A Mixed Methods Approach to Modeling Personal Protective Equipment Supply Chains for Infectious Disease Outbreak Response

by

Emily J. Gooding

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Signature of Author: ____
Technology & Policy Program
May 3, 2016

Certified by: ____
Jarrod Goentzel
Research Associate, Massachusetts Institute of Technology
Thesis Supervisor

Certified by: ____
Marianne Jahre
Professor of Logistics, Lund University & BI Norwegian Business School
Thesis Supervisor

Accepted by: ____
Munther A. Dahleh
William A. Coolidge Professor of Electrical Engineering and Computer Science
Director, Institute for Data, Systems, and Society
Acting Director, Technology and Policy Program

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ABSTRACT

Personal protective equipment (PPE) is critical to the protection of healthcare workers responding to infectious disease outbreaks. The ability of the PPE supply chain to provide adequate and consistent supply when there is a large spike in demand has not been well-considered. Humanitarian logistics literature rarely considers infectious disease outbreaks as possible humanitarian crises while epidemiology literature assumes perfectly responsive supply chains.

This thesis uses a mixed methods approach – an exploratory case study and system dynamics model – to bridge the gap between these two fields. It provides one approach for connecting epidemiology and supply chain research.

An explanatory case study of the 2014 West Africa Ebola outbreak is used to analyze the PPE supply chain and its in-crisis functionality. We gather primary data using semi-structured interviews with supply chain actors and analyze that data using qualitative coding analysis.

The system dynamics model is developed based on the results of the case study to offer insight as to how the PPE supply chain could be improved to better respond to future outbreaks. Several scenarios are simulated to test the effects of various supply chain improvement strategies. Relationship-building between supply chain actors, unconstrained shipping channels, flexible funding pools, and pre-positioning are all found to be effective supply chain improvement strategies.

Thesis Supervisor: Jarrod Goentzel
Title: Research Associate, Massachusetts Institute of Technology

Thesis Supervisor: Marianne Jahre
Title: Professor of Logistics, Lund University & BI Norwegian Business School

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Private sector supply chains are constantly adapted to be more resilient to demand shocks from the systems they serve. Efforts in forecasting, pre-positioning, and specialized contracts have aimed to improve commercial supply chains' ability to respond to large spikes in demand, while minimizing the additional cost of this preparedness.

The humanitarian sector, however, has not adapted so quickly (Van Wassenhove 2006). The nature of humanitarian crises makes them difficult to predict, and the nature of funding for humanitarian response makes supply chains difficult to prepare. Despite these challenges, there are opportunities for supply chain improvement in the humanitarian sector. We can take lessons learned from the private sector and adapt them to the unique context of humanitarian response (Van Wassenhove and Pedraza Martinez 2012). In order to do so, we must first better understand how supply chains function in a humanitarian crisis.

The specific type of demand spike we consider in this thesis is for relief supplies in an infectious disease outbreak. Models that predict the spread of disease are fairly well-developed, allowing for dynamic forecasting of needs throughout a crisis. In emergent outbreaks, however, these epidemic models are not well-utilized for demand planning (Dasaklis, Pappis, and Rachaniotis 2012). The types of equipment required for infectious disease outbreak response are unique – specialized medical supplies, personal protective equipment ("PPE" – gloves, surgical masks, coveralls, hoods, etc.), and decontamination resources are all necessary to contain an outbreak. These supplies are not amongst the products that are typically procured by humanitarian agencies. Because of their specialty nature, the supply chains for these products can quickly constrain a response. Supply bottlenecks not only slow down organizations' and governments' ability to respond, but by limiting the response, they allow the disease to spread, which in turn increases demand.

In the case of PPE for healthcare workers responding to a crisis, the implications are clear. There are few global manufacturers and suppliers of high-protection-level PPE. When demand for specific types of PPE spikes during an outbreak, this limited supply is further constrained. PPE procurement among responding organizations and governments becomes a competitive and time-intensive activity. This procurement is further complicated when epidemiological forecasting models produce confusing or unreliable results. The failure to connect these complicated pictures of expected demand with PPE supply chain strategies and deployment can result in delayed or inappropriate PPE procurement in infectious disease outbreaks, as was the case in the 2014 West Africa Ebola outbreak.

Without reliable access to PPE, fewer healthcare workers are willing to participate in the response effort, and the ones who do participate suffer a greatly increased risk of infection themselves, further perpetuating the crisis (WHO 2014g). For example, in the recent Ebola outbreak, 7.9% of laboratory-confirmed or probable Ebola cases in Guinean adults were in healthcare workers – an infection incidence 42.2 times higher than the rest of the population (CDC 2015a). In Sierra Leone, healthcare workers were infected at 103 times the general population incidence rate (CDC 2014a). The risk for healthcare workers is exacerbated by unavailable or inappropriate PPE.

In settings where the health system is resource-constrained, these problems are particularly acute. Problems with physical access, limited communication networks, government mistrust, and lack of medical infrastructure can all complicate an epidemic response. With limited resources and a complicated context, we must ensure that bottlenecks in critical supply chains do not further complicate the response effort. To improve supply chains, we must first understand how they work in crisis.

This thesis explores one type of product supply chain – personal protective equipment – as it functioned in a unique crisis – the 2014 West Africa Ebola outbreak. It uses data to build a system dynamics model that can be used to explore how some methods, already proven in the private sector, might be used to ensure a reliable, consistent supply of PPE in infectious disease outbreaks. This thesis is the first work, to our knowledge, to develop a model that links the complexities of supply chains with the control of epidemics. It is developed using the case of the 2014 West Africa Ebola outbreak, but the model provides insights for other infectious disease outbreaks.

PROBLEM STATEMENT

This thesis answers the central research question:

1. How and to what extent are epidemic forecasts used to inform PPE demand forecasts and PPE supply chain strategies, both before and during an outbreak?

This thesis analyzes the ways in which policymakers and procurement officers utilize epidemic forecasting to generate demand forecasts and to create PPE supply chain strategies, both before and during an infectious disease outbreak. This is answered with an exploratory case study and descriptive analysis of the 2014 West Africa Ebola outbreak.

The descriptive analysis performed to answer the first question shows how and to what extent epidemic forecasts are currently used. These results serve to draw the boundaries of feasibility for supply chain strategies that could be realistically implemented to improve epidemic response, the subject of the second, normative research question:

2. How can the PPE supply chain be designed to respond better to infectious disease outbreaks?

To answer the second research question, a system dynamics model that describes the PPE supply chain and its functionality during the recent Ebola outbreak is developed. This model can then be used to investigate the potential of different supply chain strategies to improve future epidemic responses.

The outcome of this thesis is a system dynamics model with which PPE supply chains can be investigated and improved to better respond to future infectious disease outbreaks. If implemented and used successfully, this has the potential to lower the risk of healthcare workers responding to an epidemic, to control that epidemic better or more quickly, and to lower the cost of response for humanitarian organizations and government agencies that respond.

LITERATURE REVIEW

REVIEW PROCESS

This thesis seeks to connect traditional supply chain methods with humanitarian response for infectious disease outbreaks. The literature analysis, in turn, spans several disciplines.

We begin by considering work by Sodhi and Tang on strategies to make supply chains more resilient to shocks (Sodhi and Tang 2012a; Sodhi and Tang 2012b). This work provides an understanding of how supply chains in commercial applications can be structured to be more resilient to large variations in demand, such as those seen for protective equipment in an infectious disease outbreak. Given the purpose of the study is to investigate how these strategies might be applied to infectious disease outbreak response, we use these findings as a basis for the three streams of literature reviewed below.

First, we review the specific area of supply chain literature that applies to humanitarian and emergency response. This literature still resides mainly in operations management and supply chain journals, but is applied specifically to the case of humanitarian emergencies. The cases considered for this literature, however, are rarely infectious disease outbreaks. The research most often focuses on natural disasters, manmade disasters, or armed conflicts.

Next, because the application of epidemic response is even more specific than generic humanitarian response literature, we must consider logistics and supply chain research done specifically for epidemic response. Often, this literature falls under the subject category of "resource allocation" and resides in public health journals.

Finally, because many of the resource allocation models that exist currently are not well-suited to be used in this thesis, we go one step further. As a final category we consider general epidemiological models of infectious disease outbreaks, which give us a better understanding of how an equipment supply chain might affect an epidemic response.

In reviewing these three categories of literature, we look specifically for research that might apply to this thesis, and for gaps in knowledge or research that might be filled by this research. These gaps are explicitly defined at the conclusion of this chapter.

A snowballing until saturation approach was used to identify articles. First, we searched for papers from well-known authors and experts in each subject area. The terminology used in these papers, along with their bibliographies, were then used to search for additional relevant literature in that field. As useful articles were identified, those bibliographies were used to continue the search. In order to ensure that this sampling method didn't produce a detrimental bias in the search, a reference search of the BartonPlus database (for inclusion in the title and/or a keyword) was conducted using the subject-specific terminology learned from all papers considered in that category. If the resulting references had already been reviewed, the subject area was considered saturated (complete). If relevant new references appeared, however, they were incorporated into the review (Bryman and Bell 2011; Coleman 1958). See Table 1 for the number of papers reviewed in each category, as well as the terminology used to validate the sample.

Table 1: Number of papers reviewed in each stream of literature and the terms and keywords used for validation.

Subject	**Number of papers reviewed**	**Terms, keywords used for validation**
Humanitarian & Emergency Response Logistics	17	humanitarian logistics, humanitarian disaster response, humanitarian supply chains
Logistics & Resource Allocation for Epidemics	30	infectious disease resource allocation, infectious disease epidemic control, epidemic logistics
Epidemiology of Infectious Disease Outbreaks	25	infectious disease outbreak epidemiology, viral hemorrhagic fever epidemiology

RISK STRATEGIES IN COMMERCIAL APPLICATIONS

Strategies to make supply chains more resilient to demand spikes and disruptions include postponement, strategic stock, flexible supply base, make and buy, economic supply incentives, flexible transportation, revenue management, dynamic assortment planning, flexible supply contracts, and flexible manufacturing processes. Postponement delays the point at which a set of products are differentiated, which makes products upstream from that point in the supply chain more flexible. Strategic stock (strategically placed safety stock) and economic supply incentives (incentives to cultivate more suppliers) both increase product availability. A flexible supply base allows for dynamic shifting among suppliers; a make and buy strategy allows for shifting between in-house production and external sourcing. Both of these strategies increase the flexibility of supply. Strategies that make transportation more flexible help increase an organization's ability to meet demand quickly. Revenue management with dynamic pricing or promotion as well as assortment planning (manipulation of consumer choice by displaying products in different ways) increase the control an organization has over the demand for its products. Flexible supply contracts give organizations the option to adjust their order quantities after an order is placed, which increases their replenishment flexibility. Finally, flexible manufacturing processes allow organizations to shift production among internal resources (Sodhi and Tang 2012a; Tang 2006).

Strategies to lower the financial risks of these demand shocks include options contracts and operational hedging (Sodhi and Tang 2012b). Several of these methods have particular relevance for PPE procurement in infectious disease outbreak response.

HUMANITARIAN & EMERGENCY RESPONSE LOGISTICS

Our search of humanitarian and emergency response logistics literature focuses on research that exemplifies the strategies detailed in the previous section. Supply chain management and logistics for humanitarian response present unique challenges when compared to the traditional commercial sector. These challenges include donor interests, political context, physical/geographic context, resource mobilization, responsibility to the media, accountability to the international community, complexity of the operating environment, robust equipment requirements, demand uncertainty, high pressure for timely execution, high staff turnover, tracking requirements, in-kind or unsolicited donations, and lack of institutional learning (Costa, Campos, and Bandeira 2012; Van Wassenhove 2006).

Much research has been devoted to finding ways the humanitarian sector can improve the responsiveness of its supply chains while operating under these constraints and challenges. Gatignon, Van Wassenhove, and Charles (2010) consider how the decentralization of a humanitarian organization's supply chain aided its response to the 2006 earthquake in Yogyakarta, Indonesia. Balcik and Ak (2014) look at the use of framework agreements and their effect on the speed and effectiveness with which post-disaster relief supplies are procured. Van Wassenhove and Martinez (2012) consider a variety of operations research methods that can be applied to humanitarian logistics, including demand forecasting, inventory management, bullwhip effect monitoring, standardization, and resource sharing. A study by Jahre et al. (n.d.) argues that credible demand forecasts can be developed, and that these forecasts should allow the humanitarian sector to move toward push-based supply chains. Pull-based approaches are based on actual demand as defined by orders placed. Push-based approaches, however, are based on forecasts and are more useful in humanitarian applications due to high demand uncertainty, high penalty for non-delivery, high supply uncertainty, and the narrow set of relief items usually offered. This study utilizes data from 63 disasters, including the needs and the response from a wide variety of donors and responders.

With specific respect to stocks of relief supplies, pre-positioning and private sector partnerships have drawn interest from researchers.

Rawls and Turnquist (2010) look at pre-positioning as a method of countering demand uncertainty and uncertainty of the transportation network after a disaster. They use a two-stage stochastic mixed integer program to solve for the optimal location and quantity of various supplies under the uncertainty of if and when a natural disaster will occur, and test their results using a case study of hurricane threats on the Gulf Coast. Salmeron and Apte (2010) develop a two-stage optimization model that allocates budget to acquiring and positioning relief supplies, also using stochastic optimization to account for uncertainty. Hong, Lejeune, and Noyan (2015) also use pre-positioning of supplies to counter uncertain demand and transportation capacities. Pre-positioning is well-established, through these and other studies, as a way to buffer the uncertainty of demand in humanitarian responses. Pre-positioning, however, can also be prohibitively expensive, and can result in wasted or expired supplies that make for angry donors and bad press for humanitarian organizations.

Partnerships with the private sector can help to reduce the risk of waste or loss, reduce costs for humanitarian organizations, and increase organizations' capacity to respond to disasters. Tomasini and Van Wassenhove (2009) argue for an increased involvement of the private sector with humanitarian response through the private sector's efficient supply chains, and Goentzel and Spens (2011) elaborate on this idea with the specific case of vendor-managed inventory for Florida's hurricane relief supplies. Goentzel and Spens demonstrate how vendor-managed inventory has saved the state of Florida money, improved its buffer capacity, and increased its ability to quickly scale up a disaster response.

LOGISTICS & RESOURCE ALLOCATION FOR EPIDEMICS

Logistics literature applied specifically to epidemics and infectious disease outbreaks is most commonly studied as resource allocation. Resource allocation for epidemic control is the optimization, typically under budget constraints, of resources dedicated to controlling an outbreak. In simpler terms, it's a study of the most efficient and effective way to spend money to control or halt an outbreak. Researchers use this to quantify and predict the impact of certain interventions on the spread of a disease. The types of resources considered vary by paper, but often include vaccines, infection prevention and control equipment, treatment facilities, and medical resources.

Table 2 contains a list of the papers considered in this review on resource allocation for infectious disease outbreaks, along with their key characteristics.

Table 2: Papers reviewed on resource allocation for infectious disease outbreaks. Table includes the resource allocated, the disease considered, and the demand forecasting mechanism utilized (where applicable) in each paper.

Author & Year	**Resource Allocated**	**Disease Considered**	**Demand Forecasting Mechanism**
Brandeau, Zaric, and Richter 2003	generally limited resource	generic infectious disease	Simple SI model – demand based on number of cases
Duintjer Tebbens et al. 2010	polio vaccines	only fully eradicated diseases	Vaccine demand depends on the stochastic risk of polio outbreak and the stock of vaccines available – as that will affect changes in vaccine demand.
Fast, González, and Markuzon 2015	evaluates based on social response disruptions as well as cost	several infectious diseases	N/A
Hick et al. 2007	ventilators	generic disaster	N/A
Jalalpour, Gel, and Levin 2015	"counts" of healthcare service needs	no disaster (generic health services forecasting)	Autoregressive moving average (GARMA) models and discrete-valued distributions
Koyuncu and Erol 2010	vaccines, ventilators, and hospital beds	pandemic influenza	Based on current case count and proportion of patients needing a resource – not predictive
Liu and Iang 2013	generic medical resources needed at	generic epidemic	Time-varying forecasting model based on predicted

	the tail end (recovered stage) of epidemic		epidemic diffusion – dynamic, but only for recovered stage of epidemic
Liu and Zhao 2012	generic medical resources needed at all epidemic diffusion stages	bioterrorism	Time-varying forecasting model based on predicted epidemic diffusion – dynamic, but only for recovered stage of epidemic
Liu, Zhang, and Zhang 2015	generic medical resources needed at all epidemic diffusion stages	pandemic influenza	Time-varying forecasting model based on predicted epidemic diffusion – dynamic, covers all stages of epidemic
Ndeffo Mbah and Gilligan 2010	disease treatments	plant pathogens	SI compartmental model – demand based on number of cases
Rachaniotis, Dasaklis, and Pappis 2012	deteriorating job loss rate and vaccines	H1N1	SIR model generates demand based on number of cases
Rainisch et al. 2015	ETU-ready hospital beds	Ebola	Demand is calculated by multiplying the rate of new infections in the US by the length of stay in the hospital
Tsao, Sun, and Liou 2015	hospital surgery	severe acute respiratory syndrome (SARS)	ARIMA analysis and historical data
Wang, de Véricourt, and Sun 2009	epidemic control measures via game theory	generic infectious disease	Demand estimated at beginning of the epidemic – is the resources required to bring R_0 down to desired level
Washington and Meltzer 2015	ETUs and Community Care Centers	Ebola	N/A
Zaric and Brandeau 2001	preventative interventions	human immunodeficiency virus (HIV)	Compartmental epidemic model – demand based on number of cases
Zaric and Brandeau 2002	epidemic control measures	endemic diseases	Compartmental epidemic model – demand based on number of cases

Most of the resource allocation models use linear programming to find an optimal solution for a specific type of disease, geography, and intervention. Brandeau (2004) advocates for the use of more simulation analysis when there are a finite set of allocation options, because of the unrealistic nature of many linear programming solutions. For long-term state epidemic equilibriums (i.e., sexually-transmitted diseases and infections), more complicated models can be useful.

For our research, we are also interested in how these studies model and forecast demand for resources throughout an epidemic. Most use constant disease transmission rates to predict the amount of resources that will be required by an outbreak, but Dasaklis, Pappis, and Rachaniotis (2012) argue that this approach is too simplistic. Their work also argues that in general, supply chain responses during an outbreak are understudied. They propose using stochastic parameters and incorporating the minimization of response time into the optimization objective function.

EPIDEMIOLOGY OF INFECTIOUS DISEASE OUTBREAKS

The majority of epidemic forecasts are generated from compartmental susceptible, infected, recovered (SIR) models and their extensions, based on differential equations. Alternative methods for predicting and describing the spread of infectious diseases have been developed, and include probabilistic statistical (Finkelstein et al. 2015), geographic spread (Rainisch et al. 2015), and mobility models (Tizzoni et al. 2014), but these are not widely used.

In epidemiological forecasting, the infectious disease spread models can be extremely complicated. When trying to use those models to generate estimates of PPE demand, there is potential for those forecasts to become unnecessarily complex. Makridakis and Hibon (2000) find that simple forecasting methods often perform as well, if not better, than sophisticated models. In the case of demand forecasting for PPE based on epidemic models, simpler solutions might be better, and might also be more realistically implemented by responding organizations.

As the 2014 West Africa Ebola outbreak is the case considered in this research, special consideration is given to epidemic models developed for or tested on Ebola viral hemorrhagic fever (also known as Ebola virus disease (EVD) or “Ebola”). Eleven papers on the epidemiology of EVD are considered in this review, and all develop approximations of disease parameters that could be used in our analysis (Barbarossa et al. 2015; Bogoch et al. 2015; Gomes et al. 2014; Gostin and Friedman 2015; Lefebvre et al. 2014; Meltzer et al. 2015; Meyers et al. 2015; Pigott et al. 2014; Poletto et al. 2014; G Rainisch et al. 2015; Rivers et al. 2014).

Two studies provide specific ways to incorporate the effects of increased infection prevention and control measures, such as PPE availability, on disease dynamics (Barbarossa et al. 2015; Rivers et al. 2014). Barbarossa et al. (2015) assume gradual changes (using time-dependent control parameters) in the hospital transmission rate after an "intervention" introducing additional protective clothing for healthcare workers. Rivers et al. (2014) also model increased infection prevention and control measures by decreasing the static hospital transmission rate.

SUMMARY & RESEARCH MODEL

Within the infectious disease epidemiology literature reviewed, the EVD model developed by Rivers et al. (2015) seems to be the most appropriate for use in our work, as it provides a way to directly incorporate the effect of improved PPE availability on the spread of the epidemic in West Africa.

Of the logistics and resource allocation for epidemic control papers considered in this review, three stand out for their specific consideration of supply chain strategies. Brandeau et al. (2007) investigate supply chain planning for bioterrorism response, He and Liu (2015) look at emergency medical logistics for general public health emergencies, and Shrestha, Wallace, and Meltzer (2010) look at the probability of shortage in U.S. national pediatric vaccine stockpiles. None of these studies, however, consider the supply chains of personal protective equipment.

Finally, despite the recent increase in publications in the field of humanitarian logistics, some relevant gaps remain. Dynamic, post-disaster inventory modeling is still under-considered, as are optimization models with objectives other than responsiveness or cost minimization (Caunhye, Nie, and Pokharel 2012). With regards to the second gap, a study by Gralla, Goentzel, and Fine (2013) found that amongst humanitarian practitioners, the scale of the response in terms of amount of cargo delivered is actually the most valued objective and that cost is the least important of the objectives considered during the initial phase of a crisis response. Though this does not imply that response scale *should* be the most important objective, it provides evidence that a cost-minimizing objective approach might not be the most relevant during a crisis. This thesis is both descriptive and normative – it seeks to provide the basis to find relevant ways to improve PPE supply chains. Studies like Gralla, Goentzel, and Fine's help to inform the relevancy of certain strategies and the likelihood that they could be used in practice, which is helpful in using the model developed here to improve supply chain response in future outbreaks.

Though there exist wide bodies of literature in epidemiology and in emergency response logistics, there is remarkably little research on the connection between the two. Some resource allocation models draw a tenuous link, but their demand forecasting assumptions are overly simplistic. Moreover, resource allocation models tend to assume perfectly reactive supply chains. They assume that as soon as a resource is needed, it is available at the location where it will be used. Humanitarian logistics literature proves that this assumption is unrealistic. In reality, there are delays and additional supply chain costs associated with certain resource allocation schemes. The supply chain strategy has a direct effect on the ability of responders to control an epidemic, particularly in the case of personal protective equipment that healthcare workers require. The demand for this equipment is affected by the spread and scale of the disease, and the supply chain's response directly affects the spread of the disease by increasing (or decreasing) healthcare worker's capacity and ability to treat patients.

The complexity of these links has not yet been investigated. To our knowledge, the consideration of PPE supply chains to determine how they affect epidemic response has never before been done. In addition, this type of study, done using an abductive research design (see Methods chapter) is also unique. This thesis seeks to fill this critical gap by connecting the PPE supply chain to the availability of PPE supplies in an outbreak, which in turn affects our ability to contain an epidemic.

Table 3: The four fields of literature analyzed and the learnings from each that are used for this thesis.

Literature field	Risk Reduction Strategies in Commercial Applications	Humanitarian & Emergency Response Logistics	Logistics & Resource Allocation for Epidemics	Epidemiology of Infectious Disease Outbreaks
Relevant learnings	Strategies for making more shock-resistant supply chains	How supply chain strategy can affect resource availability in a crisis	How resource availability can affect epidemic spread	Dynamics of an infectious disease

Table 3 shows the relevant literature and the learnings from each field that this thesis utilizes. This thesis spans all four disciplines reviewed. This review of relevant literature forms the conceptual model for developing the interview guides used in the exploratory case study (described in the Methods chapter). Interview guides are designed to investigate how these four subject areas intersected during the 2014 West Africa Ebola outbreak. This thesis uses social science research methods to develop a system dynamics model of how resource allocation of PPE in the recent Ebola outbreak was affected by its supply chain, and how PPE supply chains, in general, might affect the dynamics of an outbreak. This model can be used in conjunction with risk reduction strategies to improve future humanitarian responses.

METHODS

This chapter describes the analytical approach used to answer the research questions. First, we explain and justify the overall research design. Next, we detail the methodology used to structure, execute, and analyze the exploratory case study. Finally, we provide the modeling approach used for the simulation portion of the thesis.

RESEARCH DESIGN

This thesis seeks to answer the following two research questions surrounding PPE supply chain strategies for infectious disease outbreak response:

1. How and to what extent are epidemic forecasts used to inform PPE demand forecasts and PPE supply chain strategies, both before and during an outbreak?
2. How can the PPE supply chain be designed to respond better to infectious disease outbreaks?

The method use to answer these two questions is an abductive case study and simulation (system dynamics model), defined by Dubois and Gadde (2002) as "systematic combining," the constant and fluid movement between empirical and modeling work. In an abductive study, the researcher expands her understanding of the theory and of the empirical phenomena by oscillating between theory and empirical observations (Dubois and Gadde 2002). Abductive research is underutilized in logistics literature. This type of research is appropriate for this thesis because our objective is to uncover new phenomena. In this study, we move fluidly between the theories from the literature review, the empirical observations of the exploratory case study (described below), and the system dynamics model – to expand our understanding of each (Dubois and Gadde 2002; Kovács and Spens 2005).

EXPLORATORY CASE STUDY

An exploratory case study method is used to answer the first research question. This design is used for several reasons. First, it is used because the phenomenon explored (sudden, large demand for PPE) is rare and has only been experienced in several unique cases such as the outbreaks of SARS, avian influenza, and Ebola – infectious disease outbreaks that have strict PPE requirements for responding healthcare workers. Second, a case study is used because we want to explore phenomena for which there is no existing repository of accessible data, and for which there is no single, clear stakeholder who would have the relevant information (Yin 2009). Third, we want to ground our answers to the second research question in the realities experienced by humanitarian practitioners responding to an infectious disease outbreak, and exploratory case studies are a good way to connect a theory to the reality in which it might be applied (Edmondson and Mcmanus 2007; Stuart et al. 2002; Pedraza Martinez, Stapleton, and Van Wassenhove 2011). Finally, a literature meta-analysis conducted by Kunz and Reiner (2012) found that the case study method should be used more often in humanitarian logistics research.

The main argument against case study usage in literature has been that the results are too specifically tied to the case, and are not generalizable to other applications (Yin 1994). Abductive research hinges upon the ability of the researcher to distinguish between the particular and the generalizable components of the case (Danermark et al. 2001). This thesis only seeks to generalize the results to other contexts in which this specific type of product will be used in an infectious disease outbreak response – but the results are generalizable beyond a specific infectious disease. The insights gained on the PPE supply chain are generalizable to other (non-Ebola) infectious disease outbreaks. Therefore, a case study offers a rich perspective on this particular problem.

SYSTEM DYNAMICS MODEL

The descriptive analysis performed in the exploratory case study shows how and to what extent epidemic forecasts were used in the 2014 West Africa Ebola outbreak (also referred to as the "Ebola outbreak"). These results are then used in conjunction with supply chain theory to develop a system dynamics model that describes the PPE supply chain and its functionality during the Ebola outbreak. These results also serve to draw the boundaries of feasibility for a supply chain design that could be realistically implemented to improve epidemic response – the subject of the second, normative research question. The qualitative interviews in the case study show many phenomena present in this case that are effectively modeled by system dynamics. The information gathered in these interviews show the feedback processes, balancing loops, and time delays that were present in the PPE supply chain.

Besiou, Stapleton, and Van Wassenhove (2011) show that the methodology of system dynamics can and should be applied to research on humanitarian operations. The authors argue that humanitarian operations are dynamic, complex, and interrelated systems that are characterized by time delays and feedback loops, and therefore lend themselves well to the system dynamics approach. System dynamics has also been used extensively to model physical supply chains. Beginning with inventory management simulation in the 1960s (Forrester 1961), the system dynamics methodology has been applied to a plethora of different products and companies to gain insights about their supply chain systems (e.g., Das and Dutta 2013; Langroodi and Amiri 2016; Lehr, Thun, and Milling 2013).

System dynamics simulation is also appropriate because we seek to develop a model that realistically depicts the behavior of the PPE supply chain during an outbreak. This model can then be used to test the efficacy of certain, alternative supply chain strategies and improvements. The system is dynamically complex and involves the coordination of actors in different supply chain echelons; the purpose of the thesis is to generate insights on these interactions and propose system improvements; therefore, system dynamics is an appropriate and useful methodology (Vlachos, Georgiadis, and Iakovou 2007).

DATA COLLECTION

This research is based on the collection of both primary and secondary data (Bryman and Bell 2011). Primary data are gathered through qualitative, guided interviews with 17 stakeholders in the PPE supply chain. Secondary data on the epidemic spread and forecasts are gathered from World Health Organization (WHO) Situation Reports, other WHO resources, and the United Nations Office for the Coordination of Humanitarian Affairs' (UN/OCHA) Humanitarian Data Exchange. Secondary data on PPE forecasting methods used by the responding organizations were also acquired, often in the form of Excel spreadsheets or simple calculators used during the Ebola outbreak. Secondary data on overall response efforts, actors involved, and financial data on response activities were gathered from UN/OCHA and the U.S. Agency for International Development Office of U.S. Foreign Disaster Assistance (USAID/OFDA).

METHODOLOGY OF QUALITATIVE INTERVIEWS

The first research question is investigated through a series of qualitative interviews conducted with PPE manufacturers, medical supply distributors, and procurement officers and technical units in emergency response organizations. These interviews elicit responses that, when aggregated, can point to how connections between epidemic forecasts, demand forecasts, and supply chain strategy for PPE products operate currently and how they might be improved.

Qualitative interviews are chosen as the method for investigating this first research question for several reasons. First, qualitative interviews keep boundaries for framing a research project more open than immediate, quantitative analysis. By asking open-ended questions and avoiding the prescription of answers, we let the respondent guide the framing of the problem and allow them to be creative in generating possible solutions. Second, they reduce the inherent bias we introduce as researchers. By interviewing professionals in the industry and practitioners in the field to learn what *they* think is the functionality of the supply chain in crisis, we are able to form a framework not defined by our own biases, but rather by the reality these practitioners face.

Conducting this analysis also increases the likelihood that the results of our research are useful. To answer the second research question before conducting the context-specific analysis of this first question might result in solutions that are not feasible in practice.

INTERVIEW DESIGN

Literature on qualitative interview structures and informal discussions with colleagues inform both the structure and design of the interview. Questions are drafted based on the literature review and initial studies of the secondary data on the outbreak (see: abductive approach described in the Research Design section). These questions use language simple enough for interviewees to understand, but technical enough to signal to respondents that they should feel comfortable explaining complex parts of their job without oversimplifying their answers (Rubin and Rubin, n.d.). To draft questions with this specific language, we conduct preliminary research to gain an understanding of each organization's terminology, and use it to explain questions during the interview.

Questions are designed in a way that provide space for the respondents to answer honestly, but they are specific enough to elicit information that addresses our research question. We design questions to be broad enough that they do not narrow the answer options, yet not so specific that they prescribe what those answers are (Rubin and Rubin, n.d.).

We focus on questions that elicit the respondent's own experiences and knowledge – things they can reasonably speak to – and ask few explicit opinion questions. These opinion questions are also clustered at the end in an effort to limit the introduction of the respondent's own bias to the end of the interview. When opinions are established at the beginning of an interview, respondents will often try to structure the rest of their answers to be consistent with that original opinion (Rubin and Rubin, n.d.).

