DISSERTATION

RESILIENCE OF HEALTHCARE AND EDUCATION NETWORKS AND THEIR INTERACTIONS FOLLOWING MAJOR EARTHQUAKES

Submitted by

Emad Mohamed Shafik Hassan

Department of Civil and Environmental Engineering

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Doctoral Committee:

Advisor: Hussam N. Mahmoud

Bruce R. Ellingwood
John W. van de Lindt
Sammy Zahran
Steven McCabe
Amy Cerato

ABSTRACT

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Healthcare and education systems have been identified by various national and international organizations as the main pillars of communities' stability. Ensuring the continuation of vital community services such as healthcare and education is critical for minimizing social losses after extreme events. A shortage of healthcare services could have catastrophic short-term and long-term effects on a community including an increase in morbidity and mortality, as well as population outmigration. Moreover, a shortage or lack of facilities for *K-12* education, including elementary, middle, and high schools could impact a wide range of the community's population and could lead to impact population outmigration. Despite their importance to communities, there are a lack of comprehensive models that can be used to quantify recovery of functionalities of healthcare systems and schools following natural disasters. In addition to capturing the recovery of functionality, understanding the correlation between these main social services institutions is critical to determining the welfare of communities following natural disasters. Although hospitals and schools are key indicators of the stability of community social services, no studies to date have been conducted to determine the level of interdependence between hospitals and schools and their collective influence on their recoveries following extreme events.

In this study, comprehensive frameworks are devised for estimating the losses, functionality, and recovery of healthcare and educational services following earthquakes. Success trees and semi-Markov stochastic models coupled with dynamic optimization are used to develop socio-technical models that describe functionalities and restorations of the facilities providing these services, by integrating the physical infrastructure, the supplies, and the people who operate and use these facilities. New frameworks are proposed to simulate processes such as patient demand on hospitals, hospitals' interaction, student enrollment, and school administration as well as different decisions and mitigation strategies applied by hospitals and schools while considering the disturbance imposed by earthquake events on these processes.

The complex interaction between healthcare and education networks is captured using a new agent-based model which has been developed in the context of the communities' physical, social, and economic sectors that affect overall recovery. This model is employed to simulate the functional processes within each facility while optimizing their recovery trajectories after earthquake occurrence. The results highlight significant interdependencies between hospitals and schools, including direct and indirect relationships, suggesting the need for collective coupling of their recovery to achieve full functionality of either of the two systems following natural disasters. Recognizing this high level of interdependence, a social services stability index is then established which can be used by policymakers and community leaders to quantify the impact of healthcare and educational services on community resilience and social services stability.

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DEDICATION

To my beloved family

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Chapter 1. INTRODUCTION

1.1 Statement of the Problem

The nature of earthquakes, being relatively short in duration with high consequences, has always attracted vast research attention towards reducing the disruptions that frequently occur in their aftermath. The focus has primarily been on achieving certain performance objectives such as life safety and collapse prevention. Some studies and guidelines have focused on maintaining a certain level of infrastructure functionality after an earthquake (Federal Emergency Management Agency, 2007, 2010). Ensuring the continuation of vital community services, such as healthcare and *K-12* education, is critical for enhancing communities' socio-economic stability after extreme events (Butler & Diaz, 2016). However, a large number of hospitals and schools (the main providers for healthcare and education) are vulnerable to earthquakes (American Society of Civil Engineers, 2017; Applied Technology Council, 2017). For instance, Olive View Hospital and West Anchorage High School were severely damaged during the 1971 Sylmar earthquake and the 1964 Alaska earthquake, respectively, as shown in Figure 1-1. Ensuring the continuation of healthcare services and reducing overcrowding in emergency departments is critical for minimizing social and economic losses after extreme events. Similarly, recovering the educational services following earthquakes is key for ensuring the stability of communities.

Figure 1-1: (a) Olive View Hospital damaged during the 1971 Sylmar earthquake (Çelebi et al., 2003) and (b) West Anchorage High School damage during the 1964 Alaska earthquake (Federal Emergency Management Agency, 2010).

The catastrophic impacts resulting from the shortage of healthcare and educational services (Hinojosa et al., 2019; Jacques et al., 2014; Mulyasari et al., 2013; Singer et al., 2011; The Institute for Public Policy & Economic Development, 2013) has inspired the establishment of guidelines and studies to provide extensive retrofitting and mitigation strategies to enhance the safety of existing and new hospital and school buildings (Federal Emergency Management Agency, 2002; Fujieda et al., 2008; Nakano, 2004; Office of Statewide Health Planning and Development, 2021) Other studies pertaining to healthcare systems have established the basis for assessing the functionality of hospitals following earthquake events (Gian Paolo Cimellaro et al., 2010b; Kirsch et al., 2010; Kuo et al., 2008), modeled the hospital's surge capacity (Sheikhbardsiri et al., 2017), and developed real-time electronic hospital bed tracking/monitoring systems (Denver Health, 2005). However, the guidelines and studies stopped short quantifying the functionality of the various components, accounting for the mutual interaction between the hospital and the supporting lifelines, simulating patient distribution, and modeling the interaction between hospitals as a network. Moreover, previous studies in the area of the education system have focused on measuring the performance of schools during normal operating conditions (Mayer et al., 2000; National Research Council, 2012) or during and after earthquakes (Augenti et al., 2004;

Beaglehole et al., 2018; Oyguc & Guley, 2017). However, these studies did not introduce models that could be used to predict school functionality after extreme natural disasters. Models that include quantitative representations of different components of a typical school, specify service components of functionality, and account for the mutual interaction between schools and their supporting lifelines are required for full functionality assessment.

Many national and international organizations are currently listing healthcare and education systems as essential institutions for community stability and well-being (National Academy of Engineering, 2008; NIST, 2016a, 2016b; UNICEF, 2017; United Nations, 2015). However, to date, studies on their interaction, their collective effect on their respective recovery, and the stability of the social services of communities are lacking. Quantifying the interaction, especially between these social institutions, is critical for community resilience analysis (Cimellaro, 2016; Mahmoud & Chulahwat, 2018; NIST, 2016a). Their collective role in societies is essential for building robust communities (Butler & Diaz, 2016), informing public policies (NIST, 2016b), and influencing social indices (Flanagan et al., 2018; Stern & Epner, 2019).

1.2 Objectives of Dissertation

The main objectives of this study are to 1) devise frameworks for estimating functionality and recovery of healthcare and education systems; 2) utilize the developed frameworks to investigate the resilience of both systems independently; and 3) evaluate their collective impacts on the community social services stability. These main objectives are illustrated in Figure 1-2.

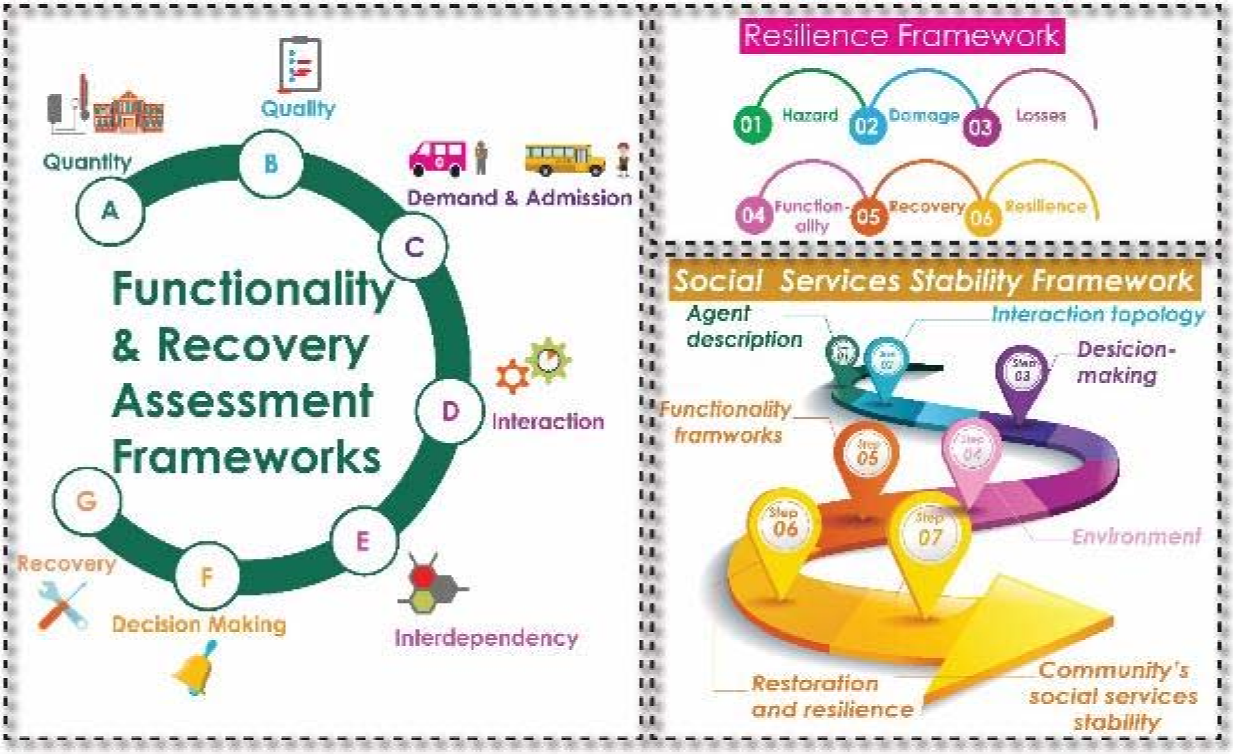

Figure 1-2: Research objectives of the dissertation.

To achieve the outlined objectives, a new framework for the spatial and temporal assessment of the functionality of healthcare services provided by a cluster of hospital facilities following an earthquake is first introduced. Specifically, new models describing the interdependency between hospitals and the community built-environment, the interactions among hospitals, and patient-hospital connections are devised and discussed in detail. Both the quantity and quality of the healthcare services functionality provided by each hospital are quantified while considering the main physical, social, and economic parameters affecting each of these functionalities. Three main matrices are utilized to measure the hospital functionalities including hospital staffed beds, patient waiting time, and patient treatment time. The functionality interdependence between each hospital and its supporting infrastructure is modeled using a success tree. A new sub-framework is introduced to estimate the daily patient demand on each hospital after the earthquake while taking into consideration the probability of patients being transferred between hospitals based on hospital functionality and/or patient selection and condition. A second sub-framework is developed to simulate the interaction between hospitals while considering the probability of staff, supplies, and repair resources transfer.

Similar to the healthcare services functionality, a new framework is presented to estimate the spatial and temporal functionality of public *K-12* schools after earthquakes, which enroll approximately 90% of *K-12* students in the U.S. Both the quantity and quality functionality of the educational services are estimated while considering the role played by parents, teachers, and administrative personnel, in maintaining the functionality of schools. The framework accounts for interdependence between schools and their supporting lifelines. The quantity and quality of educational services are quantified in terms of the schools' enrollment capacity at each grade and the class capacity combined with the student academic and social outcomes, respectively. Post-earthquake decisions made by the schools and school districts including student enrollment, transportation, and staff and supplies transfer, among others are modeled.

The recovery of each healthcare and education facility is modeled using a semi-Markov process. The framework estimates the near-optimal recovery trajectories of the hospitals and schools based on dynamic optimization to achieve pre-defined objective resilience functions while accounting for the limitations in repair resources, specialties of repair crews, and possible repair sequences. The estimated repair recovery trajectories of the healthcare and education facilities are coupled with the recovery of the community built environment including buildings and the main utilities (water, power, transportation, telecommunication, wastewater, drinking water, and fuel systems) to form the recovery of the hospitals and schools working spaces while considering the different mitigation strategies such as the availability of backup systems and backup space.

To reach full recovery of healthcare and educational services, hospitals and schools need also to restore the full functionality of their staff and assemble their essential supplies that might be impacted during the earthquake. Mathematical functions are developed in this study to estimate the recovery of the staff and supplies based on different communities' physical, social, and economic parameters after the earthquake. Decision frameworks are introduced to mimic hospitals' and schools' administrations' decisions that can enhance patient satisfaction at hospitals and student outcomes at schools.

The interaction between healthcare and education systems as well as their impact on resilience and social services stability of communities after natural disasters, is quantified using an agent-based model. The model utilizes the healthcare and education functionality frameworks and is structured using a socio-technical approach that is based on guidelines and case studies for real communities after disasters. The results are then used to construct a social services stability index, which can be used to quantify the impact of healthcare and educational services on community resilience and social stability.

To test the capabilities of the frameworks, Centerville (a mid-size virtual community) (Ellingwood et al., 2016) is used and is subjected to different earthquake scenarios. The results, from the virtual community analysis, are used to highlight the capability of the frameworks that were developed to predict the behavior of these complex interactions among these infrastructure systems. The testbed is also used to quantify the sensitivity of the estimated resilience of the healthcare and educational services to the frameworks' main parameters in an uncertainty propagation analysis. The impacts of different recovery decisions and mitigation strategies on healthcare and education systems' functionality are assessed. Finally, the levels of interdependency between each hospital and school facility as well as the whole healthcare and education systems are calculated.

The following tasks are conducted to achieve the above objectives:

<u>Task 1:</u> Conduct a comprehensive literature review

<u>Task 2:</u> Introduce a new framework to estimate healthcare system functionality

<u>Task 3:</u> Present a framework to quantify education system functionality

<u>Task 4:</u> Devise a framework to estimate the recovery and resilience of hospitals and schools

<u>Task 5:</u> Build an agent-based model for healthcare and education systems

<u>Task 6:</u> Apply the developed frameworks to Centerville as a community testbed

<u>Task 7:</u> Assess the interdependencies and interactions between healthcare and education systems.

1.3 Overview of Dissertation

This dissertation includes seven chapters. Chapter 1 introduces the problem as well as the objectives of this study. Chapter 2 reviews the background and literature surveying the current knowledge on modeling healthcare and education systems after natural disasters with a focus on earthquake hazards. The chapter starts with an overview of the impact of historical earthquakes on healthcare and education systems. The role played by healthcare and education systems after natural disasters in community resilience and social stability is discussed.

In Chapter 3, details of the newly developed functionality framework of the healthcare services are presented. The functionality of hospitals, as main healthcare providers, is described as the combination of the quantity of the healthcare services, measured by the number of available staffed beds in each bed category, and the quality of the offered healthcare services, measured as a combination between the patient waiting and treatment times. A new patient-driven model, that is used to distribute patients to the hospitals in the community, is introduced. The details of the hospitals' interaction model are discussed in this chapter, which is utilized to simulate patients, staff, and supplies transfer between hospitals. The inputs for these models are also described, which include the healthcare system components data, community demographics data, and the functionality of infrastructure and medical and non-medical suppliers.

Chapter 4 introduces a new framework to quantify educational services functionality, where the quantity and quality functionality of the *K-12* public schools are measured using a combination of the schools' enrollment capacity as well as the teacher, classroom, and school quality indices. To mimic the role played by different agents in the process such as student enrollment and transfer, transportation, staff appointment, and school interaction a new framework for the school administration is developed. The inputs for these frameworks, as well as how the possible decisions made by school administration impact the educational services, are discussed.

In Chapter 5, the interdependent recovery framework is presented, which utilizes a semi-Markov chain stochastic model, coupled with dynamic optimization, to achieve near-optimal recovery trajectories for hospitals and schools. In the chapter, the developed agent-based model for healthcare and education systems is also discussed. Descriptions of the different agents and their interactions as well as the decision-making heuristics, are all provided.

In Chapter 6, the first detailed descriptions of the healthcare and education systems components in Centerville, as well as the characteristics of the main physical, social, and economic features of the community, are provided. Second, the main results obtained from subjecting Centerville to different earthquake scenarios are presented, which include a) functionality, recovery, and resilience analysis of healthcare and education systems, b) sensitivity and uncertainty quantification of the introduced models and frameworks, c) interdependency assessment between healthcare and education systems, d) impacts of healthcare and education resilience on the community's social services stability, and e) effects of different mitigation strategies on the resilience and the community's social service stability.

Chapter 7 summarizes the main findings of the research. The contribution of this study to the fields of natural hazard and community resilience is emphasized. Finally, a set of recommendations is provided, and future work is outlined for enhancing the resilience of healthcare and education systems.

Chapter 2. BACKGROUND AND LITERATURE REVIEW

2.1 Overview

Maintaining social services stability following natural disasters is critical for sustainable cities and communities. Availability of healthcare and education facilities, in particular, is key to bring normalcy back to communities and reduce the potential for population outmigration, which commonly occurs as an outcome of a shortage of public services (Hinojosa et al., 2019). Therefore, it is not surprising that various national and international organizations have recognized the importance of healthcare and education systems to communities' stability. For example, the United Nations listed quality education and good health as two of its 17 sustainable development goals for the year 2030 (United Nations, 2015). Similarly, requirements for substantial advancements in these two systems are part of UNICEF's New Strategic Plan (UNICEF, 2017) for the year 2018 to 2021. This international recognition of the importance of good healthcare and education systems has also been noted in the United States (U.S.) by various leading scientific organizations, including the National Academy of Engineering (2008) and the National Institute of Standards and Technology (2016). More specifically, the National Institute for Standards and Technology has listed hospitals and schools among the essential institutions for providing social services stability within a community (NIST, 2016a). Despite the recent advances in acknowledging the role played by these facilities, to date, comprehensive studies on functionality and recovery of these facilities following extreme hazard events are either limited or non-existent.

Because of their significant potential role in enhancing health and long-term economic mobility in a community, disturbances to healthcare and education networks can seriously impact its welfare (Butler & Diaz, 2016). Policymakers have recognized that achieving good health is tied to eliminating poverty and providing proper education (Butler & Diaz, 2016; UCSF Center on Social Disparities in Health et al., 2015). The health of individuals can be an essential factor in their success at school and in the workplace (Butler & Diaz, 2016; UCSF Center on Social Disparities in Health et al., 2015). Recognizing this interaction, many schools have partnered with hospitals to address mental health issues and other health concerns for students (National Academies of Sciences, Engineering, 2019b). Recent efforts in the U.S. have been geared towards aligning health and education metrics through the Healthy Schools campaign at the state level or through a partnership between the Healthy Schools Project partnered with Trust for America's Health and others. Emphases have been placed on incorporating health metrics into education accountability systems and on integrating education metrics into the healthcare system (National Academies of Sciences, Engineering, 2019b). Although major initiatives have been made to link hospitals and schools in communities, to date no studies have been conducted to assess the impact of major disasters on their interaction and their dependency on each other during recovery.

2.2 Impacts of historical earthquake events on hospitals and schools

Hospitals and schools both are vulnerable to extreme natural disasters as shown in Figure 2-1 (Applied Technology Council, 2017; Giri et al., 2018; NIST, 2013). For instance, the 1989 Loma Prieta earthquake damaged two hospitals (Pointer et al., 1992) and resulted in severe damage to three schools (EERI, 1990); the 1995 Kobe earthquake collapsed four hospitals (Ukai, 1997); and damaged approximately 4,500 schools (Nakano, 2004), and the 2008 Sichuan earthquake caused the collapse of many hospitals and schools (Miyamoto et al., 2008). Earthquake damages also resulted in total casualties of 35,000, 3,757, and 10,000 injuries from the Loma Prieta, PDD Kobe, and Sichuan earthquakes, respectively (Ukai, 1997). These casualties created a surge in medical demands for the affected healthcare facilities (Pointer et al., 1992), which significantly impacted the available medical services in terms of accessibility and effectiveness. Damage to school buildings can result in death and injuries to staff and students (Miyamoto et al., 2008), an increase in post-traumatic stress for schoolchildren (Uemoto et al., 2012), and a halt in educational services due to school closure (Hinojosa et al., 2019).

Figure 2-1: Impacts of historical seismic events on (a) hospitals and (b) schools.

2.3 Healthcare system models

Ensuring the continuation of healthcare services and reducing overcrowding in emergency departments is critical for minimizing social and economic losses after extreme events. Different parameters play various roles in the level of functionality or recovery restoration of healthcare facilities that can be achieved following a major event. While availabilities of the main hospital's components such as staff, space, and supplies are essential for maintaining hospital facilities' functionality, other parameters including hospital demand and the impact of other facilities on the healthcare system can affect this functionality. Furthermore, parameters including, but not limited to, the type of damaged components, extent of damage, and available funding resources (e.g., insured losses or federal sources) can affect the recovery of these facilities. This section discusses previous research studies conducted to investigate and/or model hospitals and their functionality components, patient distribution, and the mutual impact between healthcare facilities.

2.3.1 Healthcare system functionality

Healthcare quality is not only measured by a physical metric (e.g., number of available beds) but also by the level of consumer satisfaction. Hospital functionality can be defined by combining the quantity (Q_V) and quality (Q_S) of the services (Cimellaro et al., 2011; Hassan & Mahmoud, 2019, 2020a). The quantity portion of the offered services is usually estimated based on hospital capacity or the number of staffed beds available for patients based on daily rates (Denver Health, 2005). Noteworthy, healthcare service not only depends on the hospital itself but also on the surrounding lifelines. For example, a reduction in transportation network capacity will lead to delays in ambulances' response or even an entire halt to their service. According to Jacques et al. (2014), for these beds to be available for service, representing the quantity portion of the service, three main components are required: 1) trained personnel such as physicians, nurses, and supporting staff; 2) qualified space; and 3) sufficient supplies. The quality portion of the offered service, on the other hand, is difficult to describe. Previous studies identified several dimensions to represent the quality of the healthcare service (Kalaja et al., 2016; Maxwell J. R., 1984). One way to do so is by defining the service as a function of losses to different hospital departments while considering the possibility of service redistribution among the departments (Jacques et al., 2014). The patient waiting time could also be used to represent the quality part of the functionality (Hassan & Mahmoud, 2019; McCarthy et al., 2010). Previous studies (Cimellaro et al., 2010b; Kirsch et al., 2010; Kuo et al., 2008) have been significant in establishing the basis for assessing the functionality of hospitals following an earthquake as well as building a real-time electronic hospital bed tracking/monitoring system that can serve as a demonstration management tool to assist in a quantifying the ability of a system or a cluster to care for a surge of patients (Denver

Health, 2005). Other studies highlighted the impact of transportation network damage on healthcare systems after earthquakes (Dong & Frangopol, 2017; Lupoi et al., 2013).

Research studies on modeling the functionality of healthcare systems and their components after seismic events have yet to include a comprehensive analytical model that accounts for the impact of different hospital components on its functionality, the dynamic change in patient distribution in the aftermath of an extreme hazard event, the mutual interaction among healthcare system facilities, and the interdependency between the hospitals and their supporting lifelines. For instance, McDaniels et al. (2008) developed a conceptual framework that can be used to understand the main factors influencing the resilience of healthcare systems in terms of two dimensions: robustness and rapidity after a seismic event. To understand the impact of different decisions on the estimation of these two dimensions of system resilience, flow diagrams were used, and the results of several data-gathering were utilized. Miniati and Iasio (2012) introduced a methodology that can be used to assess the seismic risk health structures, which include, in addition to the building structure parameters, a combination of the theory of complex systems analysis with the use of the Leontief model (Haimes & Jiang, 2001) and a rapid seismic vulnerability assessment with field data collected using the World Health Organization evaluation forms. Lupoi et al. (2013) investigated the seismic resilience of a regional Healthcare system including the road network connecting the hospitals in the investigated region. The author developed and implemented a dynamic model to simulate patient demand and hospital performance. Mulyasari et al. (2013) utilized a survey to assess the earthquake preparedness of hospitals in eight Japanese cities. The survey focused on structural, nonstructural, functional, and human resources as the main functionality parameters. Jacques et al. (2014) utilized a holistic and multidisciplinary approach to investigate the performance of a hospital system in which data collected using a standardized survey was used to build a fault tree that can assess the functionality of hospitals based on three main contributing factors: staff, structure, and stuff. Perrone et al. (2015) presented a methodology to visually screen RC hospital buildings exposed to seismic events and assign a safety index for these hospital buildings. The introduced methodology was applied to two Italian hospitals located in different seismic zones as well as two hospitals damaged by the 2009 L'Aquila Earthquake and the 2012 Emilia Earthquake. Malavisi et al. (2015) introduced a simplified framework to measure the ability of the emergency departments to provide medical service after emergency incidents as a function of patient waiting time. The authors utilized Umberto I Mauriziano hospital, Turrin as a case study. The presented framework was used to develop a metamodel that provides the waiting times of patients as a function of the seismic input and the number of available emergency rooms. Cimellaro and Pique (2016) presented a discrete event simulation model for measuring the resilience of emergency departments during a seismic event using the patient waiting time as a performance parameter. The authors then developed a metamodel for different emergency codes considering the seismic input and the available resources. Hassan and Mahmoud (2018, 2019) recently developed a framework to investigate the performance of the healthcare facilities after seismic events (*the details of these studies will be presented in Chapter 3 of this dissertation*). Both the initial drop of functionality and different recovery stages were modeled. A success tree analysis was utilized to model the quantity portion of functionality considering different hospital components including personal, space, and supplies as well as the supporting infrastructure for the healthcare facilities. This quantity portion of functionality (staffed beds) was then combined with the quality functionality as a function of the total patient waiting time including the travel time to the hospital to form a total functionality index. Shang et al. (2020) proposed an evaluation framework based on the state tree method that can be used to measure the impact of different components on both the functionality and the seismic resilience of emergency departments from an engineering perspective. Ceferino et al. (2020) introduced a methodology to investigate emergency department response after seismic events that is a function of the loss of hospital functions and multi-severity injuries as a result of earthquake damage.

While the studies, mentioned above, focused on the healthcare system after seismic events, other studies considered different natural hazards including wildfire (Hassan & Mahmoud, 2021b; Schulze et al., 2020), climate events (Chand & Loosemore, 2012, 2016; Chow et al., 2012; Loosemore et al., 2010, 2013, 2014; Loosemore, Carthey, et al., 2011; Loosemore, Chow, et al., 2011; Loosemore & Chand, 2016), and other disasters (Arboleda, 2006; Arboleda et al., 2009; G. P. Cimellaro et al., 2013; Fischbacher-Smith & Fischbacher-Smith, 2013; Guinet & Faccincani, 2016; Hassan & Mahmoud, 2020b; Kanno et al., 2011; Takim et al., 2016; Vugrin et al., 2015; Wears et al., 2007) Furthermore, many studies were conducted to model healthcare system components during normal working conditions. For instance, Hiete et al. (2011) investigated the impact of power outages on the healthcare sector. Maglogiannis and Zafiropoulos (2006) introduced an approach to investigate the risk in healthcare information systems using central risk analysis and management methodology to study the assets, threats, and vulnerabilities of the distributed information system. Lamothe and Dufour (2007) introduced an investigation of the empirical data gathered in a Canadian teaching hospital to highlight the interdependencies that drive some of its configurations at the healthcare unit level. Geroy and Pesigan (2011) presented a qualitative report on the implementation of activities aimed at reducing disaster risks through safer health facilities in the Western Pacific region. Heng and Loosemore (2011) investigated the healthcare delivery system using a case study approach and a social network perspective to explore the brokerage role of facility managers in achieving effectiveness in the healthcare delivery system. Zhong et al. (2014) provided a validated framework to comprehensively measure hospital disaster resilience using a Modified-Delphi. Kisekka et al. (2015) investigated the antecedents of healthcare workers' perceptions of organizational resilience to offer solutions for effective management of extreme events in hospitals. Righi and Saurin (Righi & Saurin, 2015) introduced a framework for the operationalization of the "attribute view" of complexity while using an emergency department of a University hospital as an illustration. Sujan (2015) introduced a study that can improve patient safety, which depended on reporting and organizational learning to explore current perceptions of healthcare staff. Kadri et al. (2016) defined, characterized, and proposed a generic procedure to evaluate the resilience of an emergency based on the definition of a strain situation, transition states, and corrective actions. Wachs et al. (2016) investigated resilience skills by the emergency department with a focus on case studies in two emergency departments: one in Brazil and the other in the U.S. (Achour & Price, 2010) introduced a review of the resilience strategies of healthcare facilities including research papers, governmental and non-governmental reports, code and guidance documents, and databases.

2.3.2 Patient demand

In addition to capacity, patient demand is a critical parameter for hospital functionality assessment. Hospital demand after a hazard, in terms of the number of patients, is affected by the treatment of the usual day-to-day as well as hazard-related injuries. The demand on hospitals during usual operation is commonly estimated using forecasting approaches based on statistical data while considering the types of diseases or injuries (Barros et al., 2010; Farmer & Emami, 1990; Jones et al., 2002; Schweigler et al., 2009) or by defining a service area for each hospital (Jia, 2016). Other approaches estimate the hospital choice as a function of patient-to-hospital distance and hospital staffed beds such as the gravity model presented by Jia et al. (2019), which was developed based on 2,376,743 inpatient discharge records for Florida in 2011; however, this type of model is not dynamic and ignores many parameters related to patients, patient-to-hospital connection, and hospital that can be impacted after seismic events. Other studies have introduced general frameworks to investigate the patient demand and distribution after disasters other than earthquakes. For example, Toader et al. (2019) introduced a multi-agent model to model patient distribution after mass incidents. Postma et al. (2011) analyzed the patient distribution data collected after the 2009 Turkish Airlines crash near Amsterdam. Hall et al. (2018) introduced a study to identify the main factors influencing patient distribution after the mass casualty incidents. Doi et al. (2017) introduced a simulation model called the patient access area model, which simulates patients' access time to healthcare service institutions using a geographic information system. Wellay et al. (2018) introduced a community-based cross-sectional study in Northern Ethiopia to investigate the demand for health care services and associated factors among patients. Extending these models or devising new ones to consider patient location, infrastructure functionality, such as telecommunication and the transportation network, is therefore critical for a proper estimate of demand on hospitals following extreme events.

In the case of earthquakes, a proper estimation of demand requires an assessment of fatalities and injuries in the first place. There are few models available in the literature that can be used for such an assessment. For instance, in HAZUS-MH 2.1 (2015) a quantitative model that relates damage to the built environment to the number of casualties, for various building types, is presented. Coburn and Spence (2002) introduced a semi-empirical casualty model that is based on seismic intensity and casualty rates of historical earthquake events for specific building types. Ohta et al. (1983) developed an empirical relationship to estimate earthquake casualties based on the total number of damaged buildings. Porter et al. (2007) presented an empirical earthquake casualty model for all countries as a function of earthquake intensity rather than the building type.

Hospitals located in high-risk areas commonly have a surge capacity. This capacity is available in emergency cases such as seismic events to overcome the sudden increase in the number of patients. Hospitals can extend their normal operation capacities by applying different strategies such as increasing patient rooms' capacity and utilizing rooms that are not typically used for treating patients. Different models exist to estimate the hospitals' surge capacity. For example, the Agency for Healthcare Research and Quality (AHRQ) (2010) developed a model to estimate the total number of casualties and the required resources to treat injuries at different units in a hospital after specific biological, chemical, nuclear, or radiological scenarios. Other studies provided qualitative and conceptual frameworks to determine the hospitals' surge capacity (Hick et al., 2008; Kaji et al., 2006; Shabanikiya et al., 2016). However, as noted by Watson et al. (2013), previously published research on surge capacity varied in its conceptualization, terms, definitions, and applications, which restrained the development of standardized models, measurements, or metrics.

2.3.3 Hospitals' interaction

The interaction between healthcare facilities is essential, especially during and after large-scale natural disasters as it allows for redistribution of services, repair resources, medical staff, and patients as needed (McDaniels et al., 2008). However, to achieve this level of interaction pre-arranged agreements between healthcare facilities have to exist (Paterson et al., 2014), which is more likely for facilities under the same administrative umbrella. The travel distance between the healthcare facilities and the availability of transportation and telecommunication networks can also affect this interaction.

Hospital’s ability to provide services during and after a sudden increase in patient numbers has been a major concern (Cimellaro et al., 2019). As such, the hospital preparedness programs were introduced to enhance health care systems' capabilities in performing core functions common to all emergency responses. This is realized through exercising different scenarios to identify critical components for patient care and estimate hospitals’ preparedness (Agency for Healthcare Research and Quality (2010). Demand on hospitals can change when patients are transferred to other hospitals. The decision to transfer patients could be because the hospital transferring the patient has reached its capacity (Nuti & Vanzi, 1998), the patient waiting time has become larger than what would be considered acceptable, or the hospital is not properly equipped to treat the patient injury (Kulshrestha & Singh, 2016). To date, no comprehensive model exists to estimate the probability of transferring patients between hospitals after earthquake occurrence.

Modeling the healthcare facility interaction, especially after seismic events, is a dynamic and complicated process, where many parameters can disturb the transfer process and impact the decision-making related to the transfer tasks (Ceferino et al., 2020). Therefore, comprehensive models that consider not only the healthcare facilities but also other community buildings, services, and individuals are critical to simulate the interaction between these facilities accurately. Hassan and Mahmoud (2020) recently introduced an analytical framework that dynamically estimates the functionality and recovery of healthcare facilities while considering the mutual effects between these facilities (*the details of these frameworks will be presented in Chapter 3 of this dissertation*). This framework permits hospitals to transfer patients, staff, supplies, and repair resources based on various socio-technical factors related to hospitals, staff, patients, etc.

2.4 School functionality estimation

K-12 Schools can be categorized into public and private schools. Public schools can be further categorized into charter and magnet schools. Moreover, each one of the previously mentioned categories can be sorted into different sub-categories based on school license and type of state approvals. Schools at higher categories, usually serve a larger number of students and are approved by the state department of education. Although schools are essential for any modern community (Transfer, 2008), a large number of schools in the U.S are vulnerable to earthquakes (Rodgers, 2011). Within the U.S. there are 49 million students attending public schools and around 6 million attending private schools. Therefore, schools play a crucial role in the community recovery process. Safer schools can increase community resilience and reduce the potential for population out-mitigation as well. Unlike hospitals, schools typically are designed for risk category III as per ASCE/SEI 7-16 (2016) with seismic importance factors of only 1.25, which increases the damage probability of schools (Hancilar et al., 2014). To reduce the vulnerability of schools to earthquakes, various national plans, including extensive retrofitting strategies for existing schools, have been introduced (Applied Technology Council, 2017; Federal Emergency Management Agency, 2002). In addition, school emergency plans have been established to help reduce social losses.

2.4.1 Education system functionality

K-12 Education facilities play a crucial role in societal stability before and after disasters especially for school children and their families (Reber, 1986; Ungar et al., 2019). To measure the functionality of the educational services, two main indices are widely used: service availability (UNESCO, 2019) and quality of the education providers (Mayer et al., 2000). A school's short-term functionality depends on the offered quantity of educational service. However, in the long-term, the quality of the offered service must be added to the quantity portion of functionality to arrive at total education functionality. In the event of an earthquake, the quantity portion of school functionality can be measured, for example, by the number of students that have a position in the school. On other hand, the quality portion of functionality may be represented in relation to the student-to-teacher ratio. Similar to hospitals, schools do not only depend on the performance of their physical facilities but also on staff, supplies, and supporting lifelines. Therefore, evaluation of school functionality should account for damage to the other supportive components of the educational service. Previous studies (Mayer et al., 2000; National Research Council, 2012) have investigated different tools that can be used to measure the performance of schools during normal operating conditions. Other studies have investigated school performance during and after earthquakes (Augenti et al., 2004; Beaglehole et al., 2018; Oyguc & Guley, 2017). However, these studies did not introduce models that could be used to predict functionality after extreme natural hazard events, such as earthquakes. Models that include analytical representations of different components of a typical school, specifying a service component of functionality, and accounting for the mutual interaction between schools and their supporting lifelines are required for full functionality assessment.

Elementary and secondary (*K-12*) schools generally can be classified as either public or private schools. State regulations govern school operations, depending on the school type; these include the presence of qualified staff, proper space, and sufficient supplies and services. However, following extreme natural hazard events, many districts allow schools to run without supporting infrastructure for a limited time, provided that these schools are safe for students and staff (Balingit, 2017; Rundquist, 2012). Different options for delivering education also exist; one of these options is homeschooling, which allows parents to teach their children from home.

2.4.2 Student enrollment

In normal operation conditions of public schools, students are enrolled based on their address and using the school zones (Joint Economic Committee – Republicans, 2019). These school zones are established based on the number of schools' seats at each grade, the number of students in each zone, and school busses transportation availability. However, parents are also allowed to select a different school for their school children (school of choice). In the U.S., school districts and school administrations control the process of student enrollment and transfer.

