Safety*

Science, *110*, 300–312.

Boness, T., & Mayes, H. (2018). Improving Patient Transport in New South Wales. *Impact*, *2018*(1), 42–45.

Boon, H. S., Mior, S. A., Barnsley, J., Ashbury, F. D., & Haig, R. (2009). The Difference Between Integration and Collaboration in Patient Care: Results From Key Informant Interviews Working in Multiprofessional Health Care Teams. *Journal of Manipulative and Physiological Therapeutics*, *32*(9), 715–722.

Boyd, A., Chambers, N., French, S., King, R., Shaw, D., & Whitehead, A. S. (2012). A scoping study of emergency planning and management in health care: What further research is needed. *Final report. NIHR Health Services and Delivery Research programme.*

Brailsford, S. C., Desai, S. M., & Viana, J. (2010). Towards the holy grail: Combining system dynamics and discrete-event simulation in healthcare. In B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, & E. Yucesan (Eds.), *Proceedings of the 42nd winter simulation conference*, Baltimore, MD.

Brailsford, S. C., Eldabi, T., Kunc, M., Mustafee, N., & Osorio, A. F. (2019). Hybrid simulation modelling in operational research: A state-of-the-art review. *European Journal of Operational Research*, *278*(3), 721–737.

Brailsford, S. C., Gutjahr, W. J., Rauner, M. S., & Zeppelzauer, W. (2007). Combined discrete-event simulation and ant colony optimisation approach for selecting optimal screening policies for diabetic retinopathy. *Computational Management Science*, 4(1), 59–83.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., & Von Winterfeldt, D. (2003). A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra*, *19*(4), 733–752.

Bruneau, M., & Reinhorn, A. (2007). Exploring the concept of seismic resilience for acute care facilities. *Earthquake Spectra*, *23*(1), 41–62.

Buhat, C. A. H., Duero, J. C. C., Felix, E. F. O., Rabajante, J. F., & Mamplata, J. B. (2021). Optimal Allocation of COVID-19 Test Kits Among

Accredited Testing Centers in the Philippines. *Journal of Healthcare Informatics Research*, *5*, 54–69.

Cabrera, E., Luque, E., Taboada, M., Epelde, F., & Iglesias, M. L. (2012). Optimization of emergency departments by agent-based modeling and simulation. In *Proceeding - IEEE 13th International Conference on Information Reuse & Integration*, 423–430.

Carenzo, L., Costantini, E., Greco, M., Barra, F. L., Rendiniello, V., Mainetti, M., Bui, R., Zanella, A., Grasselli, G., Lagioia, M., Protti, A., & Cecconi, M. (2020). Hospital surge capacity in a tertiary emergency referral centre during the COVID-19 outbreak in Italy. *Anaesthesia*, 75(7), 928-934.

Caunhye, A. M., Nie, X., & Pokharel, S. (2012). Optimization models in emergency logistics: A literature review. *Socio-Economic Planning Sciences*, *46*(1), 4–13.

Caunhye, A. M., & Nie, X. (2018). A Stochastic Programming Model for Casualty Response Planning During Catastrophic Health Events. *Transportation Science*, *52*(2), 437–453.

Chalmers, J., Ritter, A., Heffernan, M., & McDonnell, G. (2009). Modelling pharmacotherapy maintenance in Australia. *A report prepared for the Australian National Council on Drugs. Sydney: Drug Policy Modelling Program, University of New South Wales*.

Chen, T. L., & Wang, C. C. (2016). Multi-objective simulation optimization for medical capacity allocation in emergency department. *Journal of Simulation*, *10*(1), 50–68.

Chong, W. W., Aslani, P., & Chen, T. F. (2013). Shared decision-making and interprofessional collaboration in mental healthcare: A qualitative study exploring perceptions of barriers and facilitators. *Journal of Interprofessional Care*, *27*(5), 373–379.

Christie, P. M. J., & Levary, R. R. (1998). The use of simulation in planning the transportation of patients to hospitals following a disaster. *Journal of Medical Systems*, *22*(5), 289–300.

Cimellaro, G. P., & Piqué, M. (2016). Resilience of a hospital emergency department under seismic event. *Advances in Structural Engineering*, *19*(5), 825–836.

Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010). Seismic resilience of a hospital system. *Structure and Infrastructure Engineering*, *6*(1–2), 127–144.

CNN.com (2020). *China's Red Cross is under fire for not getting supplies to hospitals fighting coronavirus. That's a problem for the government.* Retrieved from https://edition.cnn.com/2020/02/06/asia/red-cross-china-donations-intl-hnk/index.html. Accessed February 2, 2021

covidanalytics.io (2020) *Optimization can solve the ventilator shortage.* Retrieved from https://www.covidanalytics.io/ventilator_allocation. Accessed February 2, 2021

Crowe, S., Vasilakis, C., Skeen, A., Storr, P., Grove, P., Gallivan, S., & Utley, M. (2014). Examining the feasibility of using a modelling tool to assess resilience across a health-care system and assist with decisions concerning service reconfiguration. *Journal of the Operational Research Society*, *65*(10), 1522–1532.

Crowe, S., Gallivan, S., Vasilakis, C., Bull, C., & Fenton, M. (2015). Informing the management of pediatric heart transplant waiting lists: complementary use of simulation and analytical modeling. In *Proceeding - 2015 Winter Simulation Conference*, 1654-1655.

Dangerfield, B. C. (1999). System dynamics applications to european health care issues. *Journal of the Operational Research Society*, *50*(4), 345–353.

Dansky, K. H., & Miles, J. (1997). Patient satisfaction with ambulatory healthcare services: Waiting time and filling time. *Hospital and Health Services Administration*, *42*(2), 165–177.

Deo, S., & Gurvich, I. (2011). Centralized vs. decentralized ambulance diversion: A network perspective. *Management Science*, *57*(7), 1300–1319.