The information that each question seeks to elicit from the respondent is carefully determined as well. We draw from our lab's own operational experience running procurement activities for an organization during the 2014 West Africa Ebola outbreak (Goentzel and Heigh 2015). We look at the types of questions that research literature has asked and identify gaps in knowledge (see: Literature Review). We conduct preliminary research in the form of calls with key experts and desk research to determine what might be the most interesting and appropriate questions to ask. All of these activities inform the development of the content of each question we include in our interview guides, which can be found in the Appendix.

A semi-structured format is used for the interviews, the guiding questions in which map to the research questions created from experience, literature review, and preliminary research. The interview is split into sections, the order of which is adjusted to make the most logical sense to the respondent.

SAMPLING (INTERVIEWEES)

Respondents for the qualitative interviews were identified in two ways – snowball sampling and an important actor verification (Coleman 1958). First, several procurement and supply chain officers, medical supply distributors, and manufacturers were connected to our lab's work supporting the Ebola outbreak response. These potential respondents were contacted and asked to participate in the study. If interviewed, these respondents were asked if they knew of others who had experience with the procurement or provision of PPE during the outbreak. Those respondents were then contacted, and if interviewed, were asked the same question. Second, in a process parallel to the snowball sampling, key organizations, suppliers, and manufacturers in the Ebola outbreak response were identified, and employees at these organizations and companies (if they were not included in the snowball sample) were contacted and interviewed. These key organizations include WHO, Médecins Sans Frontières (MSF), International Medical Corps, DuPont, and 3M. Unfortunately, no representatives from MSF accepted the invitation to interview within the timeline of the thesis. In total, 17 people were interviewed for the study.

Interviews followed a protocol approved by the MIT Committee on the Use of Humans as Experimental Subjects (COUHES). A full list of interview dates, job functions, and types of respondents (anonymized) is found in the Appendix.

QUALITATIVE CODING

We use systematic, descriptive coding to create categories that help us to aggregate the data and search for patterns. In this methodology, coding categories emerge, are combined, and are eliminated as data is coded – it is a recursive and iterative process (Weston et al. 2001). We used the software package QDA Miner to code and analyze the qualitative interviews.

Descriptive codes are ones that condense, summarize, or describe data. “In Vivo” codes are ones taken directly from what the participant herself says; they are taken from a direct quote (Saldana 2009). This thesis utilizes descriptive coding for several reasons. First, English is not the first language of many of the interview participants – so word choice is not always consistent with what might be expected of native English speakers. Second, the interview respondents work in different organizations and in different functions within those organizations, so again, the wording or language is often not consistent across interviews despite them describing identical phenomena. For these reasons, descriptive coding allows us to conduct a more robust analysis of the data gathered without being limited by semantics.

Codebook Basis

The existence of the conceptual model (see: Literature Review) before coding the interviews gives us a starting point from which our Codebook is developed. First, a list of categories is generated from this conceptual model, the thesis’s research questions, notes from preliminary interviews, and the interview questionnaire itself. Sub-themes are generated within each category to delineate different types of expected responses and phenomena. Finally, codes are developed within each sub-theme that describe the phenomena the study seeks to investigate and characterize patterns we expect to emerge. Definitions for each of these codes are developed and refined. In some cases, examples and keywords are attached to a certain code to help better define how it applies to these interviews.

Testing & Adjustment

This Codebook is then applied to two representative interviews for testing – one interview with a procurement officer and one with a distributor of medical supplies. Upon using this Codebook to characterize these interviews, further revisions to the coding system are made. These changes are mainly made to clarify definitions or provide examples. One substantive change is the addition of the “product consistency” code as distinct from the “standard confusion” code. This code is added to acknowledge the difference between consistent supply of product and the ability of a product to meet a certain technical specification – this difference is not captured by the first version of the Codebook. Additional market phenomena that were mentioned several times by these representative interview respondents are also added with the “high demand” and “limited supply” codes. The category “Inventory decision-making” is created to house the codes on pre-positioning, contracts, and inventory risk. The “inventory risk” code is split into three distinct codes – “usage versatility,” “demand uncertainty,” and “holding expense” – to better characterize and delineate the interview responses.

Application to the Full Interview Set

As the remaining interview transcripts are coded, we make structural and definitional changes to the Codebook. Emergent sub-themes and codes are added to the Codebook as they develop (Saldana 2009).

Some structural changes are made to the Codebook while coding the full set of respondent interview transcripts. For example, all codes related to inventory, a key area of inquiry for the study, are combined into one category (“Inventory and procurement decision-making”). This new category and its sub-themes (“Pre-crisis” and “In-crisis”) better describe how inventory decisions are made and the realities of the consequences of those decisions.

Several codes are combined to minimize the amount of researcher inference or judgement involved in the coding of the interviews. For some sets of codes, it is difficult to determine which one (if either) fits a response. In some cases, the wording of the respondent’s answer is so ambiguous that both codes are alluded to, but neither is concretely stated. For this reason, the codes “lack of data” and “poor quality data” are combined into “data problems,” and the definition of that code is expanded to include both previous phenomena. The codes “limited supply" and "high demand" are also particularly problematic for this reason, and are combined into "supply-demand mismatch."

Definitional and nomenclature changes are made to improve the coding process and further minimize the amount of researcher interpretation. Coding definitions are adjusted to better reflect the wide spectrum and meanings of interview responses. For example, the definition of "pre-positioning" is condensed into something that makes it more meaningful for analysis. The previous definition is too broad to be useful. We do, however, expand the definition of "data problems," to include data that was problematic because it was so quickly changing throughout the crisis – an experience that is reported by several interview respondents. One final example is the definitional expansion of "improved product availability" to include the increase in global supply as a possible availability improvement.

Codes themselves are also renamed to more accurately reflect the responses of interviewees. Several examples include: the changing of "contracts" to "contract usage," "overstock" to "overstock experienced," and "competition" into "organizational competition."

In some cases, both the code name and the definition are adjusted. For instance, we change the "standard confusion" code to "specifications issues" and adjust the definition's wording to better explain what that code means. We change the definition and naming of the "cautiousness" code to better characterize the interview responses. The definition and name of "unnecessary procurement" is also adjusted, and the new name and definition can be found in Codebook Version 3 in the Appendix.

In some cases, we create entirely new codes. We create these new codes to better characterize and identify emergent patterns in the interview data, as well as to streamline the coding and analysis process. We add the code "ordered max available" after noticing that this particular inventory policy was mentioned by several interview respondents. It is an unexpected phenomenon, more extreme than we anticipated, and therefore we want to capture it. We also add a "quotes" code for our own, internal usage. We use this code to mark meaningful quotes that capture the essence of what a respondent was communicating.

After each of these changes is made, the previously coded interviews are re-coded and re-analyzed under the framework of the new Codebook. This iterative process results in our final

Codebook (Version 3), which can be found in the Appendix. Though the repetitive, reflective nature of this process should eliminate some bias, one limitation of the coding process we use in this study is that the coding is done almost entirely by one person, with limited feedback from a larger team. This lowers the chance of coding discrepancies or definitional confusion, but increases the likelihood of more rooted biases in the coding process (Saldana 2009).

METHODOLOGY OF SYSTEM DYNAMICS MODELING

System dynamics is a methodology created to analyze complex systems. It is a structural, behavioral way to represent a system – the system is represented by its interactions (J. Sterman et al. 2015). System dynamics is useful for capturing the interactions of different actors within a system that is typically characterized by time delays and feedback loops. Time delays are situations in which an output lags by some amount of time behind an input. Feedback loops are sequential series of cause and effect such that a change in one variable eventually comes back around to affect that variable (Besiou, Stapleton, and Van Wassenhove 2011).

A system dynamics model typically incorporates some combination of feedback loops, stocks, and flows (J. D. Sterman 2000; Forrester 1961). The stocks and flows represent the physical interactions of the system – in this case, for example, the transfer of PPE from a manufacturer to a distributor. The feedback loops represent the interactions of supply chain actors and their decision-making with the physical system. These loops represent how actors' decisions are affected by, and how they affect, the physical system (J. Sterman et al. 2015).

To analyze this case and generate insights about a supply chain's interaction with epidemic response, we develop a system dynamics model. First, we develop a base model that describes the ideal (not realized) supply chain functionality during an epidemic response. This model is adapted directly from relevant supply chain literature (e.g., Georgiadis and Besiou 2008). After the base model is developed, we incorporate the feedback mechanisms and phenomena identified in the interviews into the model, and show how the supply chain functioned in reality. The development of this model is presented in the System Dynamics Model chapter.

EXPLORATORY CASE STUDY

In this chapter, we first give a thorough contextual overview of the 2014 West Africa Ebola outbreak – the case study used in this analysis. We then present the results of the qualitative interviews using qualitative coding analysis (see: Methods). In the final section, we analyze and discuss those results and how they inform the subsequent modeling effort.

2014 WEST AFRICA EBOLA OUTBREAK

This section provides relevant background information on the Ebola virus disease, the 2014 West Africa Ebola outbreak, key actors in the humanitarian response to that outbreak, the importance of PPE to the response, and the possibility of a similar outbreak in the future.

EBOLA VIRUS DISEASE

The Ebola virus disease (EVD), sometimes referred to as Ebola hemorrhagic fever, is first transmitted to humans from wild animals. There are five identified species of Ebola virus: Zaire, Bundibugyo, Sudan, Reston, and Taï Forest. The largest outbreaks in history have been due to the first three virus species, and the 2014 outbreak in West Africa was an outbreak of the Zaire species. After transmission from animals, the virus can then be transmitted between humans through contact with secretions, bodily fluids, or contaminated materials. Contact with the body of a deceased person who was infected with EVD can also transmit the virus (WHO 2016b).

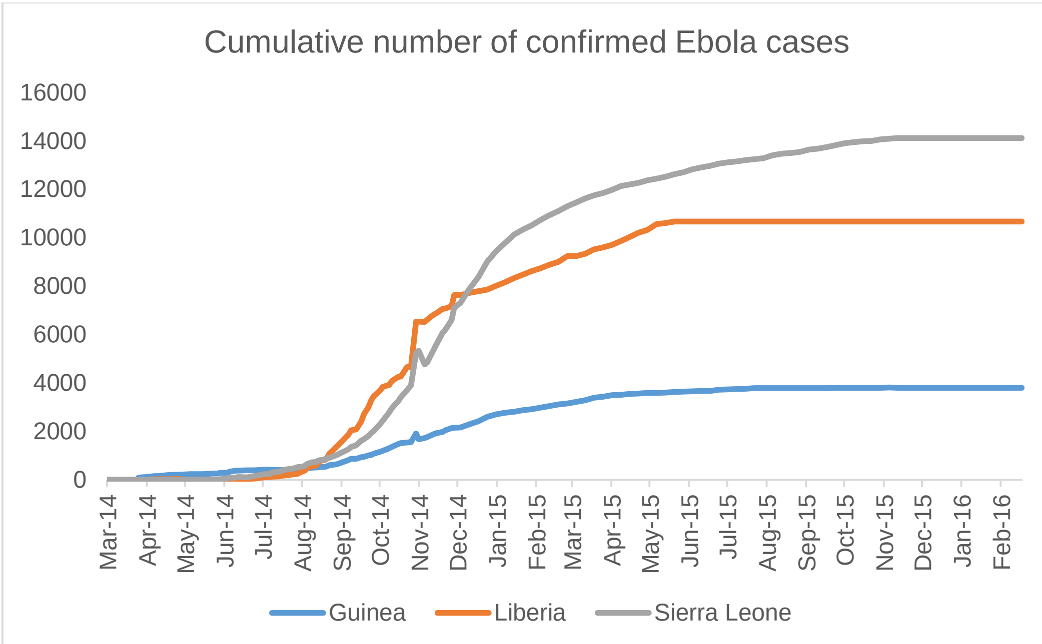
Infected individuals are not contagious until the onset of symptoms, which happens between two and 21 days after infection (the incubation period). Symptoms of EVD are similar to other febrile diseases like typhoid and malaria, and can include fever, fatigue, muscle pain, headache, sore throat, vomiting, diarrhea, rash, and internal and external bleeding. Diagnosis of EVD requires laboratory testing of fluid samples, which itself poses an extreme biohazard risk. There is not yet a cure or a vaccine for EVD, though two vaccine candidates have passed Phase I clinical trials with promising results (WHO 2015b). Once infected, patients receiving care are rehydrated, specific symptoms are treated, and they are monitored until they recover. According to WHO, containment of an EVD outbreak requires activities such as safe burial practices, contact tracing and monitoring, quarantine of infected patients, and good hygiene – all of which require the use of appropriate PPE (WHO 2016b).

Prior to the outbreak in West Africa, Ebola was not unknown. The Centers for Disease Control and Prevention (CDC) reports 29 distinct outbreaks of the Ebola virus in humans, primarily in Central and East Africa, beginning with the first documented outbreak in 1976.[1] EVD predominantly affected rural populations, limiting the spread of the virus. The maximum number of infected individuals in any outbreak prior to 2014 was 425, during an outbreak of the *Sudan virus* in northern Uganda in 2000-2001. The case fatality rate for this outbreak was 53%. The primary means of human transmission was through traditional funeral practices and through medical care of EVD patients without adequate protective measures (CDC 2015b).

OUTBREAK IN WEST AFRICA

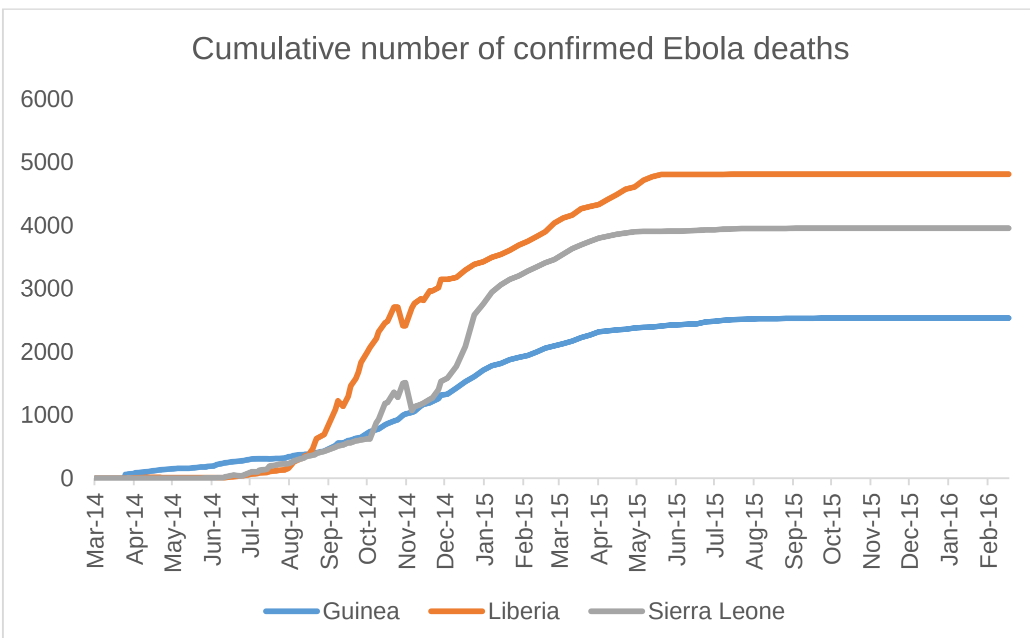
This Ebola outbreak was the largest in history; the number of infected individuals was larger than that of all previously documented outbreaks combined. It began in Guinea near the border with Sierra Leone and Liberia, and travelled to both of those countries as well as Nigeria, Spain, the United States, Senegal, and Mali (WHO 2016b). The cumulative reported case counts of the three most affected countries are seen in Graph 1.

[1] One additional outbreak took place simultaneously with the 2014 West Africa outbreak. This was an outbreak of the *Ebola virus* in Democratic Republic of Congo, from August to November 2014. It infected 66 individuals and had a case fatality rate of 74% (CDC 2015b).



Graph 1: The total reported suspected, probable, and confirmed cases in Guinea, Liberia, and Sierra Leone provided in WHO situation reports beginning on March 25, 2014 through the most recent situation report on February 17, 2016. Data compiled by CDC.

The cumulative reported death counts of the three countries are seen in Graph 2.

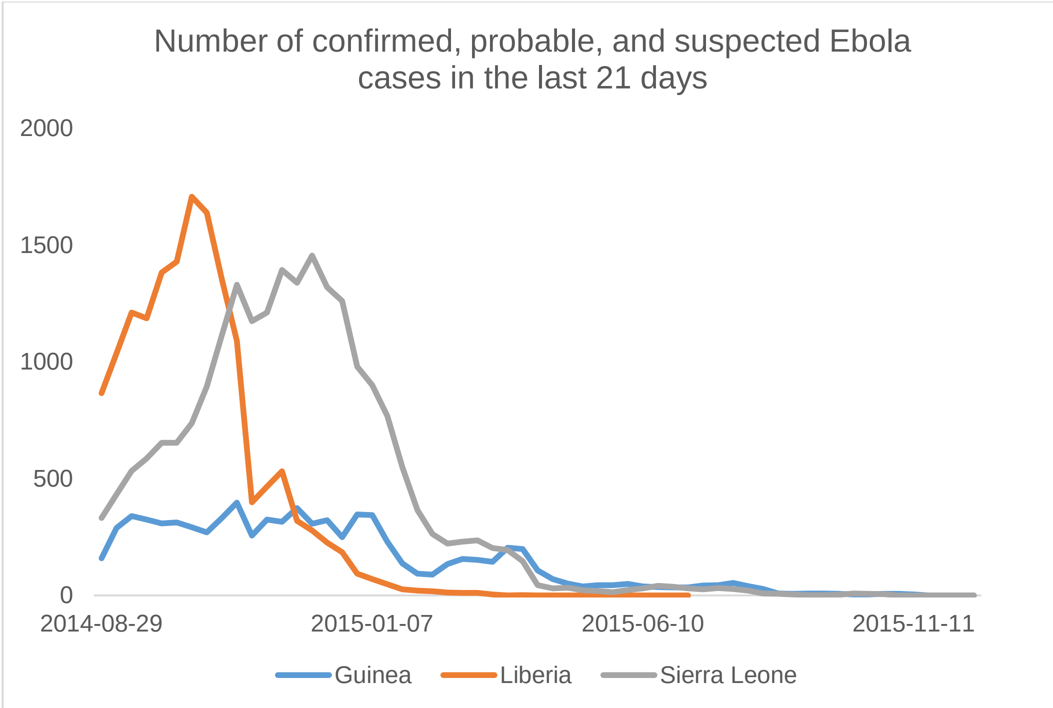


Graph 2: The total deaths caused by Ebola in Guinea, Liberia, and Sierra Leone provided in WHO situation reports beginning on March 25, 2014 through the most recent situation report on February 17, 2016. Data compiled by CDC.

The EVD epidemic began in rural Guinea in late 2013. Lack of detection of the virus led to its spread to the neighboring countries of Sierra Leone and Liberia. MSF deployed teams to the affected region to treat and contain the disease. In March 2014, Guinea and Liberia confirmed Ebola outbreaks to WHO. By the end of March, EVD had reached Conakry, the populous capital city of Guinea. By the end of May, EVD had been confirmed in the capital cities of both Liberia (Monrovia) and Sierra Leone (Freetown), and Sierra Leone officially declared an Ebola outbreak to WHO (Moon et al. 2015).

In June, MSF was calling the situation “out of control” and was asking for increased international help (Medecins Sans Frontieres 2014). The lack of international attention continued. One report published in *The Lancet* attributed this to failures in political leadership, the lack of WHO technical capacity in the affected countries, and WHO’s failure to mobilize global assistance despite evidence that the affected countries’ capacities had been overwhelmed (Moon et al. 2015). The WHO Director-General declared the outbreak officially a Public Health Emergency of International Concern (PHEIC) on August 8, 2014 (WHO 2016b). On September 26, 2014, CDC released an alarming forecast that detailed several hypothetical scenarios in which hundreds of thousands of people were infected (Meltzer et al. 2015).

The historical epidemic curve as measured by the number of EVD cases in the previous 21 days (the incubation period) is shown for the three most affected countries in Graph 3. The peak of the epidemic in Liberia occurred in late September, while the peak in Sierra Leone occurred in December of 2014. In total, the epidemic infected more than 28,000 people and left more than 11,000 dead (WHO 2016a).



Graph 3: The cumulative number of confirmed, probable, and suspected Ebola cases in the previous 21 days in three most affected countries. Data taken from Humanitarian Data Exchange.

KEY ACTORS IN THE RESPONSE

According to UN/OCHA, by November of 2014 there were 127 international non-governmental organizations (NGOs) responding to the Ebola crisis in some way – through contact tracing, treatment, triage, social mobilization, food distribution, water and sanitation assistance, health system support, etc. (UN Office for the Coordination of Humanitarian Affairs 2014). Though all of these activities are critical to the containment of EVD and many require the use of adequate and appropriate PPE, there were several organizations whose operations required PPE procurement on a notably larger scale, or who worked with NGOs and governments to coordinate operations on a larger scale. MSF and WHO are two of these key actors.

In March 2014, MSF became the first major international actor to establish operations treating EVD patients in Guinea, Sierra Leone, and Liberia. They established Ebola Treatment Unit (ETU) facilities[2] in all three countries. At the peak of their operations, MSF employed over 4,000 national and 325 international staff to fight the epidemic (Medecins Sans Frontieres 2016). MSF was (and is) seen as the lead operational organization in EVD response because of their

[2] Sometimes called Ebola Treatment Centers (ETC).

experience combating the disease. MSF conducted many of the trainings and offered technical guidance for clinicians treating EVD patients.

WHO was the lead coordination agency for the UN's response after it declared a PHEIC in August 2014. The UN Security Council unanimously voted on September 18, 2014, to establish a more operational body – UN Mission for Ebola Emergency Response (UNMEER) to fight the disease (*The Liberian Observer* 2014). WHO and UNMEER coordinated the activities of responding organizations, offered technical guidance, managed disease surveillance, and worked closely with the affected countries' ministries of health.

Other important actors who procured large volumes of PPE were those operating ETUs during the crisis. These actors included International Medical Corps (IMC), Save the Children, China CDC, International Federation of the Red Cross (IFRC), Samaritan's Purse, Heart to Heart International, International Rescue Committee (IRC), Oxfam, United Nations Children's Fund (UNICEF), International Organization on Migration (IOM), and several countries' ministries of health. These facilities were often funded by governmental aid organizations such as the U.K. Department for International Development (DFID) and USAID/OFDA. The U.S. Government alone provided over $2.3 billion in humanitarian funding to fight the EVD outbreak (USAID/OFDA 2016).

PERSONAL PROTECTIVE EQUIPMENT

Infection prevention and control (IPC) is critical to the effective containment of EVD. PPE is one component of IPC, and is especially critical for healthcare workers caring for suspected, probable, or confirmed Ebola patients. Patients often arrive at non-ETU healthcare facilities initially, so it is important that all healthcare workers – in hospitals, clinics, and ETUs – have adequate PPE.

The PPE "kit" used for EVD protection varies depending on the organization, healthcare facility, level of protection, and user. All PPE used for protection from EVD infection, however, includes some combination of the following items: examination gloves, surgical masks, face masks, coveralls, hoods, boots, heavy duty gloves, gowns, aprons, face shields, goggles, surgical tunics, surgical trousers, alcohol rub, chlorine, surgical caps, biohazardous disposal bags, and cadaver bags.

According to WHO:

> "Health-care workers caring for patients with suspected or confirmed Ebola virus should apply extra infection control measures to prevent contact with the patient's blood and body fluids and contaminated surfaces or materials such as clothing and bedding. When in close contact (within 1 metre) of patients with [Ebola virus], health-care workers should wear face protection (a face shield or a medical mask and goggles), a clean, non-sterile long-sleeved gown, and gloves (sterile gloves for some procedures)" (WHO 2016b).

Due to several factors – the magnitude and geographical scope, the lack of adequate IPC training for healthcare workers, the lack of adequate IPC materials, etc. – healthcare workers in the 2014 West Africa Ebola outbreak suffered increased rates of EVD infection when compared with previous EVD outbreaks (WHO 2014g). In 2014, 7.9% of laboratory-confirmed or probable Ebola cases in Guinean adults were in healthcare workers – an infection incidence 42.2 times higher than the rest of the population (CDC 2015a). In Sierra Leone, healthcare workers were infected at 103 times the general population incidence rate (CDC 2014a). The infection of healthcare workers further breaks down health infrastructures in affected countries that are critical to halting the spread of EVD, and also discourages foreign medical workers from coming to assist (WHO 2014g).

TECHNICAL SPECIFICATIONS FOR PPE

Before and during the crisis, various organizations released guidance on the use of PPE for protection against EVD. The most well-known and oft-utilized documents came from MSF, CDC, and WHO. MSF's guidelines for responding to Filovirus hemorrhagic fevers were published in a 2008 document that outlined almost every activity that needs to be done to respond to an outbreak of this kind (Sterk 2008). CDC and WHO PPE guidelines were updated throughout the crisis (e.g., CDC, n.d.; CDC 2014b; WHO 2014d; WHO 2014b; WHO 2014; WHO 2014c; WHO 2015; WHO 2014a; WHO 2014g; WHO 2014e). Other organizations such as UNICEF also published their own technical guidelines during the crisis (e.g., UNICEF Programme Division 2014; UNICEF Supply Division 2014c; UNICEF Supply Division 2014b; UNICEF Supply Division 2014a). Manufacturers of PPE also published guidelines on how their own products met technical specifications needed for effective EVD protection (e.g., 3M

Personal Safety Division 2014; DuPont 2014; Kimberly-Clark Professional 2014; Lakeland 2014; MedLine 2014a; MedLine 2014b).

WHO's most recent guidance on infection prevention and control for healthcare workers in an EVD-present setting was released in December of 2014. This document includes IPC guidance for general and direct patient care, environmental cleaning, waste management, and non-patient care, all of which are critical to preventing the spread of EVD. It includes instructions for donning (putting on) and doffing (taking off) PPE, utilizing proper hand hygiene, and making chlorine solutions for disinfection (WHO 2014c).

FUTURE RISKS

Though the likelihood of another Ebola outbreak on the same scale is low, it is probable that there will be another global outbreak of a virus that requires the use of PPE in its containment. Figure 1 shows the 2015 global risk landscape as taken from World Economic Forum data, created by the Internal Displacement Monitoring Centre. The spread of infectious disease ranks high in impact, second only to water crises. It outranks energy price shocks and weapons of mass destruction in likelihood (Ginetti, Lavell, and Franck 2014). Though the threat of Ebola in West Africa appears to have subsided, the threat of another devastating epidemic remains.

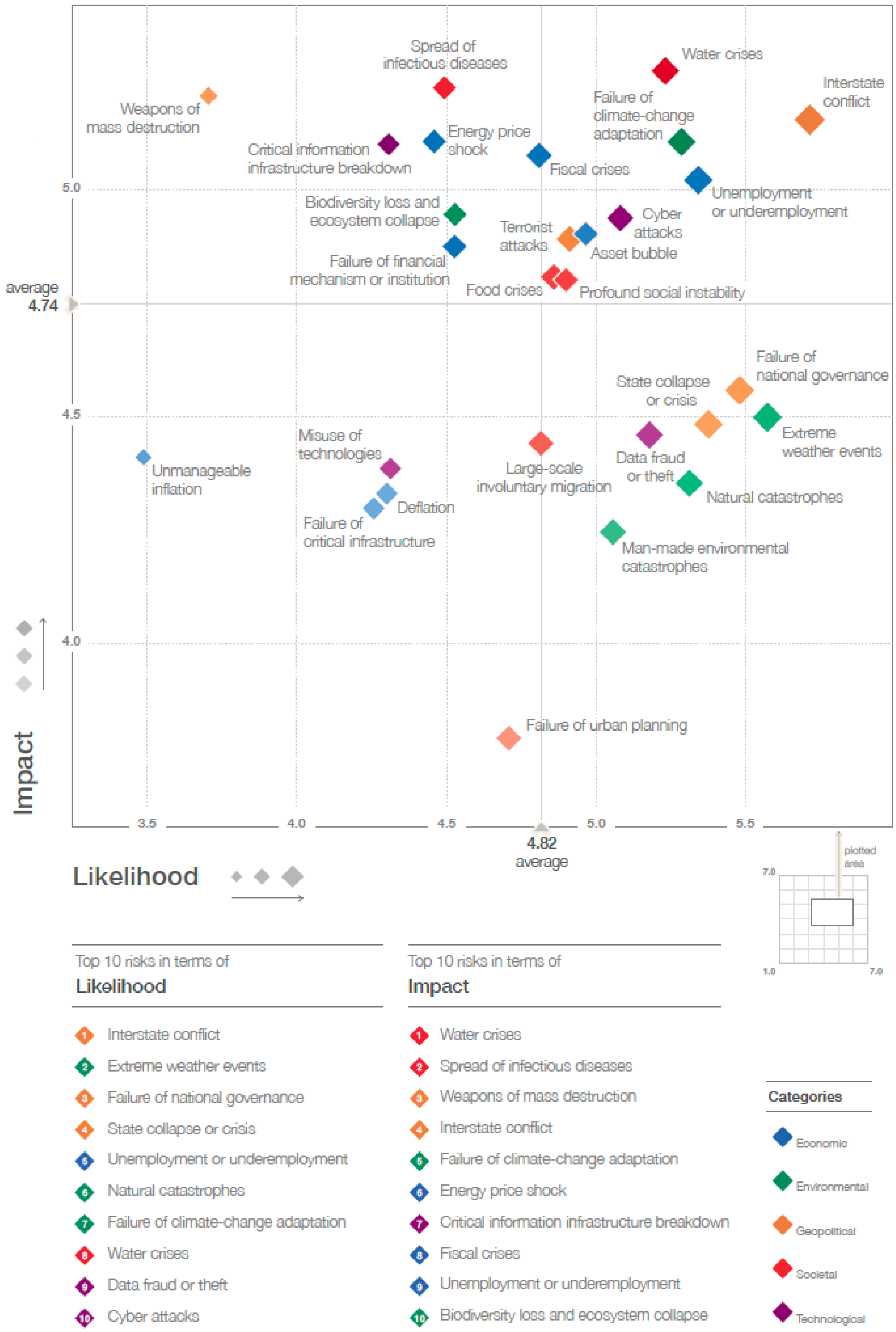


Figure 1: Global risk landscape (2015) as taken from World Economic Forum data, created by the Internal Displacement Monitoring Centre.

RESULTS OF QUALITATIVE INTERVIEWS

This section details the results of the qualitative interviews. The structure of the PPE supply chain is described first. Then, the decision-making processes of interview respondents are reported. Next, we report findings on the causes and effects of problems in the PPE supply chain as a whole. Finally, we describe how respondents reported that they would improve future outbreak responses.