Following natural disasters such as earthquakes, some students might transfer to other schools because of school damage. In this situation, schools might increase class capacity or reduce the transportation service, or in some cases totally suspend it, due to damage to roads, shortage in staff, or damage to buses. Student enrollment after seismic events is influenced by many parameters. However, to date, no models exist to simulate the students' enrollment process and all the decision-made during this process.

Schools can also be used as temporary shelters, or as centers for community disaster relief (Singh, 2019) and recovery coordination (Applied Technology Council, 2017; Fujieda et al., 2008). Using schools as shelters is, however, a function of the disaster occurrence time, space availability, and school building safety. For instance, educational services are impacted by earthquakes differently during the academic year than when school is not normally in session.

2.4.3 School administration

Public schools are centrally managed systems, where the administration and school district play an essential role in school management and guidance (Patterson, 1966; Salgong et al., 2016). The school administration's responsibilities include for example managing the various daily school activities, and providing instructional leadership to the schools they managed (Döş & Savaş, 2015). School administration includes principals, superintendents, and other administrators (Gates et al., 2003). They are responsible for many of the critical decisions after disasters to maintain the school's functionality. These decisions include defining school restoration objectives, school reopening times following disasters, student admission and transfer, staff appointment and transfer, and supplies alternatives and transfer.

School reopening after an earthquake occurrence is one of the main decisions made by the school administration and school district (U.S. Department of Education, 2007); however, this decision also involves different agents such as building and fire departments, the office of public safety, and the community. Generally, schools can be partially reopened using backup space and backup systems or stay closed until buildings are fully functional (Bounds, 2014; U.S. Department of Education, 2007). Other learning approaches can also be provided by schools after disasters such as homeschooling and virtual learning (Gates et al., 2003). The school administration is also responsible for appointing staff to replace staff that are impacted during or after the earthquake, subject to the availability of funds available for these appointments (Gates et al., 2003), and can also transfer staff temporarily to solve the staff shortage problem. The school administration is also responsible for managing the supplies and repair resources and transferring them between the schools to bridge the gap in any supply shortage and to achieve their recovery objectives (Digital Promise, 2014). Therefore, it is essential for the recovery model to include the school administration to simulate the effect of their different roles on the recovery process (Hassan et al., 2020).

2.5 Recovery assessment models

Different parameters play important roles in determining the level of functionality restoration or recovery that can be achieved at healthcare and education facilities following extreme natural hazard events. These include type of damaged components, extent of damage, and available funding resources (e.g., insured losses or state and federal sources). Restoration efforts usually do not result in the functionality returning to its original level before the disturbance. The characteristic behavior of functionality is manifested through some sort of oscillation, which can be described using the equation of motion for a lifeline as noted by Cimellaro et al. (2010a) or even for an entire community as recently noted by Mahmoud and Chulahwat (2018). The recovery process of infrastructure or its components is usually represented by plotting functionality over time. As shown in Figure 2-2 (a), the change in functionality due to the earthquake is categorized into four different stages, which can be defined as:

- Pre-disaster stage, which is the original level of functionality before the hazard.
- Immediate functionality reduction, which takes place at the time of hazard occurrence. Therefore, it is time-independent in the case of earthquake hazards. It can be expressed as a function of direct losses, the efficiency of the backup systems, and interdependency as shown in Figure 2-2 (b).
- Assessment and planning stage, which takes more time compared to the immediate functionality drop stage. Therefore, it is considered time-dependent. It can be expressed as a function of direct losses and damage level that controls the assessment and planning process as shown in Figure 2-2 (b).

- Recovery stage, which is time-dependent and is mainly a function of direct losses, available resources, and interdependency as shown in Figure 2-2 (b). The duration of the recovery stage has a substantial impact on indirect losses.

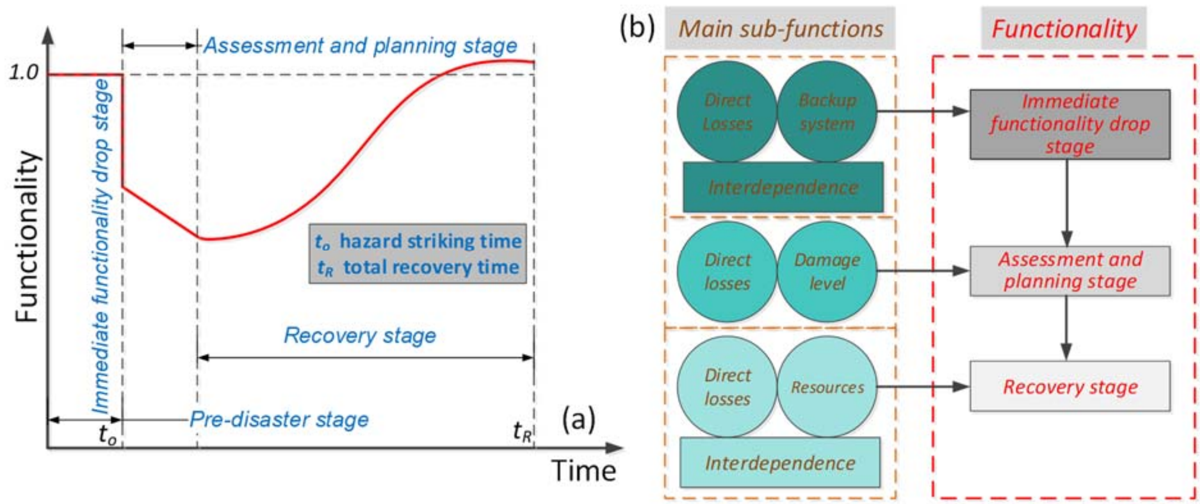

Figure 2-2: Restoration of functionality (a) different stages and (b) main sub-functions.

Various studies have investigated the use of different approaches for estimating multiple recovery stages for different lifelines. For example, the statistical curve-fitting model, used in ATC-25-1 (1992) to establish a restoration curve for the water supply system, utilized data available in ATC-13 (1985), expert opinion, and regression analysis. A statistical curve fitting model was also used by Zorn and Shamseldin (2015) to quantify recovery of different infrastructure and compare their restoration and in HAZUS-MH 2.1 (2015) to estimate recovery of different building classes subjected to natural hazards. Other studies utilized different functions to estimate recovery based on single or multiple parameters (Cimellaro, 2016). The deterministic resource constraint model Isumi et. al. (1985) is another method to estimate restoration after hazard occurrence in a simplified way. In this approach, equations and rules are utilized to account for limitations in available repair resources as a function of time. However, proper estimations of repair crews and their specific tasks are needed to minimize uncertainties. This model was introduced in Isumi et. al. (1985) and used in Ballantyne and Taylor (1991) to estimate losses to the Seattle water system after earthquakes. Network models are also used to estimate the restoration process of series of lifelines where each lifeline is represented using a node connected to another node or lifeline with links. Optimization tools are commonly used with network models to find the optimal repair sequences. Markov chain stochastic models have also been used to estimate restoration curves for lifelines (Burton et al., 2016; Kozin & Zhou, 1990; Lin & Wang, 2017) and have been modified to account for the interaction between lifelines (Zhang R. H., 1992). A Markov chain stochastic model simulates the functionality of each lifeline by a discrete state in which repair resources can be optimally allocated to each lifeline (Hassan et al., 2020; Hassan & Mahmoud, 2020a) as shown in Figure 2-3.

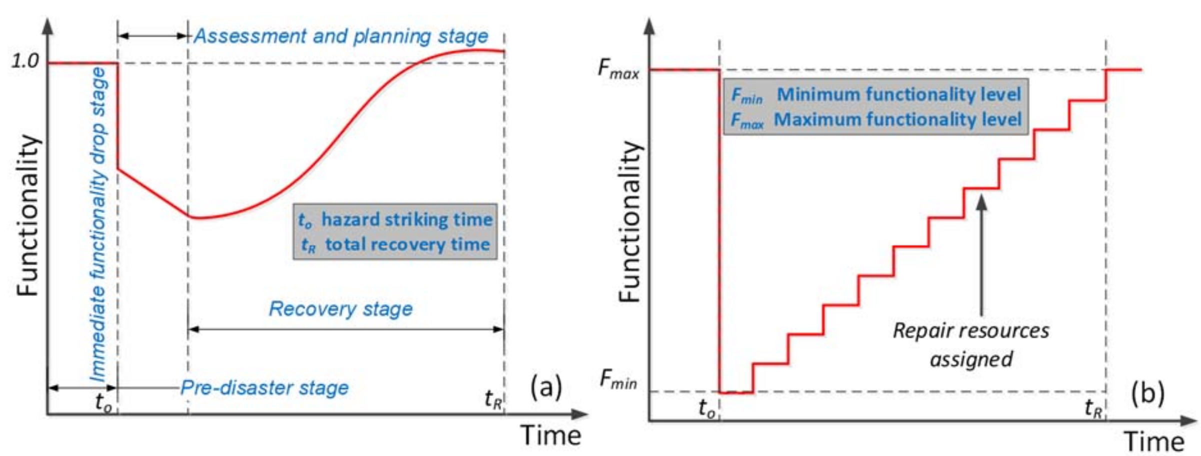

Figure 2-3: (a) Regular recovery process of the infrastructure or lifeline after hazard occurrence, and (b) discrete state of functionality.

A Markov chain is a stochastic process involving discrete states. When using the Markov process in restoration analysis, each system at any stage of the restoration process is considered to be random with discrete states (Possan & Andrade, 2014). The main assumption in this approach is that the present state may only be a function of the preceding state and independent of other previous states. The conditional probability that a system transitions to another state, given that it is in one state, is called a transition probability and can be defined as a function of the available restoration resources that could be allocated for that system at various stages of the restoration process. In the case of the restoration processes of various systems, the effect of interactions on the transition probability for any system can be added based on Zhang (1992) as a function of the present states of other systems. The restoration process could also be represented using a semi-Markov model (Yu, 2010), which is equivalent to a Markov renewal process in many aspects, except that a state is defined for every given time. Therefore, the semi-Markov process is an actual stochastic process that evolves over time. Assuming a system with m possible states and n restoration time steps, the probability of that system being at state Q_j at time t_n can be calculated based on Equation (2.1) according to Ang and Tang (1984).

$$P_{i,j}(t) = P\left(Q_n = Q_j \middle| Q_m = Q_i\right) \tag{2.1}$$

The transition probability normally is written in a matrix form with dimension (m x m). Assuming that the restoration process is non-reversible (either staying at the present state or shifting by one step) and the system states are mutually exclusive and collectively exhaustive, then all values in the matrix must lie between 0 and 1 and the summation of each row must equal 1. The transition probability matrix can be expressed as shown in Equation (2.2) according to Kozin and Zhou (1990).

$$P_{i,j} = \begin{bmatrix} 1-p_{1,2} & p_{1,2} & \cdots & 0 & 0 \\ 0 & 1-p_{2,3} & & 0 & 0 \\ & \vdots & \ddots & \vdots & \\ 0 & 0 & \cdots & 1-p_{m-1,m} & p_{m-1,m} \\ 0 & 0 & & 0 & 1 \end{bmatrix} \tag{2.2}$$

Assuming that the probability of that system being at an initial state is Q_0, which can be expressed as shown in Equation (2.3), then the probability law of capacity restoration state of that system at time t_i, Q_i, can be calculated based on Equation (2.4) based on Kozin and Zhou (1990). On other hand, the economic return vector is shown in Equation (2.5), which represents the economic return for the system at different states. It can be expressed in a simple form as a function of the current system state based on Zhang (1992) as shown in Equation (2.5).

$$Q_0 = [p_1(0), p_2(0), p_3(0), \dots\ p_m(0)] \tag{2.3}$$

$$Q_i = Q_0(P_0)(P_1)(P_2) \dots (P_{i-1}) \tag{2.4}$$

$$R_n = [r_n(1), r_n(2), r_n(3), \dots\ r_n(m)] * Q_i \tag{2.5}$$

2.6 Resilience quantification models

Once the functionality is determined, the resilience of a system can be estimated. There are many definitions of resilience that span different fields and disciplines, starting from the early definition of ecological resilience by Holling (1973) to the recent definition of infrastructure resilience in Presidential Policy Directive-21 (PPD-21) (2013). Other definitions are also provided by different organizations and studies. For example, in the PPD-21 (2013), resilience is defined as the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. The European Commission (EC), on the other hand, noted the importance of considering resilience at multiple scales while bearing in mind sustainable developments. Resilience is defined by the EC as the ability of an individual, a household, a community, a country, or a region to withstand, cope, adapt, and quickly recover from stresses and shocks such as violence, conflict, drought, and other natural disasters (European Commission, 2014). Bruneau et al. (2003) noted that resilience can be measured as a combination of technical, organizational, social, and economic aspects. Bruneau et al. also presented four main dimensions that can be used to build a resilience framework: rabidity, robustness, redundancy, and resourcefulness. Various efforts (Hiwasaki et al., 2014; United Nations Development Programme, 2014) have been carried out worldwide with a focus on improving the built environment and/or enhancing human capacity to ensure rapid recovery as per the resilience definitions.

From a quantitive perspective, various studies have been conducted to develop mathematical models for estimating resilience (Bruneau et al., 2003; Mahmoud & Chulahwat, 2018). Recent efforts have focused on developing integrative tools for resilience quantification (Center for Risk-Based Community Resilience Planning, 2020; The European Commission's science and knowledge service, 2020). These tools integrate physical, social, and economic fabrics of communities to determine the cumulative functional loss for the built environment (Bruneau et al., 2003), economic (Rose & Krausmann, 2013), and social parameters (Olsson et al., 2015). For example, the conceptual framework introduced by Bruneau et. al. (2003) was refined and applied to various infrastructure by Chang and Shinozuka (2004), and Cimellaro et. al. (2010a). Other frameworks utilized the concept of graph theory to quantify resilience. For example, Berche et. al. (2009) used a directed graph to quantify the resilience of transportation networks. Resilience has been also quantified using a Fuzzy inference system by Heaslip et. al. (2010). Recent resilience frameworks include the use of dynamic models to estimate community resilience (Mahmoud & Chulahwat, 2018). Moreover, Didier et. al. (2018) presented a compositional demand/supply resilience framework to quantify the resilience of civil infrastructure systems. To quantify resilience, however, terms such as losses, functionality, recovery, interdependence, and resources should be evaluated (Cimellaro, 2016). Resilience based on Cimellaro et. al. (2010a) is defined as the area underneath the functionality recovery curve. A wide spectrum of single and/or compounded indices can be used to measure community resilience including, for instance, employment rate, household income, education attainment, and hospital capacity, among others (Edgemon et al., 2019).

Because of the importance of healthcare and education networks for modern community resilience, the level of uncertainty associated with those networks must be properly quantified. Therefore, a comprehensive definition of functionality as well as an accurate estimation of other terms that are used to estimate the functionality, are pivotal for proper quantification of resilience.

2.7 Sensitivity and uncertainty analysis

Similar to most forecasting models, estimations of the resilience of healthcare and education systems are sensitive to the implemented functionality and recovery frameworks as well as the input data for each framework. Proper assessment of functionality requires proper quantification of losses and accurate estimation of infrastructure damage.

Different methods can be used to quantify analytical models' accuracy e.g., sensitivity and uncertainty analysis. Sensitivity analysis is used to gain insights into the behavior of analytical models including their structure and their response to changes in the model inputs (Ferdous et al., 2007). Probabilistic distributions of each component are used to estimate failure frequency in the sensitivity analysis. In addition, sensitivity analysis is commonly utilized to determine the factors that drive the analysis and the decision process. It can be also utilized to define the weakest link in infrastructure systems, investigate better design alternatives, and evaluate the effect of the adopted solution on system safety (Contini et al., 2000). Different methods and applications of sensitivity analysis have been introduced in previous studies, for instance: He (2014) classified sensitivity analysis methods into factor screening, global sensitivity analysis, distributional sensitivity analysis, and regional sensitivity analysis. Borgonovo and Plischke (2016) introduced a review of recent advances in sensitivity analysis, which is categorized as local sensitivity analysis methods or global sensitivity methods. Cacuci (2003) discussed the use of both local and global sensitivity analysis for linear and non-linear systems. Ionescu-bujor and Cacuci (2004) presented a review of recent deterministic sensitivity analysis methods and Cacuci and Ionescu-bujor (2004) reviewed recent statistical sensitivity analysis methods.

Uncertainty analysis is an essential component of any mathematical or analytical model that deals with uncertain data input and/or is used to forecast future incidents. Uncertainties can result from a lack of knowledge and information of the presented model parameters or the intrinsic variability of these parameters. In addition, uncertainties associated with mathematical or analytical models in the field of risk assessment can be classified into aleatory uncertainty and epistemic uncertainty (Wen et al., 2003). Aleatory uncertainty represents the statistical uncertainty and epistemic uncertainty results from lack of knowledge (Drouin et al., 2009). Different methods and applications of uncertainty analysis have been introduced in previous studies. Hack and Caten (2012) introduced a review of uncertainty analysis methods and applications that have been published between 2004 and 2010. They focused on uncertainty tools presented by the International Organization for Standardization (ISO) including GUM and Monte Carlo Simulation. Different techniques can be used to estimate uncertainties (Zio & Pedroni, 2013) including for example 1) imprecise (or interval) analysis, which uses the interval arithmetic method to evaluate the ranges of all the model parameters; 2) probability bound analysis, which employs both interval arithmetic method for parameters with complex aleatory uncertainties and traditional probabilistic analysis for other parameters; 3) evidence theory analysis, which utilizes probability intervals to description epistemic-based uncertainty; and 4) possibility theory analysis, which applies a family of probability distributions with particular characteristics that allow for the experts' opinion to be accounted for. Monte Carlo Simulation is a widely used tool to estimate modeling uncertainty. It is flexible, simple to implement, and can consider variables' correlation; however, it requires the identification of probabilistic distribution for all variables, which might necessitate some assumptions for parameters' distribution, mean, and variance (Zio & Pedroni, 2013). Despite the importance of uncertainty quantifications, only handful of studies have been conducted to evaluate uncertainties in resilience models.

2.8 Interdependence modeling

2.8.1 Overview

Interdependence between different lifelines in modern urban communities hinders the ability to recover fast compared with the communities that have independent lifelines (Cimellaro, 2016). The interdependence can be in different forms: Physical, Geographical, societal, etc. Backup systems and redundancy can delay, or in some cases prevent, the failure of the dependent lifelines due to the failure of main service providers. Different tools have been used previously to estimate the resilience of different lifelines: empirical models, network-based models, system dynamics-based models, among others (Hasan & Foliente, 2015). Paton and Johnston (2006) introduced values for the interdependence between 16 different lifelines, which were based on expert opinion. On other hand, the Input-Output Inoperability Method is one of the common methods that have been used to estimate interdependence between various infrastructure (Haimes & Jiang, 2001). It estimates functionality for every lifeline separately before accounting for interdependence. This method has been modified by Cimellaro (2016) to account for the shortcomings of the original method such as redundancy, temporal evaluation of the systems, and non-significance input and output. The interdependences between the hospitals and the *k-12* schools have never been addressed before. Therefore, in this study, the interdependence between the hospitals and the schools as well as with other lifelines will be investigated.

A higher degree of interdependency between elements of the built environment can increase community vulnerability and complicate recovery after any disruption (Cimellaro, 2016).

The National Institute for Standards and Technology, in their Community Resilience Planning Guide volume II and chapter 10 (NIST, 2016a) highlighted the importance of the interdependencies within and among the so-called social institutions. In this special publication, healthcare and education institutions are classified among the main social institutions and their interdependency can be used to identify the characterizations of the social community. Interdependencies can be classified into functional, physical, budgetary, social, and economic (Ouyang, 2014). Different approaches have been utilized to model infrastructure interdependency, including empirical, agent-based, system dynamics, economic theories, and network analysis (Ouyang, 2014). Identifying the degree of interdependency between the built environment is challenging as it requires comprehensive models to simulate all possible processes and decisions made within each of these infrastructures and their impact on each other. There is a shortage of analytical models that can be used to simulate large social systems, let alone the interdependency between these systems. Previous studies were either empirical (Cimellaro, 2016), statistical (Gan & Gong, 2007), or described as a theory with no quantification (Wright, 2001). The interdependency between healthcare and educational services can be direct or indirect (Pederson et al., 2006). Direct interdependency can only capture the simple relationship between the investigated services. On the other hand, the indirect interdependency pertains to quantifying the more complicated relationship between a) the investigated service providers, b) each provider and their supporting infrastructure that form the community, and c) the sub-components within each provider. Capturing such complex interaction requires more detailed models that can mimic the disruptive events within not only each facility but also the impact of each facility on the other. Modeling this interaction with that level of detail can be achieved using agent-based models as shown by Hassan and Mahmoud (2021) (*the details of this study will be presented in Chapter 5 of this dissertation*).

2.8.2 Agent-based modeling

Agent-based models are common for actions and interactions of agents describing individuals or entities, and they have been applied in many fields, including epidemiology, business, and social science (Conte & Paolucci, 2014). An agent comprises a set of autonomous decision-making entities that can be individuals, groups, or systems (Gilbert, 2008). These entities have a set of characteristics and rules that allow them to interact, learn, and adapt. Modeling agents' behaviors and interactions can be conducted using self-contained algorithms or logical operations formalized by equations (Bonabeau, 2002). Agent-based modeling is a robust method utilized to investigate systems' behavior, study the relationships among their dynamic components, and present a natural description of complicated systems (Hassan & Mahmoud, 2021a). Furthermore, it provides a flexible modeling tool for different levels of system complexity in which features such as aggregation of agents, agent sub-components, and different levels of descriptions for agents can be made (Bonabeau, 2002). However, these models have several limitations, including the uncertainty associated with their expected results (Kieu et al., 2020).

2.9 Social services stability models

Social stability is one of the prerequisites and main components for the communities to continue and thrive. Many institutions and research studies investigated and quantified community social stability (Agency for Toxic Substances and Disease Registry, 2018; Birner & Ege, 1999; Federal Emergency Management Agency, 2020; German & Latkin, 2012; Râsvan, 2009). For example, the Agency for Toxic Substances and Disease Registry (2018) introduced an index to measure the U.S. census tracts' social vulnerability that resulted from external stresses including natural disasters that accounts for 15 different social factors including socioeconomic status, housing type, and transportation. The stability of communities' social services is an essential component to achieve many of the common long and short terms community resilience goals and objectives (NIST, 2016a). Hospitals and schools are classified among the main social institutions in the community, which provide two of the main social services (healthcare and education). Due to the fact that natural disasters such as earthquakes can have devastating impacts on communities' social stability and many institutions that contribute to the stability of their services, different studies have considered the community preparedness for earthquakes that can efficiently reduce the social consequences of these disasters (Ejeta et al., 2015; McIvor, 2010; Miller et al., 2013). For instance, Bakic and Ajdukovic (2019) found a significant change in the level of psychosocial outcomes of the community individuals after disasters. Varda et al. (2009) concluded that disasters can change the stability of the social networks and impact the recovery process. However, a recent review study by Burger et al. (2019) highlighted the weaknesses and the current gaps in research related to the computational studies in the area of communities' social stability after disasters.

Major social changes and social instability can take place in communities after major disasters such as earthquakes. However, the role played by hospitals and schools in communities' social stability can be significant in bringing normalcy back to these impacted communities. Therefore, many national and international organizations recognized the services provided by hospitals and schools as an essential component for any stable community (National Academy of Engineering, 2008; NIST, 2016b, 2016a; NSF, 2020; UNICEF, 2017; United Nations, 2015). In addition, many research studies investigated the relationship between the healthcare and education systems and the community's social stability. For example, German and Latkin (2012) found a strong correlation between social stability and health outcomes. While other case studies concluded that education playing the main role in communities' social stability. Butler and Diaz (2016) described hospitals and schools as the hub for community health and stability. Therefore, additional investigation into the role played by social institutions such as hospitals and schools especially after major earthquake disasters to enhance the community's social stability is needed (Hassan & Mahmoud, 2021a).

2.10 Summary

This chapter briefly reviewed the available literature on the modeling of healthcare and education systems after seismic events. It also provided a discussion on the commonly used indices to quantify their functionality, recovery, and resilience as well as their interdependency and impact on communities' social services stability. A summary of conclusions reached from this review includes the following:

- Historical seismic events impacted healthcare and educational services. Earthquakes caused severe and complete damage to many hospitals and school buildings, resulted in many casualties, disturbed supporting infrastructure, increased demand on hospitals and class size in schools, affect community resilience and social services stability.
- Different healthcare system frameworks were introduced to model different components of the healthcare facilities; however, many of these models did not consider both quantity and quality of the service, interdependency between hospitals and their supporting infrastructure, change in patient demand after the seismic events, and the interaction among the healthcare facilities within the healthcare system.
- Many of the existing education system models were either theoretical or only model the school building components. No comprehensive models exist to simulate the dynamic

variation in quantity and quality of the educational services while considering the main parameters influencing this service.

- Many frameworks were presented to estimate recovery and resilience after seismic events. Quantification of sensitivity and uncertainty of the introduced frameworks to model healthcare and education system are essential components to evaluate the main controlling parameters of these services and the uncertainty propagation in the estimated recovery and resilience.
- Various interdependency models exist in the literature to investigate and determine the level of interdependency between different communities' infrastructure including agent-based modeling; however, no analytical models exist to quantify the interdependency between the healthcare and education systems.
- Social services stability of communities was impacted after earthquake disasters; therefore, many indices and studies were introduced to measure and investigate such impact. Hospitals and schools were found in many studies to highly impact communities' social stability. However, there is a lack of studies investigating and/or quantifying the individual and collective impact of schools and hospitals on social services stability.

Chapter 3. FUNCTIONALITY OF HEALTHCARE SYSTEMS

3.1 General

Modeling the functionality of main social institutions such as the healthcare facilities after the occurrence of extreme events is now at the forefront of research. Hospitals are used in this study as the main facility providing healthcare services. Estimating post-disaster functionality of either single or multiple hospitals requires proper flow and interaction of information of the physical, economic, and social components of the involved sectors. Understanding this functionality is essential, particularly for these critical infrastructure, which is vital for a community's well-being. Healthcare functionality can not only be measured in terms of the availability of service but also the level of consumer satisfaction. This functionality is directly impacted by the disturbance resulting from the earthquake event on healthcare facilities and the built environment and the people they depend on. After earthquake events, hospitals might need to manage the different consequences such as shortage of medical and non-medical staff, damage to hospitals, deficiency of the supporting infrastructure of the hospitals, lack of medical supplies, which can be coupled with the increase in the number of patients resulting from the earthquake casualties or/and patients transferred from other hospitals. These consequences can significantly reduce the healthcare system's functionality, requiring decisions to be made to ensure the continuation of healthcare services. In this chapter, a framework of the healthcare services functionality is introduced that dynamically models the behavior of the healthcare system after earthquake events.

3.2 Understanding the healthcare service

The major components that impact the healthcare systems' functionality, which could also be affected by an earthquake, are shown in Figure 3-1. Healthcare system components can be categorized under the following domains: regulators, providers, payers, suppliers, and consumers (Finnell & Dixon, 2016). Regulators are either governmental or private agencies that control the service, providers are the facilities providing the service, payers are either the insurance company or the patients themselves, suppliers are the resource providers such as pharmaceutical companies, and consumers are the patients that impose a demand on the healthcare system. Noteworthy that these components comprise many other subcomponents that are interdependent and any shortage of these subcomponents can consequentially affect the healthcare service functionality.

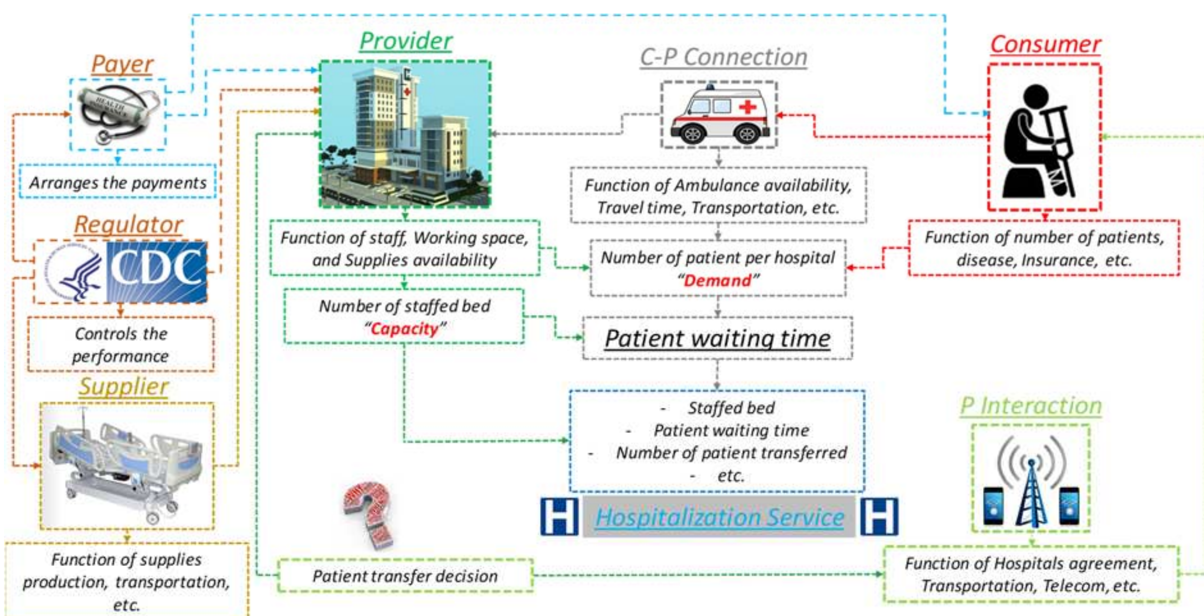

Figure 3-1: Components of healthcare service.

Healthcare system regulators are those agencies that prepare and apply rules that control providers, payers, and suppliers of the healthcare system (Longest, 2009). The main function of regulators in the healthcare system is to guarantee a certain quality of the offered services. There are various types of regulations that are applied by a wide range of agencies in the healthcare system including federal, state, and local level agencies as well as private organizations (Institute of Medicine, 2009). Payers can be classified into governmental agencies, private insurance companies, and patients (Institute of Medicine, 2009). Unlike during normal operations, during and after emergencies payers have less control over the consumers' selection. Suppliers refer to manufactures of medical equipment and supplies such as oxygen, surgical, and *Rx* supplies (U.S. Food and Drug Administration, 2019). In addition to medical supplies, other supplies are essential including food and fuel (Vugrin et al., 2015). After natural hazards, not only the functionality of healthcare system components drop but also supplies can experience a significant disruption in their production, making the situation even worse. Even though alternative supplies can exist, arranging and transporting shipments and storing them upon arrival can be challenging (Mulyasari et al., 2013). Moreover, earthquakes usually cause damage to the transportation network, which can hinder the shipping of supplies and in some cases halt shipping entirely. Transferring these supplies between hospitals after a natural disaster is expected to enhance the resilience of the healthcare system (Redlener & Reilly, 2012).

Healthcare service providers range from large facilities such as hospitals to smaller ones such as walk-in clinics. However, treatment of critical cases and serious injuries are usually handled at well-prepared hospitals (Mulyasari et al., 2013). Hospital size is commonly measured by the total number of active staffed beds, which, for proper operation, require trained staff, working space, and adequate supplies (Jacques et al., 2014). In addition to their medical teams, hospitals have supporting staff working in the accounting and administrative departments. Hospital working space not only depends on physical structural and non-structural components or medical equipment but also on other utilities such as electric power and drinking water. Hospital supplies include both medical and non-medical supplies that are usually stored in rooms and storage facilities attached to hospitals. Damage to the rooms and storage facilities can also affect supplies availability. Recipients of healthcare service after an earthquake can be classified into different severity levels, based on their needed medical care (HAZUS-MH 2.1, 2015). Medical care depends on the nature of the injury or disease, which might require a specific medical team or in some cases multiple teams (Finnell & Dixon, 2016). To estimate the patient demand on hospitals, a dynamic model that can capture the disruption to community facilities and effectively model the connection between patients and hospitals is needed. In addition to the previously mentioned components, the connection between consumers and providers and the interaction between the healthcare facilities are essential for any comprehensive framework.

3.3 Component functionality of hospitals

Healthcare service is measured by a physical metric (e.g., number of available beds) and the level of consumer satisfaction. Hospital functionality can be defined by combining the quantity (Q_V) and quality (Q_S) services (Cimellaro et al., 2011; Hassan & Mahmoud, 2019). The quantity of the offered services is usually estimated based on hospital capacity or the number of staffed beds available for patients based on daily rates (Denver Health, 2005). Noteworthy, healthcare service not only depends on the hospital itself but also on the surrounding lifelines on which the hospital depends. For example, a reduction in transportation network capacity will lead to delays in ambulances' response or even an entire halt to their service. According to Jacques et al. (2014), for these beds to be available for use, representing the quantity portion of the service, three main components are required: 1) trained personnel such as physicians, nurses, and supporting staff; 2) qualified space, and 3) sufficient supplies. The quality portion of the offered service, on the other hand, is difficult to describe. Previous studies identified several dimensions to represent the quality of the healthcare service (Kalaja et al., 2016; Maxwell J. R., 1984). One way to do so is by defining the service as a function of losses to different hospital departments while considering service redistribution among the departments (Jacques et al., 2014). The patient waiting time could also be used to represent the quality part of the functionality (Hassan & Mahmoud, 2019; McCarthy et al., 2010). Previous studies highlighted the impact of transportation network damage on the waiting time and healthcare services after earthquakes (Dong & Frangopol, 2017; Lupoi et al., 2013).

The probability of total functionality of the healthcare system, $P(Q_H)$, can be expressed as a combination of the probability of quantity, $P(Q_V)$, and the conditional probability of quality, $P(Q_S|Q_V)$, of the offered service as shown in Equation (3.1). The total functionality can be accurately calculated by considering the correlation between quantity, Q_V, and quality, Q_S, functionality (i.e. the first-moment of the total functionality) or simplified (i.e. using weighted geometric means) by combining the two functionalities as shown in Equation (3.2) (Cimellaro et al., 2011); where α_V and α_S are weighting factors for quantity and quality functionality, respectively. These weighting factors depend on the investigated community (Cimellaro, 2016; Hassan & Mahmoud, 2019) and are expected to change after the earthquake and during the recovery process. Immediately after the occurrence of a natural hazard, the quantity of the service and safety of the patients are more paramount than the quality. As time progresses, more emphasis can be placed on quality (Nuti & Vanzi, 1998). The presented healthcare functionality framework has different sub-models: a) healthcare capacity quantification model; b) healthcare quantity estimation; c) patient-driven model; and d) healthcare interaction model.

$$P(Q_H(t)) = P(Q_V(t)^{\alpha_V}).P(Q_S(t)^{\alpha_S}|Q_V(t)^{\alpha_V}) \qquad (3.1)$$

$$E\big(Q(t)\big) = \iint Q_V(t)^{\alpha_V} Q_S(t)^{\alpha_S} f(Q(t))\, dQ_S\, dQ_V \cong Q_V(t)^{\alpha_V} Q_S(t)^{\alpha_S} \qquad (3.2)$$

To provide a full description of the healthcare system's functionality, Q_H, the quantity of the service, Q_V, is combined with the accessibility, S_A, and effectiveness, S_E, of this service as an indication of the service quality, Q_S, as follows:

$$Q_H(t) = Q_V(t)^{\alpha_V}\{S_A(t)^{\alpha_A}S_E(t)^{\alpha_E}\}^{\alpha_S} \tag{3.3}$$

where, α_A and α_E are weighting factors for accessibility and effectiveness of the service, respectively.

3.3.1 Quantity functionality

The hospital's overall functionality comprises a quantity portion and a quality portion. The quantity aspect of the functionality can be assessed using the success tree shown in Figure 3-2, which comprises a series of basic events, *R,* connected with logical *AND*/*OR* gates to form either intermediate or top events. The availability condition of each sub-component (basic event) at time *t* is calculated to estimate the probability of staffed bed availability, P_B, which is used to determine the total available number of staffed beds at each healthcare facility. These staffed beds are defined as the licensed beds that are immediately available to be occupied by a patient. The mean value of P_B represents the quantity functionality, Q_V, of this healthcare, which is calculated as:

$$E[Q_V(t)] = (\frac{1}{N_{em}}\sum_{n=1}^{N_{em}} P_B^n)^{\alpha_{em}} + (\frac{1}{N_{in}}\sum_{n=1}^{N_{in}} P_B^n)^{\alpha_{in}} \tag{3.4}$$

Where, N_{em} and N_{in} are the number of emergency and inpatient beds in the investigated facility, respectively; α_{em} and α_{in} are weighting factors for emergency and inpatient beds, respectively, and *B* is the total number of the staffed beds.

