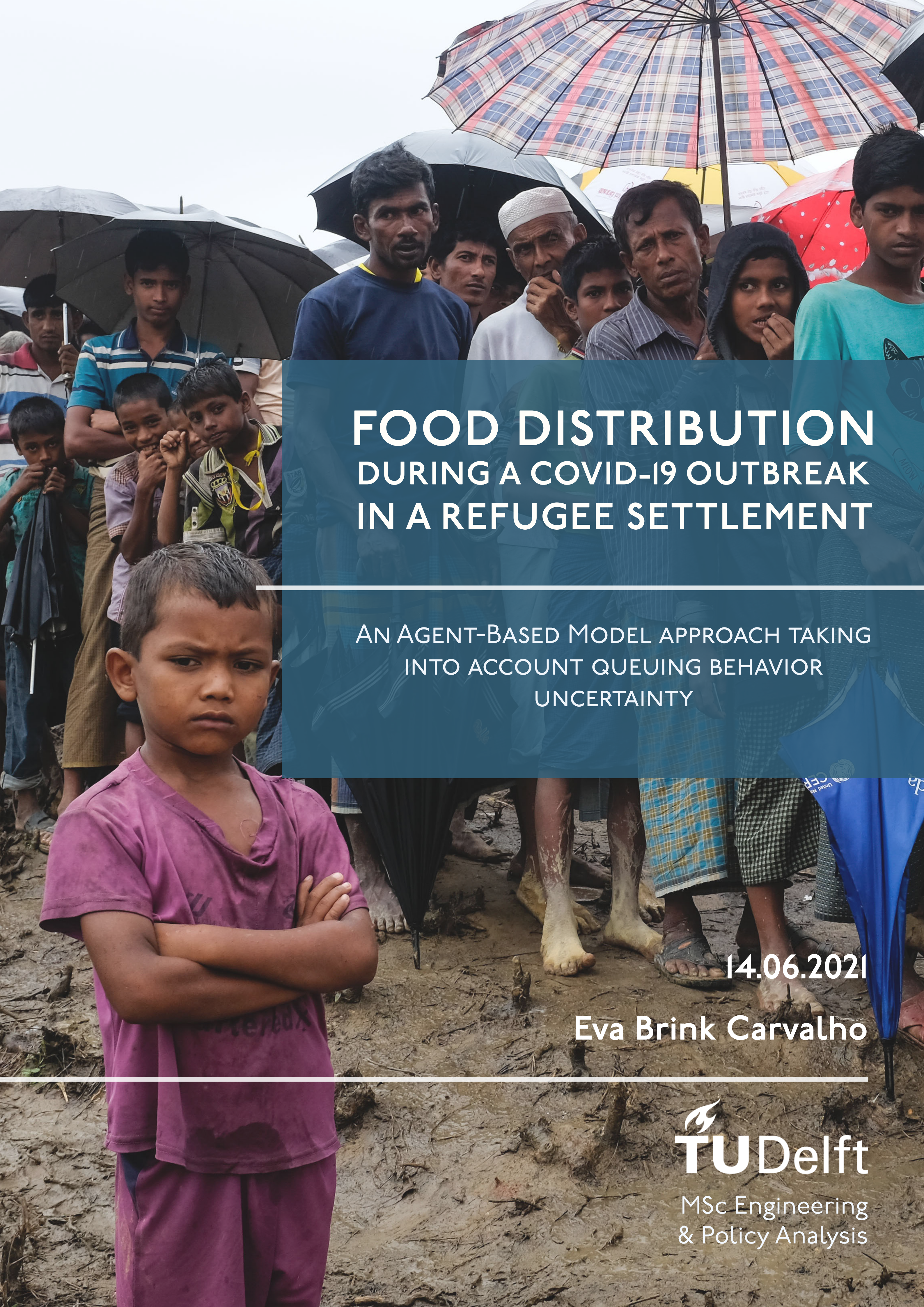

FOOD DISTRIBUTION
DURING A COVID-19 OUTBREAK IN A REFUGEE SETTLEMENT

An Agent-Based Model approach taking into account queuing behavior uncertainty

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MSc Engineering & Policy Analysis

Food distribution during a COVID-19 outbreak in a refugee settlement: An Agent-Based Model approach taking into account queuing behavior uncertainty

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An electronic version of this thesis is available at
`https://repository.tudelft.nl/`
The associated code and model are available at
`https://github.com/evabrinkk/MScGraduationProject`.

TU Delft

Preface

Throughout the last couple of months I have re-discovered love and friendship in the most variate ways.

To everyone around me: thank you for dragging me (in the most loving and supportive way of dragging) to the finish line.

I couldn't have made it without you.

Eva Brink Carvalho
Delft, June 2021

Executive summary

At the end of 2019, a new SARS virus was discovered in Wuhan (China) - SARS-CoV-2. When infected with this virus, a person is said to have the associated disease - COVID-19. One and a half year later, the global number of new COVID-19 cases continues to be extremely high, putting a high strain on health-care facilities with continuous reports of hospitals at full capacity. Protective measures commonly implemented to reduce COVID-19 infection risk are often related to social distancing and avoiding crowded spaces. However, often living in overcrowded settlements with shared facilities, refugees and other persons of concern cannot easily follow these guidelines and often have to queue up to do tasks as simple as using latrines or getting food.

To reduce the infection risks in refugee settlements, it is important to identify the risk of these tasks and of the uncertain behavior of people when waiting in a queue. Therefore, this study focuses on the dynamics of queues and the potential of food distribution policies to control COVID-19 outbreaks. The main research question this study aims to answer can be formulated as follows:

What food distribution policies show robust performance under queuing behavior uncertainty while minimizing COVID-19 infections in the context of an outbreak in a refugee settlement?

To answer this question, an agent-based modeling (ABM) approach is chosen. By focusing on individuals, their behavior and their interactions with each other and evaluating their impact on the system state, ABM is a powerful tool to observe the spread of a virus that is transmitted by direct contact with infected people.