Dhamodharan, A., & Proano R. (2012). Determining the optimal vaccine vial size in developing countries: A Monte Carlo simulation approach. *Health Care Management Science, 15*, 188–196.

Dong, Y., Chbat, N. W., Gupta, A., Hadzikadic, M., & Gajic, O. (2012). Systems modeling and simulation applications for critical care medicine. *Annals of Intensive Care*, *2*(1), 1–14.

Du, M., Sai, A., & Kong, N. (2020). A data-driven optimization approach for multi-period resource allocation in cholera outbreak control. *European Journal of Operational Research*. *291*(3), 1106-1116.

El-Rifai, O., Garaix, T., & Xie, X. (2016). Proactive on-call scheduling during a seasonal epidemic. *Operations Research for Health Care*, *8*, 53–61.

Espíndola, O. R., Albores, P., & Brewster, C. (2018). Disaster preparedness in humanitarian logistics: A collaborative approach for resource management in floods. *European Journal of Operational Research*, *264*(3), 978–993.

Esposito Amideo, A., Scaparra, M. P., & Kotiadis, K. (2019). Optimising shelter location and evacuation routing operations: The critical issues. *European Journal of Operational Research*, *279*(2), 279–295.

Fairbanks, R. J., Wears, R. L., Plsek, P., Woods, D. D., Hollnagel, E., & Cook, R. I. (2014). Resilience and Resilience Engineering in Health Care. *The Joint Commission Journal on Quality and Patient Safety*, *40*(8), 376–383.

Farahani, R. Z., Lotfi, M. M., Baghaian, A., Ruiz, R., & Rezapour, S. (2020). Mass casualty management in disaster scene: A systematic review of OR&MS research in humanitarian operations. *European Journal of Operational Research*, *287*(3), 787-819.

Fitzpatrick, R., Davey, C., Buxton, M. J., & Jones, D. R. (1998). Evaluating patient-based outcome measures for use in clinical trials. *Health Technology Assessment*, 2(14), i-iv, 1-74. PMID: 9812244.

Fries, J. F., Spitz, P., Kraines, R. G., & Holman, H. R. (1980). Section of the Arthritis Foijndation Measurement of Patient Outcome in Arthritis. *Arthritis & Rheumatism*, *23*(2), 137–145.

Galindo, G., & Batta, R. (2013). Review of recent developments in OR/MS research in disaster operations management. *European Journal of Operational Research*, *230*(2), 201–211.

Glasgow, S. M., Perkins, Z. B., Tai, N. R. M., Brohi, K., & Vasilakis, C. (2018).

Development of a discrete event simulation model for evaluating strategies of red blood cell provision following mass casualty events. *European Journal of Operational Research*, *270*, 362–374.

Gong, Q., & Batta, R. (2007). Allocation and reallocation of ambulances to casualty clusters in a disaster relief operation. *IIE Transactions*, *39*(1), 27–39.

GOV.uk (2019). *NHS Emergency Planning Guidance.* Retreived from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/215643/dh_125842.pdf. Accessed February 2, 2021

Gould, D., Gammon, J., Donnelly, M., Batiste, L., Ball, E., Carneiro De Melo, A. M. S., Alidad, V., Miles, R., & Halablab, M. (2000). Improving hand hygiene in community healthcare settings: The impact of research and clinical collaboration. *Journal of Clinical Nursing*, *9*(1), 95–102.

Griffiths, J. D., Price-Lloyd, N., Smithies, M., & Williams, J. E. (2005). Modelling the requirement for supplementary nurses in an intensive care unit. *Journal of the Operational Research Society*, *56*(2), 126–133.

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., Thulke, H. H., Weiner, J., Wiegand, T., & DeAngelis, D. L. (2005). Pattern-oriented modeling of agent-based complex systems: Lessons from ecology. *Science*, *310*(5750), 987–991.

Gul, M., & Guneri, A. F. (2015). A comprehensive review of emergency department simulation applications for normal and disaster conditions. *Computers and Industrial Engineering*, *83*, 327–344.

Güneş, E. D., & Yaman, H. (2010). Health network mergers and hospital re-planning. *Journal of the Operational Research Society*, *61*(2), 275–283.

Gutjahr, W. J., & Nolz, P. C. (2016). Multicriteria optimization in humanitarian aid. *European Journal of Operational Research*, *252*(2), 351–366.

Han, S., Preciado, V., Nowzari, C., & Pappas, G. (2015). Data-driven network resource allocation for controlling spreading processes. *IEEE Transactions on Network Sci- ence and Engineering*, *2* (4), 127–138.

Harper, P. R., & Shahani, A. K. (2007). Modelling for the planning and management of bed capacities in hospitals. *Journal of the Operational Research Society*, *53*(1), 11–18.

He, S., Sim, M., & Zhang, M. (2019). Data-driven patient scheduling in emergency departments: A hybrid robust-stochastic approach. *Management Science*, *65*(9), 4123–4140.

Henry, D., & Ramirez-Marquez, J. E. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. *Reliability Engineering and System Safety*, *99*, 114–122.

Holguín-Veras, J., Pérez, N., Jaller, M., Van Wassenhove, L. N., & Aros-Vera, F. (2013). On the appropriate objective function for post-disaster humanitarian logistics models. *Journal of Operations Management*, *31*(5), 262–280.

Holling, C. (1996). Engineering Resilience versus Ecological Resilience. *Engineering Within Ecological Constraints*, *1996*, 31–43.

Jacobson, S. H., Sewell, E. C., & Weniger, B. G. (2001). Using Monte Carlo simulation to assess the value of combination vaccines for pediatric immunization. In *Proceeding - 2001 Winter Simulation Conference*, 1421–1428.

Jerić, S. V., & Figueira, J. R. (2012). Multi-objective scheduling and a resource allocation problem in hospitals. *Journal of Scheduling*, *15*(5), 513–535.