The proposed success tree analysis provides a functionality framework for the entire healthcare facility while accounting for interdependency with other major lifelines. Three main components are required to keep the hospital operational including trained staff, appropriate space, and adequate supplies (Barbisch & Koenig, 2006). These components not only depend on the hospital building itself but are also highly related to the functionality of the surrounding community's physical, economic, and social sectors.

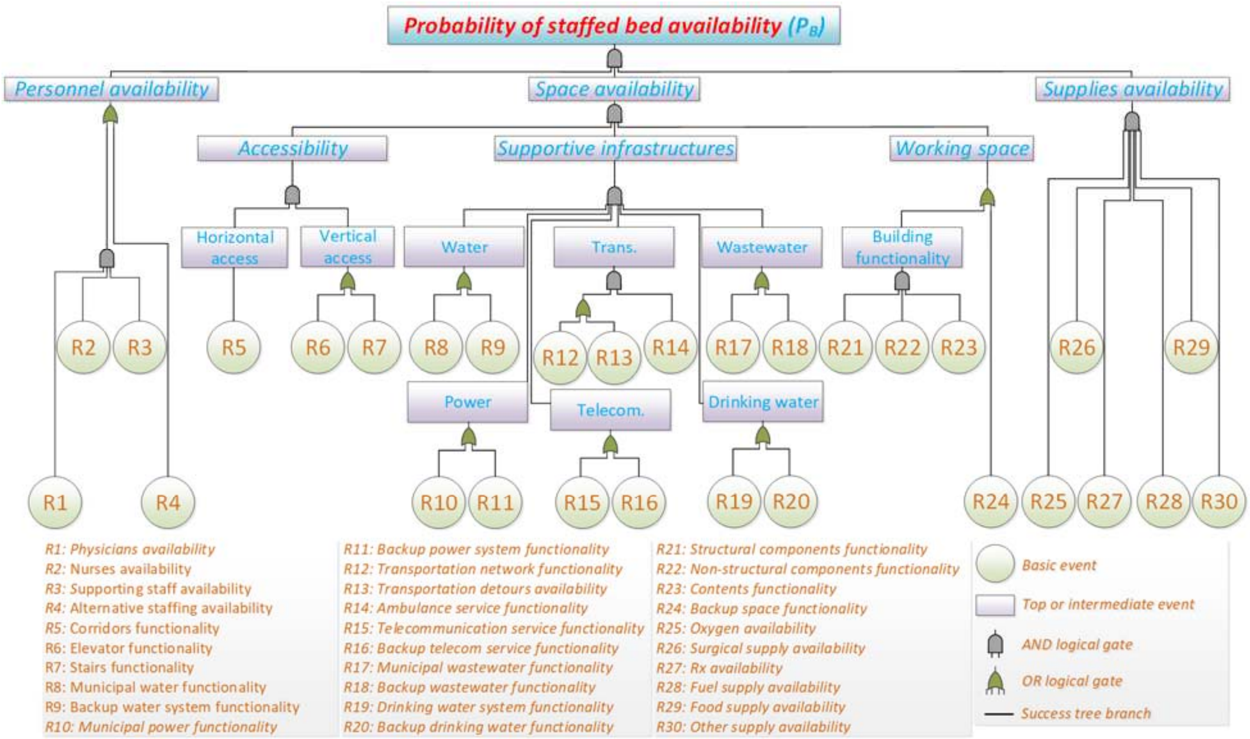

Figure 3-2: Success tree for determining the availability of staffed beds in a hospital.

To connect the basic events in the success tree analysis to the top and intermediate events, *AND*/*OR* gates are used. The probabilities for different gates are calculated using Equation (3.5).

$$P_{OR} = 1 - \prod_{i=1}^{n}(1 - P_i),\ and\ P_{AND} = \prod_{i=1}^{n} P_i \qquad (3.5)$$

Where, P_{OR} and P_{AND} denote "*AND*" and "*OR*" gate operations, respectively, P_i refers to the basic event (i) probability, and n is the total number of considered basic events.

For the trained staff (*R1* to *R4*), the initial functionality drop is a consequence of the direct social losses of the hospital, L_{DS}. However, the three main factors that determine the availability of staff after the earthquake, which are the availability of the original hospital staff and their ability to work long shifts as well as the possibility of utilizing support from other hospitals. The availability of the original staff is not only a function of the hospital causalities but also of the extent to which the hospital staff are among those who decided to relocate following the earthquake due to lack of housing and essential services. This is accounted for in the framework by specifying the recovery associated with events *R1* to *R3* to be dependent upon the availability of alternative staff, *R4*, housings, F_h, and utilities, F_u, functionality levels. The staff support from other hospitals is based on the percentage of staff, *ST*, shortage in the subject hospital, the willingness of the other hospitals to send the support, M_s, and ability of the original staff to work additional hours, ST_{add}. Staff shortage is assumed to occur in cases when staff availability, *ST*, is less than space, *SP*, and supplies availability, *SU*. The staff availability at any time *t* is calculated as follow:

$$ST^t = f(ST^{t-1}, {F_h}^t, {F_U}^t, {L_{DS}}^t, R4^t, M_s^t, ST_{add}^t) \tag{3.6}$$

For the horizontal and vertical accessibility of the hospital (*R5* to *R7*), the initial functionality drop is a result of the expected non-structural damage of the hospital's corridors, elevators, and stairs. However, the accessibility can be recovered if enough repair resources are allocated for the rehabilitation of the corridors, elevators, and stairs. The allocation of repair resources is based on the building recovery process. The supportive infrastructure functionality (*R8*, *R10*, *R12*, *R13*, *R15*, *R17,* and *R19*) is expected to drop directly after the earthquake and enhance over time if the required repair resources are provided. The initial reduction in infrastructure functionality is assumed to be based on data available in ATC-13 (1985) and HAZUS-MH 2.1 *Technical Manual* (2015).

Because of the importance of the hospital as a critical facility, efficient backup systems are utilized to maintain the hospital functionality (*R9*, *R11*, *R16*, *R18,* and *R20*). These backup systems can, however, only support hospital functionality for a limited time. This is because water and drinking water backup systems are assumed to stop within days if the water treatment plant does not provide the service, or if these backup systems are not refilled. Similarly, the power backup system can only support the hospital for a limited time, depending on the availability of fuel supply. The operability of these backup systems, R_i, is a function of the earthquake damage level, EQ_d, hospital consumption, C, and refill and maintenance availability, $R\&M$, (Office of Inspector General, 2015) such that:

$$R_i^t = f(R_i^{t-1}, EQ_{d,i}, C_i^t, (R\&M)_i^t) \tag{3.7}$$

The ambulance service functionality (*R14*) is expected to reduce after the earthquake based on the direct loss ratio. This includes drivers' injuries or death, structural components loss ratio, $L_{S,DE}/R_S$, non-structural components losses ratio, $L_{NS,DE}/R_{NS}$, and losses of the telecommunication network. Where, $L_{S,DE}$ and $L_{NS,DE}$ are the direct economic losses for structural and non-structural components, respectively, while R_S and R_{NS} refer to the replacement cost of structural and non-structural components, respectively. The structural components loss ratio term is used to represent the shortage of the ambulance's storage, while the non-structural components loss ratio term is utilized to refer to the shortage of the ambulance vehicle itself. Recovery of an ambulance service depends on the availability of supportive staff and repair resources.

The functionality of the working space (*R21*, *R22, and R23*) also reduces after the earthquake as a function of the structural loss ratio, $L_{S,DE}/R_S$, nonstructural loss ratio, $L_{NS,DE}/R_{NS}$, and content loss ratio, $L_{C,DE}/R_C$. Where, $L_{C,DE}$ and R_C are the direct economic losses and replacement cost of the contents, respectively. The recovery processes of these components are also a function of the allocated repair resources for the hospital building. It is important to note that backup spaces, to treat more patients, are assumed not to exist during the short-term functionality of the hospital. The possibility of obtaining backup spaces during the long-term recovery is higher since such an arrangement usually takes more time to be effective. Therefore, backup space availability is simplified as a function of the time after the earthquake and the assigned resources to prepare the backup space.

Supplies availability (*R24* to *R29*), is assumed not to immediately drop after the earthquake except if storage rooms are extensively damaged, which is dependent on structural and non-structural components damage fragilities of the hospital. Hospital medical supplies are assumed to decrease as time passes following the earthquake and are a function of the number of patients being treated. Availability of the medical supplies can, however, be increased and maintained if an additional and a sufficient number of supplies is delivered to the hospital after the earthquake. Nevertheless, ensuring supply delivery requires enough funding, a proper transportation system, and productive suppliers. Therefore, the availability of supplies is modeled as a function of the number of patients treated at the hospital, N_t, which is indicative of not only supplies availability but also the functionality of the transportation system, and the functionality of the infrastructure or businesses producing the supplies. The availability of these supplies, SU_i^t, is a function of earthquake damage to the supplies' storage rooms, EQ_d, hospital consumption, C, and utility availability, F_U, while considering the possibility of supplies transfer from other hospitals, SU_{add}, as follows:

$$SU_i^t = f\left(SU_i^{t-1}, EQ_{d,i}^t, C_i^t, {F_U}^t, SU_{add,i}^t\right) \tag{3.8}$$

3.3.2 Quality functionality

The quality component of the hospital functionality represents patient's satisfaction with the offered healthcare service. Maxwell (1984) listed six different dimensions of healthcare quality service: relevance, accessibility, effectiveness, fairness, acceptability and efficiency, and economy. During the functionality drop after the earthquake, Accessibility of the medical services,

S_A, and effectiveness of the offered service, S_E, are the main dimension controlling healthcare quality. Therefore, in this study, both metrics are combined to represent the quality functionality of the healthcare facilities as shown in Equation (3.3).

Patient waiting time after the earthquake occurrence, W_t^a, which is defined as the time a patient waits before being seen by medical staff, is utilized to estimate accessibility to medical services. To estimate patient waiting time Equation (3.9) can be used.

$$W_t^a = W_0 + T_{tvl} + a_t[B_0 - B_t]/B_0 + a_e[N_t - N_0]/N_0 \tag{3.9}$$

Where, W_0, is the basic waiting time; T_{tvl} is the patient travel time; a_e, is the effect of staffed beds reduction; a_t is the effect of an increase in the total patients' number; N_t is the total number of patients treated at the hospital at the time, t; and N_0 is the total number of patients treated at the hospital before the earthquake occurrence time. Basic waiting time refers to the patient waiting time in the emergency department before receiving the healthcare service, which is a function of the patient's case criticality (Barros et al., 2010). Patient travel time to the hospital varies after the earthquake because of losses to the ambulances service or damage to the transportation network. The ratio between the current number of staffed beds to the original number before the earthquake, as well as the ratio between the current patient number to the original number, are used to estimate the delay time in the hospital's emergency department.

To measure the accessibility of the medical services, S_A, Equation (3.10) can be used.

$$S_A = [W_t^{max} - W_t^a)]/[W_t^{max} - W_t^b] \geq 0.0 \tag{3.10}$$

Where, W_t^a, and W_t^b are the patient waiting time after and before the disaster, respectively; and W_t^{max} is the maximum allowable waiting time.

Patient treatment time, T_t, is utilized to estimate the effectiveness of the offered service. This effectiveness is commonly used to evaluate the achieved patient outcomes accomplished by following the best-practice care guidelines. Immediately after earthquakes and as a consequence of higher demand on healthcare facilities, the medical staff may be tempted to reduce treatment time (Arboleda et al., 2007). Reduction of patient's treatment time can significantly decrease patient outcomes, increase fatality rates, and diminish the healthcare system quality. The treatment time can be calculated as per Equation (3.11)

$$T_t^t = f(\frac{R1^t}{N_n^t}, PCC) \tag{3.11}$$

Where, $R1^t$ is the available physician at any time t; N_n^t is the hospital demand; and PCC is the patient case criticality.

Healthcare effectiveness, S_E, can be measured using Equation (3.12)

$$S_E = [T_t^a - T_t^{min})]/[T_t^b - T_t^{min}] \geq 0.0 \tag{3.12}$$

Where, T_t^a is the patient treatment time after the earthquake, T_t^b, is the patient treatment time before the earthquake; and T_t^{min}, is the minimum allowable treatment time.

3.4 Patient-driven model

The demand on hospitals is estimated using a newly developed patient-driven model. The model accounts for different factors affecting the selection of a healthcare facility. For each patient i (earthquake-related or regular patient), the probability P_{in} of a patient going to a healthcare facility n can be calculated using the probability tree analysis shown in Figure 3-3, which considers various socio-technical factors related to patient constraints, healthcare facility constraints, and connection between patient and healthcare facility. Payer or insurance type can dictate the facilities at which regular patients, with less severity, can be treated (Finnell & Dixon, 2016).

However, for patients with higher injury severities, quick access to facilities for rapid treatment is important and as such, the insurance or payer will not dictate the selection of the facility (Institute of Medicine, 2015). The reputation of the healthcare facility will also affect patient selection. Social media, previous experience of the patient, and brand name can dramatically change the patient's choice (Corbin et al., 2001). The connection between patient and healthcare facility is critical especially in the case of earthquake hazard, in which transportation network functionality can be affected and the patient's travel time to the healthcare facility can be significantly increased (Lupoi et al., 2013). The healthcare facilities also can affect patient distribution. Waiting time of patients before seen by a provider, the ability of the healthcare facility to treat injuries or disease and finding a way to transfer patients to another healthcare facility can change patient destination from one facility to another. The demand on healthcare facilities is rather dynamic and changes over time after the earthquake due to changes in the basic events.

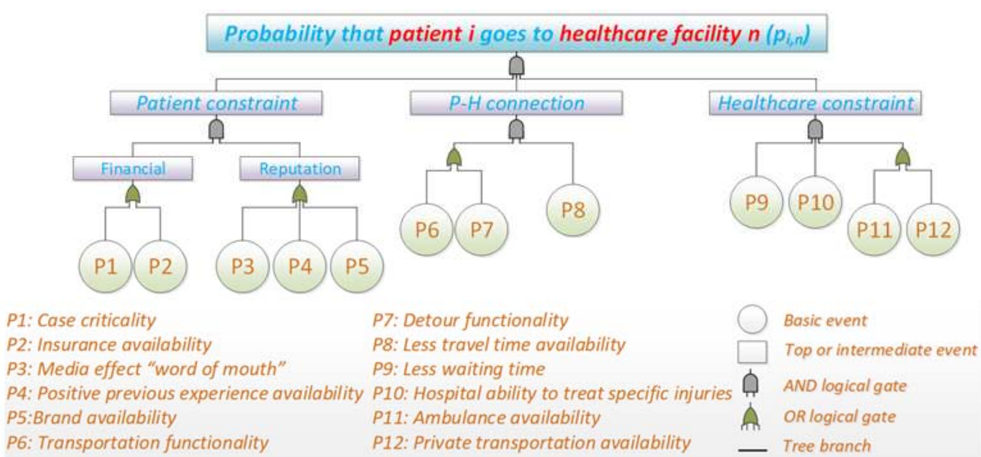

Figure 3-3: Patient-driven model probability.

The previously mentioned probability, $p_{i,n}$, can be calculated for all healthcare facilities in the investigated community, N, to form the patient selection probability vector $\boldsymbol{P_p}$ shown in Equation (3.13). The selected hospital is the one with the highest probability as shown by Equation

(3.14). A binary system is utilized to determine the most probable facility, $\lambda_{i,n}$, for each patient. Assuming that the community has a total number of patients, M_t, then the expected number of patients, N_n, at facility, n, can be estimated as the total number of patients who will select this hospital as shown in Equation (3.15). The expected demand for healthcare facilities might change further due to the patient transfer process, which will be discussed in the next section.

$$\boldsymbol{P_p(t)} = [p_{i,1}\ p_{i,2}\ p_{i,3} \cdots\ p_{i,N}] = p_{i,n} \tag{3.13}$$

$$\lambda_{i,n} = \begin{cases} 1.0 \iff (Max_{n\epsilon[1:N]} p_{i,n} - p_{i,n} = 0.0) \\ 0.0 \iff (Max_{n\epsilon[1:N]} p_{i,n} - p_{i,n} \neq 0.0) \end{cases} \tag{3.14}$$

$$E[N_n(t)] = \sum_{i=1}^{M_t} \lambda_{i,n} \tag{3.15}$$

Patients' length of stay at hospitals and resources needed to treat them are assumed to vary based on the patient severity level (Barros et al., 2010). Similar to the earthquakes, severities of regular patients are categorized into four levels. Regular patients' severity rates are a function of the community being investigated and can be deduced based on data in the literature (Weiss & Elixhauser, 2014). Earthquake-related injuries are not expected to arrive at the hospital at the same time (Cimellaro & Pique, 2016). In this study, variation in both the arrival rate and length of stay are considered for regular and earthquake-related patients.

3.5 Healthcare facilities interaction model

The interaction between healthcare facilities is essential, especially after the earthquake occurrence as it allows for redistribution of services, repair resources, medical staff, and patients as needed (McDaniels et al., 2008). However, to achieve this level of interaction pre-arrangement and agreement between healthcare facilities have to exist (Paterson et al., 2014), which is more likely for facilities with the same brand name. The travel distance between the healthcare facilities and the availability of transportation and the telecommunication networks can also affect this interaction.

The probability of patient transfer between healthcare facility i to facility j is calculated using the probability tree shown in Figure 3-4. The transfer process is a function of the patient and insurance constraints, healthcare facilities connection, and availability of the receiving facility. For a patient, who is in a critical condition at a facility that has less ability to treat him/her, the transfer decision is commonly made with no regard for the insurance type. However, for patients with less injury severity levels, the type of insurance is expected to control the transfer decision. To accomplish the transfer process, the connection between the emitting and the receiver hospitals should exist. This connection requires functional transportation, telecommunication, and agreement to transfer the patient’s medical records. The functionality of the receiver hospital can also control the transfer process. For hospitals with higher demand compared to their capacity, at the time, t, accepting new patients will increase the patients waiting time and reduce the number of available staffed beds, which will eventually impact the offered healthcare service. Therefore, waiting time at the receiver hospital in addition to the ability of the hospital to treat the transferred patient will affect the probability of a patient being transferred. Unlike patients with less severe injuries, who can be transferred using private transportation, patients with critical cases are transferred using either ambulances or air transportations depending on the case. It is worth noting that the patient transfer process is complicated and not all cases can be transferred.

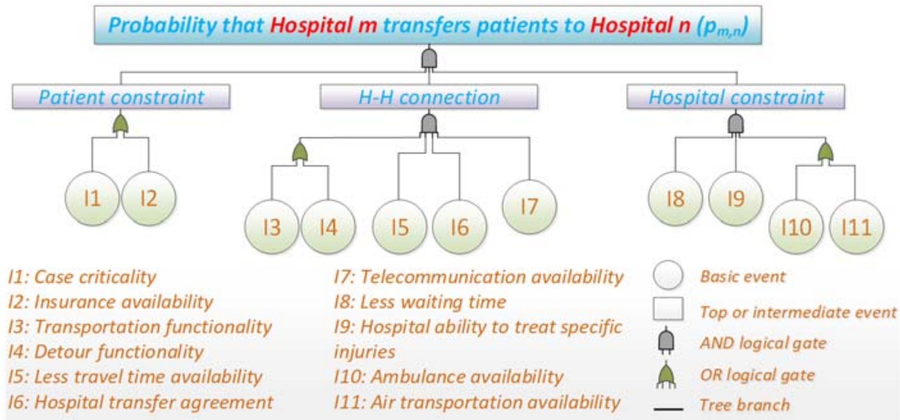

Figure 3-4: Hospitals' interaction probability.

The previously mentioned probability tree is used to calculate the transfer probability between all hospitals within the investigated cluster at any time (t) after earthquake occurrence, which is allocated in the full interaction matrix, $\boldsymbol{I_p(t)} := (p_{m,n})_{NxN}$, shown in Equation (3.16) where N is the total number of hospitals.

$$\boldsymbol{I_p(t)} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,N} \\ p_{2,1} & p_{22} & & p_{2,N} \\ \vdots & & \ddots & \vdots \\ p_{N,1} & p_{N,2} & \cdots & p_{N,N} \end{bmatrix}_t = p_{m,n} \tag{3.16}$$

Once a hospital m reaches the predefined capacity, $\varepsilon_m(t)$, or the patient cannot be treated, a transfer process to another hospital n, within the investigated cluster, is assumed to have started on the condition that the receiving hospital can accept the patient. The presented framework is labeling each hospital as either probable emitter, m, probable receiver, n, or idle as shown in Figure 3-5.

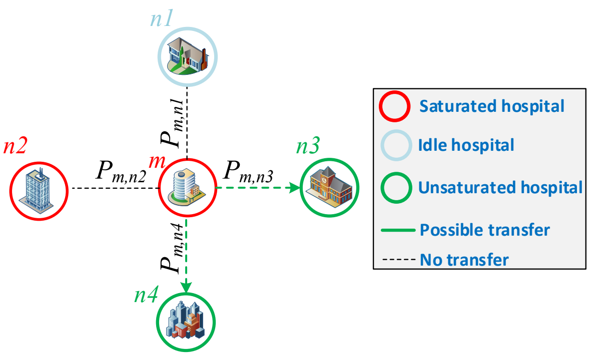

Figure 3-5: Patient transfer process mechanism.

To calculate the total number of patients transferred, $N_{dist\ m \rightarrow n}$, from hospital m to hospital n, Equation (3.17) is used where, $\varepsilon_m(t)$ is the maximum capacity of the hospital m, which varies with time-based on the available number of staffed beds, $p_{m,n}(t)$ is the interaction value between hospital m and hospital n, and N is the number of hospitals that can receive the transferred patient. After transferring patients, the demand on each hospital is updated in terms of change in the total number of patients. Equation (3.18) and Equation (3.19) show the updated demand on an emitter and a receiver hospital, respectively.

$$N_{dist_{m \rightarrow n}}(t) = \left(N_m(t) - \varepsilon_m(t)\right) \frac{p_{m,n}(t)}{\sum_{k=1}^{N}\{p_{m,k}(t)\}} \quad \forall\, n, m \tag{3.17}$$

$$N_{m,mod}(t) = N_m(t) - \sum_{k=1}^{N} N_{dist_{m \rightarrow k}}(t) \tag{3.18}$$

$$N_{n,mod}(t) = N_n(t) + \sum_{k=1}^{N} N_{dist_{k \rightarrow n}}(t) \tag{3.19}$$

In the presented model, hospitals can receive additional staff from other hospitals if staff shortage is affecting hospital functionality (when staff availability, ST, is less than space, SP, and supplies, SU, availability). However, the staff transfer process requires agreement between the facilities and willingness of other hospitals to send support, which might need a longer arrangement time. During that time, different alternatives can be explored such as reducing the time required to treat the patients if possible (Arboleda et al., 2007), which might increase the fatalities. Another possibility is by assigning additional working hours to the original staff, assuming the staff is willing to work extra time (Kisekka et al., 2015b). To estimate the number of additional staff, ST_{add}, transferring from hospital m to hospital n, Equation (3.20) is used; where ST_{req_m} is the required number of staff at hospital m and $\boldsymbol{I_{ST}}$ is the staff transfer probability matrix, defined by $\boldsymbol{I_{ST}(t)} := \left(p_{ST_{m,n}}\right)_{NxN}$ as shown in Equation (3.21). This probability is calculated based on the probability of an agreement (p_{ag}) between hospital m and n, the probability of hospital m staff accepting a transfer (p_{tf}), and the probability that the transferred staff will match the need of hospital n (p_{ma}). However, this transfer will occur if and only if hospital m has more staff than required as shown in Equation (3.22).

$$ST_{add_{m\to n}}(t) = \begin{cases} \left(ST_{req_n}(t) - ST_n(t)\right) * p_{ST_{m,n}}(t) \Leftrightarrow ST_m \leq \min\left(SP_m, SU_m\right) \\ 0.0 \Leftrightarrow ST_m > \min\left(SP_m, SU_m\right) \end{cases} \quad (3.20)$$

$$\boldsymbol{I_{ST}}(\mathrm{t}) = \begin{bmatrix} p_{ST_{1,1}} & p_{ST_{1,2}} & \cdots & p_{ST_{1,N}} \\ p_{ST_{2,1}} & p_{ST_{2,2}} & & p_{ST_{2,N}} \\ \vdots & & \ddots & \vdots \\ p_{ST_{N,1}} & p_{ST_{N,2}} & \cdots & p_{ST_{N,N}} \end{bmatrix}_t = p_{ST_{m,n}}(t) \quad (3.21)$$

$$p_{ST_{m,n}}(\mathrm{t}) = \left(p_{ag_{m,n}} \cap p_{tf_{m,n}} \cap p_{ma_{m,n}} \middle| ST_m > \min\left(SP_m, SU_m\right)\right) \quad (3.22)$$

Similar to staff transfer, supplies can be transferred between healthcare facilities only if the supply availability is less than staff and space availability. An agreement is mainly required between the facilities and functional transportation network to transfer the required supplies. Equation (3.23) is used to estimate the number of supplies, SU_{add}, transferred from hospital m to hospital n. SU_{req} is the required number of supplies at hospital n and $\boldsymbol{I_{SU}}$ is the supplies transfer probability matrix, shown in Equation (3.24). The entries of the matrix depend on the probability of having established agreement (p_{ag}), transportation functionality between hospital m and hospital n (p_{tr}), and the probability of matching supplies between both hospitals (p_{ma}). However, this transfer will occur if and only if the hospital *m* has more supplies than required. The supplies amount can be updated similar to the staff as mentioned earlier as shown in Equation (3.25).

$$SU_{add_{m\to n}}(t) = \begin{cases} \left(SU_{req_n}(t) - SU_n(t)\right) * I_{SU_{m,n}}(t) \Leftrightarrow SU_m \leq \min(ST_m, SP_m) \\ 0.0 \Leftrightarrow SU_m > \min(ST_m, SP_m) \end{cases} \tag{3.23}$$

$$\boldsymbol{I_{SU}}(\mathrm{t}) = \begin{bmatrix} p_{SU_{1,1}} & p_{SU_{1,2}} & \cdots & p_{SU_{1,N}} \\ p_{SU_{2,1}} & p_{SU_{2,2}} & & p_{SU_{2,N}} \\ \vdots & & \ddots & \vdots \\ p_{SU_{N,1}} & p_{SU_{N,2}} & \cdots & p_{SU_{N,N}} \end{bmatrix}_t = p_{SU_{m,n}}(t) \tag{3.24}$$

$$p_{SU_{m,n}}(\mathrm{t}) = \left(p_{ag_{m,n}} \cap p_{tr_{m,n}} \cap p_{ma_{m,n}} \middle| SU_m > \min(ST_m, SP_m)\right) \tag{3.25}$$

3.6 Summary

In this chapter, a new framework to estimate the functionality of the healthcare system was introduced. The framework combined the quantity functionality, measured by the number of available staffed beds, and quality functionality, measured by accessibility and effectiveness of the offered healthcare services to form a comprehensive healthcare system functionality index after earthquake disasters. Number of available staffed beds at any hospital was calculated using success tree that accounted for the availability of staff, space, and supplies while considering the different mitigation strategies that might be applied by this hospital such as alternative staff, backup systems, and backup spaces. Success trees were constructed for beds in emergency departments and inpatients and took into consideration the interdependency between each hospital and its supporting infrastructure. Patient waiting and treatment times were used to quantify the accessibility and effectiveness of the healthcare services, which were used as quality indices for the healthcare system. Different parameters were included in modeling these quality indices including, for example, patient travel time, the impact of earthquake damage on hospital's staffed beds, and the effect of the increase in patient demand after the earthquake.

The chapter also presented a new framework used to quantify the patients' distribution on healthcare facilities that accounts for various parameters related to the patient constraints, healthcare facility constraints, and connection between patient and healthcare facility. This framework can quantify the number of patients at each facility while accounting for the dynamic change in the community that might occur after the earthquake including population dislocation and distribution in the transportation network.

A framework to model the interaction between different healthcare facilities within the healthcare system was also presented. This framework models the patient, staff, and supplies transfer probability between all the hospitals in the healthcare system. It accounted for the different spatial and temporal parameters to estimate the number of patients transferred from overwhelming or saturated hospitals to other facilities with less demand. It also considered the number of staff transferred between the healthcare facilities as a function of the agreement between facilities, the staff willingness to be transferred, and matching the need of the receiver hospital. The supplies transfer process was modeled as a function of the agreement between the healthcare facilities, supply types, and transportation availability.

Chapter 4. FUNCTIONALITY OF *K-12* SCHOOL SYSTEMS

4.1 General

Maintaining educational services following natural disasters, such as earthquakes, is critical for resilient cities and communities. The continuation of educational services following extreme events is key to restoring normalcy within communities and reducing the potential for population outmigration. Earthquake disasters can have devastating consequences on children because they are among those most vulnerable to natural disasters. *K-12* public schools are used in this study as the main facility providing educational services. Modeling the functionality of the school requires simulating the interaction between different components that include community individuals as well as various community physical, economic, and social sectors. One of the educational service's main objectives is to provide schoolchildren with appropriate academic and personal training. Therefore, educational service functionality needs to be measured in terms of the availability of service and student outcomes. Education system functionality can drop after an earthquake because of the damage sustained by the school buildings and/or the built environment supporting the schools. Casualties among the workforce and community individuals, in general, will also have a strong impact on the functionality of the education system. Schools are centrally managed systems. The roles played by schools' administrations and school districts before the earthquake disasters are vital for reducing the impact of the event. These roles could include applying different mitigation strategies, such as providing schools with backup systems and backup spaces, deciding on student enrollment and transfer, reopening schools, staff appointment and transfer, and supplies transfer. In this chapter, a framework for the educational services functionality is presented to dynamically model the behavior of the education system after earthquake events.

4.2 Understanding the educational service

K-12 educational services are aimed at providing schoolchildren with appropriate academic and social experiences and training. A complex set of factors and their interactions influence the functionality and success of the educational system within a community in achieving these goals, as shown in Figure 4-1. School functionality represents the ability of a school to provide the desired level of educational services. School buildings provide essential space for teachers, administrative staff, and community volunteers to provide educational services to students. The continued availability of this space requires that damage to structural and non-structural components, as well as building contents, be kept to an absolute minimum and those essential utilities, such as power, water, and sewer, be available. Since students in a typical community attend different school grades, the continued availability of all *K-12* grades in a school is crucial to reduce the potential for dislocation and outmigration for students and their families (Hinojosa et al., 2019). Finally, most students require transportation to reach school, which is provided by either school buses or private transportation. A set of national and local regulations must be followed in school management. These regulations differ based on the school type and require the availability of qualified staff, proper space, and sufficient supplies and services. In the case of a school closure, different alternatives may be offered to students, which are determined based on the school policy and regulations.

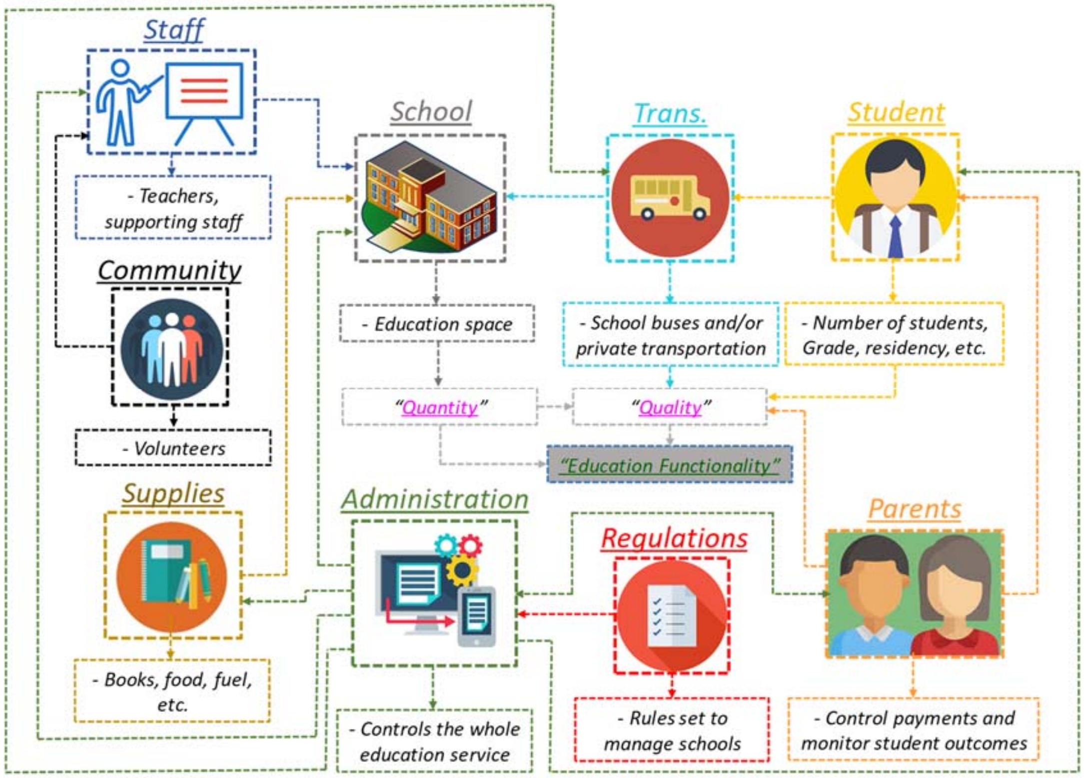

Figure 4-1: Components of educational services.

In normal conditions, student enrollment is based on the school zone. The selection of these zones depends on school capacity and the expected number of students within the zone. Some parents may select a different school for the students; however, school transportation is commonly limited to the students living in that zone. Following natural disasters such as earthquakes, some students might transfer to other schools because of school damage. In this situation, schools might increase class capacity or reduce the transportation service, or in some cases totally suspend it, due to damage to roads, shortage in staff, or damage to buses. Schools can also be used as temporary shelters, or as centers for community disaster relief (Singh, 2019) and recovery coordination (Applied Technology Council, 2017; Fujieda et al., 2008). Using schools as shelters is, however, a function of the disaster occurrence time, space availability, and school building safety. For instance, educational services are impacted by earthquakes differently during the academic year than when school is not normally in session.

In the following section, a model of post-disaster school functionality and recovery around the basic considerations introduced above is built. This model is focused on public schools, which enroll approximately 90% of *K-12* students in the U.S.

4.3 Component functionality of schools

To measure the functionality of the educational services, two main indices are widely used: service availability (UNESCO, 2019) and quality of the education providers (Mayer et al., 2000). In this study, these two indices are combined to form a comprehensive measure of the educational service. The expected value of the total functionality of the educational service, $E(S)$, at any time, t, within a community can be mathematically calculated, including the correlation between quantity, S_V, and quality, S_S, of the service, or approximated using weighted geometric means, as shown in Equation (4.1). The weighted geometric mean:

$$E\big(S(t)\big) = \iint S_V(t)^{\alpha_V} S_S(t)^{\alpha_S} f(S)\, dS_S\, dS_V \cong {S_V}^{\alpha_V} {S_S}^{\alpha_S} \tag{4.1}$$

In which α_V and α_S are weighting factors for quantity and quality, respectively (U.S. Department of Education-Office of Innovation and Improvement, 2009), is a common method to aggregate social indicators. The short-term functionality depends on the quantity of basic educational services that can be provided. Over the long-term, however, the total functionality depends, in addition, on the quality of the service. The quantity can be measured by enrollment capacity and class size, which depend on the performance of schools' physical infrastructure, availability of staff, supplies, and supporting lifelines. On the other hand, the quality can be measured by combining different indices related to teachers' credentials and experience, classroom amenities, and school context (Mayer et al., 2000). Some of these parameters can be impacted significantly in the aftermath of an earthquake. For instance, outmigration or dislocation of professional staff might affect teachers' assignments, which could negatively impact the quantity and quality of the delivered education. Moreover, damage to structural and non-structural components and to building contents, as well as the damage to the schools' supporting lifelines, might increase the class size.