THE PPE SUPPLY CHAIN

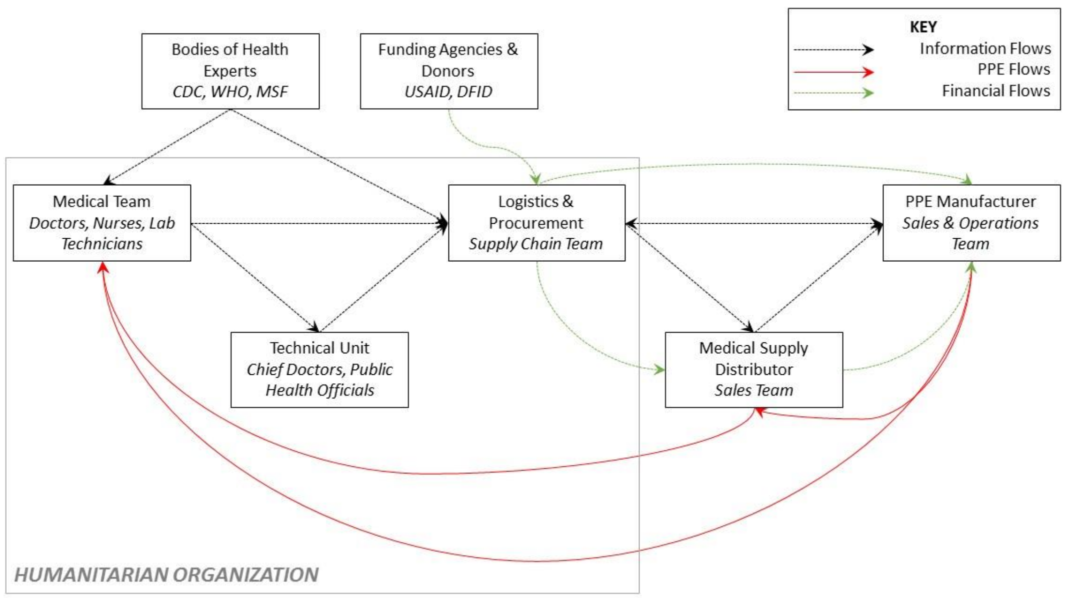


Figure 2: Generalized diagram of the key actors in the PPE supply chain and their interactions. Figure shows the financial, information, and material (PPE) flows that made up the PPE supply chain during the response.

The structure of the PPE supply chain came to light in the interviews. See Figure 2 for a generalized diagram of the financial, information, and material flows that made up the PPE supply chain during the response, taken from responses given in the interviews. At least one interviewee came from each type of actor in the diagram.

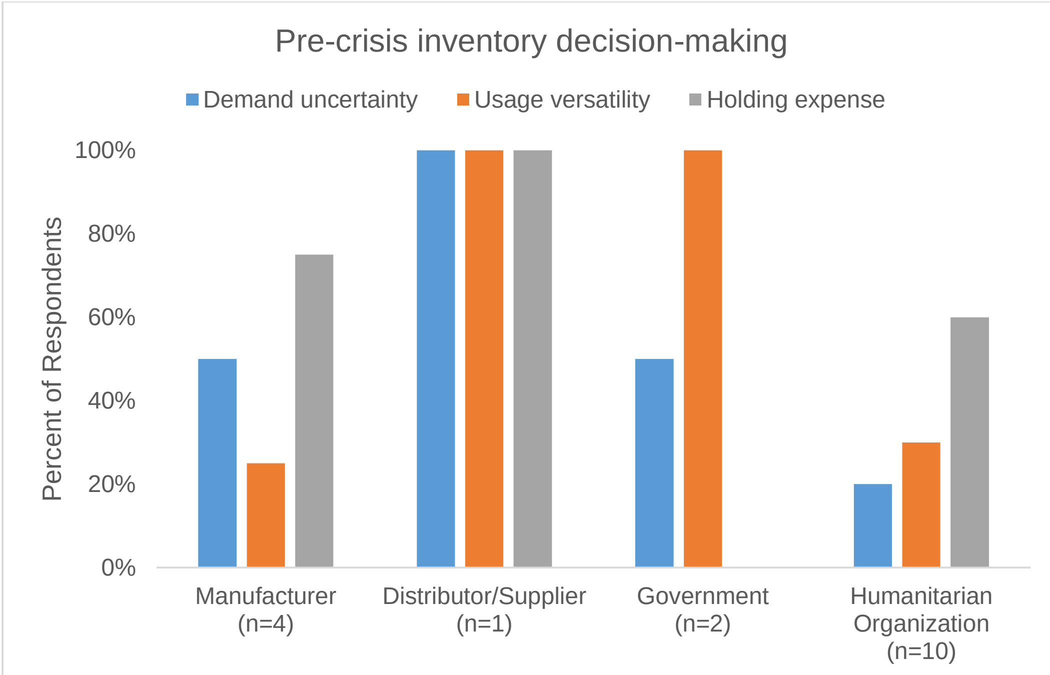
The information flows in the diagram represent a generalized version of the forecasting, planning, and technical standard-setting processes that took place. Medical teams began the process by working with a technical unit (or directly with the procurement team) to estimate their own PPE needs for providing medical care. This process was often informed by specifications for appropriate protective equipment that were provided by bodies of health experts. Then, the logistics team combined this information with estimates of epidemic spread adapted from CDC or WHO predictions to generate a demand forecast. Using information provided by the PPE manufacturers about the technical specifications of specific suits as well as guidelines for appropriate protection provided by CDC, WHO, and MSF, the logistics team then placed an order with either a medical supply distributor or a manufacturer. The material flows in the diagram represent the physical shipment of PPE from the manufacturer to the medical team on-the-ground in West Africa, sometimes going through a medical supply distributor. The financial flows show the interaction of the PPE supply chain with funding agencies and major donors who provided capital for humanitarian organizations to purchase PPE.

DECISION-MAKING IN THE PPE SUPPLY CHAIN

The focus of the research question answered by this case study concerns the use of epidemic modeling to generate forecasts for PPE. This question, however, occupies space in the larger context of decision-making in the PPE supply chain. This larger context is described first. The interview data describes this context for the time periods before the 2014 West Africa Ebola outbreak (for all products) and during the outbreak (for PPE specifically).

Pre-crisis decision-making

Respondents were asked about their general (non-crisis) inventory and procurement strategies. Graph 4 shows the percentage of certain types of supply chain actors who indicated that they used three different inventory decision-making criteria. The distributor respondent factored in all three criteria into his decision-making on inventory. Three out of four manufacturer respondents made inventory decisions based on holding expense while only one of them considered the usage versatility of the item. All of the government respondents interviewed, however, factored in usage versatility.

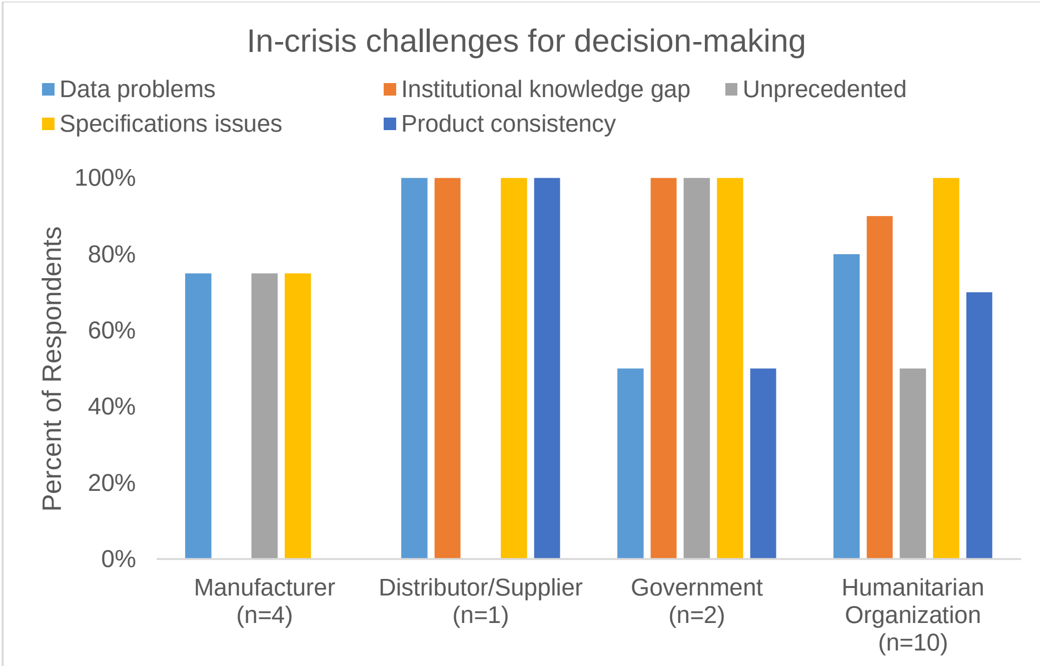


Graph 4: The percentage of certain types of supply chain actors who indicated that they used three different criteria when making decisions about inventory, before the 2014 West Africa Ebola outbreak.

Many actors reported using contract and pre-positioning mechanisms to make supply chains more able to respond to spikes in demand. The distributor used contracts but did not pre-position PPE because it primarily served humanitarian organizations who did not place large orders for PPE (before the 2014 Ebola crisis). Humanitarian organization respondents mentioned contract usage more frequently (7 out of 10 respondents) than PPE pre-positioning, which was only mentioned by one of the 10 respondents. The most commonly mentioned contracts were blanket purchasing agreements, vendor-managed inventory agreements, and options contracts. One interesting thing to note is that several respondents only had PPE pre-positioned because it was left over from the avian influenza outbreak.

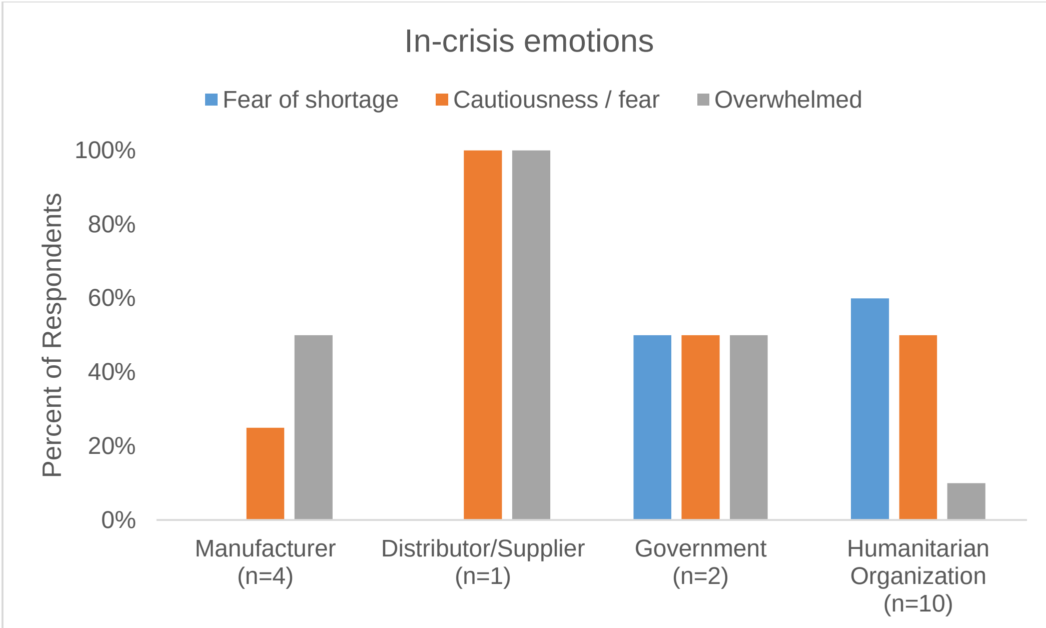
In-crisis decision-making

During the crisis, a variety of factors altered the decision-making processes of actors in the PPE supply chain.



Graph 5: The percent of respondents, by type of supply chain actor, who mentioned five different types of information gaps and challenges that affected their decision-making during the 2014 West Africa Ebola outbreak.

Graph 5 shows the percent of respondents, by type of supply chain actor, who mentioned five different types of information gaps and challenges that affected their decision-making. The data problems discussed by respondents included: lack of data, inability to access data, lack of knowledge about where data resides, poor quality or consistency of data available, and/or data that was changing too quickly. Data problems were mentioned by 13 out of the 17 respondents a total of 30 separate times. They were mentioned by a higher percentage of humanitarian organizations than government respondents. An institutional knowledge gap, defined by a respondent's indication that there was a lack of knowledge within their organization or a newness of operations for their organization, was mentioned by all respondents except for the manufacturer respondents and one humanitarian practitioner. The outbreak was described as unprecedented or unexpected in 10 of the 17 interviews. Specifications issues were also mentioned frequently, by 16 out of 17 respondents in 49 separate instances. As is evident in the graph, the only respondent who did not mention confusion or difficulty around the technical product standards was one of the manufacturer respondents. Finally, product consistency, defined as maintaining a standard and consistent supply of a *specific PPE product* was mentioned frequently by actors other than the manufacturers.



Graph 6: The percent of respondents who mentioned three different types of emotional responses to the crisis.

Graph 6 shows the percent of respondents who mentioned three different types of emotional responses to the crisis. The fear of a PPE shortage was mentioned by six humanitarian respondents and one government respondent but was not mentioned explicitly by any manufacturer or distributor respondent. A cautious mentality or approach to the response, often driven by fear, was mentioned by actors across the supply chain. The percentage of manufacturers, distributors, and government actors who mentioned feeling overwhelmed by the outbreak (4 out of 7 respondents) was much higher than the percentage of humanitarian practitioners who felt overwhelmed (only 1 out of 10 respondents).

Several interesting procurement decisions were made during the crisis by government and humanitarian actors. Seven out of 10 humanitarian organization respondents indicated that at some point during the crisis their organization followed MSF's procedures, procurement guidelines, or technical specifications. One government actor also mentioned following MSF guidelines at some point during the response. Three out of 10 humanitarian organization respondents mentioned that their ordering policy at some point during the crisis was to procure the maximum amount of PPE they could find.

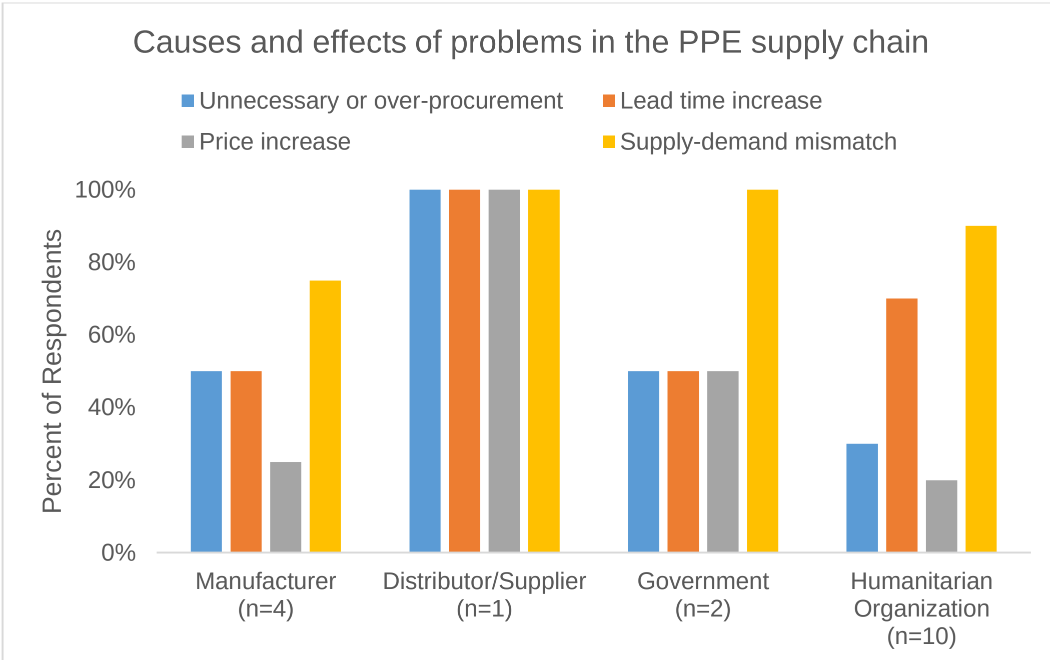
Use of epidemic forecasts (RQ1)

Within this larger context of decision-making in the PPE supply chain, a key research question this study sought to answer was around the use of epidemic forecasting models to make decisions about procurement. Both manufacturer respondents, six out of 10 humanitarian practitioner respondents, and one government respondent indicated that they used models of epidemic spread to generate estimates of PPE demand. The extent to which forecasts were used varied between actors. Humanitarian organization respondents indicated that usage conditions and the factors mentioned here were critical to their forecasting process – in many cases, more critical than epidemiological forecasts.

CAUSES & EFFECTS OF PROBLEMS IN THE PPE SUPPLY CHAIN

The supply chain issues experienced by individual actors varied, but overstocks of PPE were experienced by 10 respondents and PPE shortages were experienced by 11 respondents. A shortage *and* an overstock was experienced by five respondents. Competition in procurement between a respondent's organization and another responding organization was experienced by six out of the 10 humanitarian organization respondents.

At a global level, respondents mentioned several phenomena that affected the PPE supply chain during the outbreak. Graph 7 shows the percent of different types of supply chain actors who mentioned unnecessary or over-procurement by non-responding organizations and governments, lead time increases, price increases (for the product itself and/or for transport to affected areas), and global mismatches in the supply of PPE and the demand for it. Supply chain stress was mentioned frequently in the interviews. The mismatch between supply and demand of PPE was the most commonly cited phenomena in the study, mentioned 64 separate times and in 15 of the 17 interviews. The lead time increase was another frequently-coded phenomena, coded 25 times in 11 different interviews.



Graph 7: the percent of different types of supply chain actors who mentioned unnecessary or over-procurement by non-responding organizations and governments, lead time increases, price increases, and global mismatches in the supply of PPE and the demand for it.

FUTURE OUTBREAK RESPONSES

At the end of the interview, respondents were asked what they would do differently, or what they would ask the "system" of the PPE supply chain to do differently, in the next infectious disease outbreak. Across all types of supply chain actors two responses were common. First, 11 respondents mentioned that an increased global supply of PPE, or an increased ability of the PPE manufacturers to respond to a demand spike, would drastically improve a future response effort. Second, nine respondents indicated that their organizational experience in responding to the Ebola outbreak would help them to better respond to future epidemics.

DISCUSSION OF EXPLORATORY CASE STUDY RESULTS

DECISION-MAKING IN THE PPE SUPPLY CHAIN

Upstream sophisticated, downstream cost-driven

Holding expense was not reported as a key factor to inventory decisions made by government respondents. Humanitarian organizations, however, reported making inventory decisions based on holding expense twice as often as on usage versatility. This makes intuitive sense, as cost is often the limiting factor for these organizations. As a general trend, the actors further upstream in the supply chain utilized more sophisticated inventory and procurement decision-making models that incorporated multiple objectives and used contracting mechanisms to achieve those objectives. Downstream actors tended to be more focused on avoiding the upfront cost of holding excess inventory.

Data issues and supply chain position

Data problems were a key barrier to mobilizing the supply chain, but the types of problems respondents mentioned varied based on their position in the supply chain.

Manufacturers reported issues with delays in data – delayed orders from organizations made it more difficult for them to respond quickly. Some PPE manufacturers also mentioned that they received the same order (for the same eventual recipient) from multiple sources, and that they had to spend time validating and verifying orders from organizations before they could process them.

Humanitarian organizations struggled most with estimating PPE needs (sometimes based on epidemic forecasts) and the associated PPE "burn rates," or the rate at which a certain item is being used. Several respondents talked extensively about how these burn rates were difficult to determine because their organization had not responded to Ebola before. The burn rate used by MSF originally was based on a 10-bed ETU. But in this case, burn rates don't scale linearly – a 20-bed ETU does not need twice the materials that a 10-bed ETU does, even if both are operating at full capacity. For example, a child patient requires more attention than an adult patient, and needs more visits by healthcare workers each day. An ETU full of children would likely have a higher burn rate than an ETU full of adults. Another example is that a more experienced healthcare worker might be able to stay in the ETU longer than a less experienced worker, and therefore would use less PPE per day. Panic and fear also affected burn rates. Some healthcare workers were uncomfortable reusing some of the sterilized, reusable items in a kit, further increasing burn rates. Factors such as the reusability of an item, the healthcare worker's experience level, the type of healthcare facility, fear, climate and environmental factors, patient status, and patient age all affect a PPE burn rate estimation.

PPE consumption rates were difficult to track, making these burn rates difficult to determine even after there should have been data available to update the estimation. Respondents said things like "there was no hard data to back anything up" and "it was really a complete guessing game" when asked about their reliance on data to inform their procurement decisions. The importance of these usage conditions and other factors in the PPE forecasting process is an unexpected, yet critically important, answer to the first research question.

The government actors mentioned problems with data less often than other types of supply chain actors. Because the government actors were located centrally in the supply chain – interfacing on either side with many humanitarian organizations and many distributors or manufacturers – they likely had the most access to information in the PPE supply chain.

Perspectives on operational "newness"

Almost every respondent except for the manufacturers reported a gap in institutional knowledge when responding to the outbreak. The size and scale of the outbreak were new to most respondents, and the type of operation was new to most of the humanitarian respondents. This newness made forecasting difficult, as organizations had little to no experience upon which they could base their estimates.

For the manufacturers, the Ebola outbreak was unprecedented in size, but their business did not change significantly. They operated serving higher volumes on tighter timelines than usual, but they did not have to learn radically new skills to supply PPE to organizations. Manufacturers often compared their experiences during the Ebola crisis to their operations during previous crises such as the SARS outbreak, Middle East respiratory syndrome (MERS) outbreak, the Gulf oil spill, and the Fukushima earthquake and nuclear disaster. Only one of the humanitarian organization respondents made a similar comparison.

This difference in perspective was evident in the interviews and is bolstered by the fact that no manufacturer respondent talked about a gap in their knowledge, despite the unprecedented nature of the Ebola outbreak. The outbreak itself was new, but their operations remained similar to previous spikes in demand. For humanitarian organizations on-the-ground in West Africa, however, their operations were completely new. They were often used to responding to natural disasters or conflict-affected populations; many did not have infectious disease expertise and even if they did, they had never before responded to a viral hemorrhagic fever. One respondent outlined this plainly: “I learned a lot during the Ebola outbreak; there are all these different types of gloves!”

PPE comfort, standardization, and consistency – finding a balance

This organizational inexperience was complicated by the confusion around PPE product standards and specifications. Humanitarian organization respondents often mentioned frustration with the conflicting, evolving set of standards issued by international health bodies. These respondents spent much of their procurement efforts determining (a) the appropriate protection standard and (b) which products met that standard. One respondent, talking about these humanitarian organizations, stated that:

> “The real confusion was that they didn't understand the standards or the existence of the standards. The real issue was that the key influencers like the CDC or the WHO had not set specifications referencing the standards in the first place… the guidance documents were wrong.”

Several respondents also mentioned the balance between protection and comfort. Given the hot and humid climate in West Africa during the peak of the outbreak, some PPE with high levels of laboratory-tested protection offered too little breathability and were not wearable in the climate.

Respondents often reiterated the importance of keeping their healthcare staff safe and the time they spent determining which products would do so. The key to healthcare worker safety was not just an effective PPE kit, but maintaining a steady supply of the *exact* items in that kit so that the healthcare workers’ training still applied. Because most of the Ebola infections in healthcare workers occurred during donning and doffing, it was critical to ensure that the items in an organization’s PPE kit did not change throughout the crisis. Many respondents emphasized the importance of this product consistency.

The challenge of balancing protection, comfort, and consistency was summarized well by one respondent who stated that “those two conversations are different (technical and practical), and a scientific study that says whether something works or doesn't work doesn't necessarily speak well to a person's need to know they're protected to the best level possible, given what they know, and that it's an acceptable level of risk, given the risk of not stepping in and doing something."

One major difference between supply chain actors and their view of product specifications was that humanitarian organizations all spoke in terms of "PPE kits," but distributors noted that "kits" varied widely depending on organizational preference. Organizations also had different methods of classification for high and low risk, further complicating the procurement process. For example, one humanitarian organization called kits either "clinical" or "cleaner," while another used the terms "Risk 1" and "Risk 2," while still another used "Low-risk" or "High-risk."

Value of in-crisis experience

The emotions surrounding decision-making also varied by supply chain actor in several interesting ways. Intuitively, shortages were only feared by actors who would have seen those shortages firsthand – the humanitarian organizations and government actors. Despite fearing shortages, humanitarian respondents did not frequently report being overwhelmed by the crisis. Humanitarians execute operations with few resources and overwhelming human need all the time. Other supply chain actors, however, might not be as accustomed to this type of event and were more overwhelmed by it. Even though the humanitarians' gap in knowledge was more severe and they were more cautious, they were not overwhelmed by the crisis. One might expect that further up the supply chain decision-making is less emotional, but these data indicate that even at the manufacturer level actors were overwhelmed. Given their lack of an institutional knowledge gap, however, we can see that this was not due to their operation having to change, but rather it was due to the severity of the humanitarian emergency. One manufacturer stated:

> "The biggest frustration is that you see the need, it's the business that you're in to help people protect themselves from harm, and you have people wanting desperately to do business with you and you can't turn the levers fast enough. It's not like I've got this great big machine and I turn the knob and that if I run it and expand it slightly I can get this huge amount of incremental supply off of it in a really short period of time. It's the opposite, you turn the knobs and it takes six weeks to get people really good at making it… You feel, I don't want to say 'helpless,' that's too strong of a word, you feel disappointed that there's not more at that point that you can do."

Healthcare worker safety as the ultimate goal

The complexity of the calculations and the challenge of maintaining a safe and consistent product line, combined with the emotional stress of the situation, led many actors within the supply chain to make conservative decisions. Many organizations followed MSF guidelines, which called for extremely high levels of protection and very specific product lines. Many respondents talked extensively about how they knew these were excessive, but they were all they could trust because MSF was the only organization with experience responding to EVD. As one respondent stated, “we were taking our technical basis from MSF because they were the group that had the most significant experience with actually fighting Ebola, actually treating Ebola in the field… they had a proven track record and they were saying 'we've used this before and we know this would work.'”

Another conservative decision driven by the lack of information and the emotionally stressful environment was for procurement officers to purchase as many of an item as they could find, which several humanitarian respondents reported. In almost all of the interviews, when respondents were asked about the decisions they made, they cited concern for healthcare worker safety as their priority. Even if a respondent sourced a less biologically protective PPE item, they clarified that it was easier for a healthcare worker to don or doff the item, and would therefore be a safer product to use.

The (lack of) use of epidemic forecasting

The epidemic forecasts that supply chain actors reported using most came from CDC or WHO. However, these estimates were not frequently used to make procurement decisions for several reasons. First, organizations lacked the technical expertise in infectious disease response to be able to use complicated epidemic models for their decision-making. Second, the response efforts by humanitarian organizations were often limited to operating a certain ETU or CCC. Organizations procured PPE based on an estimate of the maximum amount that specific facility would need, not based on where the virus might spread and how many in total would be affected. One respondent expressed frustration with the forecasting process:

> “The CDC, for example, can forecast on a global scale based on population movement, based on reproductive ratio, on transmission dynamics, how many patients to expect. But

> that doesn't tell you how many patients you are going to get in your ETU, because there are other ETUs, there are other factors at play, there are transport restrictions, there are quarantine restrictions, there are things like that. So I think how many patients you're going to see in your own facility is one of the limiting factors that is sometimes almost impossible to determine."

All four manufacturers, however, reported using epidemic models in their forecasting processes for demand. This is likely because they were looking to respond to the global impact of the epidemic and needed to estimate the disease burden accordingly. Manufacturers' efforts to scale up production also had a long time horizon. Their perspective is longer-term than the humanitarian organizations, which might be a factor in their increased usage of epidemic forecasts. Manufacturers mentioned labor training as a significant constraint to scaling up their production quickly. In addition to the time and cost it takes to train a labor force, one respondent also mentioned that they were reluctant to hire people they knew would be laid off after the crisis; "you don't want to hire 500 people and then lay 480 of them off in six weeks."

CAUSES & EFFECTS OF PROBLEMS IN THE PPE SUPPLY CHAIN

Evolution of the supply chain

Five respondents reported experiencing both shortages and overstocks. The overstocks were mainly experienced at the end of the crisis, while the shortages were most often reported during September, the peak of the crisis. This indicates that there was a time delay in the pipeline of PPE. Many respondents emphasized this change in operations between the beginning and the end of the crisis, particularly around procurement. During August and September there was much confusion about product standards, difficulty in working with manufacturers, and there were challenges in accessing funding to procure PPE items. By November, however, most actors in the supply chain had learned how to better work together.

Respondents attributed part of this improvement to the development of business relationships between actors in the supply chain who had not previously worked together. One manufacturer talked about the importance of these links:

> "Having the relationships before an outbreak happens that the supply chain people on both sides of the equation know how to talk to each other fluidly and seamlessly… It's

> not systems, because the systems are very strong, but the systems aren't good at managing the huge irregularity in volumes and in geographies and it puts the normal supply chain on its side. But if you've got people that are used to working with each other, understand their systems and you can get those people together live-time in the midst of the crisis and they know each other, you find the amount of positive good they can do – they can take all of their knowledge and experience and literally apply it to the situation virtually overnight. It's pretty amazing to watch that part of it happen."

Several respondents attributed part of the improvement to the clarification of product standards and specifications. This is supported by the timeline of the release of informational (by PPE manufacturers) and guidance (by international organizations) documents during the crisis. As shown in Figure 3, several large PPE manufacturers released clarifying documents on their own products' potential use for Ebola response between August and October. WHO and CDC also published guidelines for PPE specifications in October and November, further clearing up the ambiguity that had surrounded PPE sourcing.

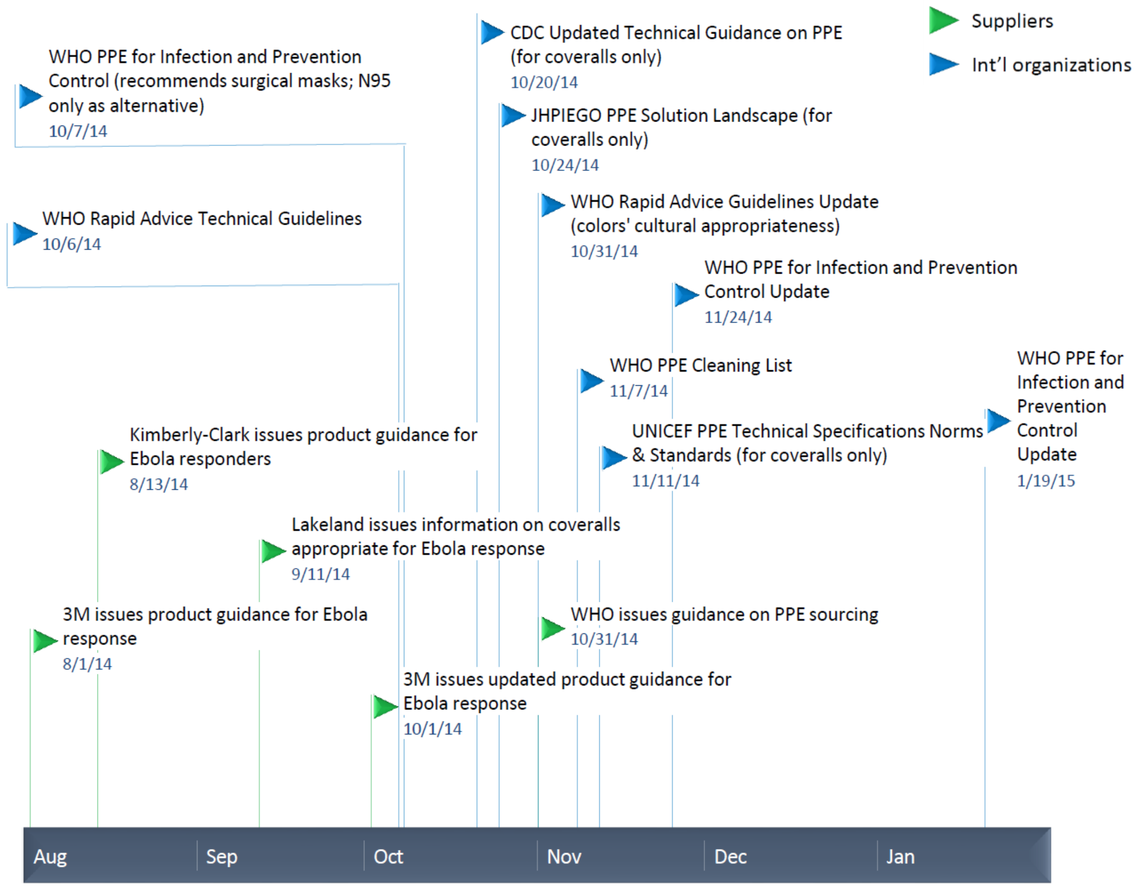


Figure 3: Timeline of the release of informational (by PPE manufacturers) and guidance (by international organizations) documents related to PPE during the 2014 West Africa Ebola outbreak.