Johnson, K. F., & Mahan, L. A. (2019). A Qualitative Investigation into Behavioral Health Providers Attitudes Toward Interprofessional Clinical Collaboration. *The Journal of Behavioral Health Services & Research*, *46*, 636–647.

Jones, S. S., & Evans, R. S. (2008). An agent based simulation tool for scheduling emergency department physicians. In *AMIA Annual Symposium Proceedings 2008 American Medical Informatics Association*, 338–342.

Jun, J. B., Jacobson, S. H., & Swisher, J. R. (1999). Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society*, *50*(2), 109–123.

Kamali, B., Bish, D., & Glick, R. (2017). Optimal service order for mass-casualty incident response. *European Journal of Operational Research*, *261*(1), 355–367.

Karam, M., Brault, I., Van Durme, T., & Macq, J. (2018). Comparing interprofessional and interorganizational collaboration in healthcare: A systematic review of the qualitative research. *International Journal of Nursing Studies*, *79*, 70–83.

Karnon, J., Stahl, J., Brennan, A., Caro, J. J., Mar, J., & Möller, J. (2012). Modeling using discrete event simulation a report of the ISPOR-SMDM modeling good research practices task force. *Medical Decision Making*, *32*(5), 701–711.

Katsaliaki, K., & Mustafee, N. (2011). Applications of simulation within the healthcare context. *Journal of the Operational Research Society*, *62*(8), 1431–1451.

Kleindorfer, G. B., O'Neill, L., & Ganeshan, R. (1998). Validation in simulation: Various positions in the philosophy of science. *Management Science*, *44*(8), 1087–1099.

Konrad, R., DeSotto, K., Grocela, A., McAuley, P., Wang, J., Lyons, J., & Bruin, M. (2013). Modeling the impact of changing patient flow processes in an emergency department: Insights from a computer simulation study. *Operations Research for Health Care*, *2*(4), 66–74.

Kruk, M. E., Ling, E. J., Bitton, A., Cammett, M., Cavanaugh, K., Chopra, M., El-Jardali, F., Macauley, R. J., Muraguri, M. K., Konuma, S., Marten, R., Martineau, F., Myers, M., Rasanathan, K., Ruelas, E., Soucat, A., Sugihantono, A., & Warnken, H. (2017). Building resilient health systems: A proposal for a resilience index. *British medical journal*, 357: *j2323.* DOI: https://doi.org/10.1136/bmj.j2323

Kruk, M. E., Myers, M., Varpilah, S. T., & Dahn, B. T. (2015). What is a resilient health system? Lessons from Ebola. *The Lancet*, *385*(9980), 1910–1912.

Lameris, H., Bakker, P. J. M., Elkhuizen, S. G., Vermeulen, I. B., Poutré, H. La,

& Bohte, S. M. (2008). Adaptive resource allocation for efficient patient scheduling. *Artificial Intelligence in Medicine*, *46*(1), 67–80.

Landa, P., Sonnessa, M., Tànfani, E., & Testi, A. (2016). Multiobjective bed management considering emergency and elective patient flows. *International Transactions in Operational Research*, *25*(1), 91–110.

Lei, L., Wang, S., Pinedo, M., Yang, J., & Qi, L. (2015). Personnel scheduling and supplies provisioning in emergency relief operations. *Annals of Operations Research*, *235*(1), 487–515.

Li, X., Beullens, P., Jones, D., & Tamiz, M. (2009). An integrated queuing and multi-objective bed allocation model with application to a hospital in China. *Journal of the Operational Research Society*, *60*(3), 330–338.

Lin, Q., Zhao, Q., & Lev, B. (2022). Influenza vaccine supply chain coordination under uncertain supply and demand. *European Journal of Operational Research*, *297*(3), 930–948.

Liu, F., & Zhao, L. (2015). Resilience of multi-hospitals network based on the collaborative scheduling. *International Journal of Systems Science: Operations and Logistics*, *2*(3), 135–143.

Lockhart-Wood, K. (2000). Collaboration between nurses and doctors in clinical practice. *British Journal of Nursing*, *9*(5), 276–280.

Lodree, E. J., Altay, N., & Cook, R. A. (2017). Staff assignment policies for a mass casualty event queuing network. *Annals of Operations Research*, *283*, 411–442.

Loyo, H.K., Batcher, C., Wile, K., Huang, P., Orenstein, D., & Milstein, B. (2013). From model to action: using a system dynamics model of chronic disease risks to align community action. *Health Promotion Practice, 14*(1), 53−61.

Lu, T. P., Tsai, P. F., & and Chu, Y. C. (2014). An agent-based collaborative model for orthopedic outpatient scheduling. In *Proceeding - IEEE 18th International Conference on Computer Supported Cooperative Work in Design*, 621–626.

Luscombe, R., & Kozan, E. (2016). Dynamic resource allocation to improve emergency department efficiency in real time. *European Journal of Operational Research*, *255*(2), 593–603.

Mandelbaum, A., Momčilović, P., Trichakis, N., Kadish, S., Leib, R., & Bunnell, C. A. (2020). Data-driven appointment-scheduling under uncertainty: The case of an infusion unit in a cancer center. *Management Science*, *66*(1), 243–270.

Maull, R. S., Smart, P. A., Harris, A,. & Al-Fatah Karasneh, A. (2009). An evaluation of 'fast track' in A&E: a discrete event simulation approach. *The Service Industries Journal, 29*(7), 923–941.

McDaniels, T., Chang, S., Cole, D., Mikawoz, J., & Longstaff, H. (2008). Fostering resilience to extreme events within infrastructure systems: Characterizing decision contexts for mitigation and adaptation. *Global Environmental Change*, *18*(2), 310–318.

Mehrotra, S., Rahimian, H., Barah, M., Luo, F., & Schantz, K. (2020). A model of supply- chain decisions for resource sharing with an application to ventilator allocation to combat COVID- 19. *Naval Research Logistics*, *67*(5), 303–320.