Combining concepts of queuing behavior theories and queue psychology, an ABM queuing model was developed. This model is highly based on a theory that divides queuing attitudes between cooperative and competitive. To integrate social observations in their decision on how to queue, individuals can also switch between attitudes if they are influenced to do so. Then, this queuing model was coupled with an existing agent-based model of a refugee settlement integrating a COVID-19 epidemiological component. By coupling the two models, refugees follow the more complex behavior dictated by the queuing model developed when queuing for food.

By analyzing results in the baseline and understanding the system dynamics, it was possible to conclude that the *status quo* of the system leads to an unwanted situation with both high waiting times at the food distribution and a general trend of convergence to a near-total infection by day 60. It was also observed that, the higher the competitiveness of a population, the higher the role the food distribution

plays in the overall infection dynamics. By evaluating results per attitude people have when queuing, this study also discusses the role of personal decisions in the overall queuing and infection dynamics.

Acknowledging the need to change the current dynamics in a settlement, two types of policies were tested: *representative* and *timeslot-based* policies. From the experimentation with these policies, it is possible to conclude that, although both have the potential to reduce waiting times in a queue and slow down the spread of the virus, only representative-based policies seem to have a relevant impact in reducing the number of total cases by day 60 and avoid the near-total infection outcome. However, as none of the policies tested has the potential to fully control the outbreak, it is recommended that these policies are only resorted to as a way to slow the spread down, giving camp managers more time to react and put other measures in place.

This study also highlighted the role of shelters as the main hotspot of infections across all replications and the source of most of the secondary infections. For this reason, it is highly recommended that policy-making focuses on finding solutions to make isolation within households a possibility.

The model showed considerable sensitivity to parameters that were not included in the experimental design but were sometimes determining factors of the outbreak development. This explains the wide range of outcomes observed in some of the runs. Moreover, by affecting the dynamics of the model, these factors can potentially undermine the effect of policy implementations. They should consequently be the focus of further research and should be taken into account when testing policies, as ignoring these can lead to unsuccessful policy implementation and waste of resources.

To complement the policy analysis, the study discusses downsides of using representative-based policies and potential emerging dynamics (such as the lack of involvement of the population, abuse of their position and corruption, among others).

This study contributes to the scientific fields by developing an ABM model that shows the impact of competitive behavior in a queue and the consequent higher waiting times. Moreover, by combining queues and infection dynamics, the model shows that competitive people are more likely to get infected and infect others and how this behavior increases the role of the food distribution in the infection chain. By focusing on refugees and developing work in the humanitarian field, this study also represents a contribution to societal field.

Finally, it is important to note that the success of policies is highly dependent on the values assumed throughout the study and the assumptions made along the process. Similarly, the spread of COVID-19 is highly dependent on the epidemiological parameters used, which are based on values from June 2020. Further work in determining accurate values for these is recommended in order to provide more realistic outcomes. Several other suggestions for further research are provided in the study.

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Acronyms

ABM Agent-Based Modeling

ATM Automated Teller Machine

CFR Case Fatality Ratio

EMA Exploratory Modeling and Analysis

DoE Design of Experiments

FIFO First-In, First-Out

GFD General Food Distribution

KPI Key Performance Indicator

NGO Non-Governmental Organization

NRC Norwegian Refugee Council

OR Operations Research

SA Sensitivity Analysis

SDG Sustainable Development Goals

SIR Susceptible-Infected-Recovered Model

UN United Nations

WASH Water Sanitation and Hygiene

WFP World Food Programme

Disclaimer

Before diving into my research, I would like to write a small disclaimer. Along this work, I made two linguistic simplifications and these should be noted.

I. Currently, there are around 79.5 million people who were forcibly displaced from home (UNHCR, 2020). This number includes refugees, internally displaced people and asylum-seekers. In an overarching term, these people are often referred to as "persons of concern". Due to their life circumstances, these people often find themselves in refugee camps. This thesis has as goal to study the spread of COVID-19 in these camps in order to support decision-making to improve standards of living of these "persons of concern". When referring to "refugee settlements" or "refugees", the whole range of "persons of concern" is meant. However, for simplification purposes, the former concept is used.

II. COVID-19 is the acute respiratory disease caused by the SARS-CoV-2 virus. Technically speaking, during an infection, what is spread is the SARS-CoV-2 virus and not COVID-19. The latter is a result of the infection by the virus. However, for simplification purposes and due to the way this is phrased in grey literature and informal language, this thesis will often mention the "spread of COVID-19". Note that this means the spread of the virus causing COVID-19, SARS-CoV-2.

Chapter 1

Introduction

Chapter 1 introduces the topic of this research. First, in Section 1.1, the context of the problem is explained, together with the academic and societal relevance of the topic. Then, in Section 1.2, the objective of this study is defined. Section 1.3 delineates the scope of this structure and, finally, Section 1.4 outlines the structure of this thesis.

1.1 COVID-19 in refugee settlements

At the end of 2019, a new strain of a coronavirus was discovered in Wuhan, China. Due to its nature and origin, the disease caused by the virus was named COVID-19 – where "CO" stands for corona, "VI" for virus, "D" for disease and "19" for the year in which it was discovered, 2019. When infected with the COVID-19 virus, patients showing mild flu-like symptoms were quickly evolving to a state in which rapid hospitalization was necessary (Li et al., 2020). As the number of positive COVID-19 cases was increasing fast, so was the number of emergency hospitalizations in the country. Making use of the countries' famous management capacities and resources to cope with the new situation, China quickly built new hospitals to specifically accommodate this new wave of healthcare demand, increased testing capacity and isolated infected population. Around March 2020, China had successfully controlled local transmissions of COVID-19. However, around the same time, the virus had started gaining momentum in the rest of the world and, on March 11th 2020, the World Health Organization (WHO) announced the COVID-19 outbreak as a pandemic (World Health Organization, 2020). Ever since, governments everywhere have been trying to contain the spread of COVID-19 by implementing all sorts of measures: closure of shops, transition to online education, curfews or even mandatory lockdowns.

However, there is still much uncertainty on how the virus spreads, what is the profile of the people who will require healthcare when infected, the reaction of the population to the circumstances and its impact on their behavior and, consequently, the effectiveness of the measures put in place.