This "evolution" of the PPE supply chain was emphasized in several interviews, and respondents commonly reflected on how certain aspects of the operation were at one point very challenging but then the problem was quickly solved. This pattern continued with other operational activities throughout the crisis.

Coping with shortages

Shortages affected the response in significant ways. One respondent talked about the impact of a shortage of PPE for burial teams:

> "Early on, I remember burial teams having to stop for a couple of days because they didn't have enough protective equipment. That was in August. And that's big. Bodies were probably the most infectious thing there, they're way more contagious than a weakly febrile person. By the time a person dies they're completely teeming with the virus. That

> was the problem – a lot of them [the bodies] stayed in the home. They were told not to touch them, then bodies would stay uncollected for days. Then in other cases people got tired of waiting and tried to move them, putting themselves at risk and potentially then being infected. Either they would wait or they wouldn't, but both of those had bad outcomes."

Several respondents talked about coping strategies that healthcare workers would use when there was a shortage of appropriate PPE. For example, one respondent talked about a shortage of hoods that led responders to cut trash bags and use them as hoods. Another respondent talked about a shortage of goggles:

> "I think at one point we had some issues with goggles, enough that it had to alter the way that providers entered the unit, because you had to have enough circulation and things like that… So I personally bought when I came to the US a bunch of ski goggles, which is essentially what they are, and brought them back in my luggage so that we could continue working…"

Competition between organizations

Many respondents mentioned the "competition" between responding organizations doing PPE procurement and that this phenomena, in itself, was new. Several respondents expressed that they believed the supply issues were primarily due to this competition and the lack of coordination between organizations procuring PPE, particularly at the beginning of the crisis (before November 2014).

Stress on the global supply chain

At a macro-level, the strain on the PPE supply chain created by the mismatch of supply and demand resulted in significant lead time increases and, sometimes, in price increases, for most actors. The price increases were most often due to transport and shipping cost increases, not due to increases in the price of the PPE item itself. Some of this stress on the supply chain could be the result of the data problems outlined in the previous section which led to poorly informed procurement decision-making. Another contributor could be the unnecessary procurement done by non-responding organizations and governments, mentioned by more than 40% of respondents. As one respondent put it, "we were competing not only with the other organizations that were responding but with thousands and thousands of institutions around the world who were not necessarily on the front line of it.”

The distributor, in particular, reported experiencing all seven codes describing stress on the supply chain. The distributor was located in the center of the PPE supply chain and was getting “squeezed” from all sides.

FUTURE OUTBREAK RESPONSES

The organizational experience gained by all PPE supply chain actors should not be understated. The relationships that were built and the technical knowledge that was gained will undoubtedly smooth out many of the challenges experienced in the 2014 outbreak in future responses. This experience, however, will not solve all of the problems the supply chain encountered. The supply chain itself can be bolstered to improve future infectious disease outbreak responses. The following chapter will use a system dynamics model to test various ways that the PPE supply chain could better respond to an infectious disease outbreak. One respondent summarized this supply chain shortfall well:

> “I think one of the things that was hard for us to appreciate was we kind of assume… that there's always a global supply of whatever we want. But that wasn't the case in Ebola, and that's something for you to be aware of, for us to be aware of… that [PPE manufacturer] had a certain number of factories, those factories have a certain number of components, that have a certain rate of staff. That's something we had never really thought about before. That we were like, ‘oh you can totally just get these whenever you want.’ But actually, no, the global supply of these items given the scale of the outbreak – which assumedly and hopefully we'll never see again – can be affected by this… And I thought that was really interesting about this humanitarian crisis, was that no, really, there isn't any in the world of a particular item, which is something I had not contemplated before because we've never really had that problem before.”

SYSTEM DYNAMICS MODEL

The qualitative interview results inform the model in three key ways. First, the interview results directly inform the structure of the PPE supply chain. The ways in which supply chain actors are connected and the ways in which PPE units are transferred between them are informed by interview responses. Second, several of the parameters in the model are estimated from interview responses: costs of PPE units, parameter changes over time, and shipment times are just a few examples. Finally, the unexpected phenomena described in the interviews inform the causal loop mechanisms that are incorporated into the model to make it increasingly representative of how the PPE supply chain functioned during the Ebola outbreak, and how it might function in future infectious disease outbreaks.

This chapter describes the development of the system dynamics model. First, we develop a base model with the PPE supply chain and the epidemic-driven demand. We validate this model with extreme conditions to ensure the behavior produced are what we would expect in the real PPE supply chain. Next, we expand this base model in three ways – each of which was identified in the interviews as an important supply chain phenomenon. We show the effect each of these three expansions has on the base model. Next, we run simulations of three different scenarios. These scenarios give insights into the effects of certain additional constraints on the system and provide insight into how several supply chain strategies might improve the PPE supply chain's response to a future epidemic. Finally, we discuss the insights gained from the model and its policy implications.

BASE MODEL DEVELOPMENT

The system dynamics model contains two types of variables: stocks and flows. Stocks are accumulations within the system – at any given time *t*, there is a certain level of each stock variable. Flows are the rates of movement between different stock variables. The base model contains both the supply chain model and the model of epidemic spread.

SUPPLY CHAIN MODEL

The base supply chain model, which includes the core structure of the supply chain and its basic functionality during an epidemic response, is developed here. For the purposes of this thesis, we assume the system to be a collection of all "PPE units." This "unit" could be a coverall, a PPE kit, or an N-95 mask – many PPE products would have similar supply chain structures. For the purposes of this exercise, we assume this "unit" is a coverall. The prices, inventories, and shipment rates in this model reflect this assumption. The software used to develop the model is Powersim Studio 10.

To begin our modeling effort, we start with a portion of the model developed by Georgiadis and Besiou (2008) to describe a closed-loop supply chain of electrical and electronic equipment. In their closed-loop model, items can be recycled back through the supply chain, but that is not relevant for PPE that is used in an infectious disease outbreak. PPE used in an outbreak response is contaminated and cannot be reused. We remove the closed-loop portion of the Georgiadis-Besiou model to create a system that more accurately represents the PPE supply chain in an infectious disease outbreak (full diagram can be found in the Appendix). The documentation for the base model with the three expansions (detailed in the next section) can be found in the Appendix.

We use the information gathered in the qualitative interviews to inform the structure of the base model. As shown in the diagram, PPE flows from manufacturers either directly to humanitarian organizations (also referred to as "HO" or "organizations") or through medical supply distributors (referred to as "distributors"). The humanitarian organizations then use that PPE at a rate determined either by their own inventories or by the amount of PPE currently required, which is calculated as the product of the total number of people infected (*Total Infected*) and the estimated burn rate (*PPE Needs per Infected Person*).

The qualitative interviews show that there were additional, behavioral phenomena that affected certain dynamics within the supply chain during the crisis, but it is useful to show first the supply chain's core structure. This model aggregates all actors of each type together (i.e. *Manufacturers Inventory* is the sum of the inventories at each PPE manufacturer around the world). This helps to simplify the dynamics and is most appropriate for the type of data collected in the interviews. The key actors and their inventories are shown in Figure 4.

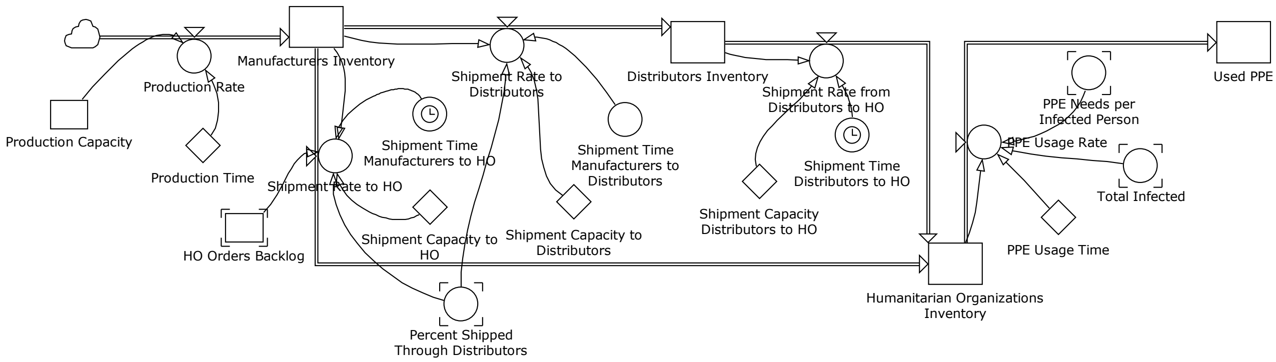


Figure 4: The key actors in the supply chain, their inventory stock variables, and the rates (flows) of material shipped between them.

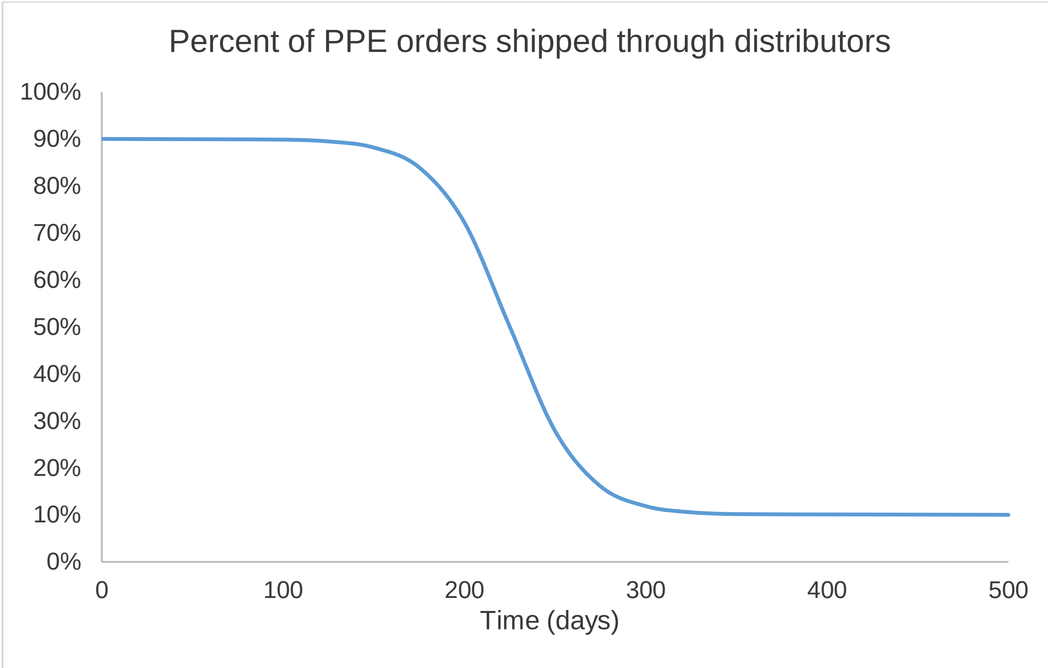
In this model, manufacturers produce at a *Production Rate* equal to either the *Production Capacity* or to their current backlog (*Manufacturers Backlog*) divided by the *Production Time* (the time it takes to produce one unit of PPE), whichever is smaller. The initial stock in *Manufacturers Inventory* is set to 80,000 Units.

As shown in Figure 4, PPE then flows from manufacturers either directly to humanitarian organizations or to distributors.

The *Shipment Rate to HO* ships either all the PPE that the humanitarian organizations have ordered but not yet received, the maximum amount that can be shipped through the channel, or the maximum amount that the *Manufacturers Inventory* can provide (given that a certain percentage must still go through the distributors), whichever is smallest.

The *Shipment Rate to Distributors* is the analogous case for that shipping channel. This flow moves PPE from *Manufacturers Inventory* to *Distributors Inventory*. The *Shipment Rate from Distributors to HO* is the minimum of what can be shipped from *Distributors Inventory* and the *Shipment Capacity Distributors to HO*, which is the maximum amount that can be shipped through this channel.

The *Percent Shipped Through Distributors* is based on interview responses that indicated that prior to the crisis, there was an important, established relationship between the manufacturers and the distributors. This relationship caused the vast majority of orders at the beginning of the crisis to be placed through medical supply distributors. As humanitarian organizations scaled up their own operations, they began to develop their own relationships with manufacturers and place more PPE orders directly. This trend is reflected in Graph 8, which is the graph used in the base model to determine the *Percent Shipped Through Distributors* throughout the crisis.



Graph 8: The sigmoidal curve used in the base model to determine the *Percent Shipped Through Distributors* throughout the crisis. Moves from 90% (beginning of crisis) to 10% (end of crisis).

All three shipment times in this portion of the model are informed by interview responses. Two of these shipment times (*Shipment Time Distributors to HO*; *Shipment Time Manufacturers to HO*), and their changes throughout the crisis, are incorporated into the model using a series of conditional statements. The shipment times increase during the peak of PPE demand to simulate the constraining of the shipping channels into crisis-affected countries (as reported in interviews), which increased lead times. The *Shipment Time Manufacturers to Distributors* remains constant throughout the crisis because this shipping channel was never severely constrained.

The humanitarian organizations then use that PPE at a rate determined either by their own inventories or by the current need for PPE. The organizations do not attempt to reduce the *HO Orders Backlog* because in reality, they did not ever use extra PPE to make up for the previous lack of PPE. The PPE needs on-the-ground are always driven by the current number of *Total Infected* people, not by how much PPE was needed in the weeks prior. This causes some *HO*

Orders Backlog to accumulate that is not depleted by the end of the simulation. The *PPE Usage Rate*, then, is the flow moving PPE from *Humanitarian Organizations Inventory* to *Used PPE.*

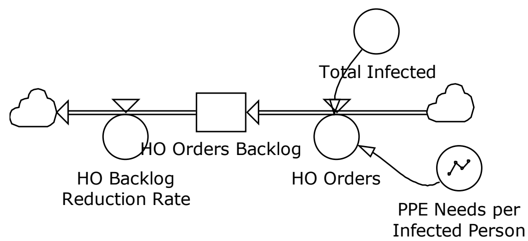
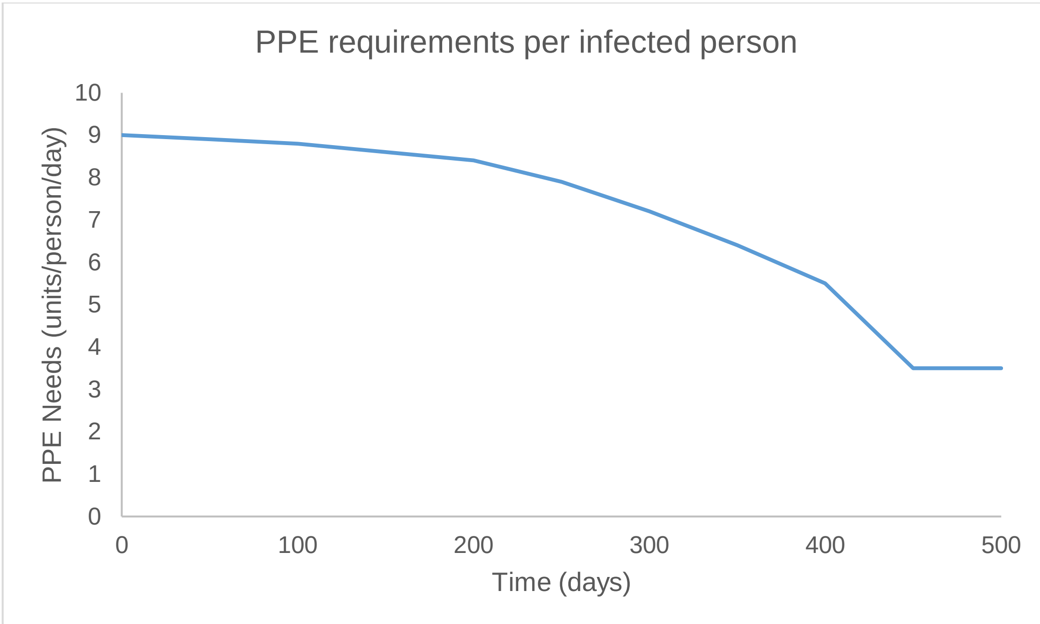


Figure 5: Diagram of the humanitarian organizations backlog series.

A series of backlogs maintains orders throughout the system. It is important to note that all orders are routed through these backlogs, even ones which can be immediately filled. The backlog system simply allows the model to keep track of (accumulate) orders for PPE that have not yet been filled and to fill them when there is available capacity. The diagram above (Figure 5) shows one of these backlog series (there are three in the model). In this particular series, the *HO Orders* is equal to the product of the *Total Infected* variable and the *PPE Needs per Infected Person*. The *PPE Needs per Infected Person* is another example of a parameter informed directly by interview responses; it accounts for some of the learning effects that improved humanitarian organizations' demand forecasting throughout the crisis. Interview respondents indicated that at the beginning of the crisis, burn rate estimates were very high (9 PPE units per person per day), but that they decreased throughout the crisis to a final estimate of around 3.5 PPE units per person per day. This trend is reflected in Graph 9, which is the graph used in the model to determine the *PPE Needs per Infected Person* throughout the crisis. The *HO Orders Backlog* accumulates and is lessened by the *HO Backlog Reduction Rate*, which is equal to the *PPE Usage Rate.*



Graph 9: Graph used in the model to determine the *PPE Needs per Infected Person* throughout the crisis. Moves from 9 to 3.5 PPE units per person per day from the beginning to the end of the crisis. Based on interview responses.

A similar backlog series exists for the remaining supply chain actors, with a few notable differences. Figure 6 shows the backlog series for distributors. The *Expected HO Orders* is the *HO Orders* transferred with an information delay of *a HO Orders* days. The *Desired DI* is equal to the product of the *Expected HO Orders*, the *Percent Shipped Through Distributors*, and the *DI Cover Time*, which is the safety stock level (in days of stock) required by the distributors. This *Desired DI* then drives the *DI Discrepancy*, which is the difference between what is actually in *Distributors Inventory* and what is desired. This discrepancy then partially fuels *Distributors Orders*, accounting for *DI Adj Time* to assess the inventory and use the information to place an order. *Expected HO Orders* is also added to this discrepancy to fuel *Distributors Orders.* Distributors are ordering up to their desired level of stock and are anticipating the future need for PPE. This backlog series is repeated for the remaining actor in the supply chain – the manufacturers.

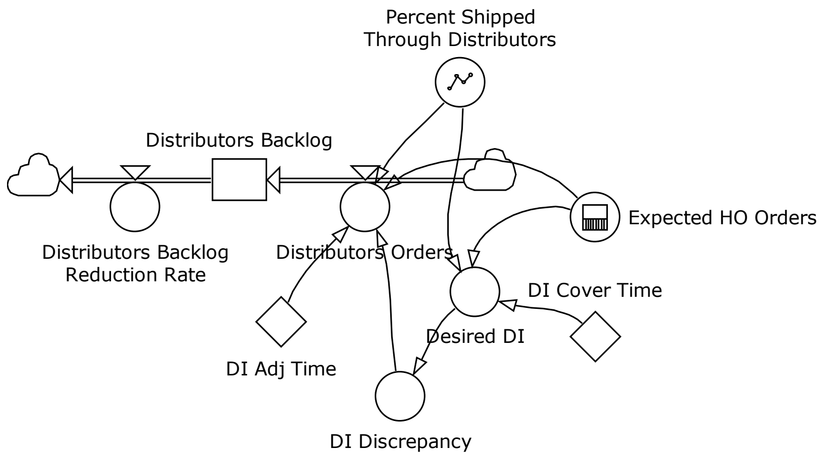


Figure 6: Diagram of the backlog series for distributors.

The final component of the base model is the cost calculation (see Figure 7). The *Cost per Day* is the sum of the *Transport Cost per Unit* and the *PPE Price per Unit* multiplied by the total amount that is delivered to the humanitarian organizations – summed for the PPE being shipped through each channel. This *Cost per Day* is then accumulated in the *Total Cost* to get a total amount spent on PPE by humanitarian organizations (assuming payment is exchanged upon delivery of goods) throughout the duration of the simulation.

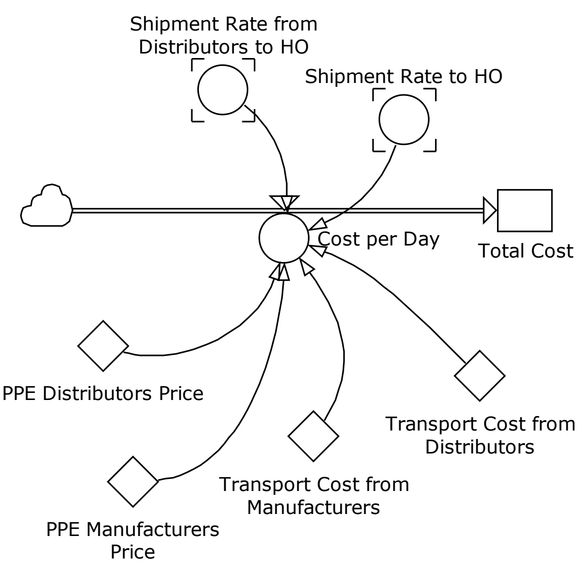


Figure 7: Diagram of cost accumulation. *Total Cost* is based on the transport costs and material costs of PPE, calculated separately for PPE procured from manufacturers directly and PPE procured through distributors.

Several additional assumptions are important to mention. First, all actors in the supply chain are either manufacturers, distributors, or humanitarian organizations. Interview responses indicate that the majority of the actors in the supply chain could be classified into one of these three categories. None of these actors have constraints on the maximum inventory they can hold at any given time. Related, there is no inventory carrying cost that is accounted for in the total cost of the system. Though the inventory carrying cost would be important to include to get a realistic estimate of the final cost, it is not relevant to the decision-making processes in the model. The critical, urgent nature of the crisis caused supply chain actors to not weigh the possibility of future inventory carrying costs heavily when making decisions about ordering. Finally, the *Production Time*, the prices of PPE (materials and transport), and the *PPE Usage Time* are all constant throughout each simulation. We believe these to be reasonable simplifying assumptions, though future work should test the sensitivity of the model to relaxing these assumptions. Even with these simplifying assumptions, the model is able to demonstrate trends and "dynamic patterns of concern" (Vlachos, Georgiadis, and Iakovou 2007).

EPIDEMIC SPREAD MODEL

The need for PPE in the supply chain model is driven by three separate SEIHFR epidemic spread models of Ebola, one for each affected country (Guinea, Liberia, and Sierra Leone). The SEIHFR model is an extension of the traditional SIR model (see: Literature Review). It is governed by a system of differential equations and is easily modeled using the same software package used for the supply chain model (Powersim Studio 10).

The structure from Rivers et al. (2014) is used for all three models and is shown below (Figure 8). The population of each country is divided into six possible compartments: Susceptible (S), Exposed (E), Infectious (I), Hospitalized (H), Funeral (F), and Recovered or Removed (R). The Hospitalized compartment includes individuals in any functioning healthcare facility – ETU, health clinic, etc. The Funeral compartment is particularly important for the spread of Ebola because many people are infected during the burial process. Full definitions of each of these compartments are given in the Appendix.

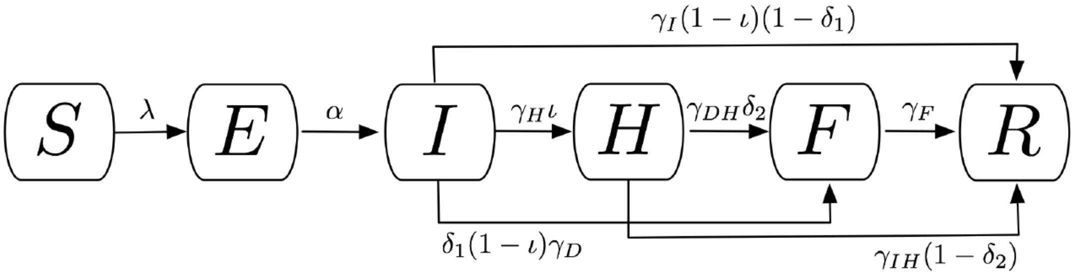


Figure 8: Basic structure of the SEIHFR compartmental model used to generate PPE demand in the base model. One of these compartmental models is generated for each affected country. Diagram taken from Rivers et al. (2014).

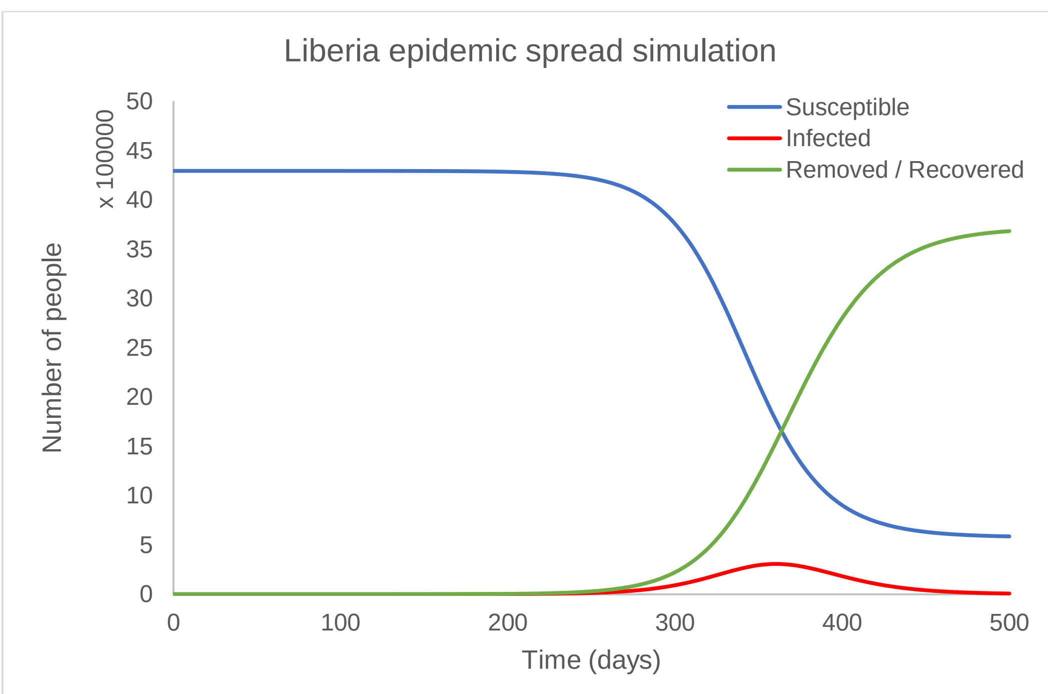
The model parameters for Liberia and Sierra Leone are adapted from Rivers et al. (2014) and are based on the initial growth phase of the 2014 West Africa Ebola outbreak. Because they are based on this phase of rapid spread, the models predict a much more serious outbreak than what actually occurred. Using this worst case scenario of need allows us to investigate the PPE supply chain as it would function in an outbreak outside of any other control measures. This is a model of the supply chain's response to an unmitigated outbreak.

The Guinea model parameters are adapted from the Uganda model in Legrand et al. (2007) because of the similar case fatality ratios and incubation periods in both outbreaks. One variable, the *Time from Hospitalization to Recovery*, is not specified in Legrand et al. (2007) so the value from Rivers et al. (2014) is used. A table of the parameters used for each country's SEIHFR epidemic spread model is shown below (Table 4).

Table 4: Epidemic spread model parameters used in the base model. Parameters taken from Rivers et al. (2014) and Legrand et al. (2007).

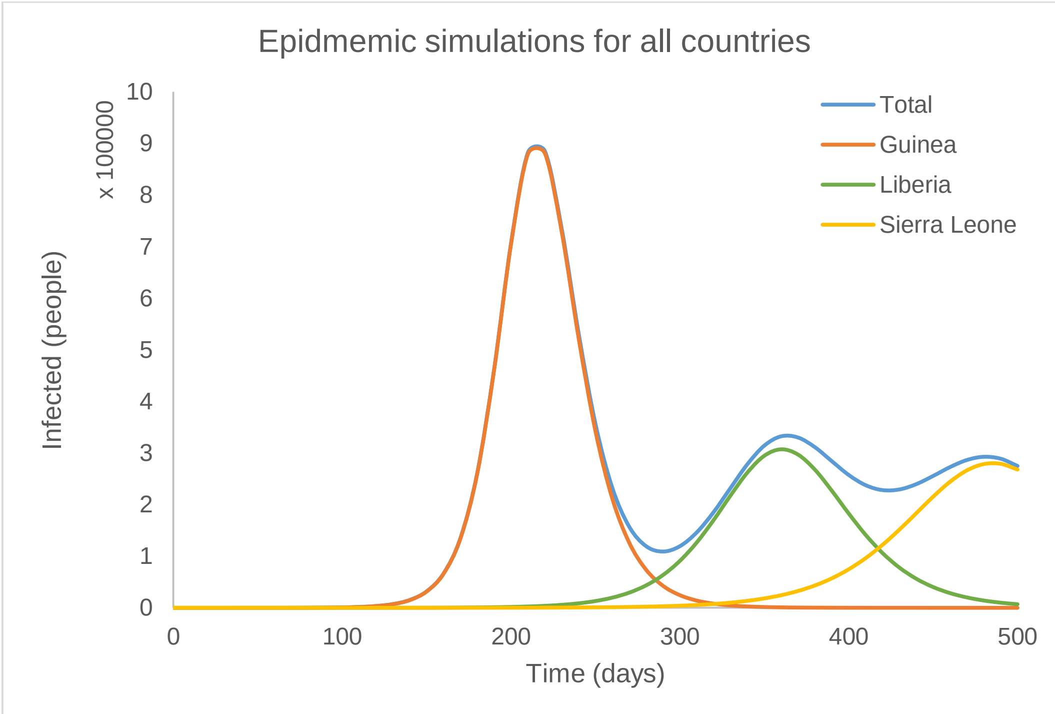
	Guinea	**Liberia**	**Sierra Leone**
Case Fatality Rate - Hospitalized	0.420	0.500	0.750
Case Fatality Rate - Unhospitalized	0.470	0.500	0.750
Contact Rate - Community	0.505	0.160	0.128
Contact Rate - Funeral	0.066	0.489	0.111
Contact Rate - Hospital	0.00171	0.0620	0.0800
Daily probability a case is Hospitalized	0.650	0.197	0.197
Duration of Infection	10.00	15.00	20.00
Duration of Traditional Funeral	2.00	2.01	4.50
Incubation Period	12.00	12.00	10.00
Time from Hospitalization to Death	3.80	10.07	6.26
Time from Hospitalization to Recovery	15.88	15.88	15.88
Time from Infection to Death	8.00	13.31	10.38
Time until Hospitalization	4.20	3.24	4.12
Total Population	11,745,000	4,294,000	6,092,000

The Susceptible, Infected, and Recovered or Removed stocks for the modeled spread of Ebola in Liberia, simulated from this SEIHFR model, are shown in Graph 10.