Mielczarek, B. (2016) . Review of modelling approaches for healthcare simulation. *Operations Research and Decisions*, *26*(1), 55–72.

Mishra, D., Kumar, S., & Hassini, E. (2019). Current trends in disaster management simulation modelling research. *Annals of Operations Research*, *283*(1–2), 1387–1411.

Morgan, J. S., Howick, S., Belton V. (2017). A toolkit of designs for mixing Discrete Event Simulation and System Dynamics, *European Journal of Operational Research*, 257, 907-918.

Na, S. H., & Banerjee, A. (2015). A disaster evacuation network model for transporting multiple priority evacuees. *IIE Transactions*, *47*(11), 1287–1299.

Najafi, M. , Eshghi, K. , & Dullaert, W. (2013) . A multi- objective robust optimization model for logistics planning in the earthquake response phase. *Transportation Research Part E: Logistics and Transportation Review,* *49*(1), 217–249.

Najafi, M., Eshghi, K., & de Leeuw, S. (2014). A dynamic dispatching and routing model to plan/re-plan logistics activities in response to an earthquake. *OR Spectrum*, *36*(2), 323–356.

Niessner, H., Rauner, M. S., & Gutjahr, W. J. (2018). A dynamic simulation–optimization approach for managing mass casualty incidents. *Operations Research for Health Care*, *17*, 82–100.

Ogawa, K., Kaneko, M., Kajihara, C., Sano, M., & Munechika, M. (2016). Systematization of countermeasures to improve business continuity of regional healthcare in a disaster. *Total Quality Science*, *2*(2), 60–69.

Özdamar, L., & Ertem, M. A. (2015). Models, solutions and enabling technologies in humanitarian logistics. *European Journal of Operational Research*, *244*(1), 55–65.

Pazirandeh, A., & Maghsoudi, A. (2018). Improved coordination during disaster relief operations through sharing of resources. *Journal of the Operational Research Society*, *69*(8), 1227–1241.

Pidd, M. (2004). *Computer simulation in management science* (5th ed.). West Sussex: John Wiley & Sons Ltd.

Rådestad, M., Jirwe, M., Castrén, M., Svensson, L., Gryth, D., & Rüter, A. (2013). Essential key indicators for disaster medical response suggested to be included in a national uniform protocol for documentation of major incidents: A Delphi study. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*, *21*(1), 1–11.

Repoussis, P. P., Paraskevopoulos, D. C., Vazacopoulos, A., & Hupert, N. (2016). Optimizing emergency preparedness and resource utilization in mass- casualty incidents. *European Journal of Operational Research*, *255*(2), 531–544.

Reuter-Oppermann, M., Van Den Berg, P. L., & Vile, J. L. (2017). Logistics for Emergency Medical Service systems. *Health Systems*, *6*(3), 187–208.

Ridler, S., Mason, A. J., & Raith, A. (2022). A simulation and optimisation package for emergency medical services. *European Journal of Operational*

Research, *298*(3), 1101–1113.

Ritchie, H., & Roser, M. (2021). *Natural Disasters*. Retrieved from https://ourworldindata.org/natural-disasters. Accessed March 8, 2022.

Robinson, S. (2005). Discrete-event simulation: From the pioneers to the present, what next? *Journal of the Operational Research Society*, *56*(6), 619–629.

Rocha, P. L., Ravetti, M. G., Mateus, G. R., & Pardalos, P. M. (2008). Exact algorithms for a scheduling problem with unrelated parallel machines and sequence and machine-dependent setup times. *Computers and Operations Research*, *35*(4), 1250–1264.

Rohova, M., & Koeva, S. (2021). Health System Resilience: Review of the Concept and a Framework for Its Understanding. *Journal of IMAB - Annual Proceeding (Scientific Papers)*, *27*(4), 4060–4067.

Rolland, E., Patterson, R. A., Ward, K., & Dodin, B. (2010). Decision support for disaster management. *Operations Management Research*, *3*(1), 68–79.

Rubinstein, R. (1981). *Simulation and the Monte Carlo Method*. New Jersey: John Wiley & Sons, Inc.

Sabbaghtorkan, M., Batta, R., & He, Q. (2020). Prepositioning of assets and supplies in disaster operations management: Review and research gap identification. *European Journal of Operational Research*, *284*(1), 1–19.

Salman, F. S., & Gül, S. (2014). Deployment of field hospitals in mass casualty incidents. *Computers and Industrial Engineering*, *74*(1), 37–51.

Sarkar, S., Pramanik, A., Maiti, J., & Reniers, G. (2021). COVID-19 outbreak: A data-driven optimization model for allocation of patients. *Computers and Industrial Engineering*, *161*, 107675.

Shiri, D., Akbari, V., & Salman, F. S. (2020). Online routing and scheduling of search-and-rescue teams. OR Spectrum, 42(3), 755-784.

Simpson, N. C., & Hancock, P. G. (2009). Fifty years of operational research and emergency response. *Journal of the Operational Research Society*, *60*(sup 1), 126–139.

Starr, M. K., & Matinrad, N. (2016). Disaster Management from a POM Perspective : Mapping a New Domain. *Production and Operations Management Society*, *25*(10), 1611–1637.

Sterman, J. D. (2001). System Dynamics Modeling: Tools for Learning in a Complex World. *California Management Review*, *43*(4), 25.

Sun, L., Depuy, G. W., & Evans, G. W. (2014). Multi-objective optimization models for patient allocation during a pandemic influenza outbreak. *Computers and Operations Research*, *51*, 350–359.

Sung, I., & Lee, T. (2016). Optimal allocation of emergency medical resources in a mass casualty incident: Patient prioritization by column generation. *European Journal of Operational Research*, *252*(2), 623–634.

Talarico, L., Meisel, F., & Sörensen, K. (2015). Ambulance routing for disaster response with patient groups. *Computers and Operations Research*, *56*, 120–133.