4.3.1 Quantity functionality

Staff, space, and supplies availability are the main components of the schools' post-hazard quantity measure. The school staff includes teachers, supporting staff, and administrative staff as well as community volunteers. Appropriate space for students entails having a safe structure, reliable non-structural components, and functioning contents (desks, computers, etc.). Schools also require various utilities (water, power, wastewater, and drinkable water), as well as infrastructure (transportation, telecommunication) to operate. Some schools are equipped with backup utilities. Books and other educational materials, food, fuel, and other supplies are also vital for operation. The probability of school seat availability for students can be estimated using the success tree shown in Figure 4-2. This success tree is comprised of various events, each of which is assumed to be statistically independent. It describes the functionality of not only the school building itself but also the surrounding community's physical, economic, and social infrastructure. Similar to previous studies (Hassan & Mahmoud, 2019; Nozhati et al., 2019), the availability of each basic event is described by appropriate probabilistic mathematical functions. The basic events in the success tree analysis are connected using *AND*/*OR* gates to calculate the probability of top and intermediate events. Probabilities for these gates are calculated using equation (2), where P_{OR} and

P_{AND} denote "*AND*" and "*OR*" gate operations, respectively, P_i refers to the basic event (i) probability, and n is the total number of considered basic events.

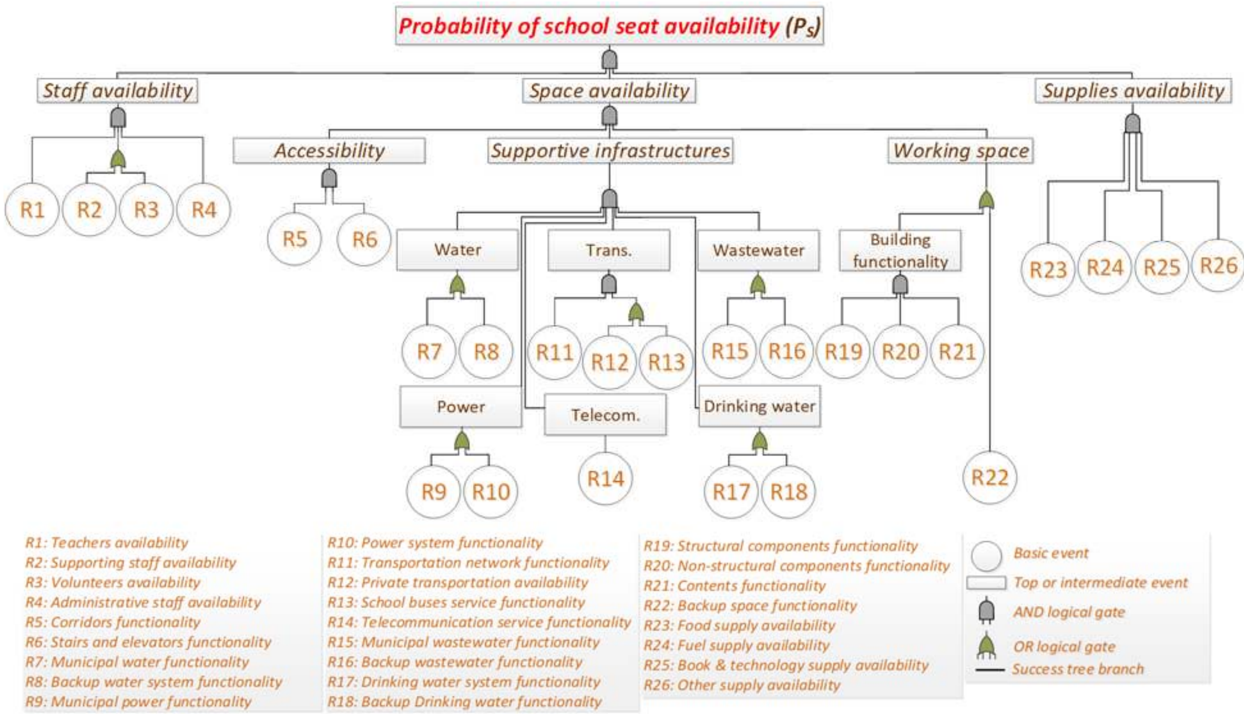

Figure 4-2: Success tree for determining the availability of seats in the school.

The probability of staff availability, $P(ST_i(t))$, for each grade, i, at a time, t, after an earthquake occurrence is estimated as the union of events that the school staff is available, as given by:

$$P(ST_i(t)) = P\{(\cup_{j=1}^{N} E_i^j)\} = P\{(1-(L_{DS})) \cup (ST_{add}) \cup (ST_{vol}) \cup (1-(ST_{dis})) \cup (1-(ST_{dif}))\} \quad (4.2)$$

Where E_i^j is the j^{th} event for the ith grade considered and N is the total number of events. This equation is utilized to calculate the staff availability, *R1*, *R2*, and *R4*, which are related to staff casualties and trauma, are expected to be impacted immediately after an event because of the direct social losses, L_{DS}. Other factors also can influence staff availability during the recovery time such as staff appointments (permanent and temporary), ST_{add}, volunteer staff, ST_{vol}, staff dislocation, ST_{dis} and staff personal responsibilities and commitments, ST_{dif}. Volunteers from the community, *R3*, can temporarily fill the gap for the required supporting staff, *R2*. The availability of *R3* is a function of the investigated community.

School space functionality considers school accessibility, the functionality of supporting infrastructure, and the availability of appropriate working space. Accessibility, *R5* to *R6*, accounts for the corridor, stairs, and elevator functionality after the earthquake. School accessibility might be influenced by damage to structural and non-structural components, which can block the corridors and impact the safety of stairs and elevators. School-supporting infrastructure includes water, *R7*, power, *R9*, transportation, *R10*, telecommunication, *R14*, wastewater, *R15*, and drinking water, *R17*. School physical entities commonly classified into structural, *R19*, non-structural, *R20*, and content, *R21*, are considered as physical school building components. During the earthquake, damage can be quantified in these components based on building fragilities, which describe the probability of reaching a certain damage level for a given hazard intensity. The framework also considers the availability of backup space, *R22*, such as using a different building or turning other rooms in the school into classrooms.

School supplies include food for students, staff, and teachers, *R23*, fuel for heating, *R24*, books, and technology supplies essential to a classroom, *R25*, and other supplies, *R26*. The availability of these supplies depends on the availability of suppliers, transportation, and storage.

The index of quality functionality after an earthquake is given by the expected number of available seats for students at grade i in each school, which is calculated using the probability of school seat availability, P_s. Equation (4.3) shows the expected value of the education quantitative index, S_V:

$$E[S_V(\mathrm{t})] = \sum_{i=i}^{I_g} \frac{1}{N_i} \sum_{n=1}^{N_i} P_{s,i}^{n} \tag{4.3}$$

Where, N_i is the total number of seats at grade i and I_g is the number of grades.

4.3.2 *Quality functionality*

The quality of the educational services that can be provided may be impacted after major disasters because of a shortage of teachers, staff, space, and supplies. The framework combines various quality measures including teacher assignment, T_a, and experience, T_e, as indicators of teacher quality; class size, C_s, and technology, C_t, as indicators of classroom quality; and leadership, S_l, and professional community, S_{pc}, as indicators of school quality as shown in Equation (4.4):

$$S_S(t) = \{T_a^{\alpha_a}(t) T_e^{\alpha_e}(t)\}\{C_s^{\alpha_s}(t) C_t^{\alpha_t}(t)\}\{S_l^{\alpha_l}(t) S_{pc}^{\alpha_{pc}}(t)\} \tag{4.4}$$

Where, the α-terms are weighting factors to represent the importance of each quality measure. Combining these indicators can be used as a quality index of the educational service mentioned in Equation (4.1).

Teacher quality, including teacher assignment and experience, can seriously be affected by staff shortages, difficulties in finding qualified staff, and a shortage of qualified community volunteers. Teacher assignment is evaluated as:

$$T_a(t) = \sum_i \left\{ \frac{ST_{i,req}(t) - E\left(ST_{i,unq}(t)\right)}{ST_{i,req}(t)} \right\} \tag{4.5}$$

Where, the required staff, $ST_{i,req}$, varies with the number of students enrolled, $N_i(t)$, and the class capacity, $R_i(t)$:

$$ST_{i,req}(t) = \frac{N_i(t)}{R_i(t)} \tag{4.6}$$

The probability of finding alternative staff, $P(ST_{alt})$, is shown in Equation (4.7) as a function of the required staff and available staff to hire, ST_{avl}. However, it is probable that this replacement staff may be less qualified, $P(ST_{unq})$ than the permanent staff, as shown in Equation (4.8).

$$P(ST_{i,alt}(t)) = P(ST_i < ST_{i,req}|ST_{avl}) \tag{4.7}$$

$$P(ST_{unq}(t)) = P(ST_{i,alt})P(ST_{mis}|ST_{i,alt}) \tag{4.8}$$

Teacher experience is calculated as the ratio between the experienced staff and the total staff, $ST_i(t)$:

$$T_e(t) = \sum_i \left\{\frac{ST_i(t) - E\left(ST_{i,inexp}(t)\right)}{ST_i(t)}\right\} \tag{4.9}$$

Teacher experience is mainly impacted by the percentage of teachers who are either appointed, transferred, or volunteered after the earthquake and have a lack of experience. The expected value of inexperienced teachers is calculated from the conditional probability of a new teacher joining the school staff, ST_{add}, and does not have enough teaching experience, ST_{mis}:

$$P\left(ST_{inexp}(t)\right) = P\left(ST_{i,add} \cap ST_{mis}\right) = P\left(ST_{i,add}\right)P\left(ST_{mis}\middle|ST_{i,add}\right) \tag{4.10}$$

Larger class size and lack of technology can seriously impact class quality. The classroom size is measured as a ratio between existing, $R(t)$, and normal, $R(0)$, teacher-to-student ratios, considering maximum acceptable class capacity, R_{max} as shown in Equation (4.11). The maximum acceptable capacity is assumed to be a function of the school regulations and community norms. The mean value of the classroom sizes for all grades is utilized to express the overall school quality as shown in Equation (4.12).

$$C_{i,s}(t) = \frac{R_{i,max} - R_i(t))}{R_{i,max} - R_i(0)} \leq 1.0 \tag{4.11}$$

$$C_s(t) = \overline{C_{i,s}}(t) \quad \forall i \tag{4.12}$$

The ratio between the current technology availability, $T(t)$, and the technology before earthquake occurrence, $T(0)$, is used as an index for classroom technology, as shown in Equation (4.13). This technology will be impacted after an earthquake because of building contents damage, L_C, and deficiencies in essential utilities, U, for classroom technology, such as power and telecommunication as shown in Equation (4.14).

$$C_t(t) = 1 - \sum_i \left\{\frac{T_i(0) - E\left(T_i(t)\right)}{T_i(0)}\right\} \tag{4.13}$$

$$P\left(T_i(t)\right) = P\left((1 - \left(L_{i,C}\right)) \cap U_i\right) \tag{4.14}$$

The absence of effective leadership in the aftermath of an extreme natural event also impacts school quality. The leadership availability is modeled as a function of current leadership availability, $l(t)$, following the earthquake as well as at time $l(0)$ before earthquake occurrence as shown in Equation (4.15). In this study, school administration, ST_{admin}, and experienced faculty, ST_{lp}, control the quality of leadership, as defined by Equation (4.16). The appointment of less qualified teachers, as well as turnover in teaching staff, can negatively impact the relationship between teachers and their students and eventually reduce student outcomes.

$$S_l(t) = 1 - \sum_i \left\{\frac{l_i(0) - E\left(l_i(t)\right)}{l_i(0)}\right\} \tag{4.15}$$

$$P(l_i(t)) = P(ST_{admin} \cup ST_{lp}) \tag{4.16}$$

The availability of professional community is estimated as the ratio between the current professional community, $pc(t)$, and its value before the earthquake, $pc(0)$, as shown in equation

(4.17). Appointing unqualified teachers, ST_{unq}, and the teacher change events, ST_{ch}, are utilized as an indicator of the professional community as shown in equation (4.18).

$$S_{pc}(t) = 1 - \sum_i \left\{\frac{pc_i(0) - E(pc_i(t))}{pc_i(0)}\right\} \tag{4.17}$$

$$P(pc_i(t)) = P\{(1 - ST_{unq}) \cup (1 -)\} \tag{4.18}$$

4.4 School administration model

The decisions that the school administration makes after disasters to maintain the school's functionality can make an enormous difference in the resilience of a school system. To mimic the role of school managers in the decision-making process, decision support frameworks are introduced that model the main decision processes, including the students' admission and transfer, staff appointment, and community engagement. Figure 4-3 shows the framework for students' admission and transfer in which different schools and transportation options are considered. The framework also considers the role played by parents in terms of school selection, funding, transportation, and homeschooling.

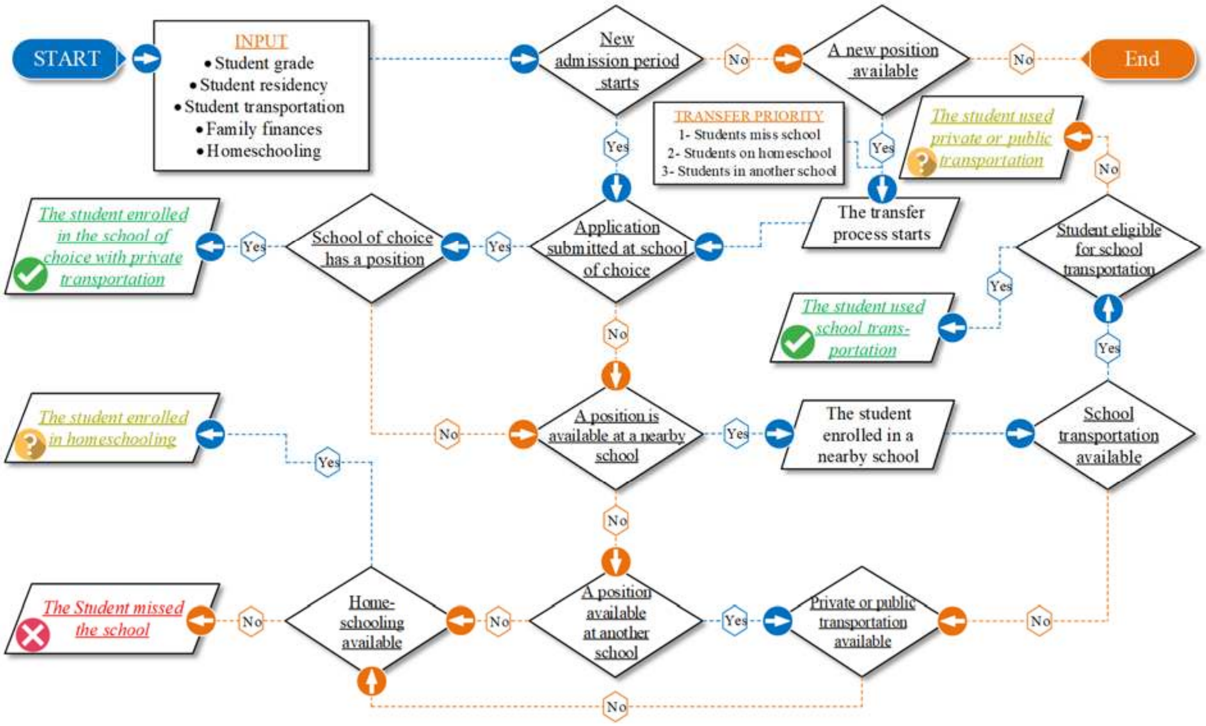

Figure 4-3: Students' enrollment and transfer process framework.

Reopening damaged schools after major disasters involve the school district, school administrators, the building and fire departments, the office of public safety, and the community (U.S. Department of Education, 2007). In this study, three cases are considered. In the first, schools can be partially opened using backup spaces during the recovery stage to provide education for a limited number of students (Decision *I*) (Bounds, 2014). In the second, where schools are not provided with backup spaces, they can only reopen if they are repaired (Decision *II*). Finally, in the third, schools might stay closed until all buildings are fully functional (Decision *III*) (U.S. Department of Education, 2007). The first and second cases might reduce the total number of students who are in temporary classrooms, being homeschooled, or missing school, but they require high levels of coordination between the school administration, parents, and students to ensure equitable temporary student placement. School districts often work with the community to find temporary classrooms for students and professional staff after disasters (U.S. Department of Education, 2007).

A similar process simulates staff appointment (temporary, part-time, and permanent) and transfer between schools, as shown in Equations (4.19-4.21).

$$ST_{add}(t)_n = \begin{cases} \left(ST_{req_n}(t) - ST_n(t)\right) P(ST_{ap_n}(t)) \Leftrightarrow ST_n \leq \min(SP_n, SU_n) \ \& \sum ST_{req} \geq \sum ST \\ \left(ST_{req}(t)_n - ST_n(t)\right) P(ST_{tr_{m\to n}}(t)) \Leftrightarrow ST_n \leq \min(SP_n, SU_n) \ \& \sum ST_{req} < \sum ST \\ 0.0 \Leftrightarrow ST_n > \min\,(SP_n, SU_n) \end{cases} \tag{4.19}$$

$$P(ST_{ap_n}(\mathrm{t})) = P\left(E_{hr} \cap E_{ma_n} \cap E_{fu_n}\right) \tag{4.20}$$

$$P(ST_{tr_{m\to n}}(\mathrm{t})) = P\left(E_{w_{m,n}} \cap E_{tf_{m,n}} \cap E_{ma_{m,n}} \middle| ST_m > \min\,(SP_m, SU_m)\right) \tag{4.21}$$

Appointment or transfer is assumed to take place only where space and supplies are sufficient to accommodate additional staff and the existing staff, *ST*, are less than the required, ST_{req}. Additionally, staff appointment is a function of having available human resources, E_{hr}, the staff matching the school needs, Ema, and the funding availability, E_{fu}. The probability of staff transfer between school m and n is calculated based on the willingness of the school district to transfer the staff between schools, E_w, the school m staff accepting a transfer, E_{tf}, and the transferred staff will match the need of school *n*, E_{ma}. The approach of an individual School to solve the staff shortage problem is shown in Figure 4-4, which starts with using the existing staff within the school, for instance, by assigning more teaching loads for teachers while assigning volunteers to substitute the supporting staff. In case the existing staff and volunteers are not enough (ST_{req}>ST), schools could request staff transfer from other schools within the school district. If the school district cannot provide all required staff since no staff is available to transfer (ΣST_{req}>ΣST), schools can then appoint temporary and part-time staff to close the gap in staff shortage. Later those temporary and part-time staff can be replaced with permanent, more qualified, and more experienced staff to increase the quality that is expected to be impacted by hiring temporary and part-time staff with fewer qualifications.

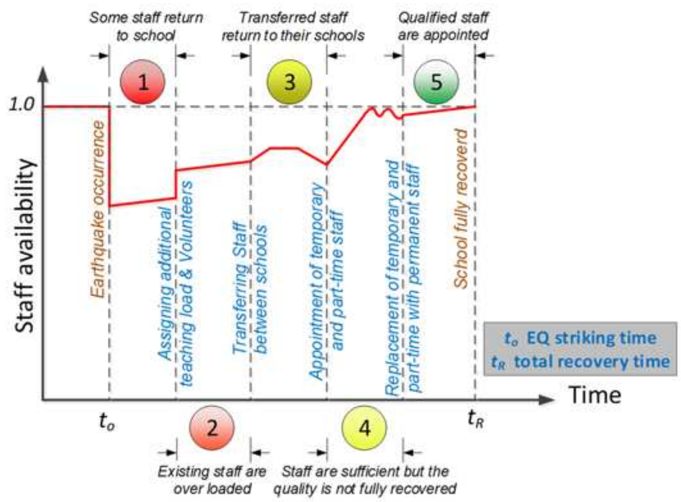

Figure 4-4: Staff shortage appointment approach.

Schools can also transfer supplies and resources to reduce the impact of the earthquake consequences on the school system. Equation (4.22) shows the expected number of supplies that can be transferred.

$$SU_{add}(t)_n = \begin{cases} \left(SU_{req}(t)_n - SU_n(t)\right) P(SU_{tr_{m\to n}}(t)) \Leftrightarrow & SU_n \le \min(ST_n, SP_n) \\ 0.0 \Leftrightarrow & SU_n > \min(ST_n, SP_n) \end{cases} \tag{4.22}$$

in which

$$P(SU_{tr_{m\to n}}(\mathrm{t})) = P\left(E_{ag_{m,n}} \cap E_{tf_{m,n}} \cap E_{ma_{m,n}} \middle| SU_m > \min(ST_m, SP_m)\right) \tag{4.23}$$

The probability that the supplies are transferred is assumed to be a function of an established agreement, E_{ag}, availability of transportation between school m and school n, E_{tr}, and the supplies matching the school need, E_{ma}. For the public schools in the same school district, E_{ag} can be considered 1.0, since public schools in a community typically are administrated centrally under the general supervision of an elected Board of Education, and in such cases "established agreements" are not relevant.

Community citizens can support education through supporting the school staff, providing donations, and encouraging students and staff to keep the school system as functional as possible. The effect of citizen behavior on school functionality following an earthquake is modeled by a) calculating the number of available volunteers, *R3*, for each school; b) tallying donations collected after the earthquake, which can be added to other recovery funding sources; and c) considering the impact of the social vulnerability index (*CVI*) (Agency for Toxic Substances and Disease Registry, 2018) on the resilience of the school system. To estimate the total number of volunteers at each school, the probability that a citizen responds to a request from the school depends on his/her gender, age, education, and income (Shi et al., 2018).

Different indices are used to quantify the quality of the educational service such as educational attainment (National Academies of Sciences, Engineering, 2019a) and student outcomes (Patry & Ford, 2016). Student outcomes can be monitored using self-reported or test-based measures (Caspersen et al., 2017). Student outcomes have been found to depend on chronic absenteeism (Bruner et al., 2011), which typically increases after major natural hazard events as a consequence of school closure, population dislocation, and stress and trauma. In this study, student's chronic absenteeism is used as a resilience index of the educational service.

4.5 Schools as community shelters

Schools can also play an important role as community shelters and as community centers for recovery management. The expected shelter capacity of each school, N_{sh}, can be calculated as a product of the school capacity, N_s, and the probability, $P(sh)$, that a school can serve as a shelter:

$$N_{sh}(\mathrm{t}) = N_s\, p_{sh}(\mathrm{t}) \tag{4.24}$$

In which the probability is:

$$P(ST(t)) = P(E_s \cap E_a \cap E_u \cap E_m | N_a > \mathrm{N}_t) \tag{4.25}$$

Where E_s = event that the school structural is safe, E_a = event that the school is accessible, E_u = event that main supporting utilities or alternatives are available, and E_m = event that the school space can be used as a shelter, conditioned on the enrollment capacity of the school, N_a, being more than the number of students attending the school, N_t.

4.6 Summary

In this chapter, a new framework to quantify the functionality of the education system was presented. The framework combined the quantity functionality, measured by the school enrollment capacity, and quality functionality, measured by the quality of teacher, classroom, and school to form a comprehensive education system functionality index after earthquake disasters. The school enrollment capacity at any time was calculated using a success tree that accounts for the availability of school staff, school space, and school supplies while considering the different mitigation strategies that might be applied by schools and school districts such as utilizing volunteers, backup systems, and backup spaces. Success trees were constructed for each grade and take into consideration the interdependency between each school and its supporting infrastructure. For the quality of the educational services provided by each school, teacher assignment and experience were used as indicators of teacher quality; class size and technology were utilized as indicators of classroom quality; and leadership and professional community were employed as indicators of school quality. Different parameters were included in modeling these quality indices including, for example, student enrollment, availability of qualified and professional staff, class capacity, school content damage, and availability of the main utilities.

The chapter also introduced a framework that can be used to simulate the main decision-made by the school administration including student enrollment and transfer, reopening schools after earthquake events, staff appointments, staff transfer, and supplies transfer. Student enrollment and transfer framework accounts for the interaction between the school administration and parents in terms of school selection, funding, transportation, and homeschooling. The framework considered different approaches in school reopening that include partially open schools, reopen schools only if they are repaired, and keep schools closed until all their buildings are fully functional. Staff appointment decisions were temporally modeled while using different hiring approaches including transferred, temporary, and volunteering staff. The supply transfer process between schools was modeled as a function of the agreement between the schools, supply types, and transportation availability.

The role played by schools as a community shelter was simulated in the proposed framework for school functionality. The shelter capacity was calculated based on the accessibility and safety of the school buildings, availability of the utilities required for the shelter, and the decision made by the school administration to temporarily turn the school into a shelter.

Chapter 5. INTERDEPENDENT RESILIENCE AND SOCIAL SERVICES STABILITY MODELING

5.1 Overview

The roles played by healthcare and educational systems in the community resilience and social services stability are substantial. Hospitals and schools are among the main social institutions in any community that provided essential and indispensable services. Therefore, ensuring quick recovery of these systems and maintaining functional hospitals and schools during and after earthquake events is a critical resilience goal for communities. To achieve this goal, this chapter builds upon previous chapters that describe the functionality of hospitals and schools, to determine recovery and resilience using a new framework. The recovery framework estimates the near-optimal repair progress for the physical components in hospitals and schools, which were damaged during the earthquake, using a semi-Markov chain model, coupled with the dynamic optimization. Once recovery is estimated, resilience is calculated as the area underneath the total functionality for each of these services. The sensitivity of the calculated resilience of the healthcare and education systems to the different functionality frameworks' components are investigated and the uncertainties associated with the estimated functionality and resilience are calculated.

Despite recent advances in quantifying the cumulative functional loss and resilience of healthcare and education systems, to date, studies on their interaction, their collective effect on their respective recovery, and the stability of the social services of communities are lacking. Quantifying the interaction, especially between these social institutions, is critical for community resilience analysis (Cimellaro, 2016; Mahmoud & Chulahwat, 2018; NIST, 2016a). Their compounded role in societies is essential for building robust communities (Butler & Diaz, 2016), informing public policies (NIST, 2016b; NSF, 2020), and influencing social indices (Flanagan et al., 2018; Stern & Epner, 2019). In this chapter, an agent-based model is devised to investigate the interaction between healthcare and education systems as well as their impact on resilience and social services stability of communities after natural disasters. The model is structured using a socio-technical approach that is based on guidelines and case studies for real communities after disasters. The model is also designed to apply different decisions and mitigation strategies that ensure the quick possible restoration of the healthcare and educational services.

5.2 Restoration and resilience frameworks

5.2.1 Overview

Immediately after the earthquake, the functionalities of healthcare and educational services are expected to drop. This drop can be in the quantity part of the service, which is driven by the failure to the structural and non-structural components as well as the contents, losses of personnel, malfunctions in utilities that support the healthcare services, or losses to the main supplies. In other cases, the drop can be manifested in the quality part of the service due to, for example, hospitals' overcrowding (Lynn et al., 2006), reduced time available to treat patients (Arboleda et al., 2007), students' chronic absenteeism (Bruner et al., 2011). Some of the components' functionality can be immediately recovered after the earthquake using the backup systems. Most of these backup systems are expected to withstand the earthquake and be functional; however, in some cases, the backup systems can fail due to the earthquake (Jacques et al., 2014). Backup systems can only maintain functionality for a short time after the event before it requires supplies or maintenance (Redlener & Reilly, 2012). However, the availability of these backup systems is critical at the assessment and planning stage, which is the first stage in the recovery process after the earthquake. During this stage, the repair process for most of the damaged components will not have started yet. The length of this stage is a function of the building damage state (Almufti & Willford, 2013).

Following the assessment and planning stage, the repair process starts. During this stage, managing the limited repair resources in the community is essential to maintain acceptable functionality for critical infrastructure. Decision-makers can use different approaches in this stage to distribute the resources, which can be targeted to either enhance social stability or to gain maximum economic benefit/return for the community. In this study, dynamic optimization is implemented for optimal distribution of repair resources to obtain the highest fitness value of the healthcare functionality. The fitness function is defined in this study by the total number of available staffed beds. Figure 5-1 shows a schematic the impact of backup systems and distribution of repair resources on different recovery stages after earthquake occurrence.

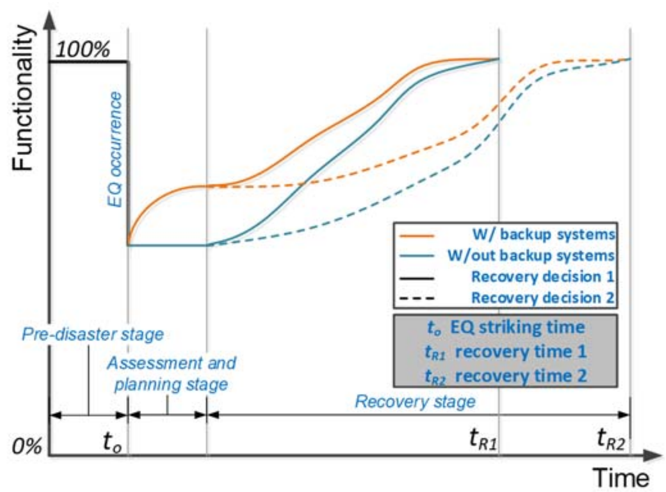

Figure 5-1: Different functionality stages after earthquake hazard.

Various parameters can dramatically affect the recovery path of an interdependent network such as a healthcare system. For the working space and supplies room recovery, maintaining the repair sequence is critical (Almufti & Willford, 2013). In this study, the repair sequence starts with the assessment and planning stage followed by the repair of the structural components and the non-structural components such as stairs, elevators, partitions, and building envelope including claddings. Some of the repair tasks are carried out simultaneously and others are sequential. Repair progress is a function of the geographical and structural properties of the investigated buildings (Kozin & Zhou, 1990). Commonly, hospitals are built using different structural systems and various materials. Therefore, repair efforts and time can be different from one system to another. In other cases, building reconstruction can be the only feasible option. In this study, repair crews are assumed to have different specialties; therefore, managing these crews is essential to achieve the targeted recovery progress. The distribution of these crews can be driven by various goals such as achieving specific social or economic targets, improving the quality of the healthcare service to maximize the number of staffed beds. This distribution also considers the maximum acceptable number of workers per hospital as a function of the total area of the investigated hospital, A_t, in units of sq. meter (Almufti & Willford, 2013).

5.2.2 Decision-making framework

Immediately after the disaster, communities start the restoration process to bring life back to normalcy. Decisions made by healthcare and education facilities as well as their staff and supporting infrastructure, during this stage, are simulated in this study to investigate the impact of these decisions on the recovery process of healthcare and education services as shown in Figure 5-2. The utilized approach divides the time after disaster into the assessment, planning, and recovery stages. The assessment and planning stage is when each facility assesses the extent of damage and arranges the repair process. The recovery stage is where the actual repair process starts, and the limited repair resources are distributed to achieve the predefined functionality level. In this study, the predefined level is set to the same level prior to an event. Markov chain process coupled with dynamic optimization is utilized to allocate repair resources to damaged facilities to estimate the optimal recovery path so as to maximize the number of staffed beds in all hospitals and the enrollment capacity for students in all grades. The details of all the components in Figure 5-2 will be discussed in the following sections.

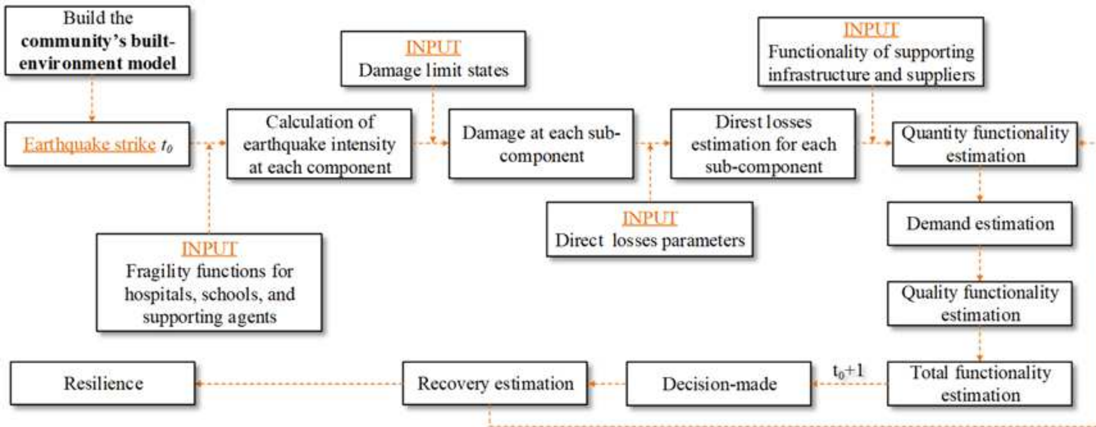

Figure 5-2: Healthcare and education system resilience quantification approach.

5.2.3 Assessment and planning stage

The assessment and planning stages of recovery are associated with the time from when the earthquake occurs to the time when the repair process starts. This includes various sub-stages, namely, damage inspection, engineering mobilization, reviewing/redesigning, financing, and biding, contractor mobilization, and permitting and procurement. Some of these sub-stages can take place simultaneously; therefore, the whole process is categorized into three sequences as shown in Table 5-1. It is important to point out that most of the sequences are also a function of the damage state of the lifeline. At the assessment and planning stages, no progress in the actual repair is expected; therefore, ensuring an accelerated return to functionality requires shortening of these stages. A reference number of the required time to complete the assessment and planning stages can be found at Almufti and Willford (2013), where the median values for essential facilities have been used and are summarized in Table 5-1.

Table 5-1: Assessment and planning stage mean expected time based on Almufti and Willford (2013).

Sequence	Sub-stage	Damage condition	Median (days)
Phase # 1	Inspection	All damage	2
Phase # 2	Engineering	Slight damage	14
		Moderate damage	28
		Severe damage	294
	Financing	All damage	7
	Mobilization	Slight damage	21
		Severe damage	49
Phase # 3	Permitting	Slight damage	7
		Severe damage	56

5.2.4 Recovery stage

Repair or restoration of each facility is estimated using a semi-Markov chain process, in which the restoration process is defined by discrete nondecreasing states. In the Markov chain process herein, the repair process at any time step can either improve the restoration state or not affect it. The current restoration state depends on the previous state but is independent of other previous states. The facility's quantity functionality is subcategorized into sub-components based on the repair crew specialty: structural components, building envelope, permanent and moveable partitions, mechanical equipment, and electrical systems. The discrete Markov chain modeling the recovery process is shown in Equation (5.1).

$$Q_l(k\Delta t) = Q_l(0)\prod_{i=0}^{k-1} A_l\, \boldsymbol{P_t}(\boldsymbol{i\Delta t})_l \tag{5.1}$$

Where, the functionality of sub-component l, Q_l, after time $k\Delta t$ is assumed to be related to the initial functionality drop, $Q_l(0)$, due to seismic damage, the interaction between the repair process of each facility and other community lifelines, A_l:

$$A_l = \prod_{j=1}^{N_f} \beta_j \tag{5.2}$$

The interaction term A_l is calculated based on factor β_j, defined in terms of the interaction factor, e_j, and the current functionality state of the lifeline j, $Q_j(t)$.

$$\beta_j(t) = \begin{cases} 1.0 \Leftrightarrow & e_j = 0.0 \\ Q_j(t)/e_j \Leftrightarrow & 0.0 < e_j \leq 1.0 \end{cases} \tag{5.3}$$

$$\boldsymbol{E} = [e_1 \quad e_2 \quad \cdots \quad e_{N_f}] = e_j \tag{5.4}$$

The transition probability matrix, $\boldsymbol{P_t}$ is represented in Equation (5.5) as:

$$\boldsymbol{P_t(t)} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,R-1} & p_{1,R} \\ p_{2,1} & p_{2,2} & & p_{2,R-1} & p_{2,R} \\ \vdots & & \ddots & \vdots & \\ p_{R-1,1} & p_{R-1,2} & \cdots & p_{R-1,R-1} & p_{R-1,R} \\ p_{R,1} & p_{1,2} & & p_{R,R-1} & p_{R,R} \end{bmatrix}_t \tag{5.5}$$

Where, the probabilities $p_{s,r}(t)$ are defined in Equation (5.6) as:

$$p_{s,r}(t) = Prob[Q(t) = Q_r | Q(t_0) = Q_s] \ , \ \sum_{s=1}^{R} p_{s,r}(t) = 1.0 \ \forall t \tag{5.6}$$

The transition probabilities $p_{s,r}(t)$, shown in Equation (5.7), are defined as the probability of the functionality state transitioning to the next (higher) level:

$$p_{s,r} = a\left[1 - e^{\left[-bx\left(0.1r^{0.5}\right)\right]}\right] \tag{5.7}$$

Where, a and b are parameters that refer to the geographical and structural properties of the investigated lifeline. The transition probabilities are also calculated as a function of the assigned repair crews, x, and the current restoration stage, r.