When confronted with these developments and expecting the worst of the impact of COVID-19 in such a volatile environment, several refugee settlements implemented strict lockdowns even before having a confirmed case. While such lockdowns can be quite successful at guaranteeing that there is no movement in and out of a camp by inhabitants, some activity in these settlements cannot be put on hold. Taking into account that several of their basic needs are provided by shared infrastructures (such as latrines, water points and food), refugees and other dislocated people still have to get out of their shelters to perform fundamental activities on a daily basis. As these camps are often overcrowded and underfunded, it is also quite usual that these resources are shared by too many people, leading to hour long queues when trying to use them (Norwegian Refugee Council, 2008; Nutting, 2019; International Rescue Committee, 2020). In a camp with COVID-19 cases, this means that any time spent in those queues can lead to potential new infections (Barr, 2020). Moreover, this risk can be increased if people do not follow queuing rules and try to cut the line instead of waiting for their turn to be served. Similarly, the violence and chaos that often emerges in these queues can be the cause of an increase in infections and represent a risk for the people queuing (International Rescue Committee, 2020) - if someone in the queue is carrying the virus and direct contact between refugees is established, there is a potential infection associated with this interaction. As food distribution events are often attended by a big part of the population of these camps, this means that they can be the source of a significant number of COVID-19 infections in such a setting if not well managed.

The study of COVID-19 spreading is, by nature, a recent topic in the academic world. However, due to the social isolation that came as a result of the preventive measures to control the spread of the virus, the extra time in everyone's life and, of course, the relevance of the matter, a considerable amount of research has already been done on the spread of COVID-19 in urban settings. Resorting to modeling techniques, some of these studies focused on testing different policies and evaluating their impact in the system by running simulations. Results from these studies are then often used to support decision-making in these settings. However, in the humanitarian world, available research is limited and none of it focuses on the specific risk of the food distribution process.

1.2 Research objective

This study has the objective of evaluating the potential impact of different policies applied at a food distribution in order to minimize COVID-19 spreading while taking into account uncertain queuing behavior. This will be done by picking up on an existing Agent-Based Model (ABM) of a refugee settlement with a COVID-19 epidemiological component (Bögel et al., 2020) and developing the queuing behavior individuals can have when waiting. This will be complemented with an extensive literature review and informal interviews with food actors from refugee settlements to validate some assumptions and getting more insights on the real system. Finally, two types of non-pharmaceutical interventions will be tested in the model and their impacts will be discussed.

When looking into the spread of the COVID-19 virus in a refugee settlement, three characteristics stand out: the complexity of decision-making in such a setting, the complexity of human behavior and the uncertainty involved in the situation (originating both from the uncertain features of the virus and the uncertainty of how people react to this new reality and to the implemented policies). Resorting to modeling techniques to simulate the behavior refugees in a settlement can have while performing daily activities, this research has the goal to provide insights and support decision-making regarding food distribution in refugee settlements during a COVID-19 outbreak.

Moreover, with the second (SDG2) and third Sustainable Development Goal (SDG3) in mind – *Zero hunger* and *Good health and well-being* – this thesis aims to contribute to the improvement of lives of those who life has not treated well and find themselves facing difficult circumstances at camps far from home with the added challenge of doing so during a pandemic.

1.3 Research scope

The focus of this study is the risk of COVID-19 infections resulting from getting food in a refugee settlement. To study this, this research is divided into two main points: the development of a model to simulate queuing behavior and the integration of this model into a COVID-19 spread model to test different food distribution solutions in refugee settlements while evaluating their infection risk. For this reason, the queuing behavior will be addressed as both dependent on the nature of the individuals queuing and on the setting of the food distribution (time needed to get serviced, length of line, etc). Other factors that can influence queuing behavior (such as fear of scarcity, fear of contagion, memory and social networks) will not be investigated. Moreover, it is not within this study's scope to answer questions associated with logistics or costs of food distributions.

1.4 Structure of this study

This study is divided into ten chapters. The first chapter of the thesis, Chapter 1, sets up the societal relevance of the problem of the spread of COVID-19 in refugee settlements and outlines the scope and structure of this study. In Chapter 2 the core concepts of this thesis are defined, together with a review of previous work done on the topic and the identification of research gaps. Aiming to tackle these, the main research question is formulated and the approach of the study is specified in Chapter 3. Chapter 4 and Chapter 5 report on the model building process, following the steps suggested in the modeling cycle and focusing on the conceptualization and implementation, respectively. In Chapter 6 the experimental design is formalized, together with the policies to be implemented. Chapter 7 focuses on the sensitivity analysis conducted on some of the model variables. Then, Chapter 8 reports on the results obtained both in the baseline and by implementing policies. Starting Chapter 9, the validity of the model is discussed. Then the results obtained are further discussed and so are the impacts of these findings. Finally, Chapter 10 answers each sub-question initially proposed, reports on the limitations of the study and highlights the contribution of this study to both the academic and the humanitarian world. To conclude, this chapter formulates suggestions for further research and further use of the study.

Attached to this thesis, a list of appendices can be found. These appendices include everything that supported the study but was not essential to be shown in the main text.

Chapter 2

Literature Review

This chapter sets up the knowledge grounds for this thesis, together with the research gaps that this study aims to address. In Section 2.1 the methods used to search for literature are outlined. The main body of this chapter is divided into three sections - *infectious diseases*, *queuing* and *food distribution in refugee settlements* (from Section 2.2 to Section 2.4) - that cover the subtopics of the thesis. By both explaining the core theoretical concepts of these topics and by reviewing existing literature on these, the foundation for this study is laid. Along this process, the research gaps are identified. Finally, a small summary of this chapter is provided in Section 2.5.

2.1 Method

To find relevant literature, the topic was divided into three main ones: infectious diseases, queuing and food distribution in the humanitarian context. Because these three topics do not often co-appear in the same papers, the search on each one of these topics was independent from the other two.

2.1.1 Literature used

While literature reviews often focus on peer-reviewed scientific articles, this was not the only source of information for this thesis. Due to the humanitarian nature of the problem (and often consequent lack of scientific coverage) and the recent nature of the virus in study, *grey literature* was included as well. Consisting of studies with limited distribution, unpublished reports, online journals, policy documents and technical reports, grey literature is argued by some to be an essential source of information to broaden the perspectives taken into account in a study (Conn, Valentine, Cooper, & Rantz, 2003). It is, however, necessary to be critical of the work that is selected. In this study, most of the grey literature consists of reports written by Non-Governmental Organizations (NGOs) like the United Nations High Commissioner for Refugees (UNHCR) and the NRC or modeling projects on COVID-19 that have not been published yet.