TheGuardian.com (2020). *China sends doctors and masks overseas as domestic coronavirus infections drop.* Retrieved from https://www.theguardian.com/world/2020/mar/19/china-positions-itself-as-a-leader-in-tackling-the-coronavirus. Accessed December 5, 2021.

Thul, L., & Powell, W. (2021). Stochastic optimization for vaccine and testing kit allocation for the COVID- 19 pandemic. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2021.11.007

Tippong, D., Petrovic, S., & Akbari, V. (2022). A Review of Applications of Operational Research in Healthcare Coordination in Disaster Management. *European Journal of Operational Research*, 301(1), 1-17.

Tobias, M.I., Cavana, R.Y., & Bloomfield, A. (2010). Application of a system dynamics model to inform investment in smoking cessation services in New Zealand. *American Journal of Public Health*, *100*(7), 1274−1281.

UNICEF.org (2021). *COVAX: ensuring global equitable access to COVID-19 vaccines.* Retrieved from https://www.unicef.org/supply/covax-ensuring-global-equitable-access-covid-19-vaccines. Accessed December 5, 2021.

Uriarte, A. G., Zúñiga, E. R., Moris, M. U., & Amos, H. C. (2017). How can decision makers be supported in the improvement of an emergency department? A simulation, optimization and data mining approach. *Operations Research for Health Care*, *15*, 102–122.

Vanvactor, J. D. (2011). Cognizant healthcare logistics management: Ensuring resilience during crisis. *International Journal of Disaster Resilience in the Built Environment*, *2*(3), 245–255.

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), 1–20.

Viana, J., Brailsford, S. C., Harindra, V., & Harper, P. R. (2014). Combining discrete-event simulation and system dynamics in a healthcare setting: A composite model for Chlamydia infection. *European Journal of Operational Research*, *237*(1), 196–206.

Vile, J. L., Allkins, E., Frankish, J., Garland, S., Mizen, P., & Williams, J. E. (2017). Modelling patient flow in an emergency department to better understand demand management strategies. *Journal of Simulation*, *11*(2), 115–127.

Wallemacq, P. (2018). Economic losses, poverty & disasters: 1998-2017. Centre for Research on the Epidemiology of Disasters, CRED. DOI:10.13140/RG.2.2.35610.08643

WHO.int (2008). *Emergency Medical Services Systems in the European Union: Report of an assessment project co-ordinated by the World Health Organization.* WHO Regional Office for Europe. Retrieved from https://apps.who.int/iris/bitstream/handle/10665/107916/E92038.pdf?sequence=1&isAllowed=y. Accessed February 2, 2021

WHO.int (2021). *COVAX.* Retrieved from https://www.who.int/initiatives/act-accelerator/covax. Accessed December 5, 2021.

WHO.int (2022). *Health systems governance.* Retrieved from https://www.who.int/india/health-topics/health-systems-governance. Accessed November 29, 2022.

Wilson, D. T., Hawe, G. I., Coates, G., & Crouch, R. S. (2013). A multi-objective combinatorial model of casualty processing in major incident response. *European Journal of Operational Research*, *230*(3), 643–655.

Xiang, Y., & Zhuang, J. (2016). A medical resource allocation model for serving emergency victims with deteriorating health conditions. *Annals of Operations Research*, *236*(1), 177–196.

Yang, K. K., Lam, S. S. W., Low, J. M. W., & Ong, M. E. H. (2016). Managing emergency department crowding through improved triaging and resource allocation. *Operations Research for Health Care*, *10*, 13–22.

Yi, P., George, S. K., Paul, J. A., & Lin, L. (2010). Hospital capacity planning for disaster emergency management. *Socio-Economic Planning Sciences*, *44*(3), 151–160.

Yi, W., & Kumar, A. (2007). Ant colony optimization for disaster relief operations. *Transportation Research Part E: Logistics and Transportation Review*, *43*(6), 660–672.

Yi, W., & Özdamar, L. (2007). A dynamic logistics coordination model for evacuation and support in disaster response activities. *European Journal of Operational Research*, *179*(3), 1177–1193.

Zhang, K., & Howard, D. H. (2015). Hospital and skilled nursing facility patient flows during Hurricane Katrina and the Midwest floods of 2008. *Health Systems*, *4*(1), 29–40.

Appendices

Appendix 1 Interview questions and quantitative data

<table>
<tr><th>Topic</th><th>Interview questions</th><th>Interviewee(s)</th><th>Quantitative data</th><th>Data sources</th></tr>
<tr><td rowspan="2">Flow of patients</td><td>Patient flow: To PAPs/TMUs<table><tr><th>Past activities[1]</th><th>Current activities[2]</th></tr><tr><td>- What were the criteria used to allocate patients to PAPs?
- How did you allocate patients to PAPs? (Vehicles?)
- Did you reallocate the patients among PAPs? If so, why? And where did you re-transport them to?
- Were PAPs affected by disasters?</td><td>- What are the criteria used to allocate patients to TMUs?
- How do you allocate patients to TMUs? (Vehicles?)
- Do you reallocate the patients among TMUs? If so, what is the plan?
- Do you increase a number of TMUs during disasters? If so, how?</td></tr></table></td><td>- Director of Phuket Provincial Public Health Office</td><td>- Resource requirement for TMU setting
- Number of patients (each category) and time between patient arrivals during Tsunami and boat capsizing
- Waiting time and treatment time at TMUs during Tsunami and boat capsizing
- Number of resources allocated to TMUs during Tsunami and boat capsizing</td><td>- Phuket Provincial Public Health Office</td></tr>
<tr><td>Patient flow: To HPs<table><tr><th>Past activities</th><th>Current activities</th></tr><tr><td>- What were patient categories?
- What were the criteria used to allocate patients from the PAPs to the HPs?</td><td>- What are the criteria used to allocate patients from TMUs to the HPs?
- Do you reallocate the patients to other HPs? If so, how?</td></tr></table></td><td>- Director of Phuket Provincial Public Health Office</td><td>- Number of emergency beds/chairs in internal HPs
- Capacity of external HPs (beds and staff)
- Number of patients who were treated at internal/external HPs</td><td>- Internal HPs
- Phuket Provincial Public Health Office</td></tr>
</table>

[1] It is the activities of collaboration in an emergency medical response that was implemented during Tsunami in 2004.