5.2.4.1 Repair crews

Community resources in the form of repair crews, x, are assumed based on the number of available crews in the investigated community. Due to the differences between the required skills of the repair crews for restoring healthcare and education facilities, the total number of available repair crews to repair each system is assumed independently. These repair crews are distributed among the facilities of each system. The distribution of the repair resources can be affected by several factors such as funding availability, type of the required repair, access to the damaged lifelines, among others. In this study, the distribution of the repair crews within the damaged facilities of each system is conducted using dynamic optimization with an objective to maximize the quantitative functionality of each system. The specialization of each repair crew assigned to the different lifelines and the proper repair sequence to eliminate interference between various repair tasks is considered based on the work by Almufti and Willford (2013). The repair sequence starts with the structural components followed by the stairs, the elevators, and the exterior repair such as partitions and claddings. The latter can be performed simultaneously with the interior repairs such as the piping, HVAC, partitions, ceilings, mechanical equipment, and electrical system as shown in the Gantt chart of Figure 5-4. Since the focus of this research is on the functionality of the hospitals and schools, an assumption is made that all repair sequences are the same for all lifelines.

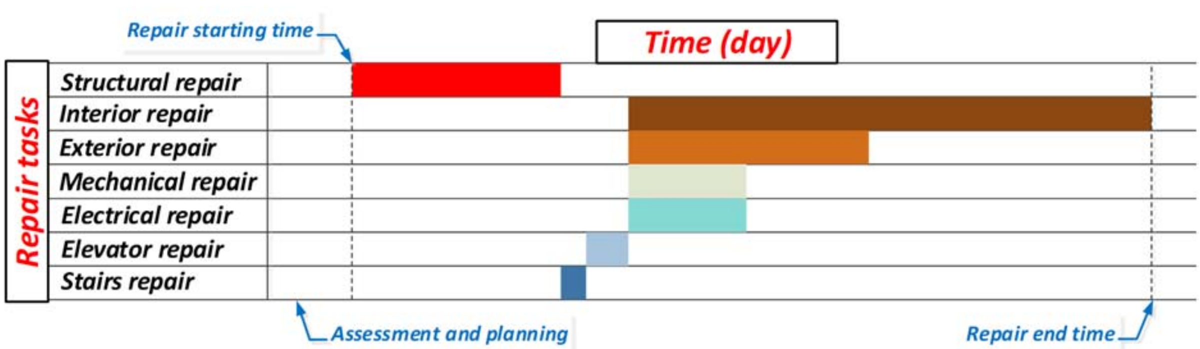

Figure 5-3: Gantt chart for the typical repair sequence.

One of the main parameters in the restoration and recovery process of a community is the total number of available repair crews, $X_m(t)$ at any time, t, and at specialty, m. The total number of available repair crews is expected to change with time after the earthquake. For instance, immediately after the earthquake, the number of repair crews is expected to be limited to that of what is available locally. However, The number of crews is expected to increase due to the aid provided by the surrounding communities as noted by Porter (2016). As repair progress and the community starts to return to normalcy, the number of repair crews reduces as shown in Figure 5-4. Six different specialties of repair crews are assumed where the first repair crew specifies in structural repair, the second in pipe and HVAC repairs, the third in interior partitions, ceiling tiles, exterior partition, and stairs, the fourth in mechanical equipment, the fifth in electrical systems, and the sixth in elevators.

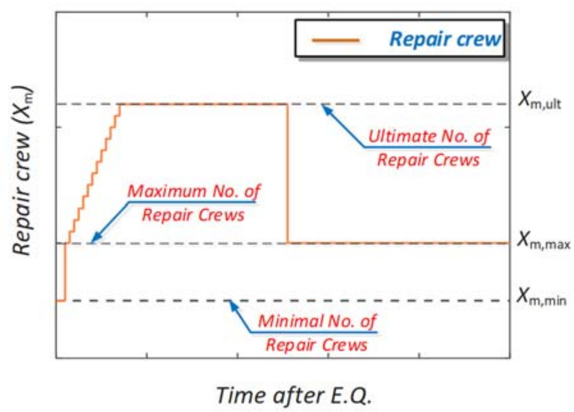

Figure 5-4: Change in the total number of repair crews with the time after the earthquake.

5.2.4.2 Optimization

The repair crews are distributed by dynamic optimization to achieve the pre-defined community objectives regarding each service. Suppose that the total available number of repair crews at each specialty, m, is $X_m(t)$, which changes as a function of the time after the disaster. The decision-makers assumed in this study assign these crews, $x_m^n(t)$, at any time, t, to repair the damaged sub-components by crew's specialty, m, in each school, n, to achieve the maximum quantity of the offered educational service for the whole community as denoted by Equation (5.8).

$$\max_{\mathcal{F}_{V(t)}} \sum_{n=1}^{N} \mathcal{F}_V^n (t) \tag{5.8}$$

Distribution of the repair crews is subjected to the following constraints a) limitation of repair resources, b) pre-defined repair sequence based on engineering judgment, and c) work environment constraint that limits the total number of repair crews, $x_{n,max}$, in any building, n, as a function of the building area, A_t, as shown in Equation (5.9) and (5.10).

$$X^m(t) = \sum_{n=1}^{N} x_n^m(t) \tag{5.9}$$

$$x_n \quad \leq x_{n,max} \qquad \forall x_{n,max}\,, \; x_{n,max} = 2.3 \times 10^{-6} A_t + 1.0, \;\; 2.0 \leq x_{n,max} \leq 26.0 \tag{5.10}$$

5.2.5 Resilience model

In this study, the PPD definition of resilience is utilized (See Section 2.6). Community resilience performance goals can be divided into population stability, economic stability, social services stability, physical services stability, and governance stability (Ellingwood et al., 2019). Each one of these five goals can be measured by different resilience metrics. For example, population stability can be measured by the number of households dislocated, percent of the population remaining in the community, etc. Resilience is defined graphically in this study as the area underneath the functionality curve (Bruneau et al., 2003), $\mathscr{F}$, from the hazard occurrence time, t_0, to the full recovery time, TR, as follows:

$$R = \int_{t0}^{TR} \frac{\mathcal{F}(t)}{TR} dt \tag{5.11}$$

The introduced framework to investigate total healthcare and education system resilience is shown in Figure 5-2.

5.3 Sensitivity and uncertainty framework

Generally, sensitivity analysis can be categorized into local and global sensitivity analyses (Borgonovo & Plischke, 2016). Local sensitivity analysis is commonly performed for deterministic models in which a model sensitivity is calculated for the input parameters around a point of interest or a reference point. For the probabilistic analysis of the framework developed herein, a global sensitivity analysis can be used to quantify the importance of the framework's different inputs as well as their interactions to framework output. It also provides a general assessment of the influence of these different inputs on the framework output as opposed to the local assessment of the local sensitivity analysis. A regression-based sensitivity method is applied to the framework in this study (Helton & Davis, 2003), which is a non-parametric method that can be used to measure model sensitivity from the Monte-Carlo simulation samples. Following the uncertainty analysis, which will be discussed later, an estimate of non-parametric sensitivity will be implemented by post-processing the obtained input-output data. Since this method is based on linear regression analysis, the input-output sample will be fitted using the response surface shown in Equation (5.12). Even though, due to the complexity of the introduced frameworks, the linear regression might not effectively capture the expected non-linearity of the sensitivity, it can give an overview of the importance of different parameters used in quantifying the seismic resilience of healthcare and education systems.

$$g(\boldsymbol{X}) \approx b_0 + \sum_{i=1}^{n} b_i x_i \qquad (5.12)$$

The sensitivity coefficient, S_{ij}, is defined as the rate of output change, Y_j, with respect to a parameter, X_i, adjustment:

$$S_{ij} = \frac{\delta Y_j}{\delta X_i} \qquad (5.13)$$

Where, the subscripts are i and $j \in (1{:}N)$ and N is the total number of samples.

The uncertainty associated with the parameters, x_i, makes the framework output, ($Y=g(\boldsymbol{x})$), a random variable. In this study, uncertainty analysis is performed numerically through Monte-Carlo simulation where a random sample of size (*N*) that follows the distribution of the framework parameter inputs, is selected, and the framework output is evaluated in correspondence with each realization of $\boldsymbol{x}$. The results are then used to obtain the statistical parameters of the framework output. This sample is also utilized in the global sensitivity analysis to identify the key parameters of the framework.

5.4 Agent-based model

5.4.1 Overview

The introduced model, shown in Figure 5-5, comprises of a) main agents (healthcare and education facilities and all their sub-components), supporting agents (community's buildings and infrastructure that support the functionality of the main agents), and sub-agents (community individuals); b) decision-making heuristics and learning rules; c) an interaction topology including buildings, supportive infrastructure, and suppliers for both the healthcare and education facilities; and d) an environment. The entire framework is structured as a multi-layer agent-based model, system, main agents, and sub-agents, in which the system represents the entire networks of hospitals or schools. Each of these systems is defined by a group of main agents (either healthcare or education facilities); each is supported by supporting agents as a built environment including water, power, transportation, telecommunication, wastewater, natural gas, and buildings as well as a group of medical and non-medical suppliers. Furthermore, each of these main agents is dependent on sub-agents that represent all community individuals and includes different staff classes as operators and regulators as well as patients, students, or students' guardians as expected service receptors.

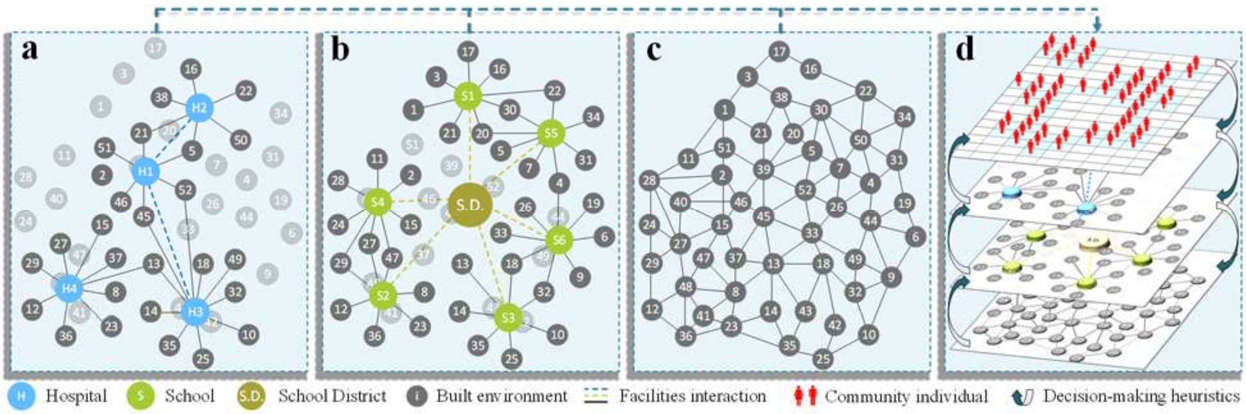

Figure 5-5: Components of the agent-based model: a) healthcare system including its supporting infrastructure, b) education system comprising of schools, school district as a main administrative component, and the supporting infrastructure, c) the community built environment containing infrastructure, building, and suppliers, and d) interaction between community individuals (sub-agents), healthcare and education facilities (main agents), and the built environment (supporting agents) in the decision-making heuristics stage.

5.4.2 Agents description and interaction topology

The healthcare system is modeled through the interaction of various sub-components, including personnel, *ST*, space, *SP*, and supplies, *SU*, as shown in Figure 3-2. *ST* is categorized into physicians, nurses, supporting staff, and alternative staff, and are all modeled as sub-agents. Utilities, *U*, as part of the space refers to the essential services provided to the healthcare system from the community's infrastructure, which includes water, power, transportation, telecommunication, wastewater, and drinking water, and are all framed as supporting agents. *SP* comprises structural, non-structural, and contents sub-components as well as building accessibility, which are all simulated as main agents. *SU* reflects the daily necessities and supplies for the medical facilities such as oxygen, surgical, *RX*, fuel, and food, among others, and is simulated as a supporting agent. The availability of these sub-components is assembled using the previously discussed complex healthcare network interaction model (Chapter 3) to estimate the functionality of the healthcare system. The probability of availability of sub-component, i, is integrated with the total number of sub-components, n, $P_B = \prod_{i=1}^{n} P_i$, to define the hospital's ability to receive and provide patients, which is expressed in terms of the available staffed beds, B, and is conditioned on the required service being available. To provide a full description of the functionality of the healthcare system, Q_H, the quantity of the service, Q_V, is combined with the accessibility, S_A, and effectiveness, S_E, of this service as an indication of the service quality, Q_S, as $Q_H(t) = Q_V(t)^{\alpha_V} Q_S(t)^{\alpha_S}$; where α_V and α_V are weighting factors for service quantity and quality, respectively. Q_V is calculated based on B and its type, being an emergency or inpatient bed, as shown in Figure 3-2.

The education system is simulated, similar to the healthcare network model, through the interaction of different sub-components including staff, ST, physical components, SP, and supplies, SU, as shown in Figure 4-2. ST is subclassified into teachers, supporting staff, administrative staff, and volunteers, which are all modeled as sub-agents. Main utilities, U, as part of the space are provided by the schools' supporting infrastructure and comprise water, power, transportation, telecommunication, wastewater, and drinking water, all of which are framed as supporting agents. School's SP includes structural, non-structural, and contents as well as building accessibility, which are all simulated as main agents. SU includes books, fuel, and food, among others, which is simulated as a supporting agent. These sub-components are used to calculate the functionality of the education system as discussed before in Chapter 4, including schools' enrollment capacity, N_i, which is an indicator of the school's quantity functionality, S_V, in each grade, i. The expected value of the school's quantity functionality, E[S_V], is calculated for the whole school as follows $E[S_V] = \sum_{i=i}^{I_g} \frac{1}{N_i} \sum_{n=1}^{N_i} P_{s,i}^{n}$; where I_g and N_i are the total numbers of grades and enrollment capacity at grade i, respectively. In addition, the quality of the educational service provided by schools, S_S, is also measured using indicators related to teacher, classroom, and school quality. Teacher quality is measured by teacher assignment, T_a, and experience, T_e. Classroom quality is measured by class size, C_s, and technology, C_t. School quality is measured by leadership, S_l, and professional community, S_{pc}. These indicators are combined with the school quantity functionality to formulate the school's total functionality, S_S, as $S_S(t) = S_V(t)^{\alpha_V} S_S(t)^{\alpha_S}$.

The supporting agents are the community's-built environment, including infrastructure and buildings that support the functionality of the investigated facilities, as shown in Figure 5-5 (a) and (b). These agents are part of the community physical component shown in Figure 5-5 (c). Buildings, including where the staff of the investigated facilities reside, are modeled as supporting agents to estimate the availability of staff in each facility. They are also used to locate staff, patients, and students, as well as the travel time for these individuals to the investigated facilities. Damage and functionality of these buildings are used to estimate the casualties after the earthquake and the expected number of the population that needs to be dislocated. Utilities that refer to the supporting infrastructure for hospitals and schools are modeled as supporting agents. The functionality of the infrastructure denotes the availability of the service provided by them at the investigated facilities. The supporting agents also include the suppliers for healthcare and education facilities. The functionality of these suppliers is utilized to estimate the full availability of the investigated facilities' supplies. The interdependency between these components is modeled using previous studies (Cimellaro, 2016), and their interaction with the investigated facilities is simulated in the functionality models for hospitals and schools as discussed previously. These interactions between community individuals (sub-agents), healthcare and education facilities (main agents), and the built environment (supporting agents) are depicted in Figure 5-5 (d).

In addition to the main and supporting agents discussed previously, all community individuals are modeled as sub-agents. These sub-agents are classified based on their relation to the main agents, as hospitals or schools' staff, patients, students, or/and student guardians. The spatial and temporal relationships among these sub-agents as well as between them and both the main and supporting agents are modeled. For instance, the relationship between school staff and schoolchildren is modeled where any family can be directly impacted by the shortage in healthcare or educational services if one of the family members works at one of these service providers. The indirect effect is also captured if a family member is a user of these facilities. Furthermore, these sub-agents are modeled to be impacted by the functionality of the supporting agents, including utilities and buildings. For example, if staff members of hospitals or schools have no housing or utilities, they will not be able to work since they must relocate. These sub-agents are also dynamically simulated such that during the investigated time frame the relation between these sub-agents and main and supporting agents can change. For example, staff can change their working facilities within the same system; patients can alter their most-probable hospitals; students can move to other schools. The agent type, attributes, and decision domain are summarized in Table 5-2.

Table 5-2: Components of the presented agent-based model.

Type	Agent type	Attributes	Decision making
Systems	Healthcare	Comprises hospitals and all their sub-components including buildings, infrastructure, suppliers, and staff.	Controls all medical services in the community. Aggregates all the decisions made by its components (agents).
	Education	Incorporates school districts, schools, and all their sub-components including infrastructure, suppliers, and staff.	Controls all the educational services in the community. Aggregates all the decisions made by its components (agents).
Main agents	Hospital	Provides medical services for all patient categories. Depends on staff, utilities, space, and supplies.	Makes all decisions related to the medical services by aggregating the decisions made by its sub-components.
	School	Provides educational services for students at a specific grade. Depends on staff, utilities, space, and supplies.	Makes all decisions related to the educational services by aggregating the decisions made by its sub-components.

	School district	Refers to the local administration of schools and depends on staff, utilities, space, and supplies.	Regulates manages and monitors the educational services for all the schools that belong to the district. Allocates resources for all the schools within the district.
Supporting Agents	Building	Refers to a housing unit in the community and can have different archetypes, structural system, damage probability, number of residents, etc.	Provides shelter for community individuals. Can collapse during the earthquake causing casualties.
	Water	Represents the municipal water network and includes different components such as water treatment plants, pumps, storage units, and distribution pipelines.	Responsible for operating and maintaining municipal water networks. Controls the repair and recovery process of the water network. Some hospitals and schools also operate their water tank.
	Power	Exemplifies the electricity network and includes different components such as stations, substations, distributing circuits, and distribution lines.	Responsible for operating and maintaining municipal power networks. Controls the repair and recovery process of the power network. Some hospitals and schools also operate their emergency power generators.
	Transportation	Describes the transportation network and includes roads and railway systems.	Responsible for operating and maintaining the transportation networks, including those used to reach hospitals and schools. Controls the repair and recovery process of the transportation network. Can provide detours to avoid damaged roads.
	Telecommunication	Refers to either cell phones, landlines, or other networks.	Responsible for operating and maintaining telecommunication networks. Controls the repair and recovery process of the telecommunication network. Some hospitals and schools also operate their internal network.
	Wastewater	Refers to the sewer network and includes collecting lines, pumps, and treatment plants.	Responsible for the collection of wastewaters. Controls the repair and recovery process of the wastewater network. Some hospitals and schools are provided with a backup system to collect and process wastewater.
	Natural gas	Refers to the fuel network and is used for heating and other purposes in hospitals and schools and its components include stations and distributing pipelines.	Responsible for the delivery of natural gas. Controls the repair and recovery process of the natural gas network. Some hospitals and schools can store natural gas to use in emergency cases.
	Medical supplies	Includes oxygen, surgical, and Rx suppliers for hospitals.	Controls the delivery of medical supplies to hospitals.
	Non-medical supplies	Comprises of Food, book, and technology suppliers for hospitals and schools.	Controls the delivery of basic supplies to hospitals and schools.
Sub-	Hospital staff	Denotes an individual employed by a hospital. Subcategorized	Can decide to work for another hospital, reduce the patient treatment time, transfer

		into physicians, nurses, supporting staff, and alternative staff.	the patients, work additional time to cover staff shortage, etc.
	School staff	Refers to an individual employed by a school or school district. Subcategorized into teachers, supporting staff, volunteers, and administrative staff.	Can decide to work for another school, control and monitor the student outcomes based on their experience, control the admission process (if they are in admin staff), work additional time to cover the staff shortage, teach different grades or topics if needed, etc.
	Patient	Implies any person receiving medical treatment in the hospital. Subcategorized into normal and earthquake-related patients.	Can decide to select the proper hospital (only if his/her case is not critical), accept or refuse the transfer, use an ambulance or private transportation to go to the hospital, pay for medical services if not insured, evaluate the provided services, etc.
	School student	Refers to schoolchild and can be in any grade between kindergarten and grade 12.	Can decide to go to school, select the school during the admission stage (school of choice application), use school transportation or private transportation, etc.
	Student guardian	Refers to a student's parent or, in some cases, another individual responsible for the student, and in this case, he/she must share the home with the student.	Can decide to send their schoolchildren to school, select the school during the admission stage (school of choice application), choose school transportation or private transportation for the student, monitor student outcomes, be responsible for providing homeschooling if needed, etc.
	Another individual	Any community individual who is not mentioned above.	Can decide to be a volunteer in healthcare or education facilities. Can share their home with individuals related to the hospitals or schools and impact their decisions.

5.4.3 Decision-making heuristics

Decisions in the presented study can be made by main agents, sub-agents, or supporting agents. The sub-agents decisions directly impact the agents they are related to and the system formed by these agents and indirectly influence other systems as well as shown in Table 5-2. The decisions are made based on current functionality states, available resources, and alternatives to achieve a set of objectives that ensure services' availability. To that end, a simulation model is developed to mimic the agent's different functions and choices before, during, and after the event and to resolve problems resulting from any disturbances in the modeled agents. These judgments are simulated using algorithms that are developed based on regulations, previously reported situations, and case studies as shown in Figure 5-6. The algorithms first locate the source of the functionality drop, Γ, which is defined as the least functional of all sub-components, as shown in Equation (5.14). Then multi-objective optimization is used to find the optimal solution or in some cases a combination of solutions, $X_\Gamma{*}$, among multiple $X_\Gamma{*} \in (x_{\Gamma,1},\ldots,x_{\Gamma,n})$, based on available resources, Ψ, to maximize the functionality, F, with minimal use of Ψ as follow:

$$\Gamma = min(ST, SP, U, SU, \{S_A, S_E\ or\ T_a, T_e, C_c, C_t, S_l, S_{pc}\}) \tag{5.14}$$

$$\max_{X_\Gamma{}^*} F\left(x_{\Gamma,i}, \min_{\Psi_\Gamma^*}(\Psi_{\Gamma,i})\right)\ \forall i \in (1, \ldots n) \tag{5.15}$$

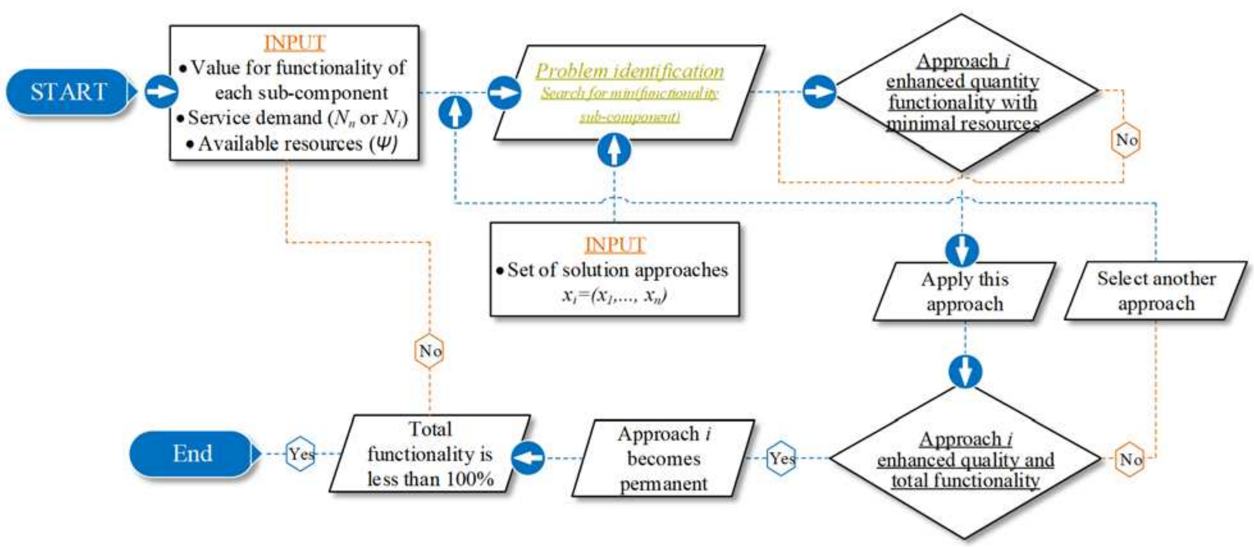

Figure 5-6: Decision-making algorithms.

The algorithm considers different approaches to increase the capacity and functionality of the healthcare system and reduce the overwhelming demand for them. These approaches have been applied and proven effective in enhancing the operation of healthcare systems after disasters. The decisions made by the sub-agents and supporting agents are embedded in these approaches. For the sub-agents, the algorithm accommodates the use of alternative staff, accepts staff transfer from other facilities, and assigns additional working hours for existing staff, which have been noted as viable options in enhancing functionality (Tariverdi et al., 2018). Other approaches can also be implemented, such as reducing patient treatment time and discharging patients with minor severities. However, hospitals' staff must cautiously apply these approaches as it can negatively affect the patients' outcomes and reduce the effectiveness of the patients' treatment. The selection between these approaches is subjected to resource availability. Different approaches can also be combined to maximize the hospital's quantity functionality while considering other sub-components, $ST = \max(U, SP, SU)$. Similarly, for the supporting agents, hospital backup systems might be used in the case of utility shortage and backup spaces for the case of space damage. Accelerating the restoration process and shortening the recovery time can also assist in increasing the availability of utilities and space, which is modeled by optimizing the distribution and transfer of repair resources among the investigated facilities. To overcome the shortage in supplies, hospitals can find alternative suppliers, transfer supplies between hospitals, and optimize the supplies usage. These approaches can be combined to increase the supplies to the same level as other sub-components $SU = \max(ST, U, SP)$. One of the main components that impact hospital quality functionality, in terms of patient waiting time, is the expected number of patients, which is calculated using a patient-driven model and is expected to increase after major disasters. To deal with the increase in patient numbers, N_n, at a, n, beyond the capacity, Bn, the healthcare system can adopt dynamic triage criteria (Benson et al., 1996), reduce patient treatment time (Arboleda et al., 2007), employ early discharge for non-critical cases, and transfer patients to other facilities. Another approach that can be implemented to reduce the patient waiting time is to share resources between the healthcare facilities including ambulances as well as available staffed bed data in each facility (Denver Health, 2005). The dynamic triage process is used to define the prioritization of patient care as a function of the injury types, severities, and resource availability, which can maximize patient survival and result in more efficient use of resources as it permits the triage process to evolve over days.

Unlike the healthcare facilities, which are mostly independently managed, public schools, which represent 90% of the U.S. schools, are centrally managed by the school district and are governed by school boards and superintendents. The administrative role played by these sectors is critical for the school system to adapt and enhance its performance. The presented algorithm for the school administration includes the decision made to a) find alternatives for the impacted sub-components, b) facilitate student admission and transfer, c) close and reopen schools after disasters, and d) monitor the quality of the service offered by each school. The role played by the sub-agents and supporting agents is modeled in each of these decisions. To find alternatives to close the gap in the school's staff, schools coordinate with their school district to assign additional teaching loads to existing teachers, allocate volunteers for the community to substitute the supporting staff, accept staff transfer from other schools, and appoint temporary and part-time staff. The total number of required staff, $ST_{i,req}$, at grade i, is calculated as $ST_{i,req} = \frac{N_i}{R_i}$, which is based on the number of students enrolled at this grade, N_i, and the classroom capacity, R_i. School administration can decide to increase the class's capacity and, in some cases, apply the double sessions system in which students are divided into groups that attend at different times of the day. However, these decisions also have a higher impact on the students' outcome, which is considered in the utilized algorithm. School administration can also provide alternatives for schools' utilities by providing backup systems or, in limited cases, run schools without some utilities. The school districts can arrange with each school to provide backup or alternative spaces as a replacement for the original non-functional buildings. To provide essential supplies at each school, the school districts can find alternative suppliers and arrange supplies transfer between schools. One of the main responsibilities of school districts is student admission and transfer and the arrangement of student transportation. Because of natural disasters, school transportation can be impacted; therefore, the school districts can arrange different transportation methods for students, including public and private transportations. Decisions made to reopen the damaged schools after major disasters require safe and functional school space and approval of different entities, including the school district, the building and fire departments, the office of public safety, and the community, etc. . The school district coordinates with each school to enhance the educational service quality provided by each facility by setting clear criteria to replace any less experienced and unqualified staff to enhance teacher and school quality, appoint more staff to increase the teacher assignment, and apply previously mentioned approaches to reduce the class size and increase the availability of technology in the classroom.

5.4.4 Environment

The environment component in the introduced agent-based model defines each component and sub-component location, including all individuals in the community. The environment is dynamic and changes with time to reflect disturbances and damages in all components of the community to allow updating of the travel time, patient distribution, schoolchildren admission, transfer of resources, and repair process after the disaster, etc.

5.5 Interdependency quantification framework

The introduced agent-based model is utilized to quantify the interdependency between healthcare and education on the system level and hospitals and schools on the agent level, which is an essential step towards understanding how social institutions interact. These interdependencies are fundamental for the resilience and sustainability analysis, including but not limited to population dislocation, and social vulnerability analysis. To estimate the functional interdependency between healthcare and education systems or agents, the Leontief-based model (Haimes & Jiang, 2001) is utilized, as shown in Equation (5.16).

$$\mathcal{F}_k = \sum_j \eta_{kj}\mathcal{F}_j + H_k, \forall k = 1,2, \dots, n \tag{5.16}$$

Where, $\mathcal{F}$ is the total functionality, η is the degree of interdependency, H is the inoperability risk of a system component, k.

5.6 Community social services stability (*SSSI*) framework

Providing appropriate healthcare and educational services is critical for the community. In this study, the social services stability index (*SSSI*) is introduced as another measure of community strength after disasters, and it measures the accessibility of community individuals to the main public services with a focus on healthcare and education as pivotal services after disasters. The *SSSI* is constructed as a composite indicator in which the wide-spread additive aggregation method, called the summation of weighted and normalized indicators method (OECD & JRC, 2015), is utilized as follows:

$$SSSI(t) = \sum_{i=1}^{N} w_i(t)\left(\frac{\mathcal{F}_i(t)}{\mathcal{F}_{i,ult}}\right) \forall t = t_0, \dots, TR \tag{5.17}$$

Where, w_i and $\mathcal{F}_i$ are the weighting factor and functionality for service i, respectively, at time t ranged from the disaster occurrence time, t_0, to the full recovery time, TR.

Each resident's need for these services is different. For instance, the number of hospital visits for seniors is significantly higher than any other age group (Hsieh et al., 2019; Samaras et al., 2010), and residents that do not have schoolchildren are not concerned with education availability. Therefore, the weighting factor w_i spatially simulates these varying needs for the healthcare system by incorporating the expected average number of hospital visits for each family. On the other hand, the number of schoolchildren per family is used to predict the w_i for this family's educational service. w_i is also temporally modeled to mimic the community changing demand overtime after the disaster. A higher value of w_i is assigned to the healthcare system immediately after the disaster and until the hospitals' demand returns to normalcy. In contrast, a minimal value of w_i is given to the education system during the school recess.

5.7 Summary

In this chapter, a comprehensive framework to estimate the near-optimal recovery trajectories for hospitals and *K-12* schools, the main providers for the healthcare and educational services were introduced. A semi-Markov chain model, coupled with the dynamic optimization was utilized to calculate the repair process for healthcare and education facilities that attains the pre-defined objectives of these systems of achieving the maximum quantity of the offered healthcare and educational services for the whole community, taking into account repair crew specialties and the possibility that repair crews from neighboring communities are available. The resilience of healthcare and educational services were then aggregated from the area underneath the total functionality curve for each facility.

The chapter also introduced a new agent-based model for the healthcare and education systems. The model comprised two main agents (representing hospitals and schools all their sub-components) as well as supporting agents (community's buildings and infrastructure that support the functionality of the main agents) and sub-agents (representing individuals in the community). Each of the model agents was an autonomous decision-making entity that had a set of characteristics and rules that allowed them to interact, learn, and adapt. This agent-based model can be used to investigate interdependency between the healthcare and education facilities, the interdependent functionality of these facilities, and communities' social stability.

The interdependency between the healthcare and education facilities can be calculated using the Leontief-based model. These interdependencies were then can be aggregated to calculate the total interaction between healthcare and educational services. To measure the stability level of social services for the community's residents as influenced by the availability of healthcare and educational services, a new notion of a so-called social services stability index (*SSSI*) was introduced. Calculations of the *SSSI* were considering the need for each individual in the community to each of the investigated services.

Chapter 6. IMPACT OF SEVERE EARTHQUAKES ON HEALTHCARE AND EDUCATION SYSTEMS

6.1 Overview

Hospitals and schools are vital for maintaining and enhancing communities' well-being. They are considered a hub for community services especially after national disasters such as earthquakes where physical and mental wellness are expected to be significantly affected. Even though functionality and recovery of hospitals and schools are complex processes by nature, restoring functionality and ensuring a rapid recovery to these facilities are critical for community resilience and stability after earthquake disasters. Due to their role in community stability and the fact that both facilities provide services to a wide spectrum of community individuals, the functionality of hospitals and schools are expected to be highly correlated. Furthermore, different mitigation strategies and decisions can be applied by healthcare and education facilities to enhance their total functionality after disasters. These strategies and decisions can enhance the availability of various functionality components including staff, utilities, space, and supplies to ensure the continuation of services provided by these facilities.

In this chapter, models and frameworks developed in previous chapters are tested on a mid-size virtual community. First, the characteristics of the healthcare and education facilities as well as their supporting lifelines are discussed. The community is then subjected to an earthquake that damaged hospitals and schools' structural, non-structural, and contents, caused casualties to community individuals, destroyed residential buildings, and disturbed the community's main utilities. The initial drop in the functionality, as well as the recovery of hospitals and schools, are calculated. Patient distribution and student enrollment are quantified. Interaction between hospitals and the role played by the school district in managing the public *K-12* schools are simulated. All these components are then used to estimate the resilience of healthcare and educational services. Sensitivity and uncertainty analysis are conducted using the developed frameworks to identify the important parameters influencing frameworks' outputs and to estimate the uncertainty associated with the estimated resilience. The agent-based model is utilized to develop an estimate for the level of interdependency between each healthcare and education facility as well as the interaction between healthcare and educational services in the investigated community. The results are then employed to calculate a social services stability index, which can be used to quantify the impact of healthcare and educational services on community resilience and social stability. Finally, the effect of different mitigation strategies applied by hospitals and schools on healthcare and education system resilience as well as the community's social services stability is quantified.

6.2 Investigated community characteristics

A virtual community, shown in Figure 6-1, is built to represent a typical middle-sized community in the mid-America region (Ellingwood et al., 2016). Three hospitals with 70, 65, and 20 total staffed beds with 315, 260, and 125 staff, respectively, are considered as the healthcare service providers (Hassan & Mahmoud, 2020a). There are eight schools distributed as four primary, two middle, and two high schools as the educational service providers. The total number of students is 925, 871, and 1155 with the corresponding number of staff of 97, 91, and 161 for the primary, middle, and high school, respectively (Hassan et al., 2020).