2.1.2 Search strategy

Infectious diseases

The search started by reading about infectious diseases and studies that integrated modeling techniques to evaluate the spread of diseases in different settings and the effect of policies to contain this. As the focus of this thesis is in the spread of an infectious disease in refugee settlements, a specific search for previous work done on this topic was carried out as well. In order to find relevant papers in this topic, citation databases such as Scopus and Google Scholar were used with the key terms “infectious diseases”, “epidemiological modeling” and “SIR model” first. Then, to find papers that look into these matters in the setting of focus of this thesis, the following key words were added “refugee settlements”, “refugee camps” or “humanitarian context”. From the papers gathered in this process, a snowball method was also used - further papers were found by looking into the bibliography of read papers.

To get COVID-19 specific research, the extra key terms “SARS-COV-2” and “COVID-19” were added to the previous ones. As mentioned before, due to the recent nature of this topic, grey literature was widely used for this. Another important source of papers was the Elsevier Public Health Emergency Collection that was formed as a reaction to the COVID-19 crisis. Finally, a particular source of information of studies covering COVID-19 in refugee settlements was a meeting organized by the UN Global Pulse. This meeting allowed to have an overview of some of the (sometimes unpublished) work being currently conducted in the topic.

Queuing

To find literature covering queuing behavior, a two step approach was followed. To understand the basics of queuing, key concepts of queuing theory were gathered. Then, to understand the behavior people have when queuing, what influences these and theories behind these behaviors a search with the key terms “queuing behavior” and “queuing psychology” was conducted. Then, to find literature about modeling approaches to this problem, the following terms were added to the previous ones, alternately: “modeling” and “agent-based modeling”. Similarly to the infectious disease search, a snowball approach was also used for this topic.

Food distribution in refugee settlements

Finally, to set the foundation for the thesis and understand how food distribution in refugee settlements is conducted, technical reports by NGOs were the main source of information. These were obtained through web searches and by looking up guidelines of different organizations.

2.2 Infectious Diseases

Infectious diseases are illnesses that result from pathogenic microorganisms, such as bacteria, viruses, parasites or fungi. These diseases can be spread, directly or indirectly, from one person to another, resulting in an exponential growth overtime (Hethcote, 2000; Oli, Venkataraman, Klein, Wendland, & Brown, 2006). Infectious diseases are not a recent problem - history has been marked by them and by the way society reacts to them. An example is the Spanish Flu in 1918, the worst pandemic up to date with an estimated death toll of 50 million people (2.7% of the world population by then) (World Health Organization, 2013). This immense impact of infectious diseases in human mortality throughout the last centuries has led to the creation of a specialized scientific field – *epidemiology* – to study them. While some epidemiology studies focus on the medical nature of diseases or in possible treatments, there is a field that focuses on the distribution and patterns of both the disease and the infected people using mathematical models (Anderson, Anderson, & May, 1991; Kakehashi, 1996; Oli et al., 2006). Amongst the latter, there is research that should be highlighted. This will be described in the following subsection.

2.2.1 Infectious Diseases and the SIR model

The work of Kermack and McKendrick (1927) represents a major development in the field of epidemiological models – by thinking about different compartments (S – susceptible, I – infected and R – recovered) in which people can be in and progress between, the scholars represented infectious diseases spreading using ordinary differential equations. By basing the movement between compartments on epidemiological parameters of the disease in study, these equations allow (to a certain extent) to predict and estimate some variables such as the duration of the epidemic, the total number of people infected and the total number of casualties. This model is widely known as the SIR model.

In further studies, different authors built upon this idea, developing more complex variations of the SIR model (Hethcote, 2000). Examples are the SIRD, the MSIR, the SEIR, which include extra compartments for the deceased (D), the maternally derived immune (M, for infections in which babies are born with immunity due to maternal antibodies) and exposed (E, for individuals who have been infected but are not contagious), amongst others.

Although SIR models have been widely used as a basis of dominant epidemiological advancements (Ellison, 2020), there is also criticism regarding their deterministic nature and their limitations. These critics often focus on the extra layers of complexity infectious diseases can have, highlighting the limitations of SIR models to deal with time-varying infectivity, multi-strain systems, superinfections or spatially relevant information (Roberts, Andreasen, Lloyd, & Pellis, 2015).

Another relevant parameter when studying infectious diseases is the notion of R_o – *the basic reproduction number*. Defined as the expected number of cases generated by one positive case in a population where everyone is susceptible, this number is used to measure the contagiousness of infectious agents and is, for this reason, a useful metric during pandemic decision-making. If R_o is equal or bigger than 1, the infection will persist or spread. If the value is less than 1, then the disease is expected to die out (Delamater, Street, Leslie, Yang, & Jacobsen, 2019; Oli et al., 2006). Consequently, decision-making is often dependent on the evolution of R_o and its interpretation.

In a recent study, Delamater et al. (2019) raise the issue of R_o's complexity. Dependent on several biological, socio-behavioral and environmental factors, R_o

is not a constant and can be controlled through the implementation of policies. Depending on the nature of the infectious disease and how it spreads, different policies can have extremely different impacts - i.e. while face masks can be an effective measure for airborne diseases, a safe water source is the priority when controlling cholera. With this in mind, it can be argued that there is a high potential in using models during outbreak control - by using the models to test different policies, it is possible to get a better understanding on their effectiveness in reducing R_o instead of implementing potentially ineffective policies into the real system and having to wait significant time to evaluate their impact.

2.2.2 Infectious Diseases in refugee settlements

As infectious diseases are not new in the world, neither are they in refugee settlements. Identifying the need to apply such models to advise decision-making in these settings and how to better contain the dimensions of outbreaks, some authors have conducted research in these topics.