Graph 10: The Susceptible, Infected, and Recovered or Removed stocks for the modeled spread of Ebola in Liberia, simulated from the SEIHFR model adapted from Rivers et al. (2014).

Graph 11 shows the peak of each country's epidemic curves and the *Total Infected* number of people at any given time in the base model simulation.



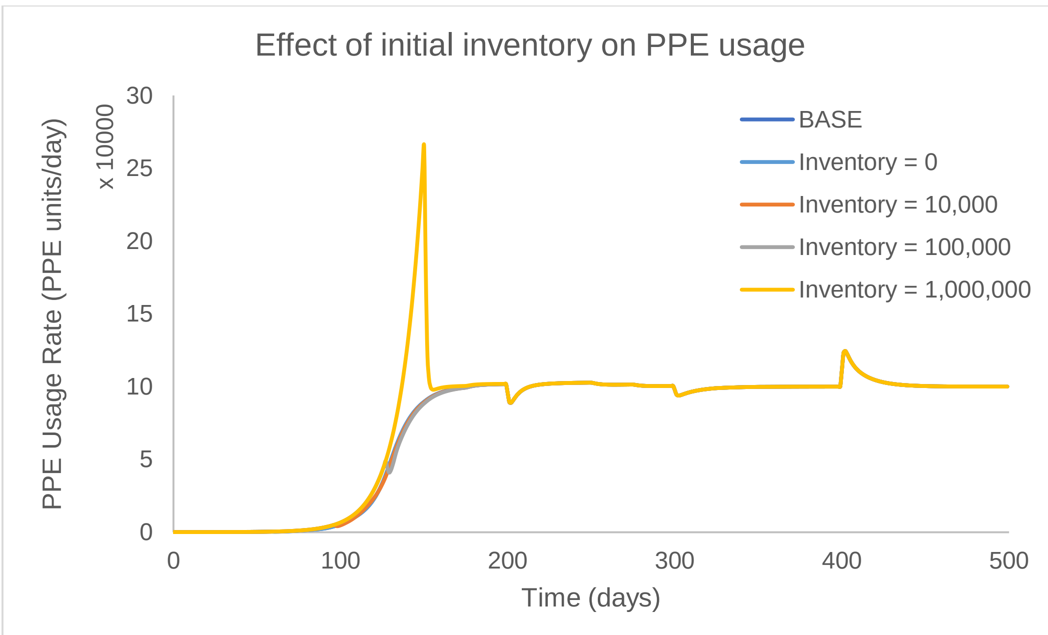
Graph 11: The Infected stock variables for the modeled spread of Ebola in all three affected countries, simulated from the SEIHFR model adapted from Rivers et al. (2014), using parameters from Rivers et al. (2014) and Legrand et al. (2007).

A complete list of the parameters used in the supply chain and epidemic models can be found in the Appendix.

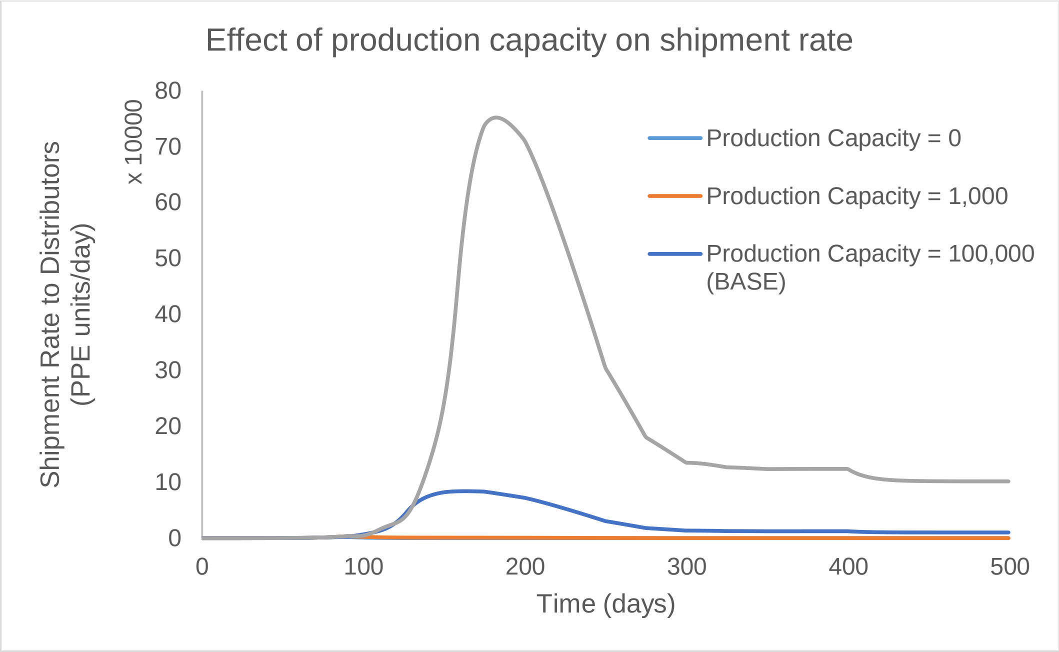
MODEL VALIDATION

The key to validation of a system dynamics model is structural validity (Vlachos, Georgiadis, and Iakovou 2007). Structural validity can be defined as a model structure in which the relationships between variables in the model reflect the reality of the modeled situation. To test the structural validity of this model, we run a series of simulations with different, extreme parameters to ensure that the model reacts in the expected way. Vlachos, Georgiadis, and Iakovou (2007) define extreme-condition tests as "assigning extreme values to selected model parameters and comparing the model generated behavior to the 'anticipated' behavior of the real system under the same extreme condition." This is the process we conduct here to validate the structure of the model.

First, we conduct an extreme-condition test on the initial amount of PPE stored in each supply chain actor's inventory. Adjusting the initial inventories has no major effects on flow variables or stock variables until the 1,000,000 units level. At initial inventories equal to 1,000,000 units, we see the *PPE Usage Rate* spikes dramatically because as more people are infected, the initial inventories are depleted. The *PPE Usage Rate* spikes because it can utilize these initial inventories during the onset of the epidemic. After these inventories are used, the *PPE Usage Rate* returns to being constrained by the *Production Capacity* upstream. Graph 12 shows this expected behavior.



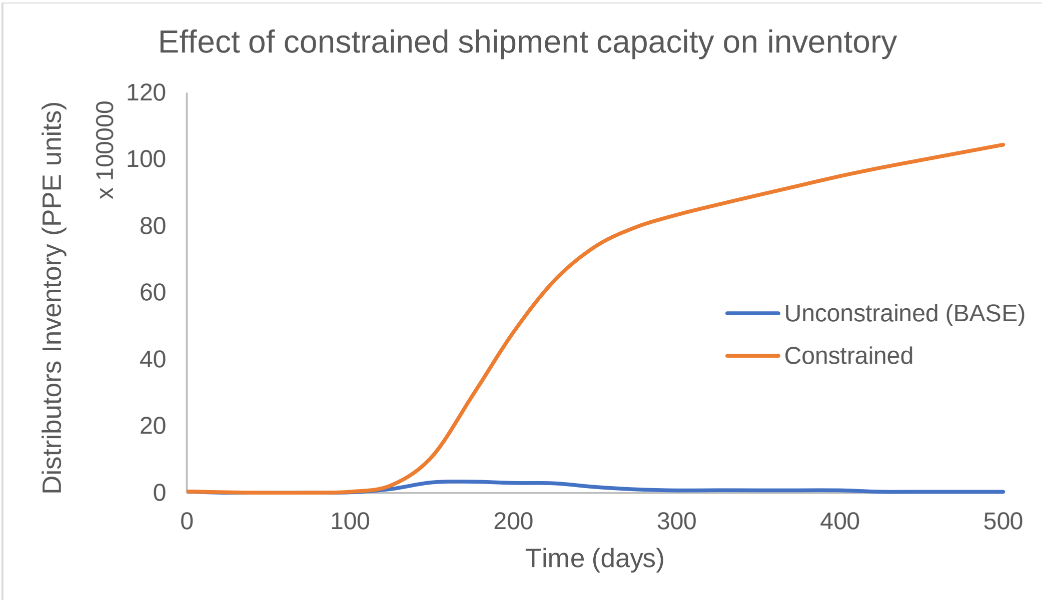
Graph 12: Graph of the *PPE Usage Rate* with various initial inventories. Each inventory level is set for all three actors: manufacturers, distributors, and humanitarian organizations. The *PPE Usage Rate* spikes because it can utilize initial inventories (see: legend) during the onset of the epidemic. After these inventories are used, the *PPE Usage Rate* is constrained by the *Production Capacity* upstream, set to 100,000 units/day.



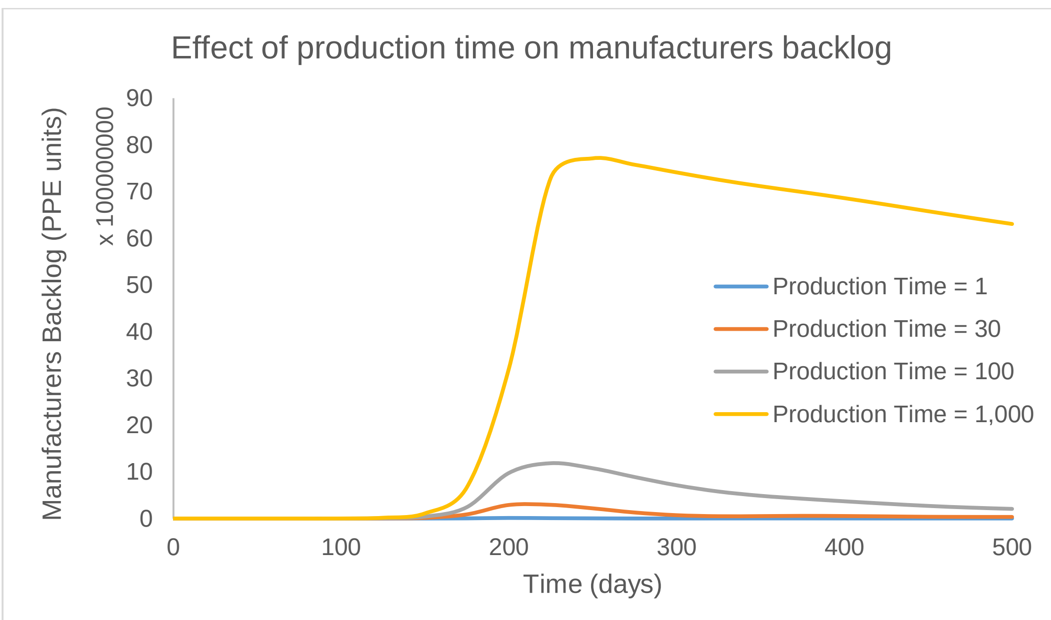
Graph 13: Graph of the *Shipment Rate to Distributors* as the *Production Capacity* is changed. As *Production Capacity* increases, the *Shipment Rate to Distributors* is free to increase and meet more of the demand.

Next, we test the effect of extreme values of *Production Capacity* on the behavior of the model. As is shown in Graph 13, as *Production Capacity* becomes less of a constraint (increases), the *Shipment Rate to Distributors* (and other shipment rates not pictured here) is free to increase and meet more of the demand. This is consistent with the expected behavior of the supply chain.

Next, we conduct an extreme-condition test on the shipment capacities. We find, as expected, that setting all shipment capacities to zero drives all shipment rates to zero, so that the only inventory that can be used to serve demand is the initial inventory in the *Humanitarian Organizations Inventory*. As we increase shipment capacities, more can be shipped through each channel. At high shipment capacities, shipment rates are constrained by the *Production Capacity*. We then test the effect of constraining one shipment capacity and un-constraining the others – driving the model to use shipping channel instead of another. As expected, the inventory accumulates with the distributor when the *Shipment Rate from Distributors to HO* is constrained by *Shipment Capacity Distributors to HO* (Graph 14). A similar effect is seen when constraining other shipment rates with capped shipment capacities.



Graph 14: Graph of the effect of constraining one shipment capacity (*Shipment Capacity Distributors to HO*) and un-constraining the others. Inventory accumulates at the distributors.

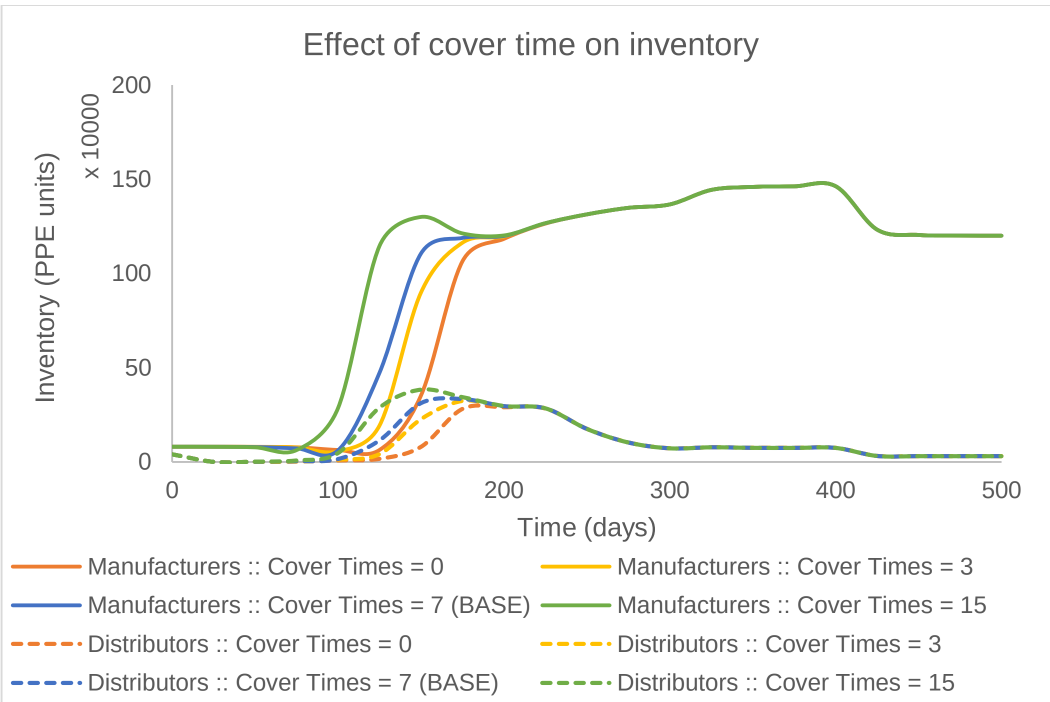


Graph 15: Graph of the changes in *Manufacturers Backlog* as *Production Time* increases, with *Production Capacity* unconstrained. As *Production Time* increases, the backlog of orders at the manufacturers also increase.

Next, we test the *Production Time* variable to ensure it produces the expected model behavior. *Production Time* is only used in the model when the *Production Capacity* exceeds the *Manufacturers Backlog* divided by the *Production Time*. In the base model, the backlog quickly exceeds the *Production Capacity*, rendering the *Production Time* uninfluential. To test the

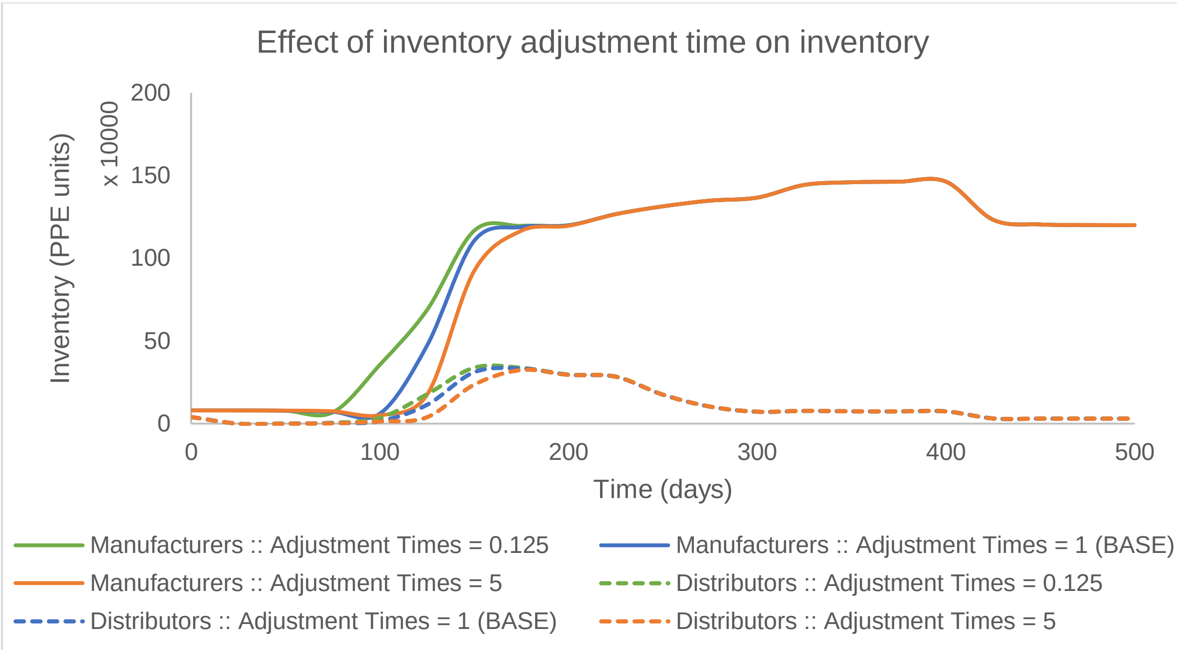
Production Time's effect, then, we must first increase the *Production Capacity* to 10,000,000 units/day (effectively unlimited). With *Production Capacity* effectively unconstrained, as *Production Time* increases, the backlog of orders at the manufacturers also increase (Graph 15). This is consistent with the expected behavior of the model.

Next, we validate the inventory cover times of both the manufacturers and the distributors. These cover times affect the desired inventory levels of each actor. Graph 16 shows that inventories increase more quickly as cover times increase. At large cover times, inventories and backlogs "overcorrect" initially to a larger degree than when cover times are smaller. This is consistent with expected behavior.



Graph 16: Graph of distributors and manufacturers inventories at various cover times. Inventories increase more quickly as cover times increase.

Using extreme conditions for the inventory adjustment times of manufacturers and distributors produces similar effects on inventories, but in the opposite direction. As inventory adjustment times decrease, the inventories "overcorrect" and fluctuate more than when the adjustment times are large. Graph 17 shows this phenomenon for both *Distributors Inventory* and *Manufacturers Inventory*. This is consistent with expected behavior.



Graph 17: Graph of manufacturers and distributors inventories at various inventory adjustment times. As inventory adjustment times decrease, the inventories fluctuate more than when the adjustment times are large.

Finally, we test the model's time step sensitivity to validate the appropriateness of a 0.125 day time step. At a time step of 2 days, certain inventories in the model fluctuate rapidly without smoothing throughout the duration of the crisis (as expected). This indicates that this time step is too large. At lower time step values, the *Total Cost* and *Used PPE* variable graphs become more granular, but are smooth enough to be reasonable.

All of these tests validate that the base model is functioning, but this base model is not yet completely representative of the PPE supply chain during the Ebola outbreak. It fails to account for manufacturers' abilities to increase production capacity, the effect of emotional decision-making ("panic") on ordering behavior, and, most critically for this thesis, the effect of PPE shortages on the spread of the epidemic. This model provides the basis upon which we can develop these additional dynamics.

Without any of these dynamics, though, the base model does provide important information about how the PPE supply chain functions in a simple scenario. This model and its testing show that the *Production Capacity* of manufacturers is a severely limiting factor. It also shows that decreasing the shipping time between actors can improve the speed with which the system reaches equilibrium. This aligns with the information provided in the qualitative interviews, in which manufacturing capacity and lead time were commonly cited as constraints on the PPE supply chain.

MODEL EXPANSION

Three causal loop mechanisms came to light in the qualitative interviews that have direct implications for the system dynamics model. These three dynamics are incorporated into the base model (described in the previous section) to build a more realistic depiction of how the supply chain functioned during the crisis. This section describes each mechanism’s conceptual development, its incorporation into the supply chain model, and the resulting effects on the model. The third mechanism connects the supply chain model back to the epidemic model, which is one of the major literature gaps identified in the Literature Review chapter.

MECHANISM 1: PRODUCTION RAMP-UP

The first causal loop diagram (Figure 1) shows how manufacturers responded to pressure during the crisis to increase their production capacity. As the difference between supply and demand increases (“Current Unmet PPE Need”), manufacturers are pressured to increase their production capacity, but there is a delay as they need time to hire new workers and add physical capacity (e.g., machinery) to their operation. Increased production capacity increases inventories at the manufacturer, which eventually decreases the need for PPE downstream in the supply chain, creating a balancing loop.

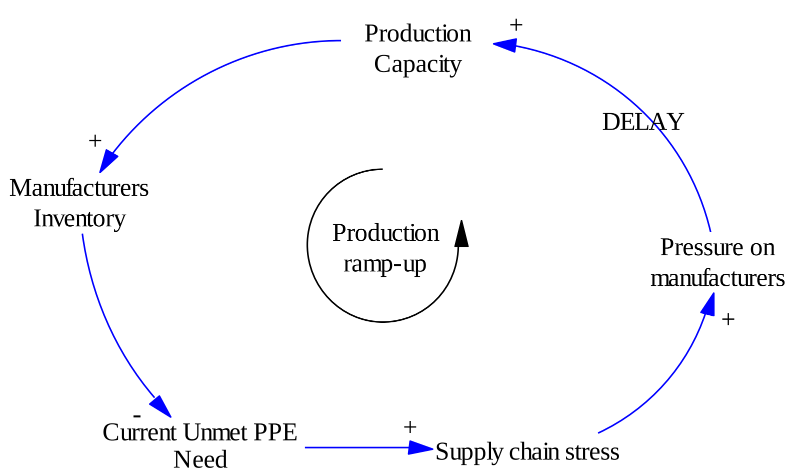


Figure 9: Causal loop diagram of how manufacturers responded to pressure during the crisis to increase their production capacity.

In the Powersim version of the model, this phenomenon is incorporated using a series of delays shown in Figure 10 (adapted from Vlachos, Georgiadis, and Iakovou (2007)). The current PPE needs are used to calculate the desired production capacity (*Desired PC*), with an information delay. The *Desired PC* and the actual *Production Capacity* are compared to find the difference between them, the *PC Discrepancy.* The discrepancy and a constant (K_r) then determine the *PC Expansion Rate*, which determines the *PC Adding Rate* with a material delay. The *PC Adding Rate* is the rate at which capacity is added to the manufacturer's *Production Capacity*. The *PC Adding Rate Switch* is used to either incorporate or exclude this phenomenon from the model.

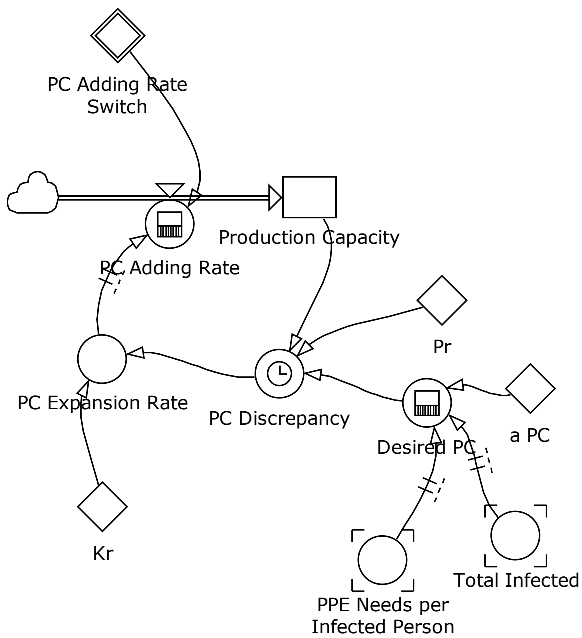
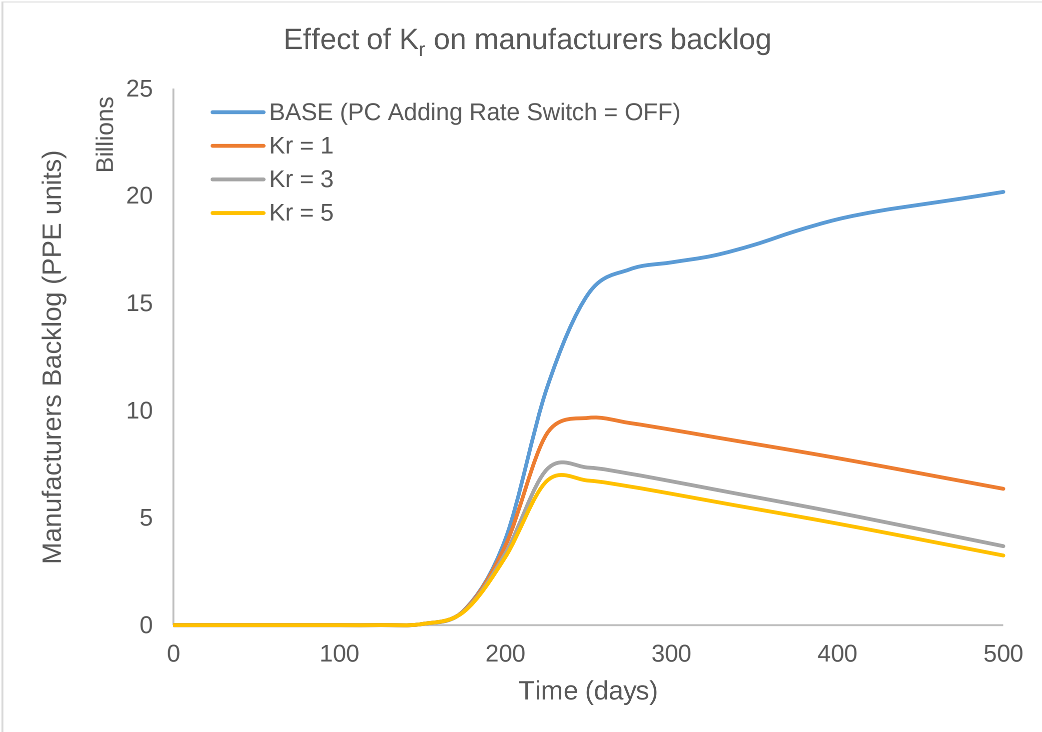
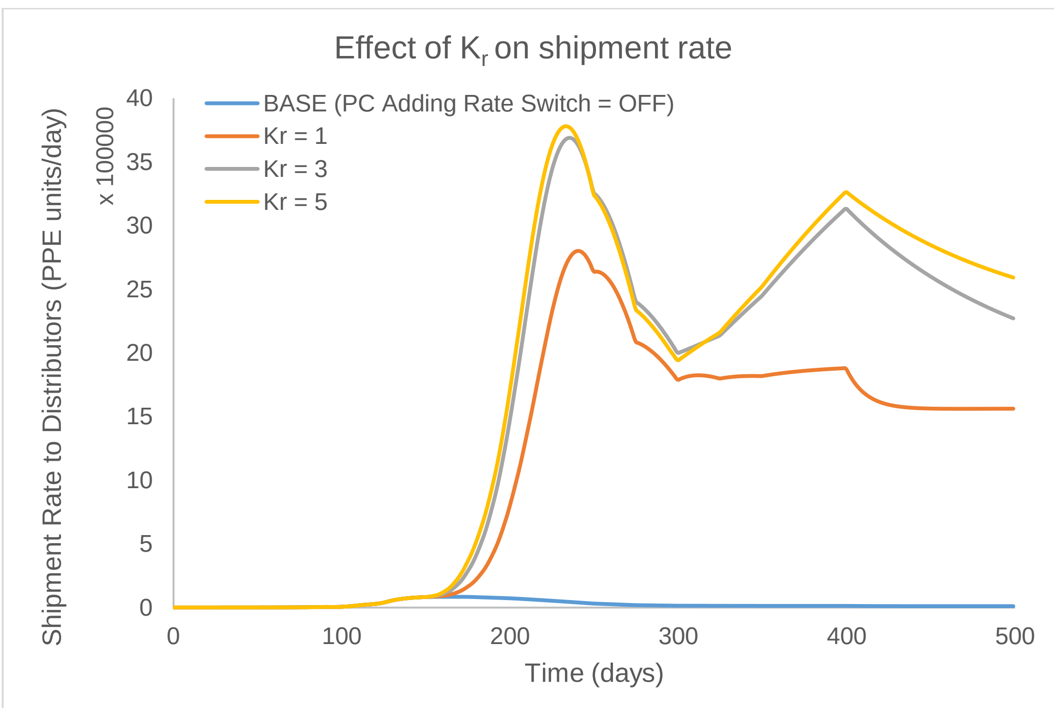


Figure 10: Incorporation of the Production Ramp-up causal loop diagram into the system dynamics model. Structure adapted from Vlachos, Georgiadis, and Iakovou (2007).

As expected, when *Production Capacity* is able to increase throughout the crisis, the *Manufacturers Backlog* decreases. As the production capacity control variable (K_r) increases, the ability of the manufacturers to increase their production capacity and reduce their backlog increases. The *Manufacturers Backlog* at various K_r values is shown in Graph 18.



Graph 18: Graph of the backlog at the manufacturers as the production capacity control variable (K_r) increases. The *PC Adding Rate Switch* is turned on for these runs.



Graph 19: Graph of the *Shipment Rate to Distributors* as the production capacity control variable (K_r) increases. The *PC Adding Rate Switch* is turned on for these runs.

The mechanism also has an important effect on shipment rates, an example of which is shown in Graph 19. As K_r increases, the *Shipment Rate to Distributors* increases, but with decreasing returns.

MECHANISM 2: PANIC DISTORTION

The second causal loop diagram (Figure 11) shows how panic affected the global supply chain, as described by interview respondents. This loop shows how increases in the total number of infected people caused stress in the supply chain, increased panic and distorted the amount of PPE ordered by humanitarian organizations. This, in turn, caused manufacturers to produce more PPE in an effort to lower the unmet demand for PPE.