[2] It is the current activities of collaboration in an emergency medical response that were in place in boat capsizing in 2018 and will be implemented in future mass casualty incidents/disasters.

Topic	Interview questions		Interviewee(s)	Quantitative data	Data sources
	- Did you reallocate the patients after they being transported to one HP? If so, why? And where did you re-transport them to? - Did you move the existing patients to nearby HPs? If so, how? Criteria used to select the HPs? - Were patients transported to external HPs?	- Do you move the existing patients to other HPs during disasters? If so, how?		during Tsunami and boat capsizing	
	Integrated ambulance system				
	Past activities	Current activities	- Director of Phuket Provincial Public Health Office - Head of evacuation services	- Number of ambulances - Percentage of other modes of transport during Tsunami and boat capsizing - Actual transportation time during Tsunami and boat capsizing	- Internal HPs - CMOs - Phuket Provincial Public Health Office
	- What organisations could provide the ambulances for patient transportation? - Could you request the additional ambulances? - Were the ambulances from HPs required to transport patients to the HPs where the ambulances belong to? - Did the ambulances transport patients to one HP each trip? Or multiple HPs for one trip? - Were patients transported to HPs by other modes of transport? (i.e. private care, taxi, etc.)	- What organisations can provide the ambulances for patient transportation? - Can you request the additional ambulances? - Are the ambulances from HPs required to transport patients to the HPs where the ambulances belong to? - Do you make multiple visits for a one-trip ambulance?		- Travel time between PAPs/TMUs and HPs as well as among HPs	- Google map
	Combination of patient categories in one ambulance				
	Past activities	Current activities	- Director of Phuket Provincial Public Health	- Number of (multiple category) patients for a one-trip ambulance	- Phuket Provincial Public Health Office - CMOs
	- Did you combine the different patient categories in one ambulance? If so, How?	- Do you combine the different patient categories in one ambulance? If so, How?			

Topic	Interview questions: Past activities	Interview questions: Current activities	Interviewee(s)	Quantitative data	Data sources
			- Head of evacuation services		
Flow of medical staff	*Flow of internal medical staff* - How many facilities were the internal medical staff assigned to? - What were the criteria used to allocate the internal medical staff to each facility? - Did you reallocate the medical staff after they being transported to one facility? If so, why? And where did you re-allocate them to?	- How many facilities are the internal medical staff assigned? - What are the criteria used to allocate the internal medical staff to each facility? - Do you reallocate the medical staff to other facilities? If so, how? - In general, how do you transport the internal medical staff to each facility? (by ambulances?)	- Head of EMS centres - Head of nursing - Director of Phuket Provincial Public Health Office	- Number of medical staff in internal HPs - Minimum number of internal medical staff from hospitals are required to be allocated to EMS/TMUs during disasters - Minimum number of internal medical staff from EMS are required to be allocated to TMUs - Number of internal staff allocated to each internal HPs during Tsunami and boat capsizing	- Internal HPs - Phuket Provincial Public Health Office
	Flow of external medical staff - When did the external medical staff arrive the affected network? - What were the criteria used to allocate the external medical staff to each facility?	- What are the criteria used to allocate the external medical staff to each facility? - In general, please prioritise the facility locations for the allocation of external medical staff? (to EMS centres, TMUs, hospitals)	- Director of Phuket Provincial Public Health Office	- Number of external medical staff from other healthcare networks during Tsunami and boat capsizing - Maximum number of external medical staff can be allocated to each facility - Number of external medical staff allocated to each internal HPs during Tsunami and boat capsizing	- Phuket Provincial Public Health Office

<table>
<tr><th>Topic</th><th colspan="2">Interview questions</th><th>Interviewee(s)</th><th>Quantitative data</th><th>Data sources</th></tr>
<tr><td rowspan="6">Flow of other healthcare resources</td><td colspan="2">Flow of field beds for PAPs/TMUs setting</td><td rowspan="3">- Director of Phuket Provincial Public Health Office</td><td rowspan="3">- Number of field beds/mattresses prepared for mass casualty incidents/disasters
- Number of additional field beds/mattresses</td><td rowspan="3">- Phuket Provincial Public Health Office</td></tr>
<tr><td>Past activities</td><td>Current activities</td></tr>
<tr><td>- Did you prepare the field beds for PAP setting before an occurrence of disasters? If so, what was the plan?
- Where did the field beds come from?
- What were the criteria used to allocate the field beds to PAPs?
- Were you supplied the additional beds by other healthcare network during disasters? If so, when did they arrive the affected network?
- Did you reallocate the field beds among PAPs during disasters? If so, why? And where did you re-allocate them to?</td><td>- Do you prepare the field beds for the TMU setting before an occurrence of disasters? If so, what is the plan?
- Where do the field beds come from?
- What are the criteria used to allocate the field beds to TMUs?
- Do you have any contingency plans to increase the field beds during disasters? If so, what is the plan?
- Do you reallocate the field beds among TMUs during disasters? If so, how?</td></tr>
<tr><td colspan="2">Sharing of other healthcare resources</td><td rowspan="3">- Head of EMS centres
- Director of Phuket Provincial Public Health Office</td><td rowspan="3">- Number of ... (regarding the data obtained in the interview) shared in the network during Tsunami and boat capsizing</td><td rowspan="3">- EMS centres
- Phuket Provincial Public Health Office</td></tr>
<tr><td>Past activities</td><td>Current activities</td></tr>
<tr><td>- Did EMS centres share any things among them? Or completely worked independently?
- Did internal HPs share other resources during disasters? If so, what were they? How to share?
- Did other healthcare networks share other resources? If so, what were they?
- What were the criteria used to allocate the other resources to each facility?</td><td>- Do EMS centres share any things among them during disasters?
- Are other resources shared among internal HPs? If so, how?
- Do you have any contingency plans to increase other resources during disasters?</td></tr>
</table>