An important study in this field is the work of Hailegiorgis and Crooks (2012) – by creating a spatially explicit agent-based model (ABM) of the Dadaab refugee camps, the authors represent interactions between humans and their environment to explore the spread of cholera. In their study, Hailegiorgis and Crooks combine the concepts of a SEIR model with a behavioral approach of Agent-Based Modeling. In other words, the authors investigate the spread of cholera by focusing on the inhabitants as individuals engaging in daily activities. These individuals all start as susceptible to cholera (and hence being part of the S group). Infected agents (I) can be inserted in the system and, along time, these agents spread cholera bacteria through excretion of feces, which can sequentially be spread throughout the environment, contaminating water or food. When faced with contaminated goods, other people get infected with cholera, increasing the size of the outbreak. Hailegiorgis and Crooks' work represents a useful tool to explore different control strategies and evaluate how they work in a refugee settlement.

Unfortunately, this model cannot be used to study the spread of COVID-19 due to the differences of transmission mechanism of the disease – while cholera spreads through contaminated food and water, the focus of the spread of COVID-19 lays in the interaction between infected and susceptible agents. However, the use of ABM to study such a topic – by not taking the population as a whole, ABM allows for heterogeneity of behavior allowing for people to interact with each other in different ways (Crooks & Heppenstall, 2012) - is an interesting development in the field of epidemiological modeling and a potential tool for studying COVID-19 spread.

2.2.3 Modeling COVID-19 in refugee settlements

As mentioned in the last subsection, Agent-Based Modeling represents a good tool to study the spread of infectious diseases. By using a bottom-up approach and focusing on people as individuals, ABM allows to cover some dynamics of human population that emerge lower level interactions and some uncertainty of how individuals behave (Eubank et al., 2004). This goes in line with the point highlighted by Delamater that, when evaluating the contagiousness of infectious agents, it is necessary to integrate the socio-behavioral factors that influence this variable such as the number of interactions people have, if they decide to stay at home, among others (2019). Moreover, this approach offers potential solutions to the shortcomings of basic SIR models as highlighted by Roberts et al. (2015), allowing to integrate spatial and temporal dynamics to the spread of the diseases. Finally, it is also the technique of choice of Joshua Epstein, a renowned epidemiologist who has applied this method to study different infectious diseases such as Ebola, pandemic influenza and smallpox (Burke et al., 2006; Epstein, 2009).

The popularity of this tool to model infectious diseases is also clear in the study of the spread of COVID-19 both in urban settings and refugee camps in the last year. Among the latter, three researches are to be highlighted – the UN Global Pulse model of Cox's Bazar (Harlass et al., 2020), the work by the University of Manchester in Moria (Gilman, Mahroof-Shaffi, Harkensee, & Chamberlain, 2020) and the work by Bögel et al. (2020). The three of these studies resort to ABM to study the spread of COVID-19 in refugee settlements and focus on the potential of non-pharmaceutical interventions. All these models also integrate concepts of the SIR model (or adaptations of this) to represent the progression of individuals regarding the virus and their health status. These models, however, differ in their geographical (and case-study) focus, among other differences.

Conceptualized to be a proof of concept, Bögel's model is not designed to simulate one settlement in specific but rather takes averages of five existing settlements (Kakuma, Moria, Za'Atari, Bidi Bidi and Cox's Bazar) to represent a prototypical refugee settlement. As one of the focus points of Bögel's study was to prove the concept of using ABM to understand the risk of COVID-19 spread in settlements, this decision did not influence its results. This, the time granularity of the model (where one time step can be assumed as one minute) and the accessibility of Bögel (considering the research was conducted at the TU Delft) are some of the reasons why this study will pick up on this model.

Moreover, by developing a prototypical model, Bögel's work can be developed further without focusing on one specific settlement and potentially later on be applied to a case study, while the geographical scope in Harlass et al. (2020) and Gilman et al.'s (2020) work is already defined. Bögel's work represents hence a higher value for NGOs that want to apply such models to camps in which they are working in, as the base model is more neutral and, hence, less context dependent.

Bögel's work

To better understand the model and why this study builds-up on it, it is necessary to first understand the high-level dynamics of it and its limitations. Similarly to Hailegiorgis and Crooks (2012), Bögel (2020) developed a model that simulates refugees performing daily activities such as fetching water, using latrines, getting food or visiting a healthcare facility in a settlement. As there are often more people who use the same facility, refugees frequently must wait for their turn to use it. By introducing COVID-19 positive people in this setting, the spread of the virus among inhabitants can be monitored as well as the places where infections occurred. Consequently, it can be determined which activities are the sources of the higher infection risk. Ultimately, the model can be used to test the efficiency of different policies in containing COVID-19.

An interesting (and challenging) feature of COVID-19 is the way it shows (or not) in infected people. Unlike Ebola and smallpox that have very visible symptoms and, consequently, are easy to identify, COVID-19 infected people might have very mild symptoms that can be mistaken for a common flu. Another important characteristic of COVID-19 in the number of *asymptomatic people* - people carrying the virus but not showing symptoms - and their infectiousness. While during Ebola and smallpox outbreaks it is estimated that only around 15% (Mbala et al., 2017) and 0% (Foster, 2020) of infected people are asymptomatic, respectively, recent studies claim that the percentage of COVID-19 asymptomatic people can be as high as 75% (Yanes-Lane et al., 2020). As this feature of COVID-19 highly impacts the perception of people of whether they are infected or not, it will consequently impact the behavior they will have, the number of contacts they will establish and, therefore, the way the virus spreads.

Bögel's approach to model this characteristic should be highlighted: to account for the number of people who might be infected and not aware of it (either because they are asymptomatic or because they assume their symptoms are a simple flu), agents have an extra *infection perception* attribute. Not necessarily in line with their actual infection state, agents can think they are healthy when they are actually infected (or the other way around). This will influence the way they behave in the settlement and if they do perform activities outside of their shelters.

It is important to note, however, that, as well as several other COVID-19 epidemiological parameters, the asymptomatic rate is still an uncertain value. Bögel considers parameters dated from June 2020. However, new research is done every day and the values are constantly adapted. Moreover, it can also be argued that epidemiological parameters from an urban setting might not directly translate the situation at settlements with vulnerable people. Either due to age distribution or underlying conditions, it is possible that common parameters might not be an accurate representation of the situation within vulnerable groups. This will be taken into account in this study and discussed in Chapter 9.