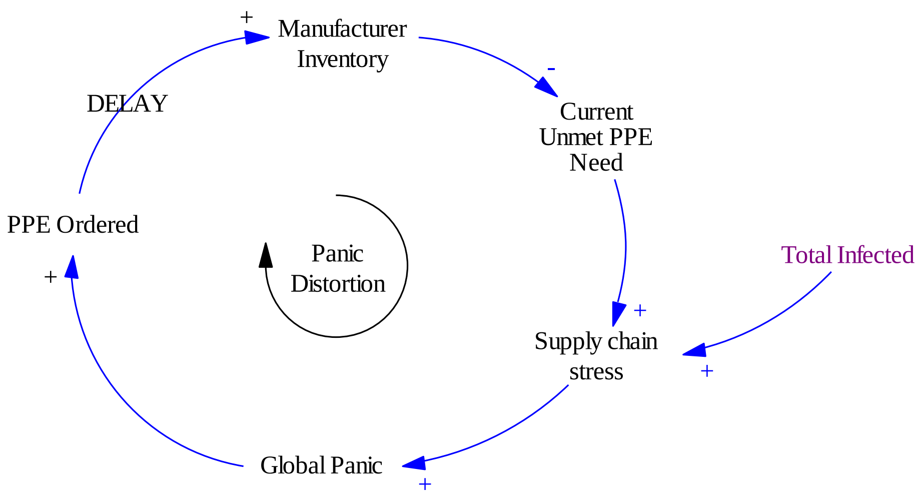


Figure 11: Causal loop diagram of how panic distorts ordering behavior.

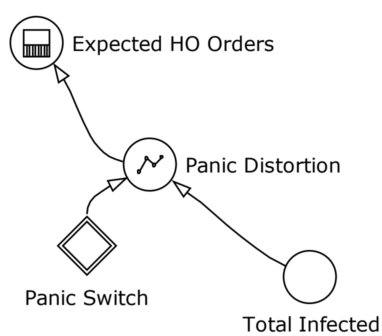
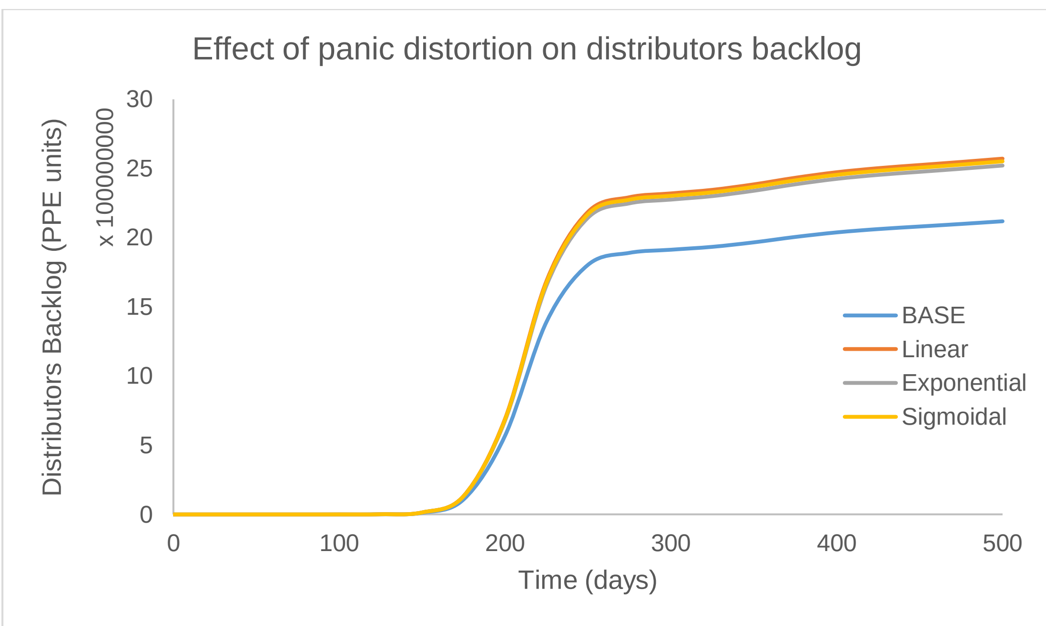


Figure 12: Incorporation of the Panic Distortion causal loop diagram into the system dynamics model.

This mechanism is incorporated into the Powersim model with a multiplier on the *Expected HO Orders* called *Panic Distortion* (Figure 12) that is based on the *Total Infected* people. Interview respondents noted that the onset of panic in the supply chain occurred around the end of August 2014. Using data from WHO, we find that there were approximately 892 *Total Infected* individuals on August 29, 2014 (see: Exploratory Case Study). The *Panic Distortion*, if activated, only takes effect when the variable *Total Infected* is greater than 892. The maximum number of infected individuals at any time during the 2014 outbreak was 2816 (according to WHO data; see: Exploratory Case Study). Therefore, we set the *Panic Distortion* to be at its maximum (20%; based on interview responses) when the variable *Total Infected* is greater than or equal to 2816. Three different types of growth for this *Panic Distortion* are built into the model – linear, exponential, and sigmoidal. If the *Panic Switch* is activated for a simulation, the *Panic Distortion* variable will increase *Expected HO Orders.*

When testing the model, we see that the type of *Panic Distortion* (linear, exponential, or sigmoidal), doesn't matter as much as the existence of the *Panic Distortion* effect itself. Each type of distortion produces similar *Distributors Backlog* (see Graph 20). This is because the epidemic model moves between 892 and 2816 infected persons quickly. The time between these two levels of *Total Infected* is the only time during which each of these three types of distortion will be different.



Graph 20: Graph of the *Distributors Backlog* over time with three different types of panic distortion.

MECHANISM 3: PPE SHORTAGE EFFECT

The third causal loop diagram (Figure 13) shows how PPE availability affected the recruitment of healthcare workers, and, consequently, the contact rates for hospitalized individuals. As the current unmet PPE need increases, shortages are more likely and fewer healthcare workers volunteer to respond. As fewer healthcare workers respond, the contact rate and number of infected individuals increase, further increasing the current unmet PPE need.

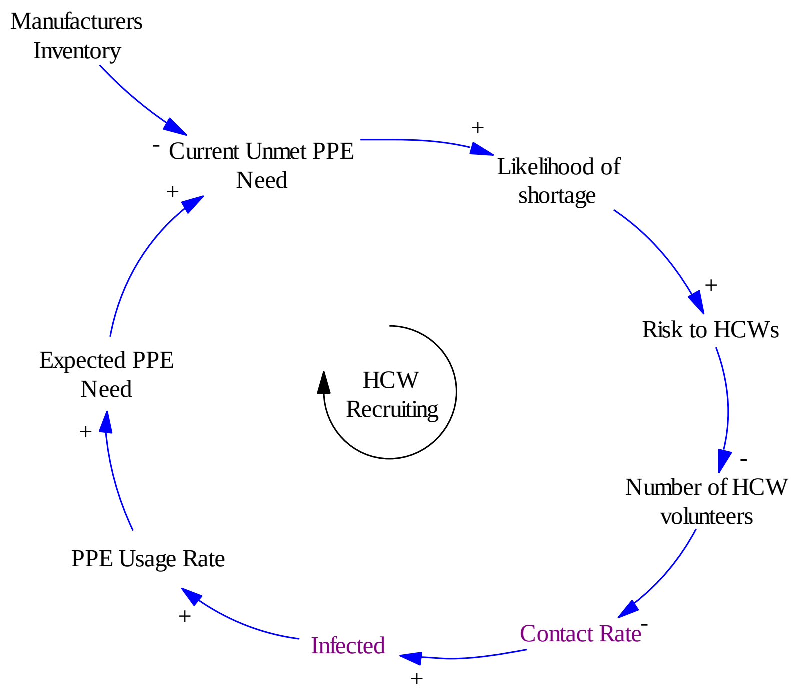


Figure 13: Causal loop diagram of how healthcare worker recruitment is affected by PPE shortages.

The incorporation of PPE shortages in this way, by affecting the contact rate in the epidemic spread model, is supported by epidemiology literature (e.g., Rivers et al. 2014). The PPE in this case would have an effect specifically on the contact rates in healthcare facilities and is incorporated into the model in this way (Figure 14). There is a constant, which we will refer to as the “multiplier,” that determines the scale of the effect that a PPE shortage can have on each country’s *Contact Rate – Hospital*.

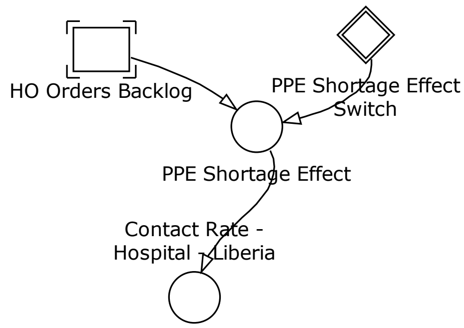
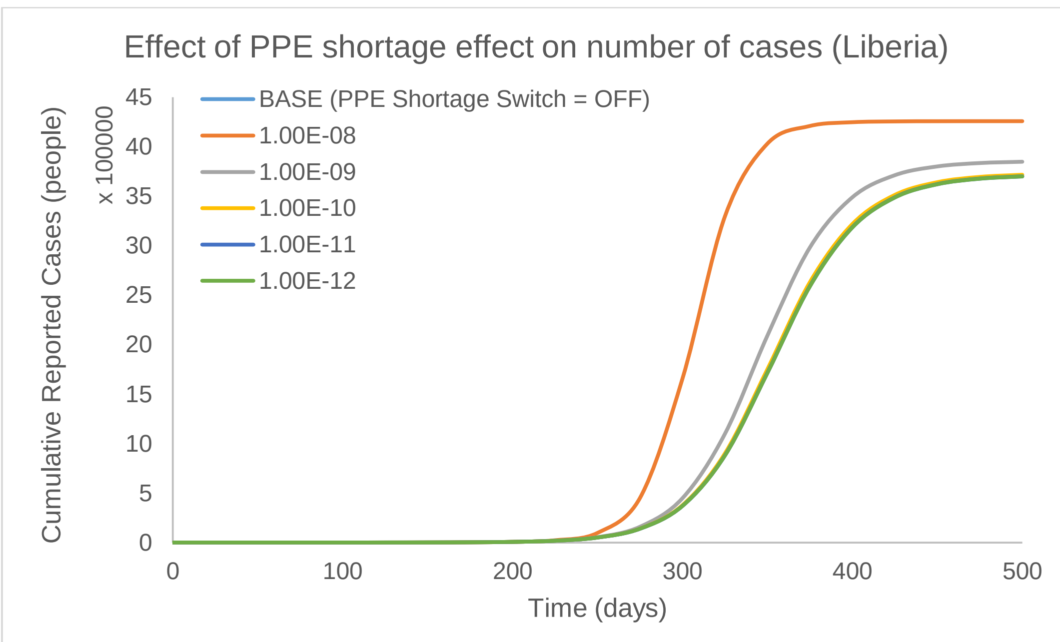


Figure 14: Incorporation of the PPE Shortage Effect causal loop diagram into the system dynamics model.

When testing the model we find, as expected, that as the multiplier increases the *Contact Rate – Hospital* increases. The pattern is the same but the magnitude is different in each country due to each country's different original *Contact Rate – Hospital*. As expected, the *Cumulative Reported Cases* in each country increase as the multiplier increases (Graph 21).

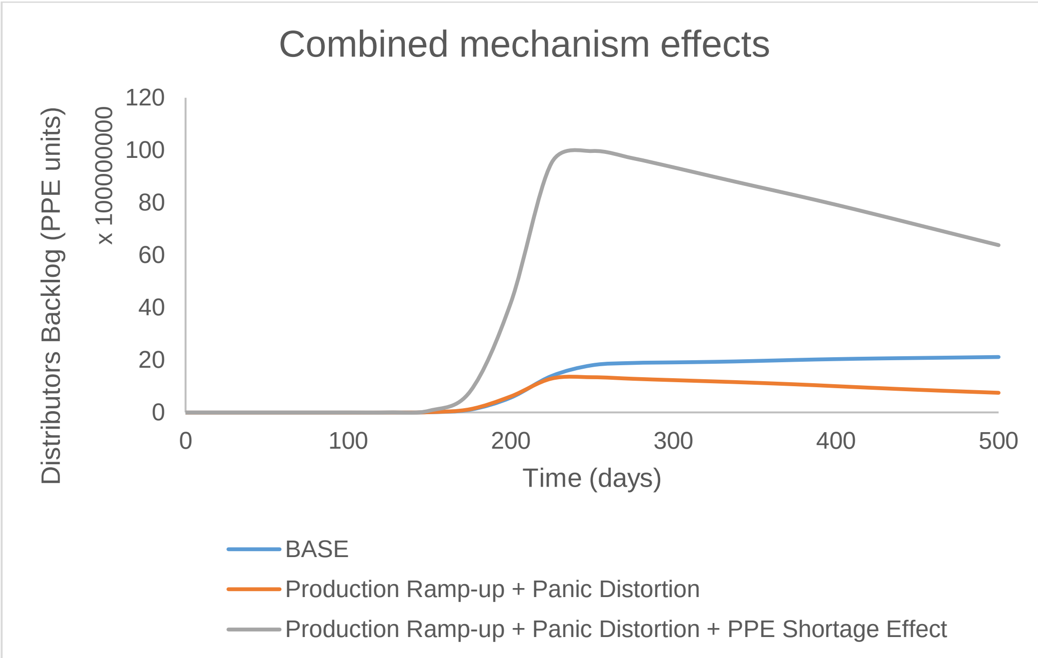


Graph 21: The total, cumulative number of reported Ebola cases in Liberia over time with various PPE Shortage Effect multipliers. As the multiplier increases, the magnitude of the effect increases. The *PPE Shortage Effect Switch* is active for these runs.

COMBINED MECHANISM EFFECTS

Combining these various mechanisms can impact the model behavior in interesting ways. For example, *Distributors Backlog* is lessened when production is able to increase (the *PC Adding*

Rate Switch is on) even despite an added *Panic Distortion* effect. However, when the *PPE Shortage Effect Switch* is on, the backlog at the distributors increase substantially (Graph 22).



Graph 22: Graph shows the combined effects of different switches on the *Distributors Backlog*.

All three of these mechanisms are levers that are dependent on the constants that drive them and the other variables in the model. As the interview responses showed, though, all three were critically important to the PPE supply chain's functionality during the 2014 West Africa Ebola outbreak. Because of the interaction effects (both in the real-world and simulated supply chains), it is impossible to tell exactly which mechanism had the most impact on the PPE supply chain and the epidemic, nor is it possible to tell the exact magnitude of each mechanism's effect. However, the incorporation of these phenomena into the model is important and useful for analyzing scenarios that might arise in the future. This is the thrust of the following section.

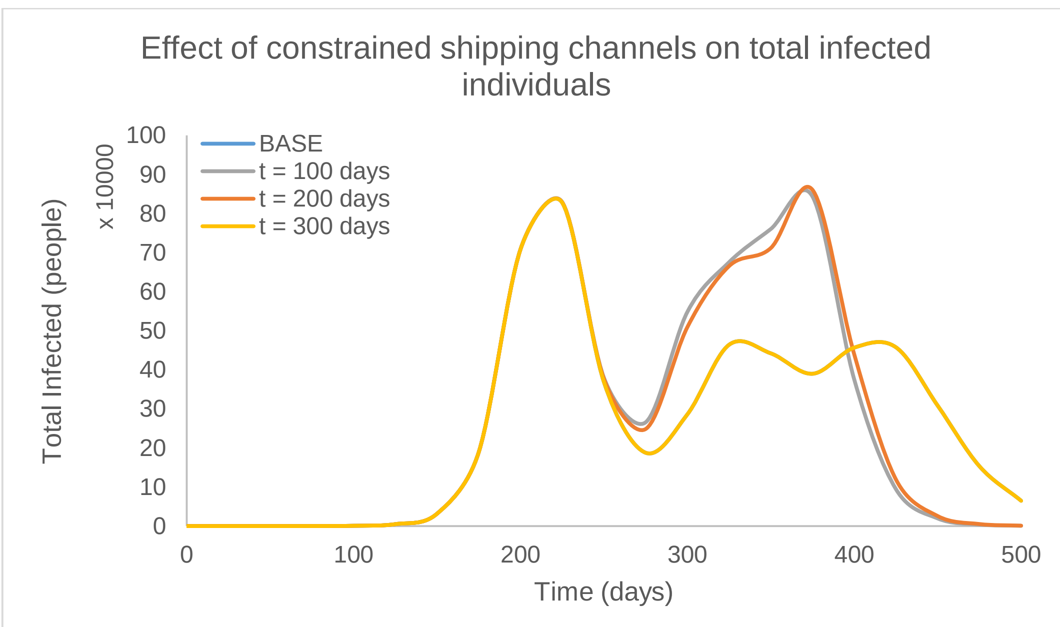
SCENARIO ANALYSIS

This section uses three scenarios to analyze the PPE supply chain using the system dynamics model. The scenarios and their effects are described below. The first two scenarios give insights into the effects of certain, realistic constraints on the PPE supply chain. The final scenario gives insight into how one supply chain strategy, pre-positioning, might improve the PPE supply chain.

We adjust the base model to incorporate all three of the mechanisms developed in the previous section – we turn all three switches on. The *PC Adding Rate Switch* is turned on, and K_r is set to 3. The *Panic Switch* is turned on and set to be sigmoidal. The *PPE Shortage Effect Switch* is turned on with a multiplier of 1 x 10^$^{-8}$. This is the base scenario (“BASE”) used in the scenario analysis; adjustments for each scenario are made to this new base scenario.

SCENARIO 1: CONSTRAINED SHIPPING CHANNELS

The first scenario we simulate is one based on the reality experienced by humanitarian practitioners during the 2014 West Africa Ebola outbreak. As the outbreak spread, many commercial airlines suspended service to the affected regions, at one point leaving just one commercial airline with freight capacity flying to affected areas. This restricted organizations’ ability to ship supplies to the affected areas. We demonstrate this by adjusting the *Shipment Capacity to HO* and the *Shipment Capacity Distributors to HO*. We generate several simulations in which the restriction goes into effect at different times in the simulation. Due to the *PPE Shortage Effect*, a constrained shipping channel affects the *Total Infected* people in addition to several other important dynamics (Graph 23).



Graph 23: Graph of the effect of constraining shipping channels to humanitarian organizations on the total number of infected people. The 100 day and 200 day constraints are similar because the burden of the disease is not serious until around t = 200 days, so both of these simulations have similar effects on the epidemic. All three "switches" developed in the Model Expansion section are turned on.

SCENARIO 2: BUDGET CONSTRAINT

The second scenario we simulate reflects the reality of many humanitarian response operations that operate with constrained budgets. In the 2014 West Africa Ebola outbreak, this was particularly a constraint at the beginning of the crisis. In June 2014, MSF called for increased attention and funding to the response effort (Medecins Sans Frontieres 2014); the levels of support at the time were not enough to slow the spread. An estimated $3.6 billion was spent to fight the Ebola outbreak before the end of 2015 (CDC 2016). The cost of procuring PPE was just a fraction of the total amount spent to control the outbreak.

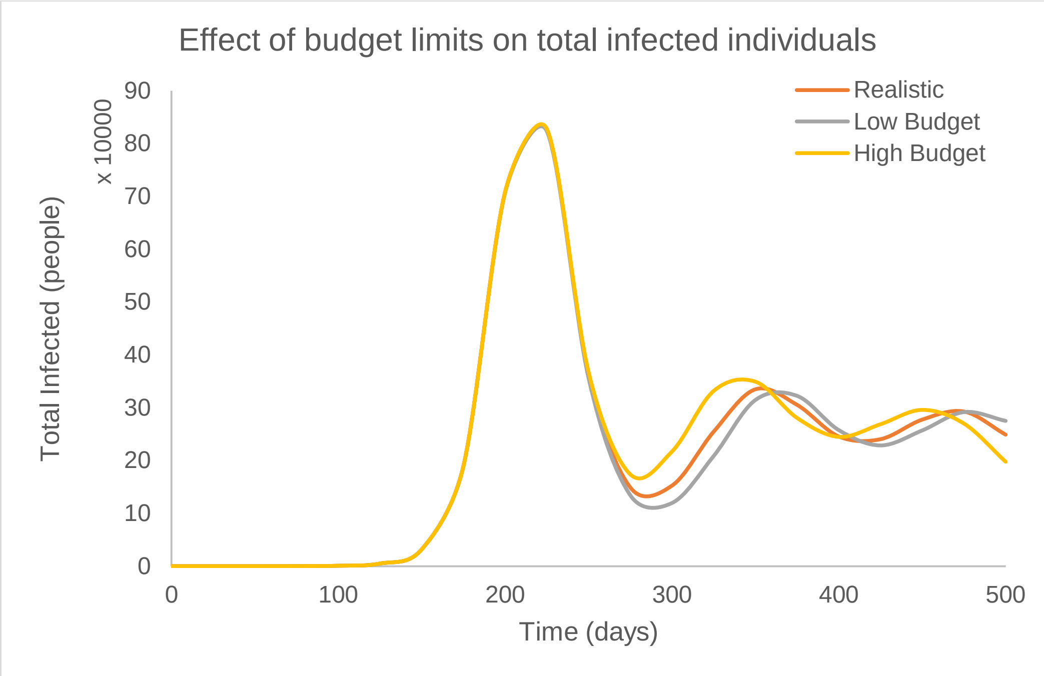
This is simulated in the model with a *Funding Limit* that affects how much PPE humanitarian organizations can order. The *Funding Limit* represents the budget that can be spent on PPE, not the overall budget for the response effort. If the *Total Cost* at time *t* is smaller than the *Funding Limit* at that time *t*, the organization can order more PPE. If not, they must wait until the *Funding Limit* is increased.

We run three budget simulations in which the *Funding Limit* varies over time (Table 5). The first simulation (Realistic) represents a potentially realistic scenario in which the funding for the humanitarian effort increases as the crisis becomes more severe. The second simulation (Low Budget) represents an extremely budget-constrained scenario. The final simulation (High Budget) represents a virtually unconstrained budget for PPE.

Table 5: Budget levels for three budget simulations conducted.

Time	**Realistic ($)**	**Low Budget ($)**	**High Budget ($)**
$t < 100$	1,000,000	1,000,000	10,000,000
$t < 200$	100,000,000	10,000,000	500,000,000
$t < 300$	500,000,000	20,000,000	1,000,000,000
$t < 400$	1,000,000,000	50,000,000	1,500,000,000
$t < 500$	1,500,000,000	100,000,000	3,000,000,000

The constrained budgets impact the dynamics of the model. As is shown in Graph 24, the High Budget allows more PPE to flow consistently through the system, which reduces the number of *Total Infected* individuals at the end of the crisis. The opposite is true for the Low Budget simulation. The budget affects the PPE supply chain's ability to respond to the epidemic, which in turn affects how severe the epidemic becomes.



Graph 24: The effect of different budgets on the total number of people infected throughout the simulated outbreak.

SCENARIO 3: PRE-POSITIONING OF PPE WITH DISTRIBUTORS AND HUMANITARIAN ORGANIZATIONS

The final scenario we explore is one based on supply chain and risk management literature: pre-positioning of relief items. The optimization of pre-positioned goods for disaster response has been widely considered and its positive impact on responses has been quantified (Van Wassenhove 2006; Gatignon, Van Wassenhove, and Charles 2010; Rawls and Turnquist 2010). We run several simulations in which various pre-positioning strategies are tested for their ability to change the total number of infected people (cumulative) and the *HO Orders Backlog* (a proxy for the severity of PPE shortages). For the base simulation run, the *Manufacturers Inventory* is set to be 80,000 units, *the Distributors Inventory* is at an initial level of 40,000 units, and the *Humanitarian Organizations Inventory* is 10,000 units. The simulations and their output are shown in Table 6.

Table 6: Pre-positioning simulations and their impact on *Cumulative Reported Cases* and *HO Orders Backlog*.

Manufacturers Inventory (units)	*Distributors Inventory (units)*	*Humanitarian Organizations Inventory (units)*	*Cumulative Reported Cases (people)*	*HO Orders Backlog (units)*
80,000	40,000	10,000	19,863,992	181,105,965
1,000,000	40,000	10,000	19,865,143	181,285,193
80,000	1,000,000	10,000	19,857,854	180,165,347
80,000	40,000	1,000,000	19,857,654	180,134,560
1,000,000	1,000,000	10,000	19,858,817	180,314,732
1,000,000	1,000,000	1,000,000	19,852,306	179,314,144
80,000	10,000,000	10,000	19,797,483	171,080,252

This purpose of this scenario is to simulate the effect of inventory pre-positioning on the outbreak of the disease. The scale of these results is sensitive to estimated parameters such as the multiplier used to determine the *PPE Shortage Effect*, the other epidemic spread model parameters, etc. Despite their sensitivity, these scenarios do show the general effects of inventory pre-positioning on the epidemic. In Table 6 we see that increased inventory at the humanitarian organizations does the most to improve the response, but in reality, it is unlikely that much PPE would be held at this level. The final entry in the table shows the result of a simulation in which distributors hold the extra inventory – a solution that might be more feasible in practice. Increasing the amount of inventory pre-positioned with distributors reduces the number of infected people (over the duration of the crisis) and reduces the severity of PPE shortages.

MODELING DISCUSSION

The model developed above and the scenarios tested are based on the experience of the PPE supply chain during the 2014 West Africa Ebola outbreak but provide insights for possible future outbreaks. Though these tests are conducted based on the spread of Ebola in 2014, it is not unreasonable to assume that the behavior shown would occur in a future outbreak – of Ebola or another infectious disease. Though the demand generation model (the SEIHFR model) and some of the model parameters might change, the structure of the PPE supply chain would be the same in any large-scale infectious disease outbreak. For the PPE supply chain, the demand signal of any large outbreak is a significant, unexpected spike. Several manufacturer respondents mentioned this in their interviews – how the Ebola outbreak was similar to previous outbreaks of SARS and avian influenza from their perspective.

This section describes several important policy implications of this model and recommendations that arise from them. This section provides insight regarding strategies that policymakers can use to improve PPE supply chain performance and slow or halt the spread of an epidemic.

First, relationship-building between different supply chain actors before a crisis would help to improve the flexibility of the supply chain. This would eliminate the constraint of the *Percent Shipped Through Distributors*, which would allow humanitarian organizations to order directly from manufacturers at the beginning of the crisis. Manufacturers and humanitarian organizations should work to maintain the relationships built during the Ebola outbreak as a first step toward relationship-building.

Second, Scenario 1 demonstrates the detrimental effect of constrained shipping channels on the spread of the epidemic. Governments and private sector transporters in future crises should work to keep shipping channels open and unconstrained. In the event that private sector transporters halt service, governments and humanitarian organizations should be prepared to open up “air bridges” and provide transport service for humanitarian supplies.

Next, Scenario 2 demonstrates how the existence of a sufficient budget in the early stages of the epidemic is critical to its control. If the PPE supply chain can quickly respond (unconstrained by financing), there is less strain on the system later. Humanitarian organizations should consider establishing flexible funding pools that can be used in the early stages of an outbreak. When used, these could be replenished using the funding that streams in at later stages of the outbreak.

Finally, Scenario 3 shows that pre-positioning of PPE before an outbreak does reduce PPE shortages and slows the epidemic, but the extent to which this strategy is cost-effective is still unknown. Though this strategy is often less resource-intensive than requiring manufacturers to increase their production capacity (which necessitates hiring and training new employees), further analysis is needed to determine the effectiveness. One way that pre-positioning could be implemented with low inventory risk to the downstream actors is through flexible contracts and agreements. For example, capacity reservation contracts guarantee delivery of any amount of product up to the specified capacity in exchange for a payment from the buyer. These help manufacturers to better plan production and ensure a baseline level of capacity for the buyer that they do not have to keep in inventory – both of which would improve an epidemic response. PPE supply chain actors should explore the use of these mechanisms to improve their operations.

CONCLUSIONS & FUTURE WORK

This thesis has answered the first research question – *How and to what extent are epidemic forecasts used to inform PPE demand forecasts and PPE supply chain strategies, both before and during an outbreak?* As the exploratory case study shows, epidemic forecasts were used by some actors in the supply chain to inform PPE demand forecasts. The ability of these actors to use epidemic forecasts to generate PPE demand forecasts was often limited by other factors complicating the PPE demand forecast – usage conditions, healthcare worker experience, etc.

This thesis provides a set of recommendations as well as an analytical approach to answering the second research question – *How can the PPE supply chain be designed to respond better to infectious disease outbreaks?*

This thesis demonstrates that building relationships between supply chain actors before a crisis, keeping shipping channels open and unconstrained, establishing flexible funding pools, and pre-positioning PPE before an outbreak are all strategies that can be used to improve the PPE supply chain's response to an infectious disease outbreak.

The analytical approach used to answer the second research question forms a basis for future research connecting epidemics and supply chains. This thesis provides an approach that integrates traditional epidemiological modeling with supply chain modeling methods, which closes the gap in literature identified in the Literature Review. It is the first work, to our knowledge, to develop a model that links the complexities of supply chains with the control of epidemics. Future researchers can use the model designed here and the insight generated from the exploratory case to study the ways in which supply chains and epidemics affect, and are affected by, each other. This interconnectedness has implications for resource allocation models. These models, if realistic, should no longer be based on a supply chain that is assumed to be functioning perfectly. This thesis shows that supply chains in crisis function sub-optimally and that new phenomena emerge as actors in the supply chain struggle to react and adapt. Resource allocation models should incorporate this dysfunction.

Finally, this thesis shows the usefulness of a mixed methods approach to conducting research on humanitarian supply chains. Humanitarian organizations are difficult to study due to their limited data, high staff turnover, and little time for self-reflection. The qualitative case study conducted in this thesis shows that real insight can be drawn from using social science research methods to collect primary data. These methods gather data that more rigid, quantitative survey methods might not. These methods also ground the research in the reality that humanitarian organizations face – a reality that is not always represented well by quantitative research. Using data gathered directly from humanitarian practitioners ensures that the research responds to an existing problem, not to a problem created by the researchers themselves. Future work on humanitarian supply chains should consider using social science research methods to inform the design and/or application of quantitative models.

APPENDIX

QUALITATIVE INTERVIEW RESPONDENTS

Respondent Job Function	Type of Supply Chain Actor	Date of Interview
Logistics	Humanitarian Organization	January 8, 2016
Sales	Distributor	January 6, 2016
Logistics	Humanitarian Organization	December 3, 2015
Logistics	Government	November 24, 2015
Procurement	Humanitarian Organization	December 15, 2015
Logistics	Humanitarian Organization	December 10, 2015
Medical	Government	December 18, 2015
Management	Manufacturer	January 14, 2016
Medical	Humanitarian Organization	January 15, 2016
Management	Humanitarian Organization	January 19, 2016
Procurement	Humanitarian Organization	January 19, 2016
Management	Humanitarian Organization	January 20, 2016
Management	Manufacturer	January 20, 2016
Management	Manufacturer	January 20, 2016
Sales	Manufacturer	January 25, 2016
Logistics	Humanitarian Organization	January 25, 2016
Medical	Humanitarian Organization	January 29, 2016

INTERVIEW GUIDE FOR MANUFACTURERS, SUPPLIERS, DISTRIBUTORS

Section 0: Background

1. Please tell me a bit about your role at [respondent's company], and what your typical duties are within that role.
2. What PPE products does your company sell that might be (or have been) used in an infectious disease outbreak?

Section 1: Pricing

1. What is the selling price of [product]?
2. What qualities of a market or of a product affect the product's pricing?
3. Are the prices affected by demand in real-time?

Section 2: Manufacturing

1. How many [product] do you typically produce (per day, per week, or per month)?
2. How many [product] can you produce each day?
3. How many [product] were you producing at the peak of the 2014 Ebola outbreak?
4. Where is [product] produced?
5. What constraints affected production at the peak of the 2014 Ebola outbreak?
6. How do you determine how many [product] to manufacture?
    a. How often did you make this estimate/decision?
    b. On what data is this estimate/decision based?
    c. During the 2014 outbreak, did you utilize epidemic forecasts or epidemiology models of the outbreak in your decision-making? If so, how did you use them? If not, why not?