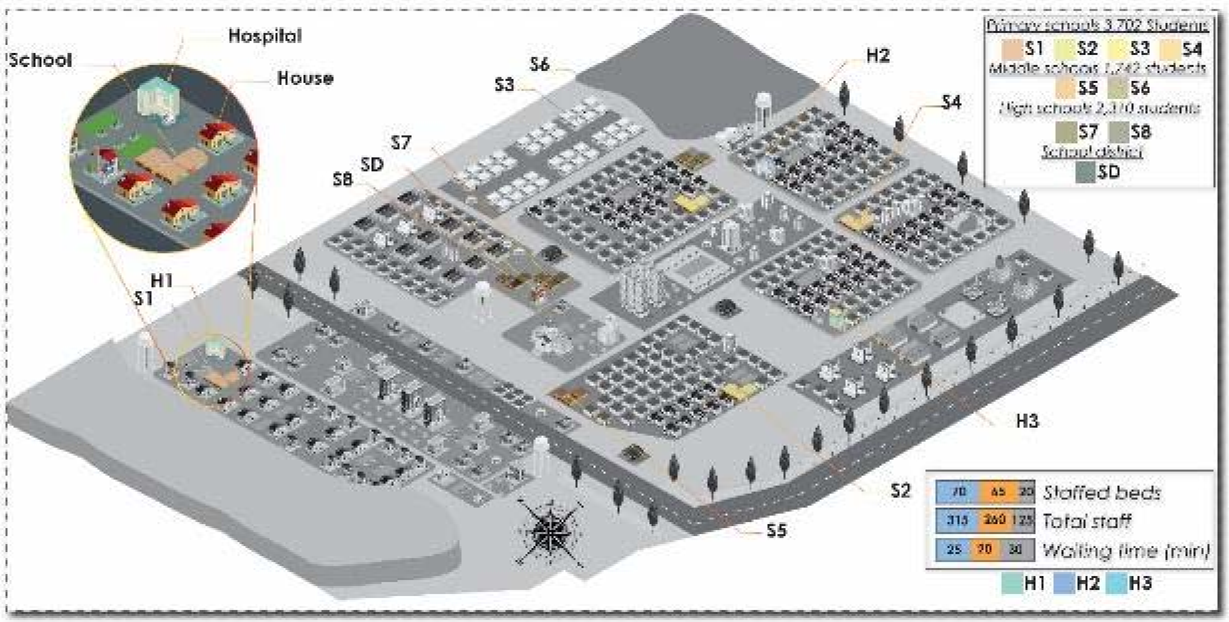

Figure 6-1: Healthcare and education facilities distribution in the investigated virtual community, which is a mid-size community in the Mid-America region with 50,000 total population served by three hospitals and eight schools. Hospital capacity and school enrollment are listed in the figure.

6.2.1 Healthcare system data

The total area, building type, height, and year built of the hospitals are shown in Table 6-1. The table also shows hospitals' rating, brand name, ambulance services, average waiting time, and building components values before earthquake occurrence. Hospitals' total areas are assumed based on the average area required for each staffed bed (French Red Cross, 2006). Different rating values are assumed for each facility based on patient satisfaction. Only hospital *A* can provide both air and ground ambulance. Unlike hospitals *A* and *B*, hospital *C* does not offer any ambulance services; however, it still can use the ambulance services of hospital *B* or patients' private transportation. The monetary values of the building components are classified into: a) structural, b) non-structural drift sensitive, c) non-structural acceleration sensitive, and d) content; and are estimated based on HAZUS MH2.1 (2015).

Table 6-1: Centerville hospitals' building general properties.

Hospital	A_t (m^2)	Building type	Height (stories)	Built year	Rating	Brand	Ambulance	Waiting time	Building components values (10^6 \$)			
									Structural	Non-structural (drift sensitive)	Non-structural (accel. sensitive)	Content
A	5,950	Steel braced frame	4	1940	5.0/5.0	I	Ground + Air	25 min	0.46	1.39	1.85	5.56
B	4,675	Concrete shear wall	3	2000	4.3/5.0	II	Ground	20 min	0.32	0.95	1.26	3.79
C	1,700	Steel light frame	1	1980	3.2/5.0	I	NA	30 min	0.12	0.35	0.46	1.38

The previously mentioned buildings' properties are then used to estimate parameters for structural and non-structural components damage fragilities based on HAZUS MH 2.1 (2015). The seismic fragilities of the hospitals in Centerville are shown in Figure 6-2 for structural components, non-structural drift-sensitive components, and non-structural acceleration-sensitive components. The lognormal median (μ) and standard deviation (σ) of the fragilities are also shown in Table 6-2, which are used later to calculate damage and losses for each component as a function of earthquake intensity.

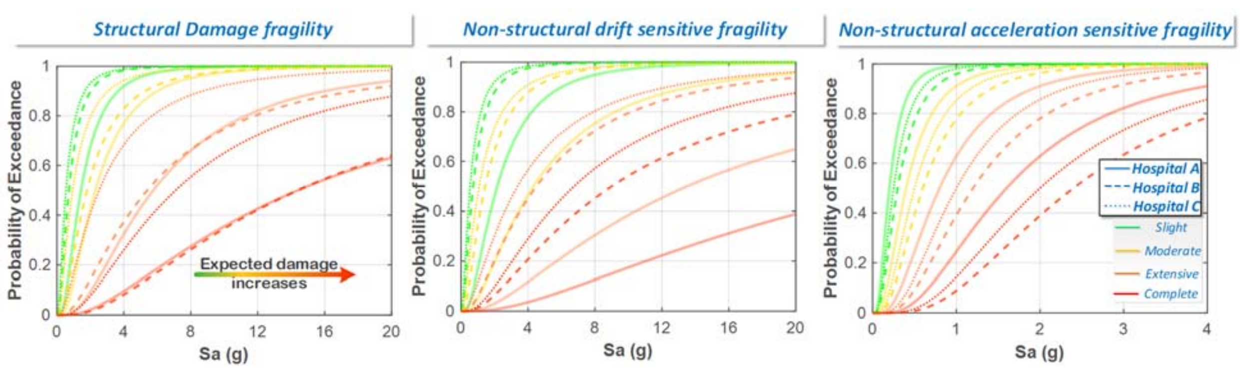

Figure 6-2: Hospital buildings damage fragility curves (HAZUS-MH 2.1, 2015).

Table 6-2: Hospital buildings damage fragility curves parameters (HAZUS-MH 2.1, 2015).

Hospital	Structural damage Spectral displacement (in)							
	Slight		Moderate		Extensive		complete	
	μ	σ	μ	σ	μ	σ	μ	σ
A	1.44	0.73	2.3	0.75	5.76	0.8	14.4	0.98
B	0.72	0.81	1.8	0.84	5.4	0.93	14.4	0.92
C	0.54	0.88	0.94	0.92	2.52	0.97	7.09	0.89
	Non-structural drift-sensitive Spectral displacement (in)							
A	2.16	0.8	4.32	0.9	13.5	1.02	27.0	1.06
B	0.72	0.87	1.44	0.88	4.5	0.97	9.0	0.99
C	0.54	0.93	1.08	0.98	3.38	1.01	6.75	0.94
	Non-structural accel-sensitive Spectral acceleration (g)							
A	0.2	0.65	0.4	0.68	0.8	0.68	1.6	0.68
B	0.3	0.69	0.6	0.67	1.2	0.66	2.4	0.65
C	0.25	0.67	0.5	0.66	1.00	0.65	2.0	0.65

Hospital beds and total staff number is assumed based on the national average published by Gamble (Gamble, 2012). These staffed beds are classified as emergency or inpatient beds as shown in Table 6-3. The table also shows the number of each staff category, backup systems, and additional space availabilities as well as the percentage of supplies availability before the earthquake. It should be noted that hospital *A* has more backup systems, added space, and supplies compared with hospitals *B* and *C*.

Table 6-3: Staff, space, and supplies availability for the Centerville hospital cluster before the earthquake.

Hospital	Beds		Staff number				Backup systems (%)						Add. space	Supplies
	E[a]	I[b]	R1	R2	R3	R4	R9	R11	R14	R16	R18	R20	R24 (bed)	R25~R30%
A	40	30	80	120	25	90	100	100	100	100	100	100	12	80
B	35	30	70	110	15	65	100	100	100	0	100	100	5	40
C	12	8	30	50	5	40	100	100	0	0	0	100	0	50

[a] Emergency beds, [b] Inpatient beds

Table 6-4 shows the input parameters for the transition probability matrix (*a* and *b*) for the three investigated hospitals, the available repair crews for the healthcare system, and interaction values. The interaction values represent the effect of the functionality of other lifelines on the repair progress of the healthcare facilities, which is assumed to be similar to the interdependency values listed in Cimellaro (2016).

Table 6-4: Input parameters for the recovery model.

<table>
<tr><th rowspan="2">Hospital</th><th colspan="2">Geo and Structural data*</th><th colspan="6">Repair crews (normal/with aid)*</th><th colspan="6">Interaction values (Cimellaro, 2016)</th></tr>
<tr><th>a</th><th>b</th><th>X1</th><th>X2</th><th>X3</th><th>X4</th><th>X5</th><th>X6</th><th>Power</th><th>Trans.</th><th>Telecom.</th><th>Water</th><th>W. Water</th><th>Fuel</th></tr>
<tr><td>A</td><td>0.81</td><td>0.17</td><td rowspan="3">5/8</td><td rowspan="3">2/5</td><td rowspan="3">2/3</td><td rowspan="3">1/3</td><td rowspan="3">3/4</td><td rowspan="3">2/2</td><td rowspan="3">0.6</td><td rowspan="3">0.6</td><td rowspan="3">0.3</td><td rowspan="3">0.6</td><td rowspan="3">0.6</td><td rowspan="3">0.3</td></tr>
<tr><td>B</td><td>0.75</td><td>0.15</td></tr>
<tr><td>C</td><td>0.85</td><td>0.20</td></tr>
</table>

* assumed data

6.2.2 K-12 Educational system data

The Centerville school system consists of three primary schools, two middle schools, and two high schools, as well as a school district administrative office, which is attached to the high school building. To accommodate the number of students from *K9* to *K12*, another high school is added to Centerville. Table 6-5 summarizes the characteristics of Centerville's schools, including grade, total area, building type, height, year of construction, and valuation of structural, nonstructural, and contents prior to the earthquake. The values in Table 6-5 are obtained from a previous study (Ellingwood et al., 2016), except for the added high school and building type for all schools, which are assumed in this study. The school area is used to calculate the maximum number of repair crews allowed in the school building at any time based on (Almufti & Willford, 2013) and, if the school is used as an emergency shelter, the capacity of that shelter according to FEMA requirements (Federal Emergency Management Agency, 2015).

Table 6-5: Centerville schools and their general building properties.

School	Grade	Type	A_t (m^2)	Building type	Height (stories)	Built year	Building components values (10^6 \$)			
							Structural	Non-structural (drift sensitive)	Non-structural (accel. sensitive)	Content
P1~P4	Elementary	Public	9,290	Reinforced Masonry Bearing Walls	1	1980	1.80	4.64	3.08	9.52
M1~M2	Middle	Public	9,290	Concrete Moment Frame	3	1990	1.71	4.39	2.92	9.02
H1~H2	High	Public	9,290	Steel Light Frame	3	1990	1.71	4.39	2.92	9.02

The seismic fragilities of the school buildings in Centerville are summarized in Figure 6-3 including seismic fragility curves for structural components, non-structural drift-sensitive components, and non-structural acceleration-sensitive components. The lognormal median (μ) and standard deviation (σ) of the fragilities are also shown in Table 6-6, which are used later to calculate damage and losses for each component as a function of earthquake intensity.

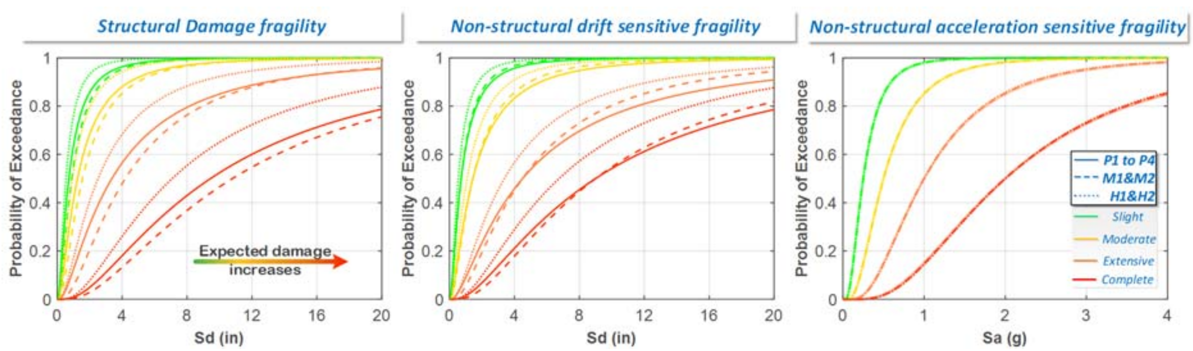

Figure 6-3: School buildings damage fragility curves (HAZUS-MH 2.1, 2015).

Table 6-6: School buildings damage fragility curves parameters (HAZUS-MH 2.1, 2015).

Hospital	Structural damage Spectral displacement (in)							
	Slight		Moderate		Extensive		complete	
	μ	σ	μ	σ	μ	σ	μ	σ
P1~P4	0.72	0.96	1.25	0.99	3.37	1.05	9.45	0.94
M1~M2	0.9	0.89	1.56	0.90	4.2	0.90	10.8	0.89
H1~H2	0.54	0.88	0.94	0.92	2.52	0.97	7.09	0.89
	Non-structural drift-sensitive Spectral displacement (in)							
P1~P4	0.72	1.00	1.44	1.06	4.5	1.12	9.0	1.01
M1~M2	0.72	0.93	1.44	0.96	4.5	0.94	9.0	0.88
H1~H2	0.54	0.93	1.08	0.98	3.38	1.01	6.75	0.94
	Non-structural accel-sensitive Spectral acceleration (g)							
P1~P4	0.25	0.68	0.5	0.67	1.0	0.67	2.0	0.67
M1~M2	0.25	0.67	0.5	0.66	1.0	0.66	2.0	0.66
H1~H2	0.25	0.67	0.5	0.66	1.00	0.65	2.0	0.65

Table 6-7 shows the total number of classrooms for each grade, the number of students per grade, staff, and the backup utilities and supplies availability immediately prior to the earthquake occurrence. The National Center for Education Statistics (NCES) (2017a), which provides an average total number of student enrollment per grade for public schools in the U.S., is utilized to calculate the number of school students in Centerville as a function of the total population. Based on NCES for 2017, the total number of school-age students is 7,754, which are distributed to the primary (pre-K to grade 5), middle (grades 6 – 8), and high (grades 9 – 12) schools as 3,702, 1,742, and 2,310, respectively. The elementary schools are assumed to have self-contained classrooms, while both middle and high schools utilize instruction by topic (math, history, etc.), which impacts the number of students in each class. The resulting average class sizes, per the National Center for Education Statistics (2017b), are 22, 26, and 24 for the elementary, middle, and high school, respectively. The number of staff and administration are also estimated based on U.S. national averages (Glander, 2017). The experience of instructional staff is determined by years of teaching experience and the highest degree earned (National Center for Education Statistics, 2019).

Table 6-7: Staff, space, and supplies availability for the Centerville school system immediately prior to the earthquake.

school	Grades	# classroom per grade (National Center for Education Statistics, 2017b)	# student per class (National Center for Education Statistics, 2017b)	# staff per school (Glander, 2017)			Backup systems (%)					Supplies
				R1	R2	R4	R8	R10	R13	R16	R18	R22~R25%
P1~P4	P-K~5	6	22	46	21	30	100	50	100	0	100	100
M1~M2	6~8	11	26	43	20	28	100	50	100	0	100	100
H1~H2	9~12	12	24	97	27	37	100	50	100	0	100	100

Based on the school's capacity and the expected travel time for students, the school district defines each school's zone as shown in Figure 6-4.

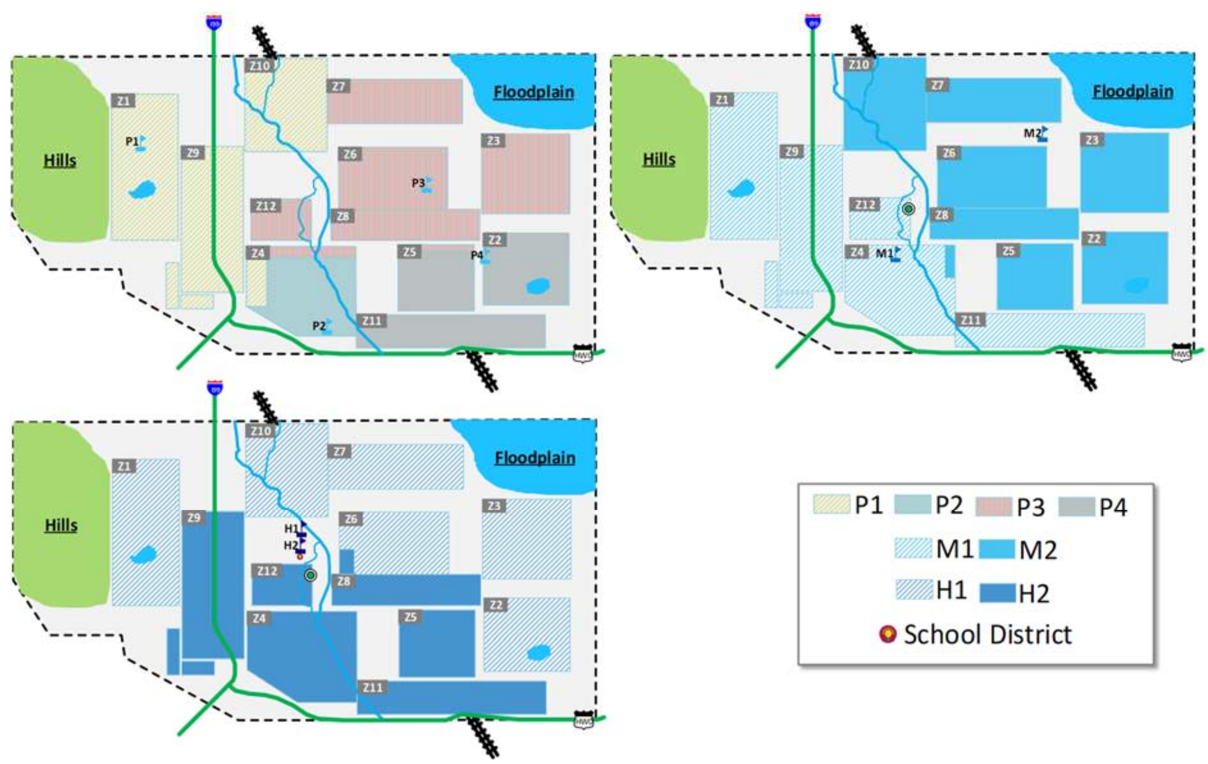

Figure 6-4: School zones before the earthquake occurrence.

Parameters for the school system recovery model are shown in Table 6-8 including the geographical and structural parameters (a and b in Equation (5.7)), the total number of available repair crews for the school system, and the interaction values between schools and their supporting lifelines. Different specialties of repair crews are considered including structural, *X1*, plumbing, and HVAC systems, *X2*, interior partitions, ceiling tiles, and components of the exterior building envelope, *X3*, mechanical equipment, *X4*, electrical systems, *X5*, and elevators, *X6*. A building repair sequence starts with the repair of the structural components to guarantee the safety of the building, followed by corridors and stairs to ensure accessibility for the subsequent repair tasks. All other repair tasks can then be executed simultaneously. The total number of available repair crews are assumed to be changing with time since the impacted community may receive additional aid from the surrounding communities. It is assumed that each repair crew consists of 10 workers.

Table 6-8: Input parameters for the recovery model.

School	Geo and Structural data*		Repair crews (normal/with aid)*						Interaction values (Cimellaro, 2016)					
	a	*b*	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	Power	Trans.	Telecom.	Water	W. Water	Fuel
P1	0.80	0.15	3/5	0/1	1/1	1/1	1/2	1/1	0.3	0.3	0.0	0.6	0.0	0.3
P2	0.83	0.13												
P3	0.89	0.17												
P4	0.82	0.14												
M1	0.88	0.18												
M2	0.84	0.17												
H1	0.81	0.15												
H2	0.85	0.16												

* assumed data

Hospitals and schools' relevant data are obtained to construct the agent-based model as summarized in Table 5-2 for the investigated community. These data include the functionality of different sub-components, available mitigation strategies, and resources at each facility (Ellingwood et al., 2016; Hassan et al., 2020; Hassan & Mahmoud, 2020a). Hospitals and school's total functionalities are modeled as discussed before in Chapters 3 and 4. Patients are distributed to the healthcare facilities during normal operation using decision-making heuristics as part of the introduced agent-based model as outlined in Figure 3-3. Interaction among the hospitals is outlined in Figure 3-4 and discussed in detail in Chapter 3. These frameworks are utilized to distribute patients and simulate the transfer of resources between healthcare facilities based on the community's demographic data (Ellingwood et al., 2016). Furthermore, schools' enrollment shown in Figure 4-3 and Chapter 4 is defined using data related to the school zones, number, and location of each school's staff and schoolchildren in the investigated community (Ellingwood et al., 2016). Optimal recovery of hospitals and schools and the community's infrastructure after an earthquake scenario are modeled using stochastic analysis coupled with dynamic optimization as discussed in Chapter 5.

6.3 Damage and recovery of supporting infrastructure

6.3.1 Healthcare system

An earthquake scenario with an M_w of 7.9 and an epicentral distance of approximately 10 km from the Southwest of Centerville is assumed. The earthquake occurrence time is selected to be 5:00 pm. Immediately after the earthquake, buildings, and infrastructure, including hospitals, are expected to suffer damage, causing several casualties and fatalities, and reducing infrastructures' functionality. IN-CORE software (Ellingwood et al., 2016) is used to generate a spatial distribution of earthquake intensity, described by *PGA* (g). HAZUS MH 2.1 (2015) is utilized to calculate the damage state for Centerville's buildings, transportation, power, water, and fuel networks as shown in Figure 6-5. The resulting mean structural damage ranges from 37% to 54% of the total building stock, which is a narrow range since the total area of Centerville is relatively small. Higher damage can be observed for the road, power, water, and fuel networks at the west side of Centerville compared with the east side. The earthquake hazard level (*PGA*) at each hospital is used to calculate losses for hospital components including structural, non-structural, and content as well as the direct social losses as shown in Figure 6-5 (b). Hospital *A* shows more direct economic and social losses compared with other healthcare facilities. These direct losses are calculated based on the methodology outlined in HAZUS MH 2.1 (2015).

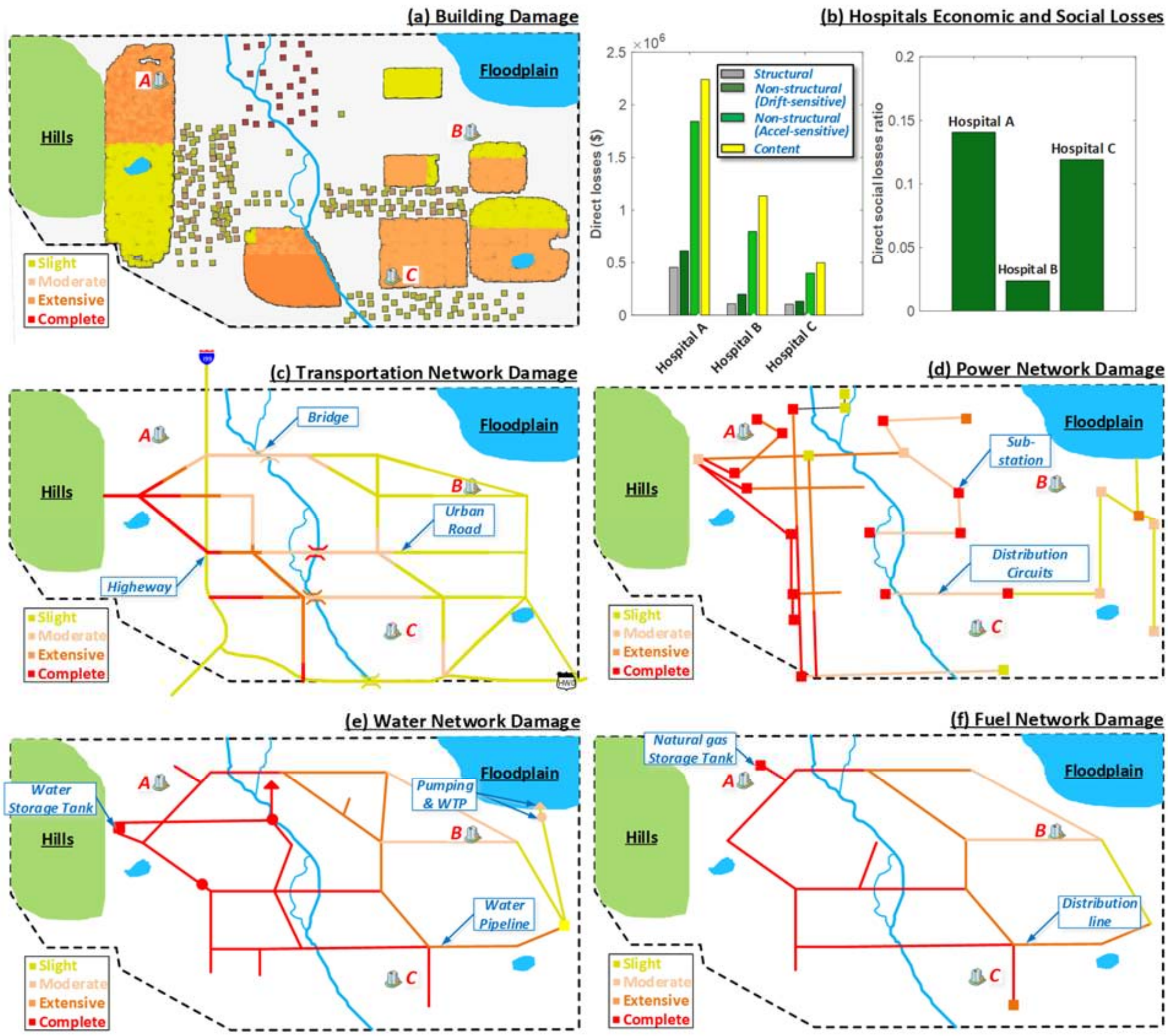

Figure 6-5: Buildings, hospitals, and hospitals' supporting infrastructure damage.

The HAZUS MH 2.1 (2015) earthquake casualty model, which uses structural damage to estimate earthquake-related injuries is utilized in this study. The earthquake injuries are classified into four severities; however, only severity 2 and severity 3 are considered as possible hospital patients based on the HAZUS model. This is because patients with severity 2 require some medical care and patients with severity 3 require immediate medical care. Severity 1 and 4 imply minor injuries and death, respectively, for which hospitalization is not required. Based on the dynamic triage criteria, earthquake-related patients with severity level 3 and regular patients that need immediate medical care have a higher priority followed by patients with severity 3 and other regular patients. Figure 6-6 shows the location for each severity in Centerville after the earthquake scenario. It can be observed that the total number of causalities is minimal and mostly fall under severity 1, which is in agreement with historical earthquake casualty rates in the U.S. in regions with code-conforming structures (Algermissen et al., 1972). This is to say that no earthquake-related patients will require hospitalization. However, routine patients still require routine medical care.

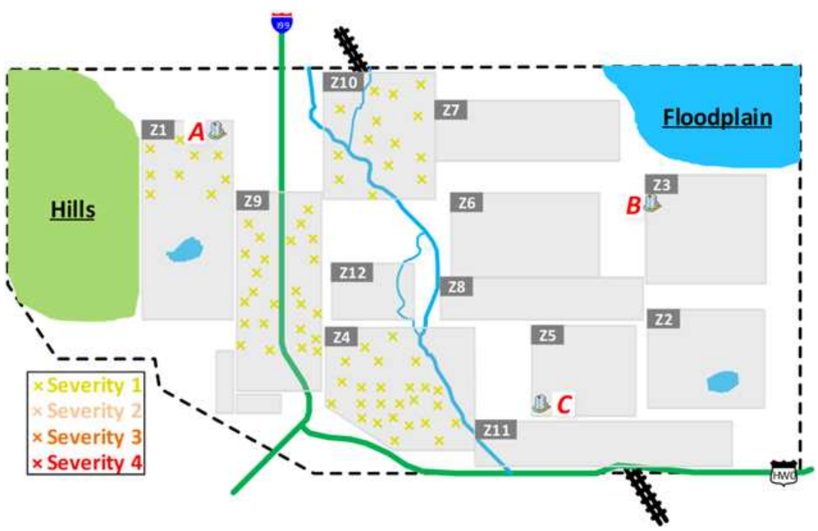

Figure 6-6: Location of different casualty severities.

Service restoration for the supporting lifelines for each healthcare facility can be estimated using the previously calculated damage and the number of allocated repair resources for each lifeline. However, the allocation of these resources requires extensive socio-economic data, which is out of the scope of this study. Therefore, the restoration curves from ATC-13 (1985) are utilized to evaluate the recovery of the hospitals' supporting lifelines using the initial damage state whereas the introduced frameworks will be used to assess the recovery of the healthcare facilities. Figure 6-7 displays the recovery of functionality after the earthquake for the supporting infrastructures of each hospital in Centerville. To estimate the travel time from each zone to each hospital, T_{tvl}, a simple graph consisting of nodes and links is devised and the Dijkstra's shortest path algorithm is utilized (Dijkstra, 1959) to calculate travel time. Each zone and hospital are represented by a single node while links are utilized for streets and bridges. The travel time between each node is obtained by multiplying the length of each link by the average driving speed on this link.

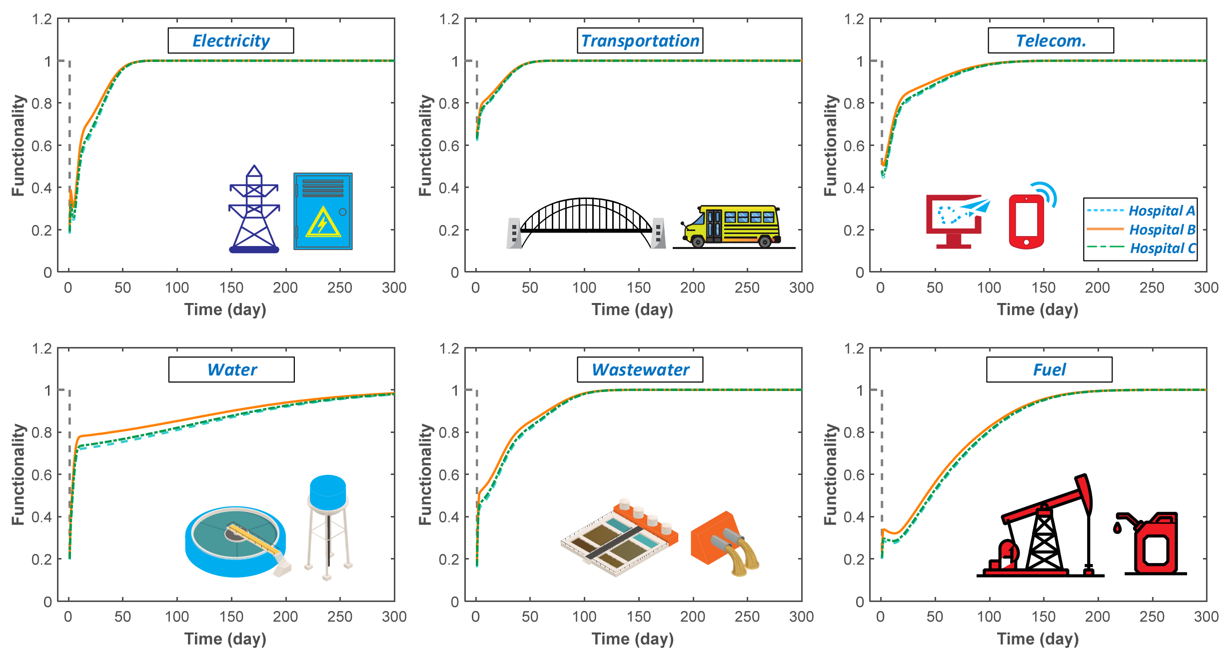

Figure 6-7: Recovery for hospitals' supporting infrastructures.

6.3.2 *Educational system*

For the educational system, the same earthquake scenario is utilized; however, the difference is the earthquake occurrence times. Two different earthquake occurrence times are considered. In the first scenario, the earthquake is assumed to occur during the middle of the school year, while in the second, the earthquake occurs during the summer break. Similar to the healthcare system, in both earthquake scenarios, the spatial distribution of the building damage is estimated from the earthquake intensity generated by IN-CORE (Ellingwood et al., 2016) and damage states in HAZUS MH 2.1 (2015), which is generated based on buildings characteristics shown in Table 6-5 including the building age and design code generation. Given the spatial distribution of the seismic demand in the community (Ellingwood et al., 2016), damage to buildings, transportation, power, telecommunication, water, wastewater, fuel, and education systems are calculated. Economic and social losses at the different schools are estimated from FEMA P-58 (2012), based on damage to the building components, expected occupancy at the time of the earthquake, and the building component values listed in Table 6-5. Figure 6-8 shows the immediate impact of the earthquake on Centerville buildings, schools, and main supporting infrastructure systems. Damage to infrastructure located on the west side of Centerville, which is closer to the epicenter and experienced higher earthquake intensities, is higher. The fact that most of the expected building damage is either slight or moderate reduces the population dislocation and the demand on the community shelters (Levine et al., 2007).

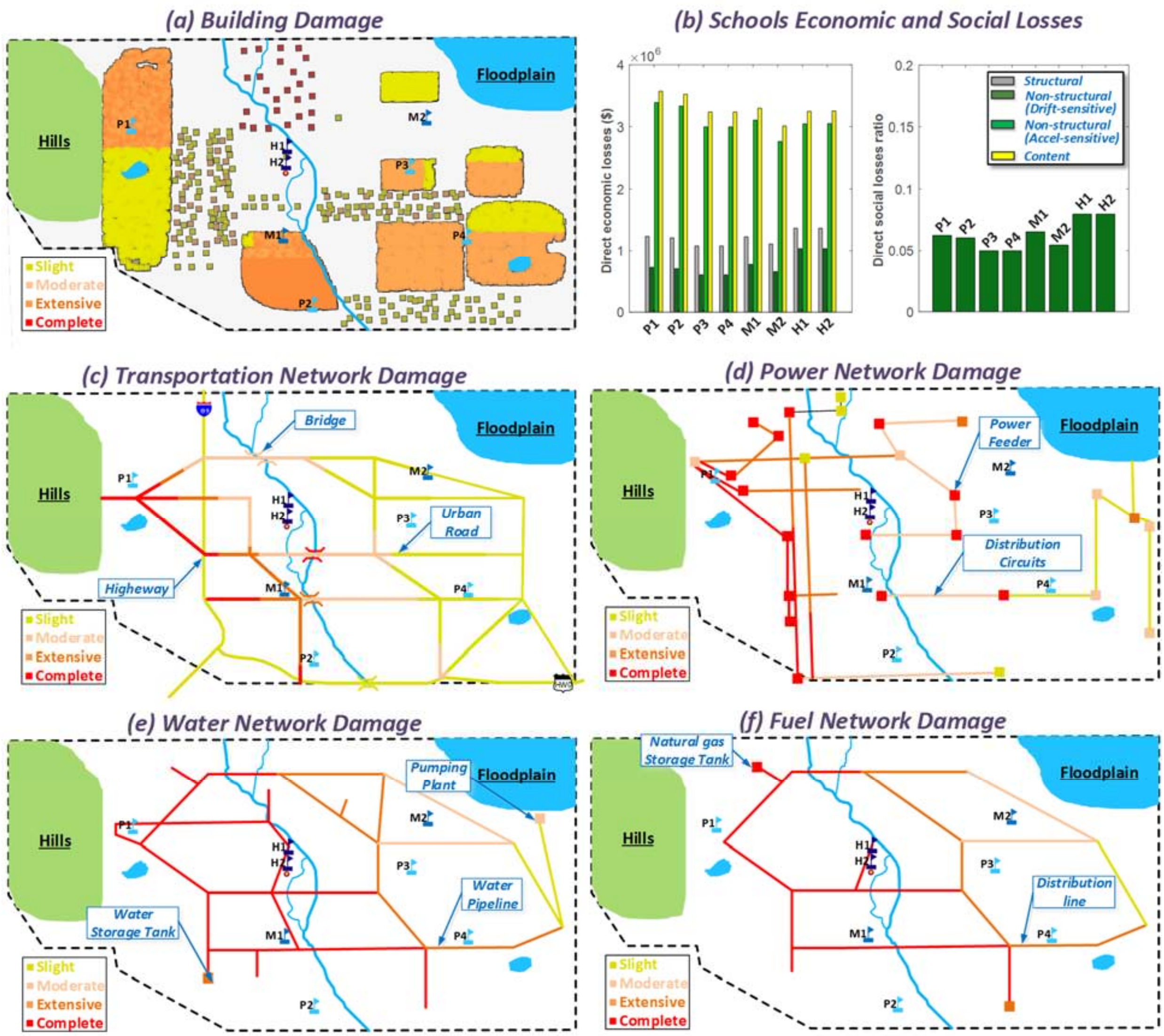

Figure 6-8: Buildings, schools, and schools supporting infrastructure damage.