When conducting experiments, Bögel concluded that there is a risk of mass infection spread during events where large queues are formed for a long period of time. An example of such an event in this model is the monthly food distribution. In its baseline scenario, the food distribution leads to a peak of infections, which consequently results in the whole settlement being infected within 50 days.

To avoid this mass infection, Bögel set up experiments to test the impact of different non-pharmaceutical interventions that can be applied to the settlement. The policies tested consisted of four levels of interventions: changing the distancing in a queue, implementing mobility restrictions (no rules, quarantine for infected individuals, no elderly moving around or isolation of households in which there are (at least) one infected person), implementing mask usage and changing the day in which the food distribution is performed.

Bögel's results show that none of these interventions is sufficient to avoid the infection of the whole population of the camp at some point - these measures can delay the moment in which the entirety of the population has been infected but cannot avoid it. The only exception is when the policy "isolation" is put in place - by restricting the movement of entire households once there is an infection (or perceived infection) in the shelter, the total number of COVID-19 cases can be controlled. However, there are several problems with this measure: compliance will never be 100% and it means that these households do not have access to the food distribution and will consequently starve. Acknowledging this, further research in looking into shifting and redefining the food distribution moment is suggested. However, this was not done in this study yet. This can be identified as the first research gap.

First knowledge gap

As access to food is a human right and one of the Sustainable Development Goals (SDG2), it is necessary that adaptations to the food distribution solution guarantee that this continues being a fair procedure and that the goods are accessible to the population (i.e. solutions such as stopping the food distribution cannot be considered). However, it is also important to guarantee that access to food does not represent an infection risk during an outbreak. For this reason, the first academic gap can be formulated as *the trade-off between fairness and accessibility of food while minimizing the COVID-19 infection risk in these distribution events.*

2.3 Queuing

Concerns around the risk of queuing are not novel. In March 2020, when countries started implementing measures such as limiting the number of customers in supermarkets, queues started forming in front of businesses around the world. Later on, these queues could be identified in more locations: pharmacies, testing centers and, in worst case scenarios, hospitals. Together with isolation, it can be argued that queues are a defining feature of the COVID crisis (Brandon, 2020). However, while in isolation there is virtually no risk of getting infected because there are no groups of people, queues are, per definition, a group of people (waiting for their turn to be served or to enter a space). If one of the individuals queuing is carrying the virus, this means that the ones around are at risk of getting infected every second they spend queuing (Barr, 2020). Moreover, the longer a queue gets, the higher the probability of an infected person being in the queue (Long, Wang, & Zhang, 2020). As a solution, it could be argued that implementing social distancing rules in a queue would reduce the infection risk to near zero. However, while placing markers on the floor is easy, getting customers to comply with these is a bigger challenge (as highlighted by the managers of a pub in Michigan that was linked to near 200 COVID-19 cases even with all the rules in place (Brandon, 2020)).

Seeing a risk in this and aiming to keep their customers safe, businesses started implementing different techniques to tackle this challenge. Two approaches to this problem are the implementation of digitally managed virtual queues and drive through solutions. However, as the first one is heavily dependent on the availability of technology on both sides (the customer to get information and the business to manage it) and the second assumes that each customer has a car, none of these solutions are feasible for refugee settlements. Other solutions can focus on optimizing queue sizes and minimizing waiting times. This is an example of the work of queuing specialists Perlman and Yechiali (2020). While this work sets up the foundation for the study of the infection risk in queues, it takes people queuing as a linear function and does not integrate potential deviations. Derjany et al. (2020) go further and combine pedestrian dynamics with stochastic infection spread models. From their results, they conclude that queue configuration has a substantial impact on the spread of a disease. However, they assume that a queue's layout is designed beforehand and do not integrate human behavior and how individual decisions might impact its shape.

In Bögel's model, the queuing is rather simplified: people gather around the place where food is distributed, patiently wait for their turn to be served (which is dependent on their order of arrival), maintaining social distancing from the rest of the elements waiting, and leave. Furthermore, Bögel's model has as assumption that people comply 100% to the social-distancing rules in places, meaning that they will never get too close to other people waiting. This, however, can be argued against. As an element comprehended human people waiting for their turn to be served, it can be argued that queues are as complex as humans. With this motivation in mind, this thesis dives into the key concepts of queuing and the field of queuing behavior.

2.3.1 Queuing Theory

Developed in the beginning of the 20th century by the early works of Erlang (Erlang, 1909), *queuing theory* aims at solving problems such as the ideal number of servers and how to reduce waiting times depending on the arrival of customers. These studies are often integrated into operations research and focus on how to optimize the performance and efficiency of the service being provided to save time and money.

When specifying queuing models, general dynamics depend on three main components: the arrival process, the service mechanism and the queue discipline (Cooper, 1981; de Lange, Samoilovich, & ven der Rhee, 2013). The *arrival process* describes the rate at which customers arrive at the service point and is usually expressed by interarrival times (which represent the time between the successive arrival of customers) which follow different distributions. The *service mechanism* focuses on the server side of the problem - it specifies the number of servers available and the probabilistic distribution of time needed to serve a customer. Finally, the *queue discipline* indicates the order in which customers waiting for a service are selected to be served.

The simplest discipline is known as first-in-first-out (FIFO). Following this logic, the first person to queue up for a service is the first person getting served. This means that, when there is a queue, a customer must wait until everyone who was there first to be served for their turn to come. Although this is one of the most common methods used when managing queues, it is not the only one. Queuing disciplines can follow an opposite logic - last-in-first-out (LIFO), a random discipline (SIRO, serve-in-random-order), disciplines that prioritize shortest processing times (SPT) or that simply prioritizing other characteristics of the customers (PR, that could prioritize age or vulnerable people, for instance) (Berry, 2006). While some customers might benefit from different queuing disciplines (e.g. a pregnant woman would benefit from a queue with a PR discipline as they could skip the queue and get served immediately after arrival), FIFO is considered to be the "fairest" queue discipline overall. Confirming this by testing the effect of the queue discipline on the waiting time variance, Kingman (1962) proved that the variance of waiting time is minimum when serving customers in order of arrival. In other words, their research claims that the time that each customer spends in a queue is more equal when using a FIFO discipline.