Topic	Interview questions	Interviewee(s)	Quantitative data	Data sources
Deviation in clinical practices	- What are duties and practices of PAPs/TMUs/HPs (EMS centres and hospitals)/CMOs? - Can medical staff from different HPs work interchangeably? - Are the ambulances among HPs / between HPs and CMOs different in terms of evacuation services/quality?	- Head of EMS centres - Head of evacuation services - Director of Phuket Provincial Public Health Office	- None	- None
Staff assignment to ambulance trip	- How many medical staff are presenting on the ambulance? - Are the medical staff presenting on the ambulance necessary to be the staff in which the ambulance belong to?	- Head of EMS centres - Head of emergency departments	- Number of required staff for a one-trip ambulance - Ambulance capacity for staff transportation - Number of FRs from CMOs	- Internal HPs - CMOs
Treatments	- How many resources are required for a treatment of different patient categories? - How long does the treatment take for different patient categories? - Are the field beds or emergency beds reserved for severe-injured patients only?	- Head of EMS centres - Head of emergency departments - Head of nursing - Director of Phuket Provincial Public Health Office	- Number of resources required for a treatment of different categories - Treatment time required for different patient categories - Waiting time, treatment time at internal and external HPs during Tsunami and boat capsizing - Length of stay during Tsunami and boat capsizing - Waiting time at HPs between 1st of January and 31st of December 2019	- Internal HPs

Appendix 2 Requesting letter for data collection

The University of Nottingham

UNITED KINGDOM · CHINA · MALAYSIA

November 11, 2019

Vachira Phuket Hospital
353 Yaowarat Rd, Talat Yai
Mueang Phuket District
Phuket 83000, Thailand

Dear Director of Vachira Phuket Hospital

I am writing to request the permission to conduct a research study in your hospital. I am a PhD student in Activities Management and Information System at Nottingham University Business School. I have granted the scholarship from Thai government. My research looks at the healthcare resilience improvement using collaborative care during disasters in Thailand. The study intends to examine the improvement of emergency medical response among hospitals when disasters attack. This doctoral research is being supervised by Prof. Sanja Petrovic and Dr. Vahid Akbarighadikolaei, Nottingham University Business School.

This request includes an access to following data by interviewing head of emergency department, head of outward patient department, head of inward patient department, and/ or others who experienced an emergency medical response during Tsunami 2004 and/ or boat capsizing on 5th of July 2018. The areas of interview questions are the flow of patients and resources; staff assignment to an ambulance trip; integrated ambulance system; medical services for treatment during disasters; and differences in clinical practices. The interview should take no longer than one hours for an individual and to be done on your convenience. Furthermore, this request also includes the use of numerical data during Tsunami in 2004, boat capsizing in 2018, and during 2019; as well as the capacity of healthcare resources in your hospital. The data collection will be in January 2020 where the appointment with interviewees and coordinators are made in advance.

This research has been reviewed and given favourable opinion by the Nottingham University Business School Research Ethics Committee. The data will be collected and treated confidentially and to be used on educational purpose only. Only my supervisors and I will have access to the raw data. All information collected while carrying out the study will be stored in a password protected folder on a University of Nottingham server. All data will be anonymised and no individual will be identifiable from any published findings.

If you have any questions about this research, please do not hesitate to contact me or my main supervisor via the contact details at the end of this letter. Your approval to conduct this study will be greatly appreciated.

Yours Sincerely

Danuphon Tippong

PhD Student at Nottingham University Business School
Email: danuphon.tippong@nottingham.ac.uk
Tel: +44 (0) 7727 155463
Line number: 094 595 1561, Line ID: keng_danuphon

Professor Sanja Petrovic
Main supervisor
Divisional Research Director (Operations Management and Information Systems)
Nottingham University Business School
Email: sanja.petrovic@nottingham.ac.uk
Tel: +44 (0) 115 8467764

Appendix 3 Letter of permission for data collection and use of data

Vachira Phuket Hospital
353 Yaowarat Rd
Talat Yai, Mueang Phuket District
Phuket 83000, Thailand

Date: ………………………………

Nottingham University Business School
Jubilee Campus, University of Nottingham
Nottingham. England, United Kingdom NG81BB

Dear Nottingham University Business School Research Ethics Committee

I am writing to permit Mr.Danuphon Tippong to collect data using interviews and to analyse the data collected during his research project. I understand that his research has been reviewed and given favourable opinion by the Nottingham University Business School Research Ethics Committee. Also, I am informed that the data collected will be treated confidentially and be anonymised, as well as to be used on educational purpose only.

Please contact (name) …………...……… (as a coordinator) Phone number ……….………… who can contact the interviewees and provide some key information during the data collection in the organisation.

Yours Sincerely,

(……………………………………………….)

Position:…………………………………..
Email:……………………………………..
Tel:..

Appendix 4 Information for research participants

Your participation in this research should be voluntary, and you may change your mind about being involved in the research at any time, and without giving a reason.

This information sheet is designed to give you full details of the research project, its goals, the research team, the research funder, and what you will be asked to do as part of the research. If you have any questions that are not answered by this information sheet, please ask the researcher or the supervisors via the contact details at the end of this information sheet.

This research has been reviewed and given favourable opinion by the Nottingham University Business School Research Ethics Committee.