Section 3: Inventory

1. How many [product] do you keep in inventory at any given time?
2. Where is that inventory held?
3. How much does it cost to keep [product] in inventory?
4. What is your inventory replenishment policy for [product]?

Section 4: Shipment

1. How many [product] can you ship per day?
2. What is the approximate lead time (from order to shipment) for [product]?
3. What affects the lead time of [product]?
4. What methods/modes of shipping are typically used for [product]?
5. Who owns the shipment in-transit?

Section 5: Contracts

1. Does your company participate in any agreements with its customers that would reduce the likelihood or risk of a stockout? For example, capacity reservation contracts, vendor-managed inventory, or pre-positioned inventory?
    a. If so, what type of contracts?
    b. With what type of customers?
    c. What products are covered?
    d. What costs are associated with these contracts?

Section 6: PPE Supply During Ebola Outbreak

1. What were the major difficulties you encountered with the in-crisis supply of PPE?
2. Were there issues with shortages or overstocks at any point during the crisis?
3. Do you have any record of activities with regard to the supply of PPE during the 2014 Ebola outbreak? Would you be willing to share that with us?
4. If you could do one thing differently with regards to the supply of PPE before or during the next infectious disease outbreak, what would you do?
5. Is there anything else you'd like to add?

INTERVIEW GUIDE FOR PROCUREMENT OFFICERS

Section 0: Background

1. Please tell me a bit about your role at [respondent's organization], and what your typical duties are within that role.

Section 1: Pre-positioning

1. Before the onset of the crisis, did your organization have any personal protective equipment (PPE) items pre-positioned and on-hand in the event of an outbreak?
    a. If yes, where were these pre-positioned?
    b. If yes, how many of these items were pre-positioned?
    c. If yes, for how long had these PPE items been pre-positioned?
2. Did your organization have any other supplies pre-positioned?
3. On what criteria do you make the decision to pre-position an item vs. procure it after the onset of a crisis?
4. Does your organization use any contract mechanisms to expand your pre-positioned inventory or to make that inventory more flexible?

Section 2: Organization's response

1. When did your organization become aware of the 2014 outbreak? How did you become aware?
2. When did your organization decide to respond to the outbreak? What triggered this response?
3. Please describe, generally, what your organization did to respond.
4. Which of these activities required the procurement of PPE?

Section 3: Procurement (during crisis)

1. Who were your main suppliers of PPE?
    a. Did these change throughout the crisis? If so, why?
2. What were the main PPE products you procured during the crisis?
    a. How much did these items cost?
    b. How many did you procure during the crisis?
3. Do you have any record of procurement activities with regard to PPE for your organization? Would you be willing to share those with us?

Section 4: Forecasting

1. How did you determine the type of PPE needs your organization had?
2. How did you estimate (quantity) your organization's future PPE needs?
    a. How often did you make this estimate?
    b. On what data was this estimate based?
    c. Did you utilize epidemic forecasts or epidemiology models of the outbreak in your decision-making? If so, how did you use them? If not, why not?
3. How often did you place an order? What was your inventory policy?

Section 5: Procurement challenges

1. What were the major difficulties you encountered with the in-crisis procurement of PPE?
2. Were there issues with shortages or overstocks at any point during the crisis?
3. Did the WHO standards for PPE affect your procurement decisions?
    a. If yes, to what degree?
    b. If yes, did these standards change your procurement strategy at any point in the crisis?
4. What were the major bottlenecks in PPE procurement?
5. Approximately what lead times were you seeing for PPE?
6. Was your procurement ever affected by the procurement of another responding organization or government? If so, how and to what degree?

Section 6: Lessons learned

1. If you could do one thing differently with regards to PPE procurement in the next infectious disease outbreak, what would you do?
2. Is there anything else you'd like to add?

CODEBOOK

The third and final iteration of the Codebook (Codebook Version 3) used to analyze qualitative interviews. It was compiled by making adjustments specified in the Methods section.

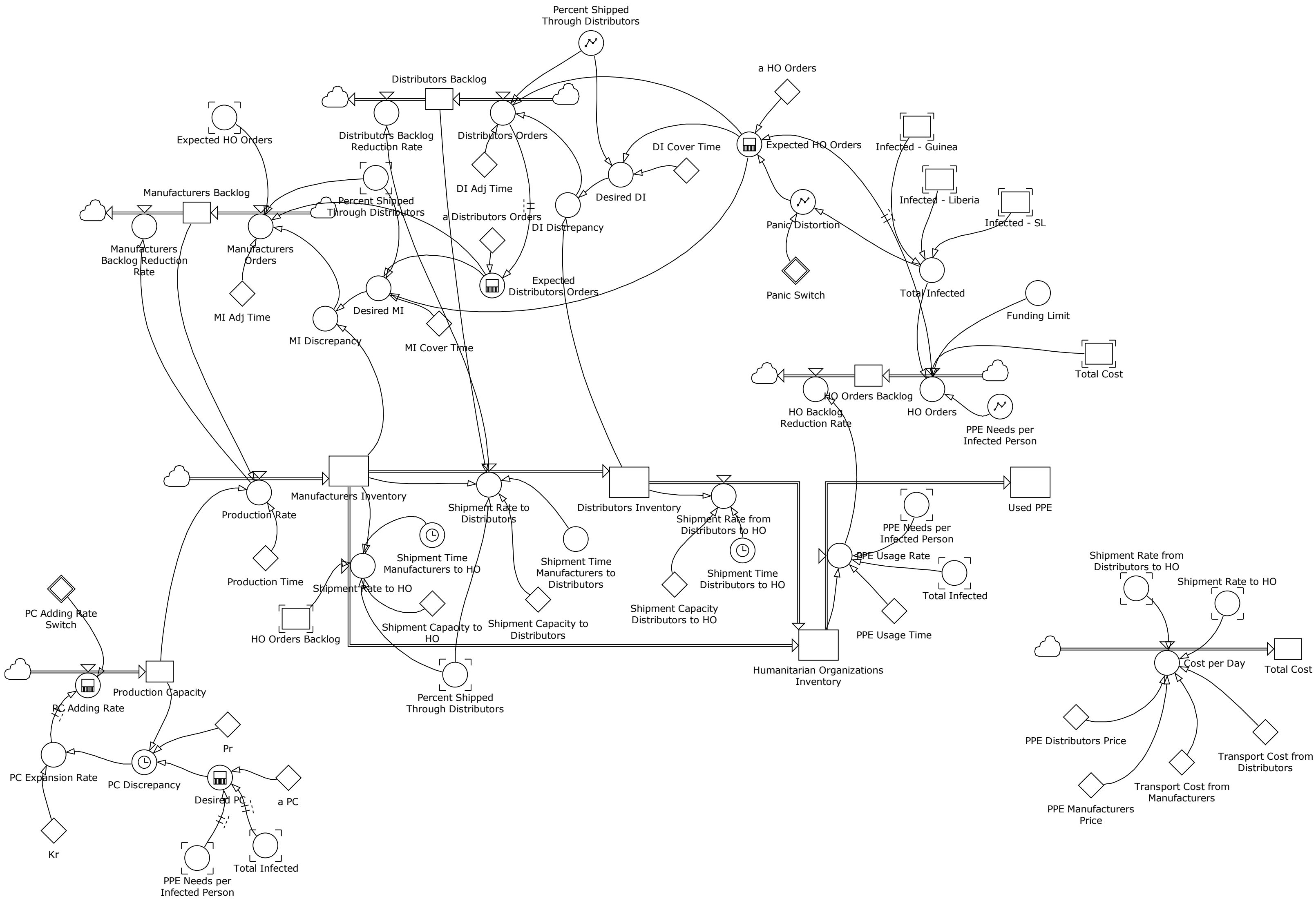
CODE			DESCRIPTION
Inventory and procurement decision-making			
	Pre-crisis		
		Demand uncertainty	*Respondent indicates that the uncertainty of future disasters (in scope, location, magnitude, or type) or of future demand affects their inventory policies.*
		Usage versatility	*Respondent indicates that the versatility of a product's usage (for different emergencies, contexts, responses, etc.) affects their inventory policy for that product.*
		Holding expense	*Respondent indicates that the expense – price and holding cost – of an item affects their inventory policy. This includes cost considerations such as shelf life and expiration.*
		Contract usage	*Respondent indicates their organization utilizes contracts or agreements to make their inventory more flexible.*
		Pre-positioned PPE	*Respondent mention, within their organization, the existence of some pre-positioned PPE supplies before the crisis.*
	In-crisis		
		Use of epidemic models	*Respondent indicates use of epidemic spread predictions in forecasting their own need for PPE items and supplies.*
		Data problems	*Respondent experiences a lack of data, inability to access data, or lack of knowledge about where data resides or how to access it. Respondent indicates that the data used or data available for use was of poor quality or consistency. Respondent indicates that data was changing very quickly, which made forecasting more difficult.*
		Ordered max available	*Respondent indicates that some portion of their ordering policy was to order whatever PPE items they found that were available.*
		Fear of shortage	*Respondent indicates that a shortage of any or multiple PPE items was feared during the crisis.*
		Shortage experienced	*Respondent indicates that a shortage of some PPE item was experienced during the crisis.*

		Overstock experienced	*Respondent indicates that an overstock of a PPE item was experienced or feared during or after the crisis.*
Operational challenges			
	Newness		
		Institutional knowledge gap	*Respondent indicates a lack of institutional knowledge in responding to the outbreak. Responses that indicate newness of operations for the organization. Examples: lack of adequate processes, lack of technical expertise, steep learning curve.*
		Cautiousness / fear	*Respondent indicates an overly cautious mentality or approach to the response, sometimes due to fear.*
		Overwhelmed	*Respondent indicates that the outbreak response was overwhelming. Can include phrases such as "out of hand," "spiraled," "out of control," or "panic."*
		Unprecedented	*Respondent indicates the outbreak was unprecedented or unexpected. Phrases such as: "not on our radar," "unexpected."*
		MSF following	*Respondent indicates their organization followed MSF's procedures, procurement guidelines, or specifications to some extent at some point in the crisis.*
	Supply chain stress		
		Organizational competition	*Respondent indicates they experienced competition in procurement of PPE between themselves and other organizations or governments attempting to respond to the crisis.*
		Unnecessary or over-procurement	*Respondent indicates that non-responding organizations or governments were procuring unnecessarily due to fear, panic, misuse of PPE, or over-preparation.*
		Specifications issues	*Respondent indicates that some confusion or complication resulted from the complexity or difficulty associated with specifications and standards. This might include: differences in the standardization of PPE kits, the standardization of products within the PPE kit, the irrationality of the standards, the difference in standards flexibility between organizations.*
		Lead time increase	*Respondent reports an increase in the lead times for one or more PPE items during the crisis.*
		Price increase	*Respondent indicates the prices for PPE items (or transport of those items) increased during the crisis.*

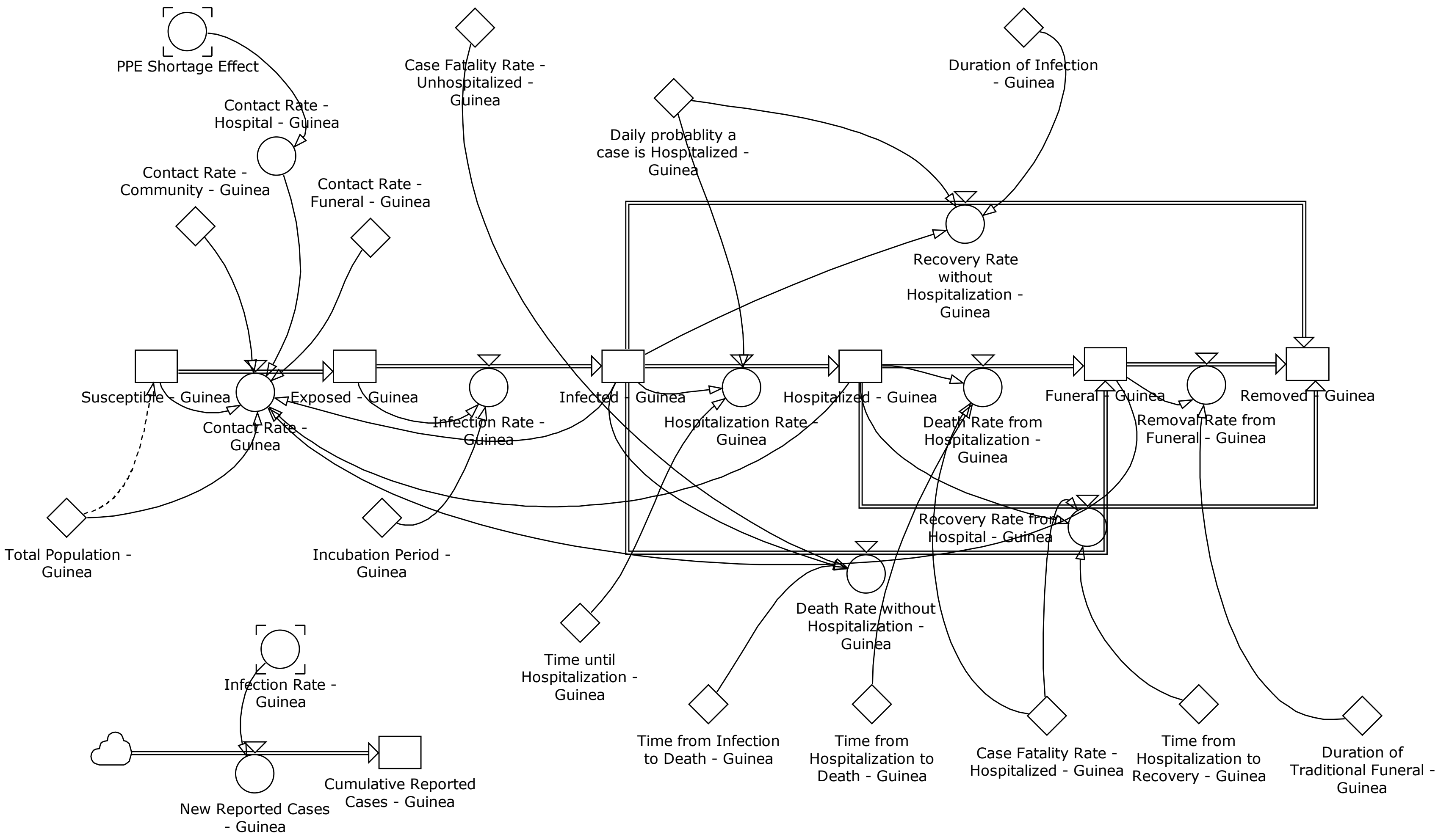
		Product consistency	*Respondent indicates the importance of having a standard, consistent PPE supply to ensure healthcare worker safety.*
		Supply-demand mismatch	*Respondent mentions the high volume of PPE being demanded/procured during the crisis and/or respondent mentions the limited amount of global PPE supply available during the crisis.* *Keywords: Availability, supply, stock out.*
Ideal			
	Improved product availability		*Respondent indicates that in the future, increased global supply and/or increased manufacturer ability to respond to demand would help the response effort.*
	Organizational experience		*Respondent indicates that organizations' experiences with Ebola will allow them to better respond to future epidemics.*

POWERSIM MODEL DIAGRAMS

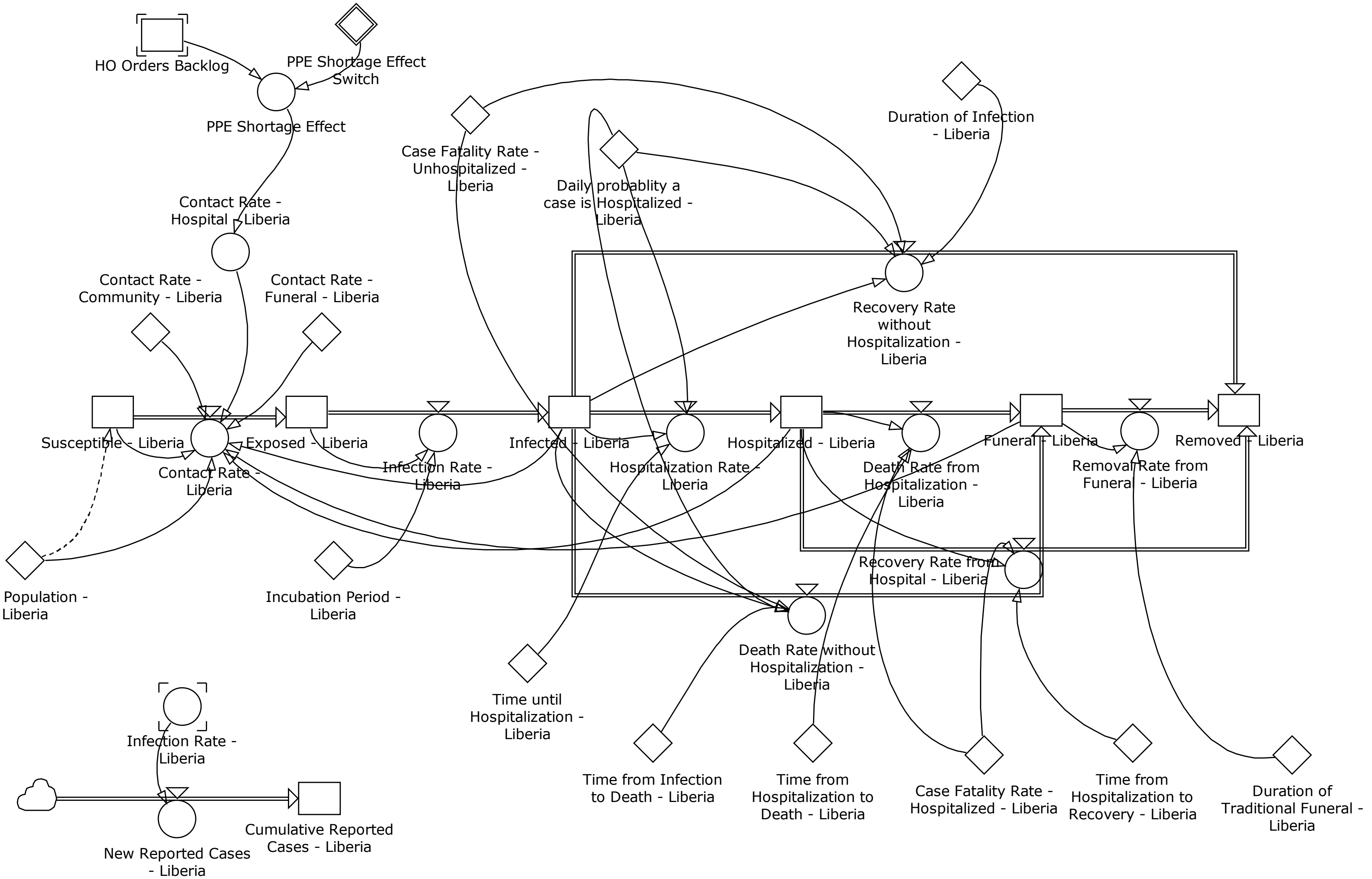
SUPPLY CHAIN MODEL



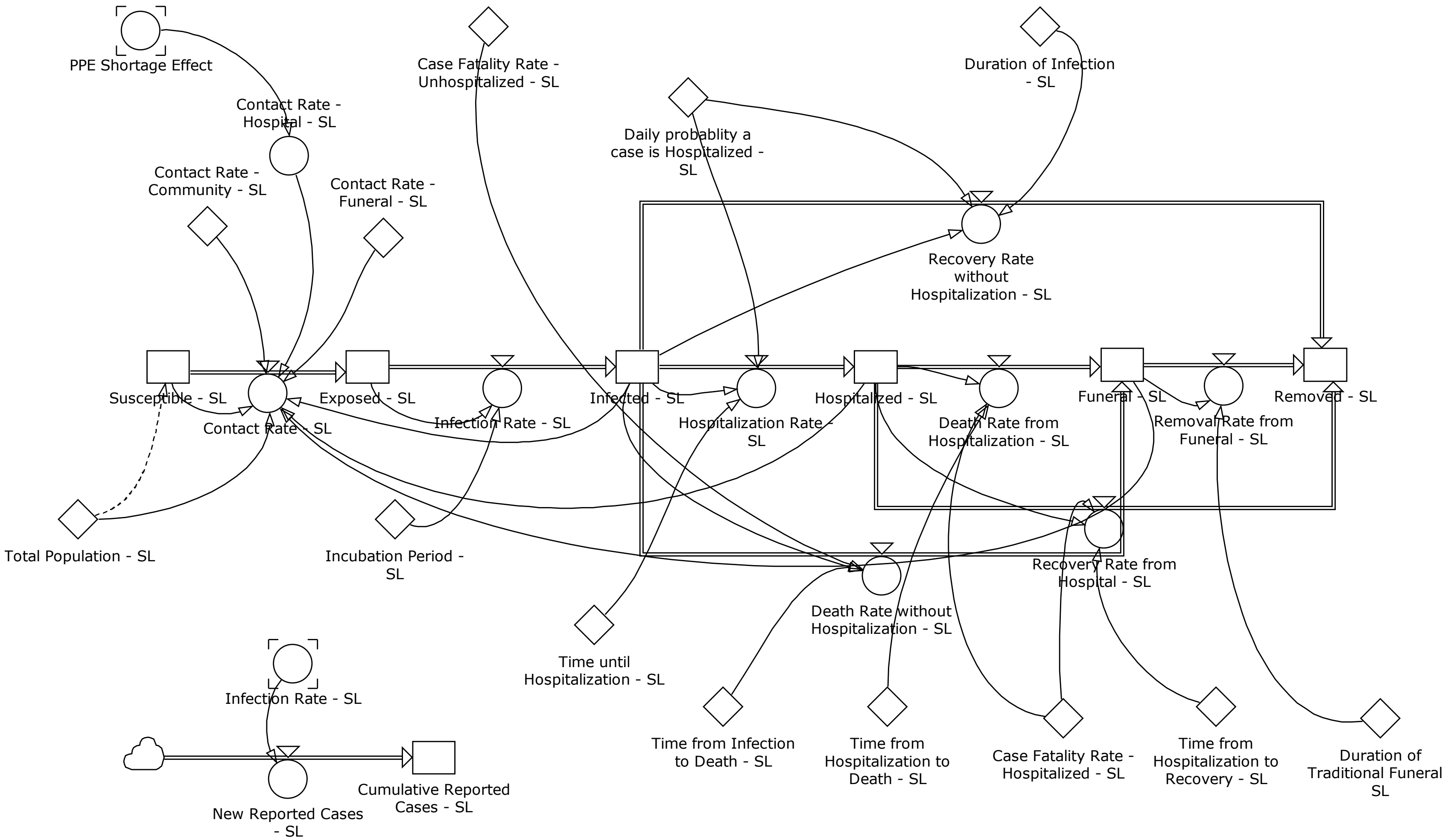
GUINEA EPIDEMIC MODEL



LIBERIA EPIDEMIC MODEL



SIERRA LEONE EPIDEMIC MODEL



MODEL DOCUMENTATION

Name	Unit	Documentation	Variable Type
a Distributors Orders	day	smoothing factor for expected distributor orders	constant
a HO Orders	day	smoothing factor for expected humanitarian organization orders	constant
a PC	day	smoothing factor for desired production capacity	constant
Case Fatality Rate - Hospitalized - Guinea		partial case fatality ratio, for hospitalized individuals	constant
Case Fatality Rate - Hospitalized - Liberia		partial case fatality ratio, for hospitalized individuals	constant
Case Fatality Rate - Hospitalized - SL		partial case fatality ratio, for hospitalized individuals	constant
Case Fatality Rate - Unhospitalized - Guinea		partial case fatality ratio, for unhospitalized patients	constant
Case Fatality Rate - Unhospitalized - Liberia		partial case fatality ratio, for unhospitalized patients	constant
Case Fatality Rate - Unhospitalized - SL		partial case fatality ratio, for unhospitalized patients	constant
Contact Rate - Community - Guinea		transmission coefficient in the community	constant
Contact Rate - Community - Liberia		transmission coefficient in the community	constant
Contact Rate - Community - SL		transmission coefficient in the community	constant
Contact Rate - Funeral - Guinea		transmission coefficient during funerals	constant
Contact Rate - Funeral - Liberia		transmission coefficient during funerals	constant
Contact Rate - Funeral - SL		transmission coefficient during funerals	constant
Contact Rate - Guinea	people/day	composite of all transmission terms; contact rate in Guinea	auxiliary
Contact Rate - Hospital - Guinea		transmission coefficient at hospitals	auxiliary
Contact Rate - Hospital - Liberia		transmission coefficient at hospitals	auxiliary
Contact Rate - Hospital - SL		transmission coefficient at hospitals	auxiliary

Contact Rate - Liberia	people/day	composite of all transmission terms; contact rate in Liberia	auxiliary
Contact Rate - SL	people/day	composite of all transmission terms; contact rate in Sierra Leone	auxiliary
Cost per Day	$/day	cost of materials and transport for PPE units shipped to humanitarian organizations each day	auxiliary
Cumulative Reported Cases - Guinea	people	cumulative number of reported cases of Ebola in Guinea	level
Cumulative Reported Cases - Liberia	people	cumulative number of reported cases of Ebola in Liberia	level
Cumulative Reported Cases - SL	people	cumulative number of reported cases of Ebola in Sierra Leone	level
Daily probability a case is Hospitalized - Guinea		derived from the proportion of infectious cases that are hospitalized	constant
Daily probability a case is Hospitalized - Liberia		derived from the proportion of infectious cases that are hospitalized	constant
Daily probability a case is Hospitalized - SL		derived from the proportion of infectious cases that are hospitalized	constant
Death Rate from Hospitalization - Guinea	people/day	death rate of hospitalized individuals	auxiliary
Death Rate from Hospitalization - Liberia	people/day	death rate of hospitalized individuals	auxiliary
Death Rate from Hospitalization - SL	people/day	death rate of hospitalized individuals	auxiliary
Death Rate without Hospitalization - Guinea	people/day	death rate of individuals who are not hospitalized	auxiliary
Death Rate without Hospitalization - Liberia	people/day	death rate of individuals who are not hospitalized	auxiliary
Death Rate without Hospitalization - SL	people/day	death rate of individuals who are not hospitalized	auxiliary
Desired DI	Units	desired amount of inventory in Distributors Inventory	auxiliary

Desired MI	Units	desired amount of inventory in Manufacturers Inventory	auxiliary
Desired PC	Units/day	desired production capacity, driven by the current daily PPE needs of all infected people	auxiliary
DI Adj Time	day	distributors' inventory adjustment time	constant
DI Cover Time	day	distributors' inventory cover time	constant
DI Discrepancy	Units	gap between the distributors' desired and actual inventory	auxiliary
Distributors Backlog	Units	unsatisfied Distributors Orders served when Distributors Inventory is available	level
Distributors Backlog Reduction Rate	Units/day	an auxiliary variable equal to the Shipment Rate to Distributors	auxiliary
Distributors Inventory	Units	distributors' inventory	level
Distributors Orders	Units/day	orders placed from distributors to manufacturers	auxiliary
Duration of Infection - Guinea	day	mean duration of the infectious period for survivors	constant
Duration of Infection - Liberia	day	mean duration of the infectious period for survivors	constant
Duration of Infection - SL	day	mean duration of the infectious period for survivors	constant
Duration of Traditional Funeral - Guinea	day	mean duration from death to burial	constant
Duration of Traditional Funeral - Liberia	day	mean duration from death to burial	constant
Duration of Traditional Funeral - SL	day	mean duration from death to burial	constant
Expected Distributors Orders	Units/day	forecast of distributors' orders using exponential smoothing with smoothing factor 'a Distributors Orders'	auxiliary
Expected HO Orders	Units/day	forecast of humanitarian organizations' orders using exponential smoothing with smoothing factor 'a HO Orders'	auxiliary
Exposed - Guinea	people	number of people in Guinea exposed to Ebola	level
Exposed - Liberia	people	number of people in Liberia exposed to Ebola	level
Exposed - SL	people	number of people in Sierra Leone exposed to Ebola	level

Funding Limit	$	total amount of money that can be spent on PPE by humanitarian organizations	auxiliary
Funeral - Guinea	people	number of cases who are dead but not yet buried	level
Funeral - Liberia	people	number of cases who are dead but not yet buried	level
Funeral - SL	people	number of cases who are dead but not yet buried	level
HO Backlog Reduction Rate	Units/day	an auxiliary variable equal to the PPE Usage Rate	auxiliary
HO Orders	Units/day	orders placed from humanitarian organizations to either distributors or manufacturers	auxiliary
HO Orders Backlog	Units	unsatisfied HO Orders served when Humanitarian Organizations Inventory is available	level
Hospitalization Rate - Guinea	people/day	hospitalization rate in Guinea	auxiliary
Hospitalization Rate - Liberia	people/day	hospitalization rate in Liberia	auxiliary
Hospitalization Rate - SL	people/day	hospitalization rate in Sierra Leone	auxiliary
Hospitalized - Guinea	people	number of people in Guinea hospitalized with Ebola	level
Hospitalized - Liberia	people	number of people in Liberia hospitalized with Ebola	level
Hospitalized - SL	people	number of people in Sierra Leone hospitalized with Ebola	level
Humanitarian Organizations Inventory	Units	humanitarian organizations' inventory	level
Incubation Period - Guinea	day	mean duration of the incubation period	constant
Incubation Period - Liberia	day	mean duration of the incubation period	constant
Incubation Period - SL	day	mean duration of the incubation period	constant
Infected - Guinea	people	number of people in Guinea infected with Ebola	level
Infected - Liberia	people	number of people in Liberia infected with Ebola	level
Infected - SL	people	number of people in Sierra Leone infected with Ebola	level
Infection Rate - Guinea	people/day	infection rate in Guinea	auxiliary
Infection Rate - Liberia	people/day	infection rate in Liberia	auxiliary
Infection Rate - SL	people/day	infection rate in Sierra Leone	auxiliary
Kr	1/day	production capacity control variable	constant
Manufacturers Backlog	Units	unsatisfied Manufacturers Orders served when Manufacturers Inventory is available	level

Manufacturers Backlog Reduction Rate	Units/day	an auxiliary variable equal to the Production Rate	auxiliary
Manufacturers Inventory	Units	manufacturers' inventory	level
Manufacturers Orders	Units/day	orders "placed" by manufacturers to their production teams	auxiliary
MI Adj Time	day	manufacturers' inventory adjustment time	constant
MI Cover Time	day	manufacturers' inventory cover time	constant
MI Discrepancy	Units	gap between the manufacturers' desired and actual inventory	auxiliary
New Reported Cases - Guinea	people/day	number of new reported cases in Guinea; equal to the infection rate	auxiliary
New Reported Cases - Liberia	people/day	number of new reported cases in Liberia; equal to the infection rate	auxiliary
New Reported Cases - SL	people/day	number of new reported cases in Sierra Leone; equal to the infection rate	auxiliary
Panic Distortion		multiplier on the Expected HO Orders accounting for global panic, after a certain number of people are infected	auxiliary
Panic Switch		switch for linear (1), exponential (2), sigmoidal (3)	constant
PC Adding Rate	Units/day^2	production capacity adding rate	auxiliary
PC Adding Rate Switch		switch for no ability (1) or ability (0) of manufacturers to add production capacity	constant
PC Discrepancy	Units/day	gap between actual and desired production capacity	auxiliary
PC Expansion Rate	Units/day/day	production capacity expansion rate	auxiliary
Percent Shipped Through Distributors		percentage of humanitarian organization orders that go through a distributor (as opposed to going directly to the manufacturer)	auxiliary
PPE Distributors Price	$/Units	price per unit of PPE sourced from distributors	constant
PPE Manufacturers Price	$/Units	price per unit of PPE sourced from manufacturers directly	constant
PPE Needs per Infected Person	Units/(people*day)	estimated number of PPE Units required by each infected person each day	auxiliary