2.3.2 Queuing behavior

Although the value of mathematical queuing models can be recognized in the field of operations and supply chain, there is an obvious limitation of these models when it comes to applying it to people queuing for commodities. Consisting of people waiting for their turn, these queues are inherently subjected to the complexity of human behavior. Considering these people as inanimate objects queuing and assuming a linear behavior, mathematical models have a limited capacity to realistically represent real world queues and how individual's choices affect the development of the queues. Even if the queue follows a FIFO discipline, if people decide (and succeed) to cut the line, this logic is broken. Recognizing these limitations of the existing models and noticing an added complexity of queues, a field around customer behavior in queues started emerging circa 1969 (Mann, 1969; Naor, 1969).

Type of queues

Observing people moving and queuing in different settings, Okazaki and Matsushita (1993) suggest a classification of queuing behavior according to the type of service people are queuing for. This classification can be seen in Figure 2.1 and is divided into three types: queuing in front of counters (Type 1), queuing in front of gates (Type 2) and queuing in front of vehicles' doors (Type 3). Similarly to queuing in a department store or hotel, queues that are formed during a typical food distribution can be included into type 1 queues.

Building on this work, Kneidl (2016) suggests a further division inside queues of type 1: organized queues with demarcation tapes (for example in airport check-in points) and organized queuing with no demarcation tapes (which can be observed at a bar, for instance). The difference between these two queues, as argued by Kneidl, is that the formation of the first is predefined by the demarcation tapes used by the queue manager. For this reason, and assuming that people will comply with the demarcation tapes, simulating these queues requires a simple one-dimensional approach and queuing theory can be directly applied. The second type of queue, without demarcation tapes, however, does not follow a specified form and grows individually as people get closer to the service point and decide where they wait. Therefore, this type of queue can also be referred to as *self-organizing queue*.

Self-organizing queues

In a context with no demarcation tapes nor queue managers placing the people waiting for a service, queues do not necessarily have to happen. As observed by Fagundes (2017), there are no laws specifying the rules for how and where to wait. However, when confronted with someone waiting to be served, one tends to wait

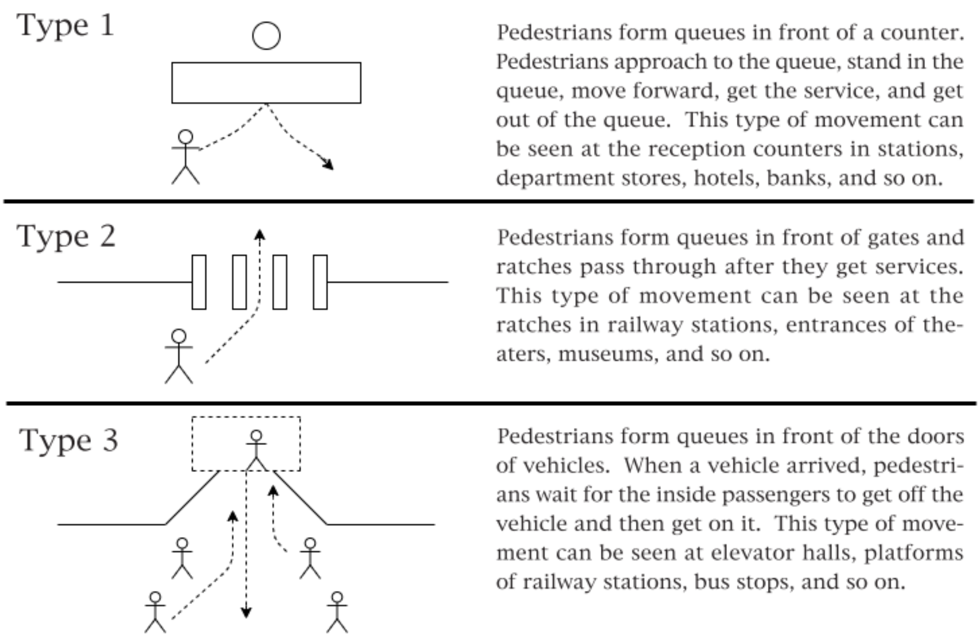


Figure 2.1: Three types of movement in queue spaces as suggested by Okazaki and Matsushita (1993)

until others are finished and only then get closer to the service point. Noting this, Fagundes characterized self-organizing queues as "a system of informal order". In their research, Fagundes uncovers some of the unwritten rules that lead to queue forming - *social norms*. Allon and Hanany (2012) highlight that customers experience tension between following these social norms and economic reasoning, in which the latter can act as a force to violate the norms. Moreover, Mann (1969) noted that cultural values are related to the respect of the principle of queuing, which can thus lead to a variance of behavior between queues in different countries.

Applying some of these theories into models, different authors have modeled self-organizing queues to study queuing behavior. Building on the observation that people tend to queue on a slight angle from the last person in line to be able to observe the beginning of the queue, Kneidl (2016) developed an agent-based model for a self-organized queue. This study comes to prove that self-organized queues highly depend on the decisions of the individuals queuing, justifying the use of agent-based modeling to model this. However, the decisions that the individuals queuing are able to make in this model are rather simple and their position cannot deviate more than a certain angle from the last person in line.

Taking another approach inspired by the idea that people can have different strategies when queuing, Köster and Zönnchen (2015) capture different queuing patterns through two basic attitudes: competitive and cooperative behavior. Combining navigation floor fields and utility functions, the researchers built a model in which cooperative people queue behind the last person in the queue and keep queuing until they are close to the server, while competitive people have the goal to approach the target as soon as possible. This approach reproduces the classic "cutting the line" behavior that had been mentioned earlier by Allon and Hanany (2012).

By allowing people to switch between strategies and testing with different mixes of initial attitude, the authors use this model to observe the types of queues that can emerge. It is important to note that, although this study incorporates the possibility of having different behaviors when in a queue, it does not integrate the factors that can make people have these behaviors. Moreover, by resorting to navigation fields and mathematical formulations for how people behave, this model limits the rationality of the agents queuing, detaching their behavior from the environment in which they are.