Damages to school buildings and supporting infrastructure are utilized to estimate the recovery of educational services based on historical data and restoration curves from ATC-13 (1985). Restoration of electricity, transportation, telecommunication, water, wastewater, and fuel supplies at each school are shown in Figure 6-9. These curves subsequently are utilized to calculate the functionality and recovery of the school buildings using the methods described in the previous section.

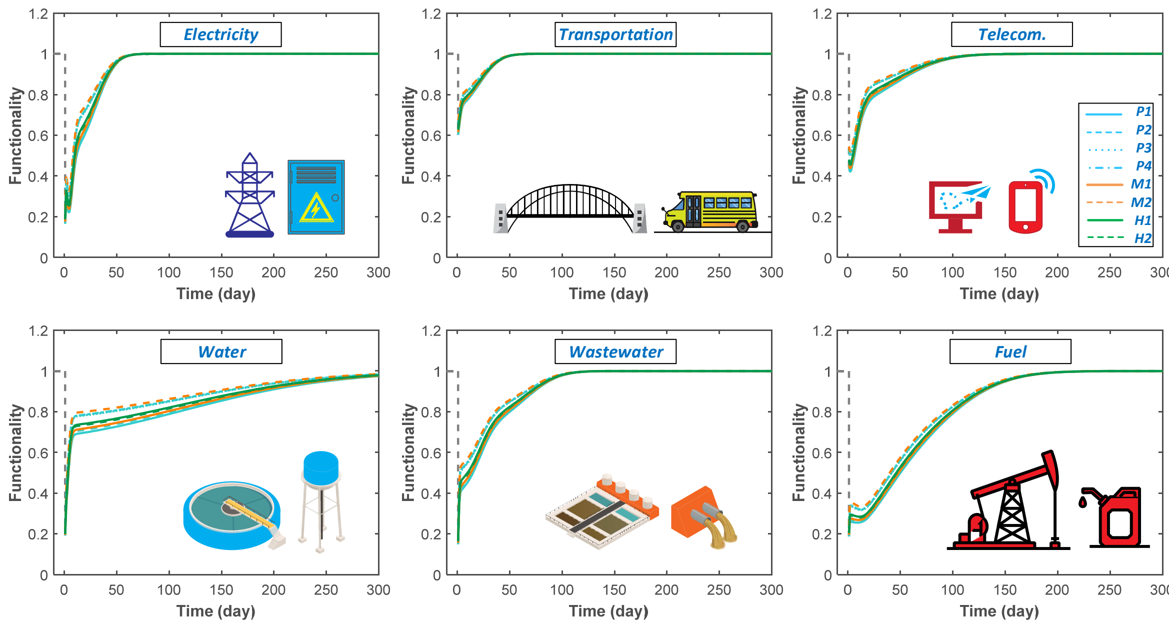

Figure 6-9: Recovery for schools' supporting infrastructure.

6.4 Recovery of the healthcare system

In this section, functionality restoration of the hospital cluster is calculated using the introduced frameworks. An investigation into the effect of interaction and resource optimization on the recovery of the different hospitals' components is carried out. Two different scenarios are tested to highlight the effectiveness of the presented frameworks in capturing the impact of various decisions on hospital cluster functionality. The first scenario considers the interaction between all hospitals while optimizing for the maximum number of available staffed beds at all times. Figure 6-10 shows the change of different functionality measures for the healthcare facilities in Centerville with time after the induced earthquake. Quantity functionality is extremely impacted by the reduction in the supporting lifelines' functionality and the damage sustained by the backup systems. However, it rapidly increases as driven by repairs and restorations of most of the supporting lifelines. Quality functionality, which depends on patient satisfaction, is shown to reduce after earthquake occurrence due to the change in patients' demand. This change in demand is highlighted by showing the patient distribution for each zone and the change in the selection over the time after the earthquake. Zones 4, 8, 10, 11, and 12 alternate between hospitals *A* and *B*. Hospital *C* is not the most selected by any zones; however, it comes as the second choice for residents of zones 2, 5, 8, and 12 immediately after the earthquake. Total healthcare functionality, on the other hand, is mainly impacted by the quantity functionality as the weight placed on the quality functionality reduces during the assessment and planning stage and the beginning of the recovery stage.

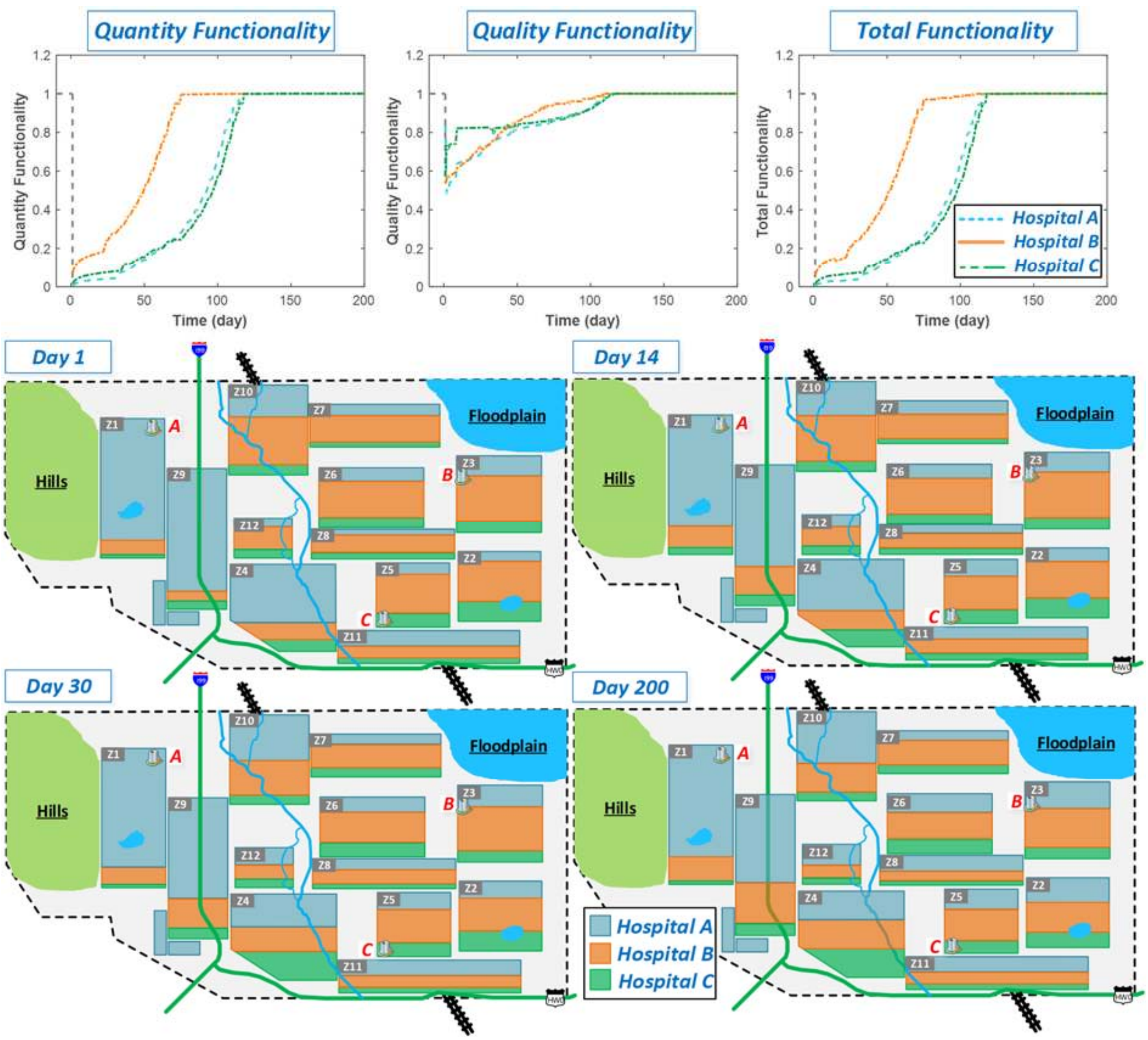

Figure 6-10: Centerville Hospitals' functionalities and patient distribution on hospitals.

Unlike the first scenario, the second scenario neglects the interaction between healthcare facilities, and instead of optimizing the distribution of the repair crews, the maximum repair resources are allocated for hospital *C*. While assigning more repair resources to hospital *C* increases the building functionality, it reduces the functionality for hospital *A* and *B* and eventually negatively impacts the healthcare service in Centerville as shown in Figure 6-11. The other decision that impacts the healthcare service is preventing the transfer of patients and resources between hospitals, which affects the number of patients at each facility as shown in Figure 6-11. By combining these two injudicious decisions, the full recovery of the healthcare service in Centerville can be delayed by an additional 30 days.

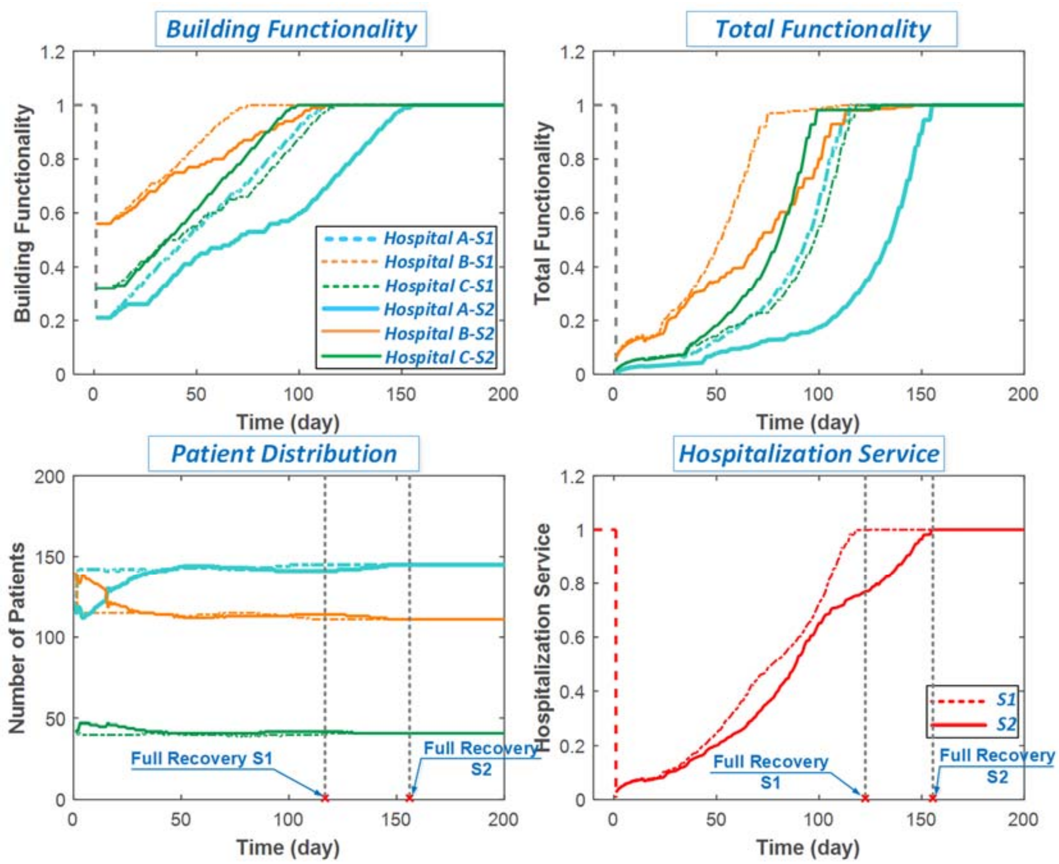

Figure 6-11: Comparison between the optimized and non-optimized recovery scenarios.

6.5 Recovery of the educational system

Functionality, recovery, and resilience of the *K-12* school system in Centerville following the two earthquake scenarios are estimated using the methods described in Chapter 4. The influence of school administrators on school reopening, cooperative interactions between schools during the recovery period, and resource optimization are investigated, as well as the different roles played by schools during community recovery such as providing community shelter.

In the first earthquake scenario when school is in session, students are directly impacted by any school closure. The semi-Markov chain model, coupled with the dynamic optimization, estimates the near-optimal repair progress of the school system that attains the pre-defined objectives of the education system of achieving the maximum quantity of the offered educational service for the whole community, considering repair crew specialties and the possibility that repair crews from neighboring communities are available. Figure 6-12 shows the quantity and quality functionalities as well as the total functionality of each Centerville school. Substantial damage to the working space within the school system and supporting lifelines immediately after the earthquake leads to the closure of all schools immediately following the earthquake. A week after the earthquake, the state of recovery of most of the supporting lifelines, coupled with the performance of operational backup utility systems and backup space in the schools, increases the supportive infrastructure availability and ends closure of most schools. For middle schools (M1 and M2) one classroom is open while for all other schools, two classrooms are open. At this stage, proper backup space is required if schoolchildren are to return to school. However, backup spaces can be utilized only when transportation and utilities reach a sufficient functionality level, which is assumed to be 50%, based on decision-makers judgment (*Decision I*) as mentioned before. It is assumed that each school can be provided with temporary backup spaces (Federal Emergency Management Agency,

2011) that can be gradually increased as needed to 25% of the school capacity in three weeks. At 169 days after the earthquake, all classes in all the schools can reopen. To work toward full recovery of educational services, each school continues its efforts towards increasing the quality by replacing the unqualified staff, ending the staff internal and external transfer, and ensuring the adequacy of the class technology, which is achieved after 94 more days.

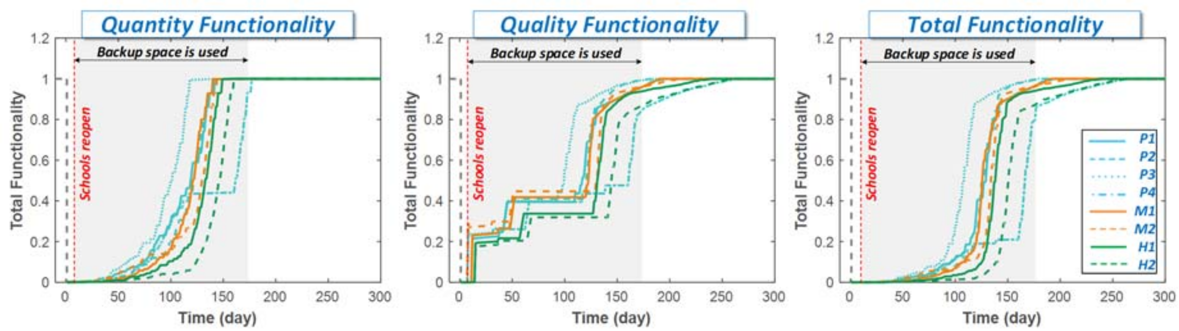

Figure 6-12: Restoration of school functionalities.

Due to damage to school facilities, schoolchildren can be enrolled in school (depending on damage level), transfer to homeschooling, or miss school. Figure 6-13 (a) displays the change in total student enrollment in Centerville following the first earthquake occurrence scenario. Limitations in available student positions throughout the first month after the earthquake increase the number of schoolchildren who miss school. Even though permanent population dislocation is expected to be minimal overall, driven mainly by minor damage in buildings and the quick recovery of utilities, it is likely to be higher for families with children missing school for a longer time. If a nearby school district with schools that have suffered less damage can enroll these children, dislocation is less likely to occur. Figure 6-13 (b) and (c) show the percentage of student enrollment per census tract 30 and 100 days after the earthquake. The variation of student enrollment in each census tract is due to dissimilarity in damage at schools within Centerville, transportation availability, and the ability of families in each census tract to provide alternatives for their schoolchildren, such as homeschooling and/or private transportation.

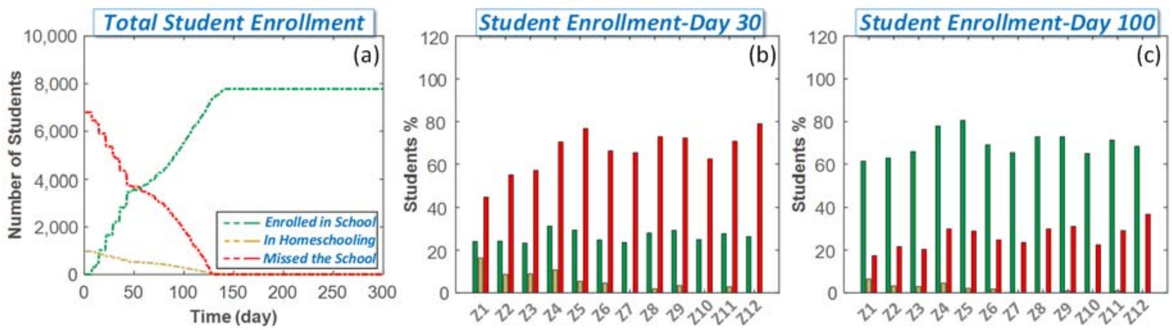

Figure 6-13: a) Total student enrollment versus time, b) the percentage of student enrollment per census tract at day 30, and c) the percentage of student enrollment per census tract at day 100.

To highlight the influence of school district administration on closing and reopening of schools, two other cases are considered, in which the schools do not have backup space (*Decision II*) or the schools remain closed after the earthquake by the school district until full recovery of all schools has been achieved (*Decision III*). Figure 6-14 (a) displays the effect of backup space on the total number of students enrolled and the delay in reopening the schools (between 33 and 67 days). Figure 6-14 (b) shows the impact of *Decision III* on student enrollment. A significant increase in school closures is apparent, in which it takes the school district 153 days to open all schools. However, *Decision III* provides the required time for the school district administration to arrange for school reopening and student return when most school infrastructure has been restored to normal conditions. The average chronic absenteeism for three investigated decisions is shown in Figure 6-14 (c). It can be noted that *Decision II* and *Decision III* significantly increase chronic absenteeism, which is utilized here as a resilience index of the educational service provided by the Centerville community.

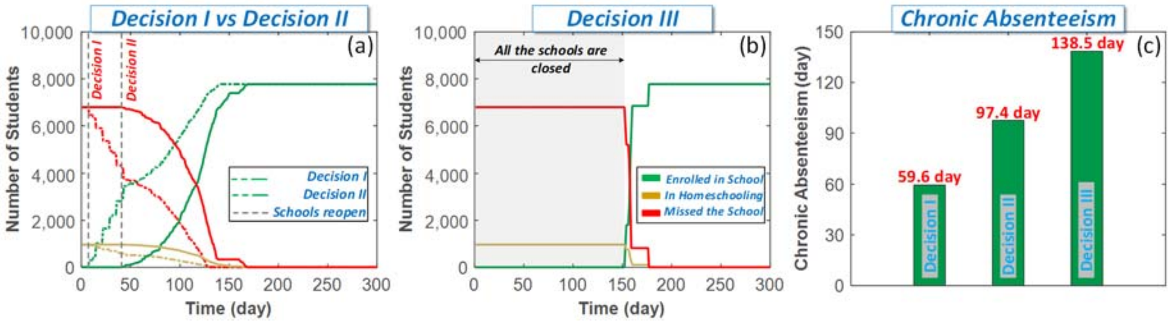

Figure 6-14: (a) the effect of *Decision I* and *II* on the student enrollment, (b) student enrollment based on *Decision III*, and (c) chronic absenteeism comparison for *Decision I*, *II*, and *III*.

In the second earthquake scenario, in which the earthquake occurs when schools are in recess, the use of school buildings and backup space for community shelter does not interrupt the main services provided by the schools. On the other hand, shelters require emergency staff, including social workers, volunteers, transportation services, utilities, space (with different contents), fuel and food supplies (Federal Emergency Management Agency, 2015). It is assumed that two days after the earthquake, the community can provide shelter in undamaged school buildings and backup spaces. The capacity of the backup spaces is assumed to gradually increase from 25% to 50% of the schools' capacities as a shelter within 18 days. Figure 6-15 shows the shelter capacities at each school. The shelter capacity can be increased by adding the classrooms, once they are repaired to the number of accommodations as shown in Figure 6-15; after 142 days all the schools' areas can be used as a shelter. Of course, if the school recess ends during this recovery period, the school utilization is likely to revert to its original intended purpose, creating social problems for community officials.

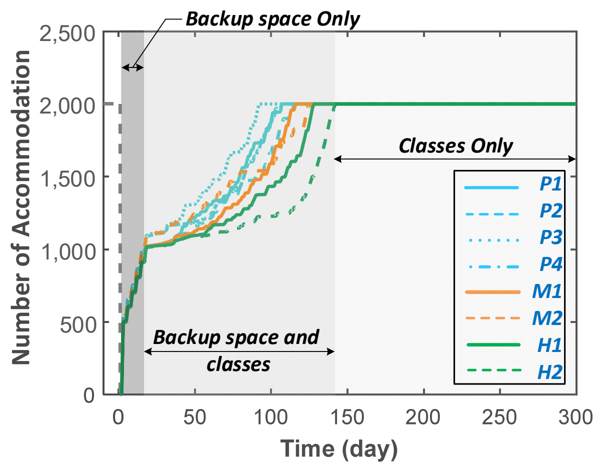

Figure 6-15: Shelter availability.

6.6 The resilience of the healthcare and educational systems

To investigate the resilience of the main social institutions in the tested community, the resilience quantification framework, which is outlined in Chapter 5 is utilized by subjecting the community to the earthquake scenarios mentioned in Section 6.3. The earthquake-associated damage to the healthcare and education facilities, as well as their supporting agents and the interaction topology, is modeled as shown in Chapter 5. Direct losses, including the earthquake casualties related to the investigated facilities' staff and users, are calculated separately using HAZUS MH 2.1. Staff casualties directly impact the functionality of hospitals and schools and users' casualties increase the demand on hospitals and chronic absenteeism in schools. The recovery of the supporting infrastructure and buildings in the investigated community (Figure 6-16 (a)) is estimated using data from ATC-13 (1985). Recovery of the hospital and school agents, shown in Figure 6-16 (b) and (c), are estimated using a semi-Markov-chain stochastic analysis while optimal repair resources allocation is determined using dynamic optimization to maximize the total number of staffed beds for hospitals and the enrollment capacity of the schools. Optimal decisions are modeled to utilize available resources and maintain the offered services by each facility.

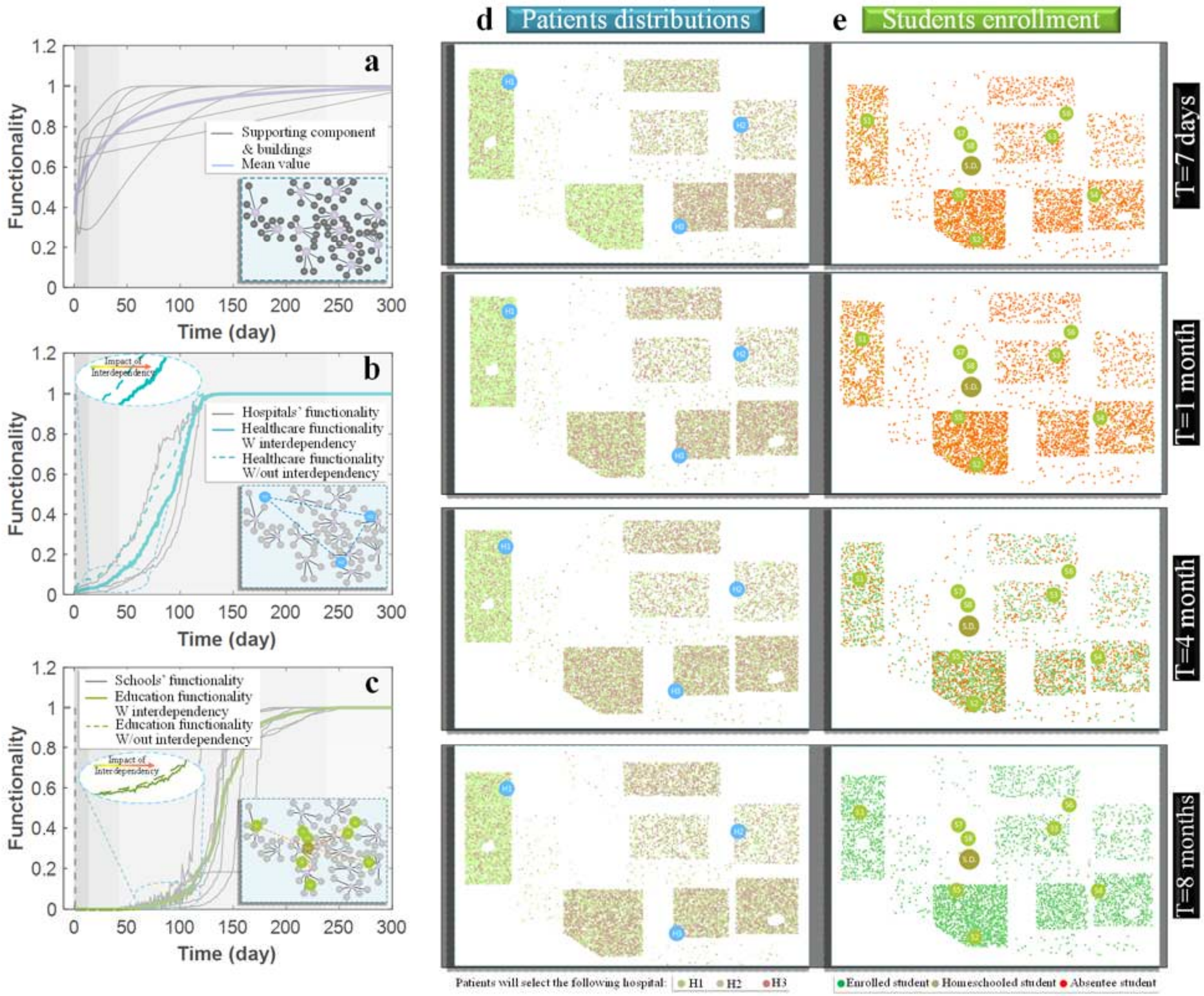

Figure 6-16: The functionality of a) supporting infrastructure, b) healthcare system, and c) education system, in addition to the change of d) patient distributions, and e) student enrollment status after the earthquake disaster.

The supporting infrastructure is shown to recover 80% of its functionality in about one month (Figure 6-16 (a)), which indicates that the earthquake damage is slight and the impact on the community's physical infrastructure is minor. Full recovery for the healthcare system is achieved within four months (Figure 6-16 (b)), while for the education system, more than eight months are needed for full recovery (Figure 6-16 (c)). Comparing the estimated functionality when considering and ignoring the relationship between the healthcare and education systems highlights the fact that delaying the restoration of one service can negatively impact the other (Figure 6-16

(b) and (c)). Schools' closure reduces the healthcare system functionality until all schoolchildren of the hospital staff are back to schools. The hospitals' drop-in functionality reduces the student outcomes by increasing the absenteeism of staff and students. Patient demand on healthcare facilities is a dynamic process, as shown in Figure 6-16 (d). The most probable hospital for each patient is shown to be sensitive to the functionality of the transportation network as well as each facility. Educational service for most of the students is discontinued for more than three months, which represents a full semester in the schools' academic calendar (Figure 6-16 (e)). Schools' enrollment is affected by the schools' buildings' safety. However, providing backup systems and backup spaces accelerates the schools' opening time after the earthquake. Homeschooling, which can be used by families for the first few months after the earthquake, is a significant option for continuing the education of their children, but it is not available for all families in the investigated community either because of student's guardian restrictions or fulfillment of different federal and state regulations (Coalition for Responsible Home Education, 2020).

6.7 Sensitivity and uncertainty analysis

6.7.1 Healthcare system

Hospitals need their staff, utilities, and supplies to be functional so that they can offer healthcare services to their community; however, hospitals' need for these components after major earthquakes differ based on various factors, including the component damage level, patient demand, among others. To evaluate the importance of each component to healthcare resilience, a sensitivity analysis is conducted. Hospital staff, which includes physicians, nurses, supporting staff, and alternative staff, is one of the main components impacting hospital functionality. Figure 6-17 (a) shows the sensitivity of the healthcare resilience to the initial drop of hospitals' staff where the sensitivity coefficient is more than 11%. Hospitals can overcome the slight reduction of staff shortage as shown in Figure 6-17 (a) by applying mitigation strategies such as assigning additional working hours to the original staff and transferring staff from other hospitals as well as using their alternative staff. Although accurate modeling of staff availability is challenging, selecting the proper model for staff availability is critical for estimating hospitals' functionality and resilience. The initial drop in staff availability can be a function of many parameters beyond the control of the hospitals including, for instance, the earthquake-related casualties among staff, building damage, and population outmigration.

Hospitals' backup systems are among the essential components that can have a considerable effect on reducing the immediate consequences of the event and maintaining the quality and quantity of the healthcare service functionality. Such systems can be utilized to run hospitals after earthquakes without the need for permanent utilities. Figure 6-17 (b) displays a significant impact of the initial drop of backup system functionality on the healthcare functionality, where the sensitivity coefficient is more than 11%. Therefore, understanding the damage to backup systems and maintain their functionality during the recovery period is essential for hospitals to enhance their functionality and resilience after earthquakes. The initial drop in backup systems functionality can result from the lack of maintenance of these systems before the earthquake and/or damage of these systems during the earthquake.

Unlike staff and backup systems availabilities, healthcare resilience for the investigated scenario is less sensitive to the initial drop of hospital supplies availability as shown in Figure 6-17 (c). This initial drop can result from damage to hospitals' contents, drop of suppliers' functionality, and dysfunction of the transportation network. Because of the damage to the hospitals' storage rooms that are used for supplies, the initial drop of hospitals' supplies only impacts the hospitals' functionality immediately after the earthquake, but the restoration of the supplies' functionality is a function of the restoration process of these storage rooms. In addition, hospitals, in this study, have different efficient mitigation strategies that are used to temporarily close the gap in their supplies' shortage even with the substantial damage to their supplies rooms as discussed in Chapter 4. Figure 6-17 (d) shows a comparison between the sensitivity coefficient resulted from the regression-based sensitivity analysis. The figure displays that the availability of the backup systems after the earthquake has more impact on healthcare resilience than the staff and supplies availability.

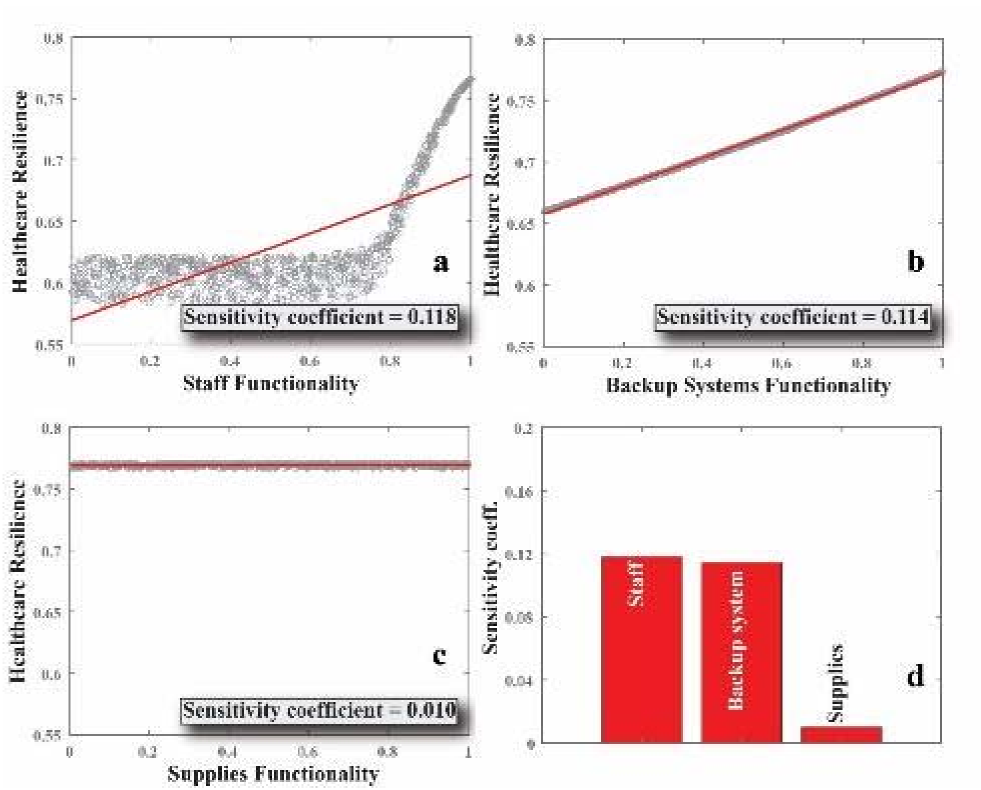

Figure 6-17: Sensitivity of the healthcare resilience to a) the staff functionality, b) the backup systems functionality, and c) the supplies' functionality as well as the comparison between the sensitivity coefficient for the three components.

To quantify the uncertainty associated with the estimated functionality and resilience of the healthcare system, the availability of three main functionality components (staff, backup systems, and supplies) are modeled by uniform distributions ***U*** (0,1). Monte-Carlo simulation with 1000 samples is used to develop Figure 6-18. The uncertainty in functionality estimations is shown to increase with time after the earthquake, as shown in Figure 6-18 (a). Figure 6-18 (b) displays the distribution of the estimated healthcare resilience, mean value, and 97.5 and 2.5 percentiles. It can be noted from Figure 6-18 (b) that healthcare resilience changes by more than 15% by only changing the initial drop in staff, backup system, and supplies availability. Therefore, a precise estimation of the initial drop of these functionality components is essential to accurately calculate the resilience.

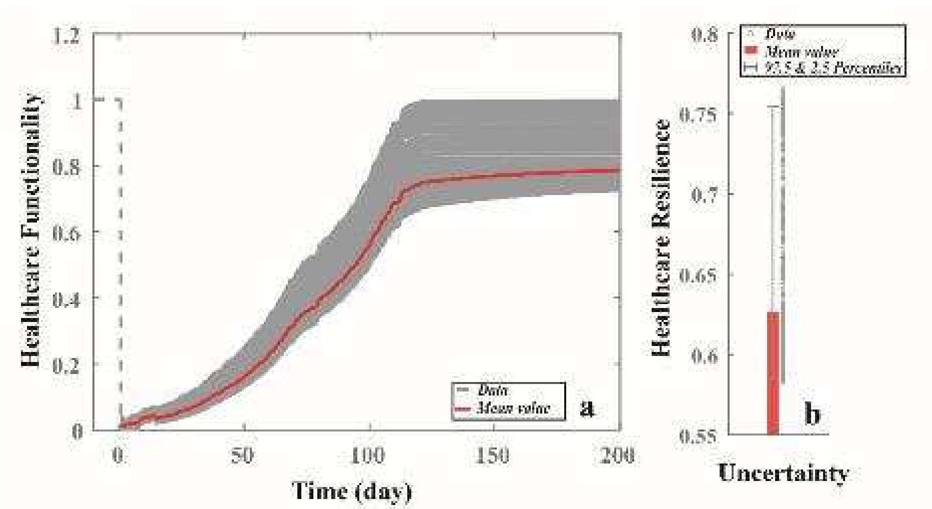

Figure 6-18: a) Uncertainty in the total healthcare functionality and b) uncertainty in the healthcare resilience.

6.7.2 Educational system

Staff, utilities, and supplies are three main functionality components for the *k-12* schools; however, the need for these components differs based on various factors, including the school grade, enrollment, component damage level, among others. To evaluate the importance of each component to the education resilience quantification, the sensitivity of the estimated education resilience to each of these components is calculated. School staff, which includes teachers, supporting staff, volunteers, and administrative staff, is one of the main components impacting school functionality. Figure 6-19 (a) shows the sensitivity of the education resilience to the initial drop of schools' staff. The figure displays a significant impact of staff shortage on education functionality, where the sensitivity coefficient is more than 17%. Schools can overcome the slight reduction of staff shortage as shown in Figure 6-19 (a) by applying mitigation strategies such as appointing and transferring staff as well as using community volunteers. Although accurate modeling of staff availability is challenging, selecting the proper model for staff availability is critical for estimating schools' functionality and resilience. The initial drop in staff availability can be a function of many parameters beyond the control of the schools including, for instance, the earthquake-related casualties among staff, building damage, and population outmigration.