PPE Shortage Effect		multiplier on the hospitalization contact rates of each SEIHFR model to account for the effect of a PPE shortage on the hospitalization contact rate	auxiliary
PPE Shortage Effect Switch		switch for PPE shortage effect (1) or no effect (0)	constant
PPE Usage Rate	Units/day	rate at which humanitarian organizations use PPE in their inventory	auxiliary
PPE Usage Time	day	amount of time required for humanitarian organizations to use each PPE unit	constant
Pr	day	production capacity review period	constant
Production Capacity	Units/day	maximum number of PPE units that can be produced each day	level
Production Rate	Units/day	rate at which manufacturers produce PPE	auxiliary
Production Time	day	amount of time required to manufacture one unit of PPE	constant
Recovery Rate from Hospital - Guinea	people/day	recovery rate from hospitals	auxiliary
Recovery Rate from Hospital - Liberia	people/day	recovery rate from hospitals	auxiliary
Recovery Rate from Hospital - SL	people/day	recovery rate from hospitals	auxiliary
Recovery Rate without Hospitalization - Guinea	people/day	recovery rate of individuals who are not hospitalized	auxiliary
Recovery Rate without Hospitalization - Liberia	people/day	recovery rate of individuals who are not hospitalized	auxiliary
Recovery Rate without Hospitalization - SL	people/day	recovery rate of individuals who are not hospitalized	auxiliary
Removal Rate from Funeral - Guinea	people/day	removal rate from funerals	auxiliary
Removal Rate from Funeral - Liberia	people/day	removal rate from funerals	auxiliary
Removal Rate from Funeral - SL	people/day	removal rate from funerals	auxiliary

Removed - Guinea	people	number of people who have been removed from the model, either through recovery or death	level
Removed - Liberia	people	number of people who have been removed from the model, either through recovery or death	level
Removed - SL	people	number of people who have been removed from the model, either through recovery or death	level
Shipment Capacity Distributors to HO	Units/day	maximum number of PPE units that can be shipped from distributors to humanitarian organizations each day	constant
Shipment Capacity to Distributors	Units/day	maximum number of PPE units that can be shipped from manufacturers to distributors each day	constant
Shipment Capacity to HO	Units/day	maximum number of PPE units that can be shipped from manufacturers to humanitarian organizations each day	constant
Shipment Rate from Distributors to HO	Units/day	flow of PPE from distributors to humanitarian organizations	auxiliary
Shipment Rate to Distributors	Units/day	flow of PPE from manufacturers to distributors	auxiliary
Shipment Rate to HO	Units/day	flow of PPE from manufacturers to humanitarian organizations	auxiliary
Shipment Time Distributors to HO	day	amount of time required to ship PPE from distributors to humanitarian organizations	auxiliary
Shipment Time Manufacturers to Distributors	day	amount of time required to ship PPE from manufacturers to distributors	auxiliary
Shipment Time Manufacturers to HO	day	amount of time required to ship PPE from manufacturers to humanitarian organizations	auxiliary
Susceptible - Guinea	people	number of susceptible people in Guinea	level
Susceptible - Liberia	people	number of susceptible people in Liberia	level
Susceptible - SL	people	number of susceptible people in Sierra Leone	level
Time from Hospitalization to Death - Guinea	day	mean duration from hospitalization to death	constant
Time from Hospitalization to Death - Liberia	day	mean duration from hospitalization to death	constant

Time from Hospitalization to Death - SL	day	mean duration from hospitalization to death	constant
Time from Hospitalization to Recovery - Guinea	day	mean duration from hospitalization to end of infectiousness for survivors	constant
Time from Hospitalization to Recovery - Liberia	day	mean duration from hospitalization to end of infectiousness for survivors	constant
Time from Hospitalization to Recovery - SL	day	mean duration from hospitalization to end of infectiousness for survivors	constant
Time from Infection to Death - Guinea	day	mean duration from symptom onset to death	constant
Time from Infection to Death - Liberia	day	mean duration from symptom onset to death	constant
Time from Infection to Death - SL	day	mean duration from symptom onset to death	constant
Time until Hospitalization - Guinea	day	mean duration from symptom onset to hospitalization	constant
Time until Hospitalization - Liberia	day	mean duration from symptom onset to hospitalization	constant
Time until Hospitalization - SL	day	mean duration from symptom onset to hospitalization	constant
Total Cost	$	total cost, of transport and materials, of all PPE shipped to humanitarian organizations	level
Total Infected	people	total number of infected people in all three countries	auxiliary
Total Population - Guinea	people	total population of Guinea; the initial susceptible population	constant
Total Population - Liberia	people	total population of Liberia; the initial susceptible population	constant
Total Population - SL	people	total population of Sierra Leone; the initial susceptible population	constant
Transport Cost from Distributors	$/Units	transport price per unit of PPE sourced from distributors	constant

Transport Cost from Manufacturers	$/Units	transport price per unit of PPE sourced from manufacturers directly	constant
Used PPE	Units		level

BIBLIOGRAPHY

3M Personal Safety Division. 2014. *Personal Protective Equipment (PPE) for Ebola Virus Disease (EVD)*.

Balcik, Burcu, and Deniz Ak. 2014. “Supplier Selection for Framework Agreements in Humanitarian Relief.” *Production and Operations Management* 23 (6): 1028–41. doi:10.1111/poms.12098.

Barbarossa, Maria Vittoria, Attila Dénes, Gábor Kiss, Yukihiko Nakata, Gergely Röst, and Zsolt Vizi. 2015. “Transmission Dynamics and Final Epidemic Size of Ebola Virus Disease Outbreaks with Varying Interventions.” *PLOS One* 10 (7). doi:10.1371/journal.pone.0131398.

Besiou, Maria, Orla Stapleton, and Luk N. Van Wassenhove. 2011. “System Dynamics for Humanitarian Operations.” *Journal of Humanitarian Logistics and Supply Chain Management* 1 (1): 78–103. doi:10.1080/10643389.2012.728825.

Bogoch, Isaac I, Maria I Creatore, Martin S Cetron, John S Brownstein, Nicki Pesik, Jennifer Miniota, Theresa Tam, et al. 2015. “Assessment of the Potential for International Dissemination of Ebola Virus via Commercial Air Travel during the 2014 West African Outbreak.” *The Lancet* 385 (9962). Bogoch et al. Open Access article distributed under the terms of CC BY: 29–35. doi:10.1016/S0140-6736(14)61828-6.

Brandeau, Margaret L. 2004. “Allocating Resources to Control Infectious Diseases.” *Operations Research & Health Care: A Handbook of Methods & Applictions*, 443–64.

Brandeau, Margaret L., David W. Hutton, Douglas K. Owens, and Dena M. Bravata. 2007. “Planning the Bioterrorism Response Supply Chain: Learn and Live.” *American Journal of Disaster Medicine* 2 (5): 231–47.

Brandeau, Margaret L., Gregory S. Zaric, and Anke Richter. 2003. “Resource Allocation for Control of Infectious Diseases in Multiple Independent Populations: Beyond Cost-Effectiveness Analysis.” *Journal of Health Economics* 22 (4): 575–98. doi:10.1016/S0167-6296(03)00043-2.

Bryman, Alan, and Emma Bell. 2011. *Business Research Methods*. 3rd ed. Oxford University Press.

Caunhye, Aakil M, Xiaofeng Nie, and Shaligram Pokharel. 2012. “Optimization Models in Emergency Logistics: A Literature Review.” *Socio-Economic Planning Sciences* 46 (1): 4–13.

Centers for Disease Control and Prevention. n.d. *CDC PPE Donning and Doffing Exercise*.

———. 2014a. “Ebola Virus Disease in Health Care Workers - Sierra Leone, 2014.” http://www.cdc.gov/mmwr/preview/mmwrhtml/mm6349a6.htm.

———. 2014b. *Guidance on Personal Protective Equipment to Be Used by Healthcare Workers during Management of Patients with Ebola Virus Disease in U.S. Hospitals, Including Procedures for Putting on (Donning) and Removing (Doffing)*.

———. 2015a. “Ebola Virus Disease in Health Care Workers - Guinea, 2014.” http://www.cdc.gov/mmwr/preview/mmwrhtml/mm6438a6.htm.

———. 2015b. “Outbreaks Chronology: Ebola Virus Disease.” http://www.cdc.gov/vhf/ebola/outbreaks/history/chronology.html.

———. 2016. “Cost of the Ebola Epidemic.” http://www.cdc.gov/vhf/ebola/pdf/cost-response.pdf.

Coleman, James. 1958. “Relational Analysis: The Study of Social Organizations with Survey Methods.” *Human Organization* 17 (4). Society for Applied Anthropology: 28–36. doi:10.17730/humo.17.4.q5604m676260q8n7.

Costa, Sergio Ricardo Argollo Da, Vânia Barcellos Gouvêa Campos, and Renata Albergaria De Mello Bandeira. 2012. “Supply Chains in Humanitarian Operations: Cases and Analysis.” *Procedia - Social and Behavioral Sciences* 54: 598–607. doi:10.1016/j.sbspro.2012.09.777.

Danermark, Berth, Mats Ekstrom, Liselotte Jakobson, and Jan Karlsson. 2001. *Explaining Society: An Introduction to Critical Realism in the Social Sciences*.

Das, D, and P Dutta. 2013. “A System Dynamics Framework for Integrated Reverse Supply Chain with Three Way Recovery and Product Exchange Policy.” *Computers & Industrial Engineering* 66 (4). Indian Institute of Technology, Mumbai, Shailesh J. Mehta School of Management, Bombay, Mumbai, 400076, India: Elsevier Science Ltd.: 720–33. DOI: 10.1016/j.cie.2013.09.016.

Dasaklis, Thomas K., Costas P. Pappis, and Nikolaos P. Rachaniotis. 2012. “Epidemics Control and Logistics Operations: A Review.” *International Journal of Production Economics* 139 (2). Elsevier: 393–410. doi:10.1016/j.ijpe.2012.05.023.

Dubois, Anna, and Lars-Erik Gadde. 2002. “Systematic Combining: An Abductive Approach to Case Research.” *Journal of Business Research* 55: 553–60.

Duintjer Tebbens, Radboud J., Mark a. Pallansch, James P. Alexander, and Kimberly M. Thompson. 2010. “Optimal Vaccine Stockpile Design for an Eradicated Disease: Application to Polio.” *Vaccine* 28 (26). Elsevier Ltd: 4312–27. doi:10.1016/j.vaccine.2010.04.001.

DuPont. 2014. *Protective Clothing for Ebola Virus Disease (EVD)*.

Edmondson, Amy C., and Stacy E. Mcmanus. 2007. “Methodological Fit in Management Field Research.” *Academy of Management Review* 32 (4): 1155–79. doi:10.5465/AMR.2007.26586086.

Fast, Shannon M., Marta C. González, and Natasha Markuzon. 2015. “Cost-Effective Control of Infectious Disease Outbreaks Accounting for Societal Reaction.” *Plos One* 10 (8): e0136059. doi:10.1371/journal.pone.0136059.

Finkelstein, Stan N, Richard C Larson, Karima Nigmatulina, and Anna Teytelman. 2015. “Engineering Effective Responses to Influenza Outbreaks.” *Service Science* 7 (2): 119–31.

Forrester, J W. 1961. *Industrial Dynamics*. Students’ Edition. Massachusetts Institute of Technology Press. https://books.google.com/books?id=4CgzAAAAMAAJ.

Gatignon, Aline, Luk N. Van Wassenhove, and Aurélie Charles. 2010. “The Yogyakarta Earthquake: Humanitarian Relief through IFRC’s Decentralized Supply Chain.” *International Journal of Production Economics* 126 (1): 102–10. doi:10.1016/j.ijpe.2010.01.003.

Georgiadis, Patroklos, and Maria Besiou. 2008. “Sustainability in Electrical and Electronic Equipment Closed-Loop Supply Chains: A System Dynamics Approach.” *Journal of Cleaner Production* 16 (15): 1665–78. doi:10.1016/j.jclepro.2008.04.019.

Ginetti, Justin, Chris Lavell, and Travis Franck. 2014. *Disaster-Related Displacement Risk: Measuring the Risk and Addressing Its Drivers*. http://www.internal-displacement.org/publications/2015/disaster-related-displacement-risk-measuring-the-risk-and-addressing-its-drivers/.

Goentzel, Jarrod, and Ian Heigh. 2015. “Supply Chains in Crisis.” *Inside Logistics*.

Goentzel, Jarrod, and Karen Spens. 2011. “Humanitarian Logistics in the United States: Supply Chain Systems for Responding to Domestic Disasters.” *Humanitarian Logistics: Meeting The Challenge of Preparing for and Responding to Disasters*, no. Vmi: 141–65.

Gomes, MFC, A Pastore y Piontti, L Rossi, D Chao, I Longini, ME Halloran, and A Vespignani. 2014. “Assessing the International Spreading Risk Associated with the 2014 West African Ebola Outbreak.” *PLOS Currents Outbreaks*.

Gostin, Lawrence O, and Eric a Friedman. 2015. “A Retrospective and Prospective Analysis of the West African Ebola Virus Disease Epidemic: Robust National Health Systems at the Foundation and an Empowered WHO at the Apex.” *The Lancet* 385 (9980). Elsevier Ltd: 1902–9. doi:10.1016/S0140-6736(15)60644-4.

Gralla, Erica, Jarrod Goentzel, and Charles Fine. 2013. “Assessing Trade-Offs among Multiple Objectives for Humanitarian Aid Delivery Using Expert Preferences.” *Production and Operations Management* 0 (0): 1–12. doi:10.1111/poms.12110.

He, Yuxuan, and Nan Liu. 2015. “Methodology of Emergency Medical Logistics for Public Health Emergencies.” *Transportation Research Part E: Logistics and Transportation Review* 79. Elsevier Ltd: 178–200. doi:10.1016/j.tre.2015.04.007.

Hick, John L, Lewis Rubinson, Daniel T O’Laughlin, and J Christopher Farmer. 2007. “Clinical Review: Allocating Ventilators during Large-Scale Disasters--Problems, Planning, and Process.” *Critical Care (London, England)* 11 (3): 217. doi:10.1186/cc5929.

Hong, Xing, Miguel a. Lejeune, and Nilay Noyan. 2015. “Stochastic Network Design for Disaster Preparedness.” *IIE Transactions* 47 (4): 329–57. doi:10.1080/0740817X.2014.919044.

Jahre, Marianne, Kaustubh Anil Navangul, Daniel Dieckhaus, Ian Heigh, and Natalia Gomez-Tagle Leonard. n.d. “Predicting the Unpredictable - Demand Forecasting in International Humanitarian Response.” *Synthese* 90 (2): 205–32. doi:10.1007/BF00485351.

Jalalpour, Mehdi, Yulia Gel, and Scott Levin. 2015. “Forecasting Demand for Health Services: Development of a Publicly Available Toolbox.” *Operations Research for Health Care* 5: 1–9.

Kimberly-Clark Professional. 2014. *Kimberly-Clark Professional Product Recommendations*.

Kovács, Gyöngyi, and Karen M. Spens. 2005. “Abductive Reasoning in Logistics Research.” *International Journal of Physical Distribution & Logistics Management* 35 (2): 132–44. doi:10.1108/09600030510590318.

Koyuncu, Melik, and Rizvan Erol. 2010. “Optimal Resource Allocation Model to Mitigate the Impact of Pandemic Influenza: A Case Study for Turkey.” *Journal of Medical Systems* 34 (1): 61–70. doi:10.1007/s10916-008-9216-y.

Kunz, Nathan, and Gerald Reiner. 2012. “A Meta-Analysis of Humanitarian Logistics Research.” *Journal of Humanitarian Logistics and Supply Chain Management* 2 (2): 116–47. doi:10.1108/20426741211260723.

Lakeland. 2014. *Ebola Virus Disease: Protective Clothing Guide*.

Langroodi, R R P, and M Amiri. 2016. “A System Dynamics Modeling Approach for a Multi-Level, Multi-Product, Multi-Region Supply Chain under Demand Uncertainty.” *Expert Systems with Applications* 51 (June). Allameh Tabataba’i University, Department of Industrial Management, Tehran, Iran: Elsevier B.V.: 231–44. DOI: 10.1016/j.eswa.2015.12.043.

Lefebvre, A, C Fiet, C Belpois-Duchamp, M Tiv, K Astruc, and L.S Aho Glele. 2014. “Case Fatality Rates of Ebola Virus Diseases: A Meta-Analysis of World Health Organization Data.” *Medecine et Maladies Infectieuses* 44: 412–16.

Legrand, J, R F Grais, P Y Boelle, A J Valleron, and A Flahault. 2007. “Understanding the Dynamics of Ebola Epidemics.” *Epidemiology and Infection* 135 (4): 610–21. doi:10.1017/S0950268806007217.

Lehr, Christian B, Jörn-Henrik Thun, and Peter M Milling. 2013. “From Waste to Value – a System Dynamics Model for Strategic Decision-Making in Closed-Loop Supply Chains.” *International Journal of Production Research* 51 (13). Taylor & Francis Ltd: 4105–16. 10.1080/00207543.2013.774488.

Liu, Ming, and Jing Iang. 2013. “Dynamic Optimization Model for Allocating Medical Resources in Epidemic Controlling.” *Journal of Industrial Engineering and Management* 6 (1 LISS 2012): 73–88. doi:10.3926/jiem.663.

Liu, Ming, Zhe Zhang, and Ding Zhang. 2015. “A Dynamic Allocation Model for Medical Resources in the Control of Influenza Diffusion.” *Journal of Systems Science and Systems Engineering* 24 (3): 276–92. doi:10.1007/s11518-015-5276-y.

Liu, Ming, and Lindu Zhao. 2012. “An Integrated and Dynamic Optimisation Model for the Multi-Level Emergency Logistics Network in Anti-Bioterrorism System.” *International Journal of Systems Science* 43 (8): 1464 – .

Makridakis, Spyros, and Michele Hibon. 2000. “The M3-Competition: Results, Conclusions and Implications.” *International Journal of Forecasting* 16: 451–76.

Medecins Sans Frontieres. 2014. “Ebola in West Africa: ‘The Epidemic Is out of Control.’” http://www.msf.ca/en/article/ebola-west-africa-epidemic-out-control.

———. 2016. “Ebola.” http://www.doctorswithoutborders.org/our-work/medical-issues/ebola.

MedLine. 2014a. *Ebola Preparedness Plan*.

———. 2014b. *Personal Protective Equipment*.

Meltzer, Martin I, Brett W Petersen, Stuart T Nichol, and D Ph. 2015. “Estimating the Future Number of Cases in the Ebola Epidemic — Liberia and Sierra Leone, 2014 – 2015” 63 (3): 2014–15.

Meyers, Linda, Thomas Frawley, Sarah Goss, and Christopher Kang. 2015. “Ebola Virus Outbreak 2014: Clinical Review for Emergency Physicians.” *Annals of Emergency Medicine* 65 (1): 17–19. doi:10.1002/ctpp.200410099.

Moon, Suerie, Devi Sridhar, Muhammad A Pate, Ashish K Jha, Chelsea Clinton, Sophie Delaunay, Valnora Edwin, et al. 2015. “Will Ebola Change the Game? Ten Essential Reforms before the next Pandemic.” *The Lancet* 386 (10009). Elsevier Ltd: 2204–21. doi:10.1016/S0140-6736(15)00946-0.

Ndeffo Mbah, Martial L., and Christopher A. Gilligan. 2010. “Optimization of Control Strategies for Epidemics in Heterogeneous Populations with Symmetric and Asymmetric Transmission.” *Journal of Theoretical Biology* 262 (4). Elsevier: 757–63. doi:10.1016/j.jtbi.2009.11.001.

Pedraza Martinez, Alfonso J., Orla Stapleton, and Luk N. Van Wassenhove. 2011. “Field Vehicle Fleet Management in Humanitarian Operations: A Case-Based Approach.” *Journal of Operations Management* 29 (5). Elsevier B.V.: 404–21. doi:10.1016/j.jom.2010.11.013.

Pigott, David M, Nick Golding, Adrian Mylne, Zhi Huang, Andrew J Henry, Daniel J Weiss, J Oliver, et al. 2014. “Mapping the Zoonotic Niche of Ebola Virus Disease in Africa.” *eLIFE*.

Poletto, C, M Gomes, a Pastore y Piontti, L Rossi, L Bioglio, D Chao, I Longini, M Halloran, V Colizza, and a Vespignani. 2014. "Assessing the Impact of Travel Restrictions on International Spread of the 2014 West African Ebola Epidemic." *Eurosurveillance* 19 (42): 20936. doi:10.2807/1560-7917.ES2014.19.42.20936.

Rachaniotis, Nikolaos P., Tom K. Dasaklis, and Costas P. Pappis. 2012. "A Deterministic Resource Scheduling Model in Epidemic Control: A Case Study." *European Journal of Operational Research* 216 (1). Elsevier B.V.: 225–31. doi:10.1016/j.ejor.2011.07.009.

Rainisch, G, J Asher, D George, M Clay, TL Smith, and K Cosmos. 2015. "Estimating Ebola Treatment Needs, United States: Technical Appendix." *Emerging Infectious Diseases* 21 (7): 1–8. doi:10.3201/eid2107.150286.

Rainisch, Gabriel, Jason Asher, Dylan George, Matt Clay, Theresa L Smith, Christine Kosmos, Manjunath Shankar, et al. 2015. "Estimating Ebola Treatment Needs, United States." *Emerging Infectious Diseases* 21 (7): 1273–76.

Rainisch, Gabriel, Manjunath Shankar, Michael Wellman, Toby Merlin, and Martin I Meltzer. 2015. "Regional Spread of Ebola Virus, West Africa, 2014" 21 (3): 444–47.

Rawls, Carmen G., and Mark a. Turnquist. 2010. "Pre-Positioning of Emergency Supplies for Disaster Response." *Transportation Research Part B: Methodological* 44 (4). Elsevier Ltd: 521–34. doi:10.1016/j.trb.2009.08.003.

Rivers, Caitlin M, Eric T Lofgren, Madhav Marathe, Stephen Eubank, and Bryan L Lewis. 2014. "Modeling the Impact of Interventions on an Epidemic of Ebola in Sierra Leone and Liberia." *PLOS Currents Outbreaks*.

Rubin, Herbert J., and Irene S. Rubin. n.d. *Qualitative Interviewing*.

Saldana, J. 2009. "An Introduction to Codes and Coding." In *The Coding Manual for Qualitative Researchers*, Second, 1–31. doi:10.1519/JSC.0b013e3181ddfd0a.

Salmeron, Javier, and Aruna Apte. 2010. "Stochastic Optimization for Natural Disaster Asset Prepositioning" 19 (5): 561–74.

Shrestha, Sundar S., Gregory S. Wallace, and Martin I. Meltzer. 2010. "Modeling the National Pediatric Vaccine Stockpile: Supply Shortages, Health Impacts and Cost Consequences." *Vaccine* 28 (38). Elsevier Ltd: 6318–32. doi:10.1016/j.vaccine.2010.06.095.

Sodhi, ManMohan S., and Christopher S. Tang. 2012a. "Strategic Approaches for Mitigating Supply Chain Risks." In *Managing Supply Chain Risk*, 172:95–108. doi:10.1007/978-1-4614-3238-8.

———. 2012b. "Tactical Approaches for Mitigating Supply Chain Risks: Financial and Operational Hedging." In *Managing Supply Chain Risk*, 172:109–33. doi:10.1007/978-1-4614-3238-8.

Sterk, Esther. 2008. *Filovirus Haemorrhagic Fever Guideline 2008*.

Sterman, John D. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Vol. 19. Irwin/McGraw-Hill Boston.

Sterman, John, Rogelio Oliva, Kevin Linderman, and Elliot Bendoly. 2015. "System Dynamics Perspectives and Modeling Opportunities for Research in Operations Management." *Journal of Operations Management* 40: 1–5. doi:10.1016/j.jom.2015.07.001.

Stuart, I., D. McCutcheon, R. Handfield, R. McLachlin, and D. Samson. 2002. "Effective Case Research in Operations Management: A Process Perspective." *Journal of Operations Management* 20 (5): 419–33. doi:10.1016/S0272-6963(02)00022-0.

Tang, Christopher. 2006. "Robust Strategies for Mitigating Supply Chain Disruptions." *International Journal of Logistics* 9 (1): 33–45. doi:10.1080/13675560500405584.

The Liberian Observer. 2014. “UNMEER: A Welcome New UN Agency To Fight Ebola—But Why So Late?,” September 24. http://www.liberianobserver.com/editorials/unmeer-welcome-new-un-agency-fight-ebola%E2%80%94-why-so-late.

Tizzoni, Michele, Paolo Bajardi, Adeline Decuyper, Guillaume Kon Kam King, Christian M. Schneider, Vincent Blondel, Zbigniew Smoreda, Marta C. González, and Vittoria Colizza. 2014. “On the Use of Human Mobility Proxies for Modeling Epidemics.” *PLoS Computational Biology* 10 (7). doi:10.1371/journal.pcbi.1003716.

Tomasini, Rolando M, and Luk N Van Wassenhove. 2009. “From Preparedness to Partnerships: Case Study Research on Humanitarian Logistics.” *International Transactions in Operational Research* 16 (5): 549–59. doi:10.1111/j.1475-3995.2009.00697.x.

Tsao, Hsiao-Mei, Ying-Chou Sun, and Der-Ming Liou. 2015. “A Rational Approach to Estimating the Surgical Demand Elasticity Needed to Guide Manpower Reallocation during Contagious Outbreaks.” *Plos One* 10 (4): e0122625. doi:10.1371/journal.pone.0122625.

UN Office for the Coordination of Humanitarian Affairs. 2014. “3W Dataset on the Organizations Involved in the Response to the Ebola Crisis.” *Humanitarian Data Exchange*. https://data.hdx.rwlabs.org/dataset/3w-dataset-on-the-organizations-involved-in-the-response-to-the-ebola-crisis.

UNICEF Programme Division. 2014. *WASH Package for Ebola Care and Treatment Centres/Units*.

UNICEF Supply Division. 2014a. *Ebola Virus Disease: Personal Protective Equipment and Other Ebola-Related Supplies*.

———. 2014b. *Ebola Virus Disease: Personal Protective Equipment and Other Ebola-Related Supply Update*.

———. 2014c. *Health Supply Chains in an Ebola Context: Assessment and Risk Mitigation Working Draft*.

USAID/OFDA. 2016. *West Africa - Ebola Outbreak Fact Sheet #6*. https://www.usaid.gov/sites/default/files/documents/1866/west_africa_fs07_01-21-2016.pdf.

Van Wassenhove, Luk N. 2006. “Humanitarian Aid Logistics: Supply Chain Management in High Gear.” *Journal of the Operational Research Society* 57 (5): 475–89. doi:10.1057/palgrave.jors.2602125.

Van Wassenhove, Luk N., and Alfonso J. Pedraza Martinez. 2012. “Using OR to Adapt Supply Chain Management Best Practices to Humanitarian Logistics.” *International Transactions in Operational Research* 19 (1-2): 307–22. doi:10.1111/j.1475-3995.2011.00792.x.

Vlachos, Dimitrios, Patroklos Georgiadis, and Eleftherios Iakovou. 2007. “A System Dynamics Model for Dynamic Capacity Planning of Remanufacturing in Closed-Loop Supply Chains” 34: 367–94. doi:10.1016/j.cor.2005.03.005.

Wang, Shouqiang, Francis de Véricourt, and Peng Sun. 2009. “Decentralized Resource Allocation to Control an Epidemic: A Game Theoretic Approach.” *Mathematical Biosciences* 222 (1). Elsevier Inc.: 1–12. doi:10.1016/j.mbs.2009.08.002.

Washington, Michael L, and Martin L Meltzer. 2015. “Effectiveness of Ebola Treatment Units and Community Care Centers —” 64 (3): 67–70.

Weston, Cynthia, Terry Gandell, J Beauchamp, C Wiseman, and C Beauchamp. 2001. “Analyzing Interview Data: The Development and Evolution of a Coding System.” *Qualitative Sociology* 24 (3): 381–400. http://link.springer.com/article/10.1023/A:1010690908200.

World Health Organization. 2014a. *Draft WHO List of Personal Protective Equipment for Infection and Prevention Control with Focus on Ebola*.
———. 2014b. *How to Put on and Take off Personal Protective Equipment (PPE)*.
———. 2014c. *Interim Infection Prevention and Control Guidance for Care of Patients with Suspected or Confirmed Filovirus Haemorrhagic Fever in Health-Care Settings , with Focus on Ebola*. *World Health Organization*. http://apps.who.int/iris/bitstream/10665/130596/1/WHO_HIS_SDS_2014.4_eng.pdf?ua=1&ua=1&ua=1.
———. 2014d. *Personal Protective Equipment (PPE) in the Context of Filovirus Disease Outbreak Response: Technical Specifications for PPE Equipment to Be Used by Health Workers Providing Clinical Care for Patients*.
———. 2014e. *Personal Protective Equipment for Ebola Outbreak - Sample of Coveralls Available on the Market*. Vol. 1. doi:10.1017/CBO9781107415324.004.
———. 2014f. *Personal Protective Equipment in the Context of Filovirus Disease Outbreak Response*.
———. 2014g. "Unprecedented Number of Medical Staff Infected with Ebola." *Ebola Situation Assessment*. http://www.who.int/mediacentre/news/ebola/25-august-2014/en/.
———. 2014h. *WHO List of Personal Protective Equipment for Infection and Prevention Control with Focus on Ebola Classified by Donation Priority*.
———. 2015a. *Draft WHO List of Personal Protective Equipment for Infection and Prevention Control with Focus on Ebola*.
———. 2015b. "Ebola Vaccines, Therapies, and Diagnostics." *Essential Medicines and Health Products*. http://www.who.int/medicines/emp_ebola_q_as/en/.
———. 2016a. "Ebola Situation Reports." http://apps.who.int/ebola/ebola-situation-reports.
———. 2016b. "Ebola Virus Disease." http://www.who.int/mediacentre/factsheets/fs103/en/.
Yin, Robert K. 1994. *Case Study Research: Design and Methods*. 1st ed.
———. 2009. *Case Study Research: Design and Methods*. Edited by L. Bickman & D. J. Rog. 4th ed. Los Angeles: Sage, Inc.
Zaric, Gregory S, and Margaret L Brandeau. 2002. "Dynamic Resource Allocation for Epidemic Control in Multiple Populations." *IMA Journal of Mathematics Applied in Medicine and Biology* 19 (4): 235–55.
Zaric, Gregory S., and Margaret L. Brandeau. 2001. "Resource Allocation for Epidemic Control over Short Time Horizons." *Mathematical Biosciences* 171 (1): 33–58. doi:10.1016/S0025-5564(01)00050-5.