Parallel to these developments, considerable research has been done on factors that might influence people's behavior when queuing. Starting from Maister (1985) and Larson (1987) and their focus on customer's experience, a field covering the psychology of queuing focuses on how queues and their characteristics can provoke feelings in customers and consequently influence their queuing attitude. Although there are different studies with different focuses, they often converge in theories that queue length, consumer's perceptions of the waiting-time, their previous experiences in similar queues and the behavior of people around them influence their own behavior (such as Maister (1985), Onions (2015), Marin, Drury, Batta & Lin (2007); Allon & Hanany (2012); Sankaranarayanan, Delgado-Alvarez, Larsen & van Ackere (2012); Ülkü, Hydock & Cui (2019), among others). Allon & Hanany (Allon & Hanany, 2012) introduce the concept of memory in the queuing process - by introducing game theory concepts, they claim that queue formation depends if they people involved have queue before, making it possible for them to understand what approach they should take in order to minimize their time waiting.

Second knowledge gap

Although there are some agent-based models that describe the queuing process, none of these models sufficiently captures people behavior and how this behavior influences the queue itself. With a purpose to study the risk queues pose during an infectious disease outbreak, it is important to understand how the decisions of individuals affect the total time one stays in a queue and how it impacts proximity between people. Different queuing behaviors will influence these two factors, which consequently influence individual's risk of getting infected. However, none of the current available ABM models focuses on this. Focusing on this, another knowledge gap can be identified: *the way people behave in a queue and how individual's decisions affect the total time in queue of others and proximity between them has limited representation in agent-based modeling.*

2.4 Food distribution in refugee settlements

From shelter to safe water, NGOs are often the source of resources for the population of refugee settlements. Food is not an exception. Working in refugee settlements all around the world, organizations such as the World Food Program (WFP), the Norwegian Refugee Council and UNHCR take on the responsibility of distributing food to persons of concern. When doing so, NGO's focus is not only on food but rather on *food security*. Defined by the United Nations' Committee on World Food Security as the state in which "all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their food preferences and dietary needs for an active and healthy life" (Food and Agriculture Organization of the United Nations, 2009), guaranteeing that this is possible in informal and temporary settlements where the population does not necessarily have income can be argued to represent a bigger challenge than in urban settings.

To cope with the complexities of such settlements and to structure this process, organizations have developed handbooks as guidelines for food distributions (e.g. Norwegian Refugee Council (2008), UNHCR (2015)). Due to the temporary nature of refugee settlements (or at least the temporary intention of these), such handbooks often focus on traditional and short-term solutions. A consequence of this design (and political) decision is the non-existence of an alternative plan in case of infectious diseases outbreaks. Confronted with the challenge of containing COVID-19 in early March, adjustments to the general guidelines were developed (Opportunity International (2020), World Food Programme (2020)). However, no research has been done on how much these adaptations contribute to containing the spread of an infectious disease. This goes in line with the first knowledge gap previously identified.

When working with food in refugee settlements, NGOs can often resort to two different main approaches: *food aid* or *food assistance*.

2.4.1 Food aid

Often referred to as General Food Distribution (GFD), a food aid response focuses on the direct transfer of food rations from the NGO to households affected by an emergency in order to meet their nutritional requirements (Emergency Nutrition Network, 2011). Although water is a necessary good, it is not included in a GFD ration. While in a refugee settlement GFDs often look like a serving point and a queue of people waiting to be served, there are some characteristics of these food distributions that can be changed.

Cooked meals or food basket

Depending on the conditions of the camp and the resources refugees have, the food being distributed can be in the form of a cooked meal or a food basket (collection of (mostly) dry ingredients to cook with). Both these solutions have its benefits and disadvantages. While cooked meals can be a guarantee that everyone has direct access to food and can meet their nutritional requirements, they require a lot more manpower to coordinate and maintain (not only the whole food preparation but also having to repeat it every day, as people do not keep the food and it constantly needs to be provided again). Because this is such a labor intensive solution, it is mostly used in situations where refugees have no way of cooking the meals themselves - such as in very recent or unstable settlements (e.g. post-Jungle Calais, in which refugees' belongings are taken away more than once a week and consequently they have no way of keeping cooking equipment with them). Another drawback of distributing cooked meals to individuals is the amount of people that is requested to line-up, creating population concentrations which consequently can raise concerns regarding overcrowding (Emergency Nutrition Network, 2011). This last point is of particular interest when distributing food during an infectious disease outbreak.

Food baskets, on the other hand, can be distributed in an amount that only requires monthly distribution. This approach has several benefits: it can be empowering refugees (as it gives them the opportunity to cook it in their own way), it minimizes effort from the NGO side, for instance, and it also means that not every single inhabitant of the camp needs to be present at the distribution moment. However, this approach is only a solution in more established settlements in which refugees not only have the material to cook the ingredients with but also to store them without letting them spoil.

Food ATMS

Within the range of food-based response in the humanitarian context, a novel approach has emerged in the recent years: the food ATM. The Food Automated Teller Machine - Food ATM - is conceptualized as a dispensary point in camps where food is kept and refugees can go to get food (World Food Programme & World Vision, 2019). Food ATMs work similarly to a market - however, in this setting, refugees walk into a warehouse full of machines containing a specific food item where they select how much food they want to withdraw. Food ATMs come to solve some common problems of food distribution: food does not have to be packaged and repackaged on-site, nor staff has to weight or scoop the wanted quantities. Moreover, food ATMs can provide a continuous food supply, allowing refugees to come back whenever they need an ingredient instead of having to wait until the next food distribution moment (provided that they have not ran out of their monthly or yearly provision). This will also result in smaller amounts of people coming to take food, considering that the ATM is available during longer periods of time. Furthermore, food ATMs also fix storage problems - by not giving the whole ration to refugees in one go and keeping it rather in a centralized and proper storage place, food waste is minimized.

However, food ATMs also have its own challenges. Not taking the whole challenge of making supply and demand meet by giving refugees the freedom to choose how much and when they want to withdraw their good into account (which is covered in van Beek's thesis (2021)), the construction of such infrastructure can be quite costly and, could be argued, not fit for (supposedly) temporary settlements.

2.4.2 Food assistance

As an alternative to basic food based response, donors and NGOs have been developing an interest on *food assistance*. Included in their 2008 strategic plan