For those schools that have backup systems, such systems can be utilized to reopen schools after earthquakes without the need for permanent utilities, which can be critical for schools in the short-term recovery. Figure 6-19 (b) displays a significant impact of the initial drop of backup system functionality on the education functionality, where the sensitivity coefficient is more than 11%. Therefore, understanding the damage to backup systems and maintain their functionality during the recovery period is essential for schools to enhance their functionality and resilience after earthquakes. The initial drop in backup systems functionality can result from the lack of maintenance of these systems before the earthquake and/or damage of these systems during the earthquake.

Unlike the staff and backup systems availabilities, the education resilience for the investigated scenario is less sensitive to the initial drop of school supplies availability as shown in Figure 6-19 (c). This initial drop can result from damage to schools' contents, drop of suppliers' functionality, and the dysfunction of the transportation network. However, the fact that schools were fully reopened after 169 days, as shown in Figure 6-12, allowed the schools to manage to recover their essential supplies before the school reopening.

Figure 6-19 (d) shows a comparison between the sensitivity coefficient resulted from the regression-based sensitivity analysis. The figure displays that the staff availability after the earthquake has more impact on education resilience than the backup system and supplies availability.

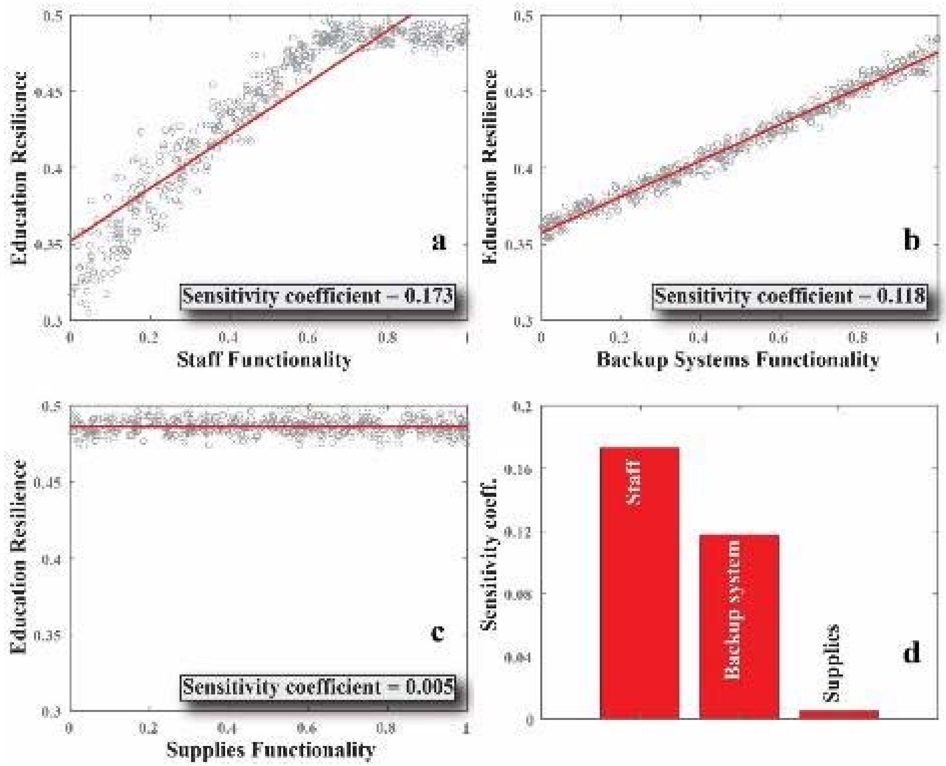

Figure 6-19: Sensitivity of the education resilience to a) the staff functionality, b) the backup systems functionality, and c) the supplies' functionality as well as the comparison between the sensitivity coefficient for the three components.

To quantify the uncertainty associated with the estimated functionality and resilience of the education system, the availability of three main functionality components (staff, backup systems, and supplies) are modeled by uniform distributions ***U*** (0,1). Monte-Carlo simulation with

1000 samples is used to develop Figure 6-20. The uncertainty in functionality estimations is shown to increase with time after the earthquake, as shown in Figure 6-20 (a). Figure 6-20 (b) displays the distribution of the estimated education resilience, mean value, and 97.5 and 2.5 percentiles. It can be noted from Figure 6-20 (b) that education resilience changes by more than 10% by only changing the initial drop in staff, backup system, and supplies availability. Therefore, a precise estimation of the initial drop of these functionality components is essential to accurately calculate the resilience.

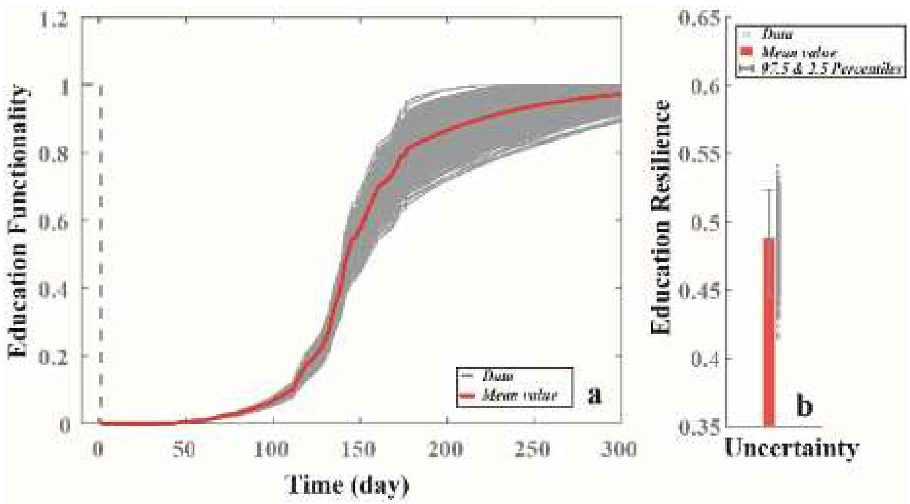

Figure 6-20: a) Uncertainty in the total education functionality and b) uncertainty in the education resilience.

6.8 Interdependence between healthcare and educational facilities

To quantify the total interdependence between the healthcare and education facilities, an agent-based model comprising two main agents (representing hospitals and schools) as well as supporting agents (representing their supporting infrastructure) and sub-agents (representing individuals in the community) is devised. The interaction among the agents, supporting agents, and sub-agents is described by the network in Figure 6-21 (a). Further details on agent type, attributes, and possible decisions can be found in Chapter 5. In this study, interdependency is quantified, among single facilities as well as between the healthcare and education systems, using the Leontief-based model (Haimes & Jiang, 2001). The model captures the impact of total functionality drops at either a single facility or the whole system, which can be healthcare or education, on the other facilities or other systems. The uncertainty associated with the location of staff, patients, and schoolchildren within the community, as well as those associated with quality functionality of hospitals and schools' sub-components, are also included in the analysis. Monto-Carlo simulation and statistical distributions are used to develop a relationship, $\boldsymbol{N}(\mu,\sigma)$, between the functionality of each investigated facility.

For the relationship between single facilities (Figure 6-21 (b)), strong dependence is noted between hospitals as well as schools with the same grades. This is a result of redistributing patients and students impacted by increased waiting time and reaching class capacity, respectively. The impact of any single school closure on hospitals is shown to range from 9 to 12% and is influenced by the shortage in hospital staff where their children either changed their school, are being homeschooled, or missed school all together. The impact of any single hospital closure on the schools can be up to 10% and is associated with staff shortage and students' chronic absenteeism. This impact is mainly caused by a reduction in healthcare services provided to the school staff and students, the long waiting time in emergency departments, and early discharge of staff and students before receiving the appropriate treatment during one school year (180 days). The hospitalization data for school staff or students are based on U.S. hospitalization statistics (Freeman et al., 2018) and are a function of the patient's age. The relationship between the healthcare and education system is also investigated as shown in Figure 6-21 (c), which demonstrates the impact of the lack of functionality of the entire system on the other. The analysis shows a higher degree of interdependency between the two systems where a complete drop of healthcare functionality can reduce that of the education by 47% and increase students' chronic absenteeism by 22.4%. On the contrary, a complete drop in education functionality is expected to reduce that of healthcare by 43%. This level of dependency is much higher than what was conceived in previous empirical (Cimellaro, 2016), statistical (Gan & Gong, 2007), or theoretical (Wright, 2001) studies.

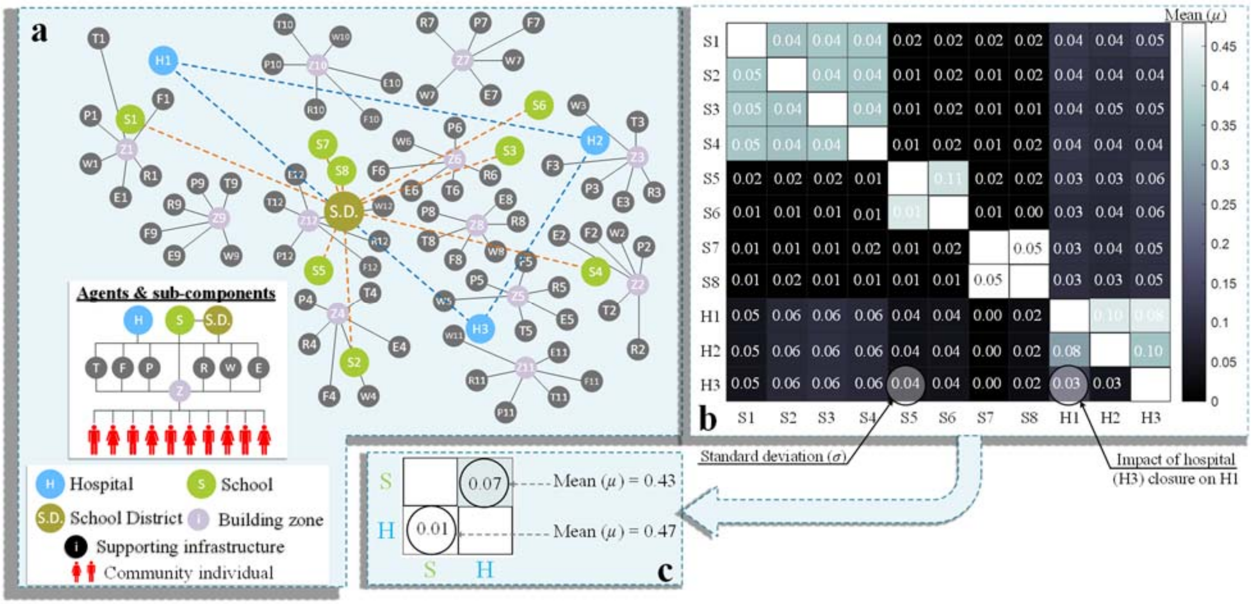

Figure 6-21: a) Components of the complex network representing the agent-based model of the investigated community, b) interdependency matrix between each healthcare and education facility, and c) interdependency between the healthcare and educational systems.

6.9 Community social services stability index

Here, a new notion of a so-called social services stability index (*SSSI*) is established, which, on a scale from zero to one, is meant to indicate how the stability of social services for the community's residents are influenced by the availability of school and hospital services. The *SSSI* is calculated by integrating healthcare and educational services while considering the need for every individual in the community to each of the investigated services. The mathematical integration of the two services is shown in Chapter 5. The *SSSI* is expected to drop directly after the earthquake but then slowly rise during the recovery stage.

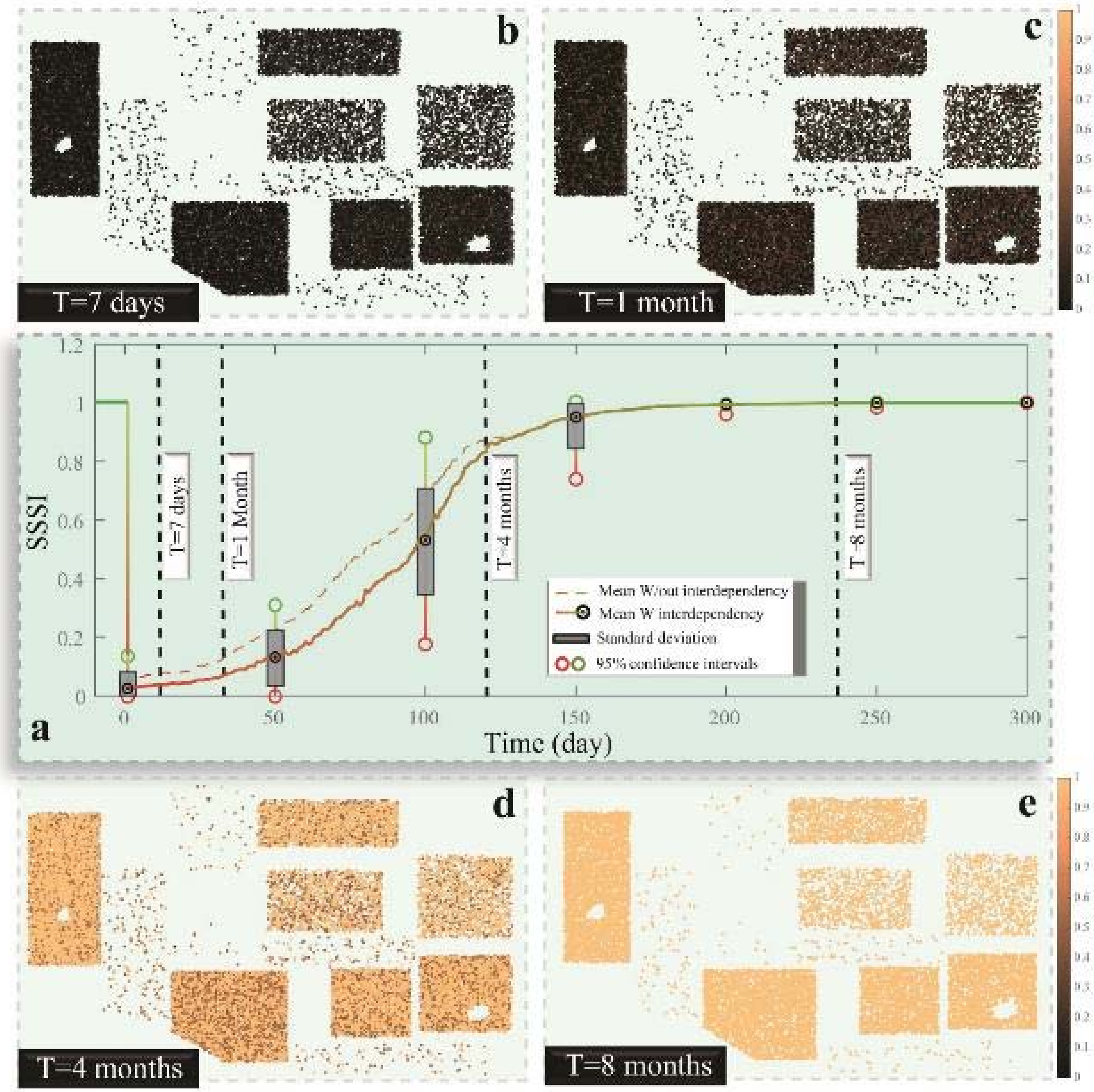

Figure 6-22: a) Recovery of the SSSI over time, and the spatial distribution of the SSSI after b) one week, c) one month, d) four months, and e) eight months.

During the first week after the earthquake, and due to the increase in patient demand and reduced available staffed beds in hospitals, a significant increase in the patients' waiting time in the crowded emergency departments is recorded (Figure 6-22). Despite the effectiveness of the dynamic triage criteria, reduction in treatment time and patient early discharge (a common practice by hospitals to increase the survival rate of the patients with high severities), lowers the patient outcome for less severe cases. This situation is also combined with the closure of all the schools in the community, which results in a substantial drop (more than 96%) in the *SSSI* for most individuals of the community. Driven by the recovery of the healthcare facilities and reduction of the patient demand, the SSSI reaches 12% of its original value prior to the earthquake in a month and a half. By the end of four months, the *SSSI* exceeds 83%, which is driven by the full recovery of the healthcare functionality and opening of most of the schools. Finally, eight months after the disaster, the *SSSI* is close to its initial value, and the community returns to normalcy. Variation in healthcare and educational services for individuals in the community is significant during the recovery time and produces disparities in the accessibility of the main services.

6.10 Impact of different mitigation strategies

Different mitigation strategies are assumed to be applied by hospitals and schools to overcome the shortage of staff, space, and supplies after the earthquake. These practical mitigation strategies are considered based on guidelines, recommendations, and lessons learned after previous natural disaster events. For instance, utilizing alternative staff, transferring staff from other facilities, and assigning additional working hours for existing staff at hospitals and schools are recommended to close the staff shortage gap (Achour et al., 2016; Applied Technology Council, 2017; Committee on the Future of Emergency Care in the United States Health System et al., 2007; Hassan et al., 2020; Hassan & Mahmoud, 2020a; Tariverdi et al., 2018; U.S. Department of Education, 2007). Providing hospitals and schools with backup systems and backup spaces are also recommended mitigation strategies that could provide healthcare and educational services without the need for permanent utilities or space (G. P. Cimellaro et al., 2013; Committee on the Future of Emergency Care in the United States Health System et al., 2007; Federal Emergency

Management Agency, 2011; Hassan et al., 2020; Hassan & Mahmoud, 2020a; Li & Zheng, 2014; Office of Inspector General, 2015; Redlener & Reilly, 2012; Sheikhbardsiri et al., 2017). In addition, using alternative supplies, optimizing the supply usage, and transferring supplies between different facilities can be significant in reducing supply shortage, limiting the services provided by these facilities (Hassan et al., 2020; Hassan & Mahmoud, 2020a; Sheikhbardsiri et al., 2017; Syahrir et al., 2015; Tariverdi et al., 2018). To further reflect on the sensitivity of healthcare and education systems to disturbances to their relevant socio-physical parameters, four different cases are evaluated to observe the impact of each case on recovery trajectories and the computed SSSI for the community, as shown in Figure 6-23. The four cases are Basic Scenario (when all the mitigation strategies are applied), Scenario 1 (when no strategies are used to manage staff shortage), Scenario 2 (when no strategies are utilized to overcome utilities outage and space damage), and Scenario 3 (when no strategies are applied to close the gap in supplies). Failing to apply these mitigation strategies will reduce the functionality, delay the facilities opening and recovery time, and impact the community *SSSI*. Failing to manage and replace staff can diminish the healthcare system functionality for more than 21 days after the earthquake and delay the attainment of full recovery for more than 240 days. While its impacts on the education system will not be notable immediately after schools' reopening, lack of proper management and staff replacement will impact the quality of the educational service and delays the full recovery of the service for more than 221 days. The backup systems and spaces are the most critical for hospitals and schools in the short and long terms. While backup systems are utilized to reopen facilities earlier, the backup spaces are essential for these facilities to continue providing services when the repair process of building components is underway. Failing to provide the required backup systems and spaces will delay the full recovery of the healthcare and education systems by 320 and 241 days, respectively. Failing to maintain the supply availability will significantly reduce the healthcare system functionality immediately after the earthquake; however, its impact will be minor in the long-term. While its impact on education system functionality will be insignificant, lack of supplies can delay schools reopening for 21 days.

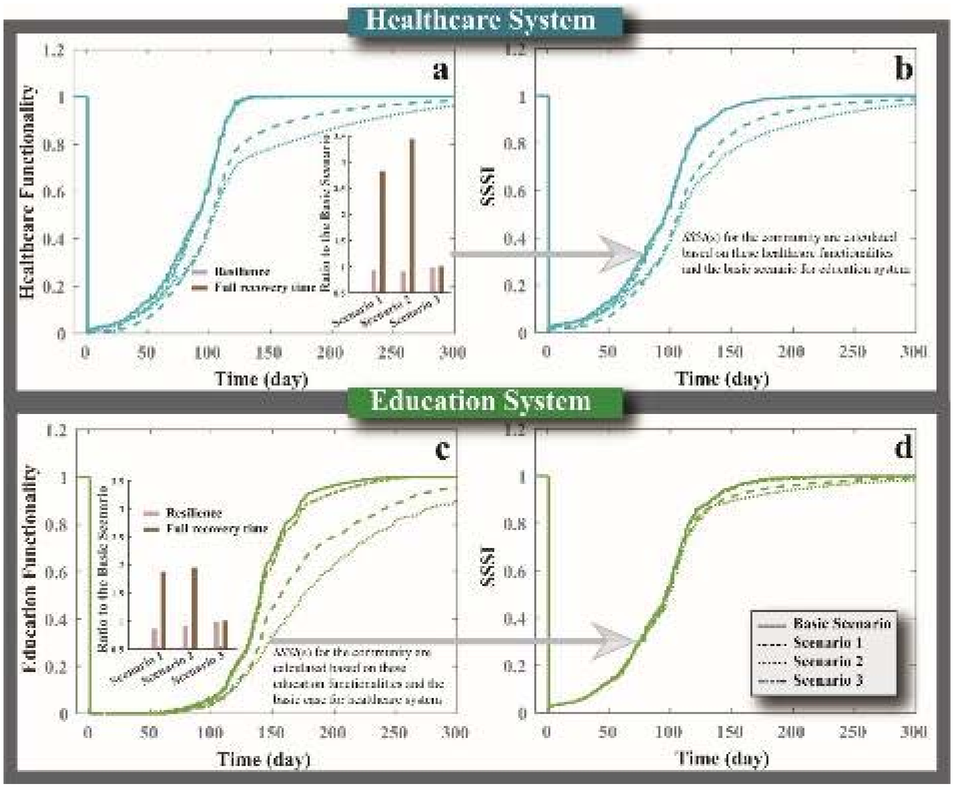

Figure 6-23: Impact of failing to apply different mitigation strategies on a) the total functionality of healthcare system, b) community's *SSSI*, c) the total functionality of education system, and d) community's *SSSI*.

6.11 Summary

In this chapter, Centerville virtual community was used as a testbed to highlight the capabilities of the introduced models and framework to calculate functionality, recovery, and resilience of healthcare and education systems after earthquakes while simulating their main processes such as patient demand, patient transfer, hospitals' interaction, student enrollment, staff appointment, staff and supplies transfer, etc. Centerville community had a total population of

50,000 that was served by a total of three hospitals and eight schools, which were managed by one school district. An agent-based model was devised for the healthcare and education systems that represent hospitals, schools, and school districts as main agents, buildings and community infrastructure as supporting agents, and community individuals as sub-agents. The sensitivity analysis of the proposed functionality frameworks for hospitals and schools was conducted and the uncertainty associated with the estimated resilience of healthcare and education systems was propagated. The Leontief-based model was utilized to estimate the level of interdependency between each healthcare and education facility and to define the interaction between healthcare and education systems. The summation of weighted and normalized indicators was used to estimate the social services stability index for community individuals as a function of the availability of healthcare and educational services. The effect of different mitigation strategies applied by hospitals and schools on healthcare and education system resilience as well as the community's social services stability was investigated.

The following conclusions can be drawn from the healthcare system analysis results:

- Ensuring the availability of qualified backup spaces and operability of backup systems before the earthquake showed a considerable effect on reducing the immediate consequences of the event and maintaining the quality and quantity of the healthcare service functionality.
- Balancing between the quantity and quality of the offered healthcare service, in addition to other social and economic factors, can dramatically affect the patient's selection. While the quality portion of the functionality did not have much impact on the overall functionality of a given hospital, it does have an influence on patients' selection of the hospital.

- Achieving a high level of interaction among hospitals in terms of pre-established agreements, coupled with an effective recovery plan, can improve recovery of the service, reduce patient waiting time, and enhance the healthcare service for the whole community.
- Changing in the patient distribution in a healthcare provider took place directly after the earthquake occurrence as an outcome of the disturbance to the community.

The following conclusions can be drawn from the education system analysis results:

- Providing schools with reliable backup utilities and sufficient backup spaces was critical for keeping the schools opens after the earthquake.
- Recovering the schools' main supporting lifelines, especially transportation, was key for school reopening.
- Providing alternative staff and using community volunteers can temporarily close the gap in staff shortage. However, it could also negatively impact the quality of educational services and student outcomes. However, staff swapping and appointing qualified staff can sustain the leadership and professional community.
- Establishing appropriate policies and decision-making processes had a substantial impact on the school's recovery trajectory and students' enrollment state.
- Using schools as shelters immediately after the earthquake was a function of the backup utility systems and backup spaces. However, it depended on the recovery progress of schools, supporting lifelines, and suppliers.

The following conclusions can be drawn from the sensitivity and uncertainty analysis results:

- Utilizing comprehensive models to estimate the availability of staff, utilities, and space at hospitals and schools was vital to accurately estimate the resilience of healthcare and education systems after earthquake disasters.

- Including the uncertainty associated with the estimation of the availability of staff, utilities, and space was critical in understanding the risk associated with the functionality and resilience quantifications.

The following conclusions can be drawn from the interdependency analysis results:

- Modeling interdependency between social institutions required comprehensive models that can capture the interaction between these institutions at different levels, ranging from systems interaction all the way to individual levels relationships.
- Considering the interdependency between hospitals and schools was critical for the community resilience analysis. This interdependency can be found between healthcare and education systems, among hospitals and schools, and within community individuals.

The following conclusions can be drawn from the social services stability analysis results:

- Restoring the functionality of healthcare and educational services immediately after the earthquake occurrence had a great impact on the community's social stability. Hospitals and schools can utilize their backup systems and backup spaces to ensure the continuity of their services.
- Ignoring the interdependency between the healthcare and education system in calculating in social service stability index, especially during the recovery period, can mislead the estimation of the community stability.

The following conclusions can be drawn from the mitigation strategies analysis results:

- Failing to manage and replace staff can diminish the healthcare and education system functionality for weeks after the earthquake and delay the attainment of full recovery for months.

- Failing to provide the required backup systems and spaces can delay the full recovery of the healthcare and education systems by months.
- Failing to maintain the supply availability can only impact the healthcare and education systems functionality immediately after the earthquake; however, its impact can be minor in the long-term on both systems.

Chapter 7. SUMMARY AND RECOMMENDATIONS FOR FUTURE WORKS

7.1 Summary and conclusion

The primary objectives of this study were to develop comprehensive models and frameworks to model functionality, recovery, and resilience of healthcare and education systems. It also introduced a generalized approach that can be used to investigate the interdependency between these complex networks and their impact on community resilience and social services stability after earthquake events. Comprehensive frameworks used to quantify the seismic resilience of healthcare and education systems were coupled with a new agent-based model comprising of system's agents, main agents, and sub-agents. A strong relationship between the two networks was observed. The study showed that interdependencies between schools and healthcare facilities could go beyond employees and direct users of these networks and encompass other individuals with minor needs for these networks because of their social relationships with others who directly interface with these networks. It also showed that the facility size and interaction topology, being healthcare or education, can play a critical role in the level of interdependency among different facilities.

From the results, it can be observed that earthquakes can be devastating for mid-size communities despite the minor damage to the community's-built environment, including physical infrastructure. In addition, the community's social services stability was founded to be sensitive even to minor disturbances. Therefore, more attention should be given to quantifying the resilience of schools and healthcare facilities in communities. Providing alternatives for healthcare and educational services providers was critical for the community's social stability. These alternatives included patients and resources transfer between hospitals, homeschooling for school students, and backup systems and backup spaces hospitals and schools, which showed a major impact on the quantity functionality of the investigated services. The study showed that the change in a community's social services stability is dynamic and sensitive to disturbances in the community.

While the models and frameworks developed in this study can provide substantial insight into the functionality components of the healthcare and education systems, how they interact, and what is their impact on communities, there were different limitations that should be reflected upon when using the proposed approach. First, although the focus of the study was on healthcare and education systems and their interaction in the aftermath of extreme events, the resilience of other socio-economic sectors, such as food suppliers and retailers, was also important for maintaining an adequate level of social services for communities. Furthermore, other resilience goals (governance stability or population stability, etc.), measured by different metrics, might be more relevant for some communities and can be integrated with the recovery of healthcare and education systems for a more complete assessment of resilience and or the *SSSI*. Although it was not included in this study, it was acknowledged that some communities might choose to return to a higher level of functionality by incorporating the concept of building back better so that they are more resilient against future events. Finally, other methods can be used to quantify the parameters in the presented models, and detailed validation of the calculated parameters to the different models is needed. The presented frameworks and modeling approach can also be applied to evaluate the impact of other hazards on the healthcare and education systems.

7.2 Contributions

Healthcare system functionality: a new framework was introduced to estimate the quantity and quality of the healthcare services provided by hospitals while accounting for the interdependency between hospitals and their supporting infrastructure. Quantity functionality was measured by the number of available staffed beds and quantity was estimated as a combination of accessibility and effectiveness of the offered healthcare services.

Patient distribution: a new patient distribution model so-called Patient driven model was proposed in this study. The model accounted for various socio-technical factors related to patient constraints, healthcare facility constraints, and connections between patients and healthcare facilities. It was a dynamic model in which the most probable hospital for each patient can change over time after the earthquake due to changes in the basic events.

Hospitals' interaction: a new framework was presented to model the interaction between healthcare facilities. The framework accounted for the probability of transfer of patients, staff, supplies after the earthquake hazards, which was an approach hospitals can use to reduce their demand and enhance their functionality. While the agreement between healthcare facilities was an essential component for hospitals' interaction in the presented framework, other different socio-technical factors related to hospitals, patients, staff, and supplies were included in the framework that can control and change the hospitals' interaction after earthquake events.

***K-12* School system functionality:** a new framework was proposed to estimate the quantity and quality of the educational services provided by *K-12* public schools while accounting for the interdependency between schools and their supporting infrastructure. Quantity functionality was measured by the school's enrollment capacity and quantity was estimated as a combination of parameters that measure teacher quality, classroom quality, and school quality.

School administration model: a framework was proposed in this study to mimic the role played by school administrations and school districts in managing the schools' administrative process including school closure and reopening decisions, student enrollment, staff appointment, staff and supplies transfer, and recovery goals. Different socio-technical factors were included in this framework while optimization was used in these decisions to ensure enhancing the schools' functionality using the minimal resources.

Recovery model: a generalized recovery model was introduced to estimate the recovery trajectories of healthcare and education facilities that were damaged during the earthquake. The semi-Markov chain model, coupled with the dynamic optimization, was utilized to estimate the near-optimal repair progress of the school system that ensured the maximum quantity of the offered educational service for the whole community, considering repair crew specialties, the possibility that repair crews from neighboring communities are available, and the delay in the repair pross that might result from interruption to the other community infrastructure.

Interdependency between healthcare and education systems: an agent-based model was introduced in this study to simulate the healthcare and education systems that include a comprehensive model for their main agent (hospitals, schools, and school districts), supporting agents (buildings, utility providers, suppliers, etc.), and sub-agents (all community individuals). This agent-based model was then used with the Leontief-based model to calculate the interaction between each of the healthcare and education facilities as well as the interdependency between the healthcare and education systems.

Community social services stability: a newly developed social services stability index (*SSSI*) was proposed in this study as a measure of community strength after disasters, and it measured the accessibility of community individuals to the main public services with a focus on healthcare and education as pivotal services after disasters.

Impact of mitigation strategies on the resilience of hospitals and schools: in this study different mitigation strategies were applied during the analysis and their impact on healthcare and education system functionality and resilience as well as the community social stability were investigated.

These strategies were used to overcome the shortage of staff, space, and supplies after the earthquake.

7.3 Recommendations

The presented study was developed to enable policymakers and community leaders to quantify the impact of healthcare and educational services on community resilience and social services stability. The following recommendations can be drawn from the introduced study's main findings:

Healthcare systems: The existence of alternative staff, offering regular training for the staff to increase their preparedness for disasters, and establishing mutual-aid agreements with other hospitals are key to hospital operation following natural hazard events. Hospitals that maintain the availability of utility backup systems, as well as backup spaces, can significantly reduce the impact of the earthquake events on their functionality. In addition, securing different providers for the main services that hospitals require and relying on multiple suppliers is pivotal to their functionality. Shortage of hospital supplies after earthquakes can lead to catastrophic consequences. Therefore, receiving the required supplies on time is vital for maintaining an acceptable level of functionality. Organizing the healthcare service between the hospitals and other healthcare facilities especially after earthquakes is the fundamental component to ensure that most of the patients will receive the appropriate service and reduce the mortality rates. Distributing repair resources among healthcare facilities and other infrastructure requires careful investigation to ensure the balance between the social and economic stability of the communities. Sustaining patient satisfaction and monitoring patient outcomes is the key to maintain resilient and socially stable communities.

Education system: Utilizing volunteer staff, appointing qualified teachers, and transfer staff between schools are key to school operation following natural hazard events. Schools need the essential utilities and appropriate space to provide the essential educational services to their students. In some cases, using backup systems and spaces can allow schools to overcome the disturbance that occurred to these components because of the earthquake. Managing school supplies after the earthquake and ensuring the availability of their main suppliers by, for example, transfer supplies between schools and find alternative supplies are important to school functionality. The role played by school administration and school districts, especially after earthquake events, is critical in managing student enrollment, staff and supplies transfer, managing the repair process of the damaged schools, and find alternatives for the damaged and impacted functionality components. Therefore, these administrations need to be well trained and well prepared for disasters. Distributing repair resources among schools requires careful investigation to ensure equality in educational services distribution. Monitoring and enhancing student outcomes, especially after disastrous events, is the key to maintain resilient and socially stable communities.

Community resilience: The premise of the concept of community resilience hinges on the community's ability to adapt to and recover from disruption to its infrastructure, social, or economic sectors. Recovery of critical facilities, such as hospitals and schools is particularly important since they are vital for the short-term and long-term functioning of the community. Therefore, ensuring the continuation of the healthcare and educational services after the earthquake events can be considered as one of the main resilience goals for communities. To achieve this goal, communities can allocate enough repair resources for the impacted hospitals and schools, provide them with volunteers to close the gap in staff shortage, and support them with the supplies needed.

Social services stability: maintaining social services stability for communities can substantially enhance their resilience and reduce their population outmigration. Ensuring the quick recovery of the main social institutions such as hospitals and schools is the key to increasing the individuals' social stability after earthquake events. Even though the needs of everyone for the services provided by these institutions are different, most of the community individuals can out-migrate because of the lack of these services. Therefore, understanding the interdependency between the healthcare and educational services and how they both influencing the communities after natural disasters are essential components to enhance communities' social services stability.

7.4 Future work

This study presented new and comprehensive frameworks to investigate the functionality, recovery, and resilience of healthcare and education systems while considering the change of community built-environment, patient demand, hospitals' interaction, student enrollment, staff, space, and supplies at each facility after the major earthquake events. The study highlighted the interdependency between hospitals and schools and their roles in community resilience and social services stability. Although this study provided some insights on the performance of healthcare and education systems subjected to earthquake hazards; however, future research directions can include the followings:

7.4.1 Advancing the presented healthcare system model

Even though hospitals are the only healthcare facilities that can treat the major injuries resulting from major earthquake events, other healthcare providers should be incorporated in the healthcare system model to account for the role played by these providers in reducing the demand on hospitals. Including the patient flow that can be achieved by modeling the hospital specific components can enhance the presented healthcare system framework by including the patient internal waiting time to the quality functionality equation. Data collected from case studies and real communities can be used to verify the hospital system sub-models and calibrate the model outputs. Different mitigation strategies that might be applied by hospitals can also be investigated and included in the presented framework that might enhance the estimation of the healthcare system's functionality and resilience.

7.4.2 Advancing the presented school model

Even though about 90% of U.S. students are enrolled in public schools, considering non-public schools such as private schools, which commonly utilize non-centralized education systems can provide a full picture of the functionality of the education system in some communities. Data collected from case studies and real communities can be used to verify the school system sub-models and calibrate the model outputs. The scalability of the introduced framework can also be investigated in which different community sizes, diverse school types, and various school districts can be tested. Different mitigation strategies that might be applied by schools such as virtual and hybrid education can also be investigated and included in the presented framework to enhance the estimation of the education system's functionality and resilience.

7.4.3 Considerations for different hazards

The presented frameworks and models are developed to investigate communities subjected to earthquake hazards. However, modifications to the model's components can be conducted to consider communities subjected to different single or multiple hazards (wildfire, flood, wind, and flooding). The presented frameworks and models are structured to be flexible, their components can be removed, adjusted, or calculated using different approaches to account for the components' damage and recovery during different hazard types. However, some challenges might be associated with this process and more investigation on model applicability will be needed.

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