My name is Danuphon Tippong, a PhD student in Operations Management and Information System at Nottingham University Business School. My research project is titled as Healthcare resilience improvement using collaborative care during disasters. The doctoral research is being supervised by Prof. Sanja Petrovic and Dr. Vahid Akbarighadikolaei, Nottingham University Business School. I would like to develop simulation models for strategy for collaboration in healthcare to improve healthcare resilience during disasters. More specifically, I would like to perform quantitative analysis to improve healthcare resilience by using collaborative care strategies.

I am inviting heads of EMS centres, heads of emergency department, heads of inward patient department, heads of outward patient department, heads of nursing, and heads of evacuation services from all healthcare facilities in Phuket, Thailand. I am also inviting a former and current director of Phuket Provincial Public Health.

You will be asked about duties and practices of different healthcare facilities; flow of patients and resources; sharing of healthcare resources; integrated ambulance system; staff assignment to ambulance trip; deviation in clinical practices; and medical services for treatment during Tsunami in 2004, and/or boat capsizing in 2018. Furthermore, you will be asked about the relevant numerical data during Tsunami in 2004, boat capsizing in 2018, and during 2019; as well as the capacity of healthcare resources in your hospital.

The data will be collected and treated confidentially and the name of your institution will not be asked for. At the end of the interview you will be asked whether you are willing for us to contact you to either discuss your responses or to research further the experiences relate to the strategy of collaborative care across hospitals during a disruption.

I am committed to carrying out my research according to The University of Nottingham Code of Research Conduct and Research Ethics (2016) and the ethical guidelines provided by the British Educational Research Association (online at https://www.bera.ac.uk/researchers-resources/publications/ethical-guidelines-for-educational-research-2018). I will also conform to General Data Protection Regulations.

Only my supervisors and I will have access to the raw data. All information collected while carrying out the study will be stored in a password protected folder on a University of Nottingham server. All data will be anonymised and no individual will be identifiable from any published findings.

Primarily, the data will inform my PhD thesis. Additionally, it is intended that my research findings will be disseminated through academic publications such as peer reviewed journal articles, book chapters, conference papers etc.

Contact details

Researcher: Danuphon Tippong
Tel: +44 (0) 7427155463
E-mail: danuphon.tippong@nottingham.ac.uk
Postal Address: BSS, Jubilee Campus, University of Nottingham, Nottingham. England, UK

Supervisor 1: Prof. Sanja Petrovic
Tel: +44 (0) 115 8467764
E-mail: sanja.Petrovic@nottingham.ac.uk

Postal Address: Si Yuan Building, Jubilee Campus, University of Nottingham, Nottingham. England, UK NG8 1BB

Supervisor 2: Dr. Vahid Akbarighadikolaei
Tel: +44 (0) 115 9514021
E-mail: vahid.Akbarighadikolaei@nottingham.ac.uk
Postal Address: Si Yuan Building, Jubilee Campus, University of Nottingham, Nottingham. England, UK NG8 1BB

Complaint procedure

If you wish to complain about the way in which the research is being conducted or have any concerns about the research, then in the first instance please contact the supervisors or contact the School's Research Ethics Officer:

Davide Pero
Nottingham University Business School
Jubilee Campus
Nottingham, UK NG8 1BB
Phone: +44 (0) 115 84 67763
Email: davide.pero@nottingham.ac.uk

Appendix 5 Consent form

Interviewer’s agreement

I understand that it is my responsibility as the interviewing researcher *to maintain the confidentiality* of the participant, to respect the requests of the participant and to gather and use the data obtained in an ethical manner. I understand that it is my responsibility to use the data collected from the interview for the educational purpose only, and to store the data securely. Only my supervisors and I can access to the data.

Researcher: Danuphon Tippong

Date………………………………………..

Participant’s statement of consent

I understand the purpose of this interview. I understand that any information that the researcher gathers from the interview for use in thesis or published findings will not contain names or identifying features. I understand that all information will be kept confidential. I also have right to review the final submission.

I understand *my participation in this interview in voluntary.* I may choose not to answer some or all of the questions with no consequences. I understand that I have the option to revoke my consent for any or all of my information to be used in this research.

I am willing for researcher to contact me to either discuss my responses or to research further the experiences relate to the strategy of collaborative care across hospitals during disasters.

I grant permission for audio recording.

☐ Yes ☐ No

Participant………………………..………………

Date……………………………………..………..

Appendix 6 Ethics approval confirmation letter

University of Nottingham
UK | CHINA | MALAYSIA

Faculty of Social Sciences
Nottingham University Business School
University of Nottingham
Jubilee Campus
Nottingham
NG8 1BB

20 November 2019

To whom it may concern,

RE:	**Project Title:**	Healthcare resilience improvement using collaborative care during disruption
	Chief Investigator:	Danuphon Tippong
	Co-Investigators:	Prof. Sanja Petrovic Dr. Vahid Akbarighadikolaei
	NUBS REC reference:	201819048

I am writing as chair of the Nottingham University Business School Research Ethics Committee (NUBS REC) to confirm a favourable ethical opinion for the above research on the basis of the documentation submitted below. This opinion was given on 20th November 2019.

The School REC operates according to the University of Nottingham's *Code of Research Conduct and Research Ethics, and the Economic and Social Research Council (ESRC) Framework for Research Ethics.*

The documents reviewed and approved are:

- NUBS REC Ethics Review Checklist
- Annex I_Quantitative Measures and Interview Questions_Danuphon Tippong
- Annex II_Participants Information Sheet_Danuphon Tippong

The following conditions apply to this favourable opinion:

1. Management permission ("R&D approval") must be obtained from each host organisation prior to the start of the study at the site concerned.
2. The research must follow the protocol agreed and any changes will require prior NUBS REC approval.
3. The appropriate NUBS REC documentation must be completed at the end of the research project.

For further information about the School's Research Ethics Committee or approval process, please contact the Research Ethics Officer, Davide Pero at davide.pero@nottingham.ac.uk or +44 (0)115 84 67766.

Yours faithfully,

AJ Crompton

Dr Amanda Crompton
Chair of Nottingham University Business School Research Ethics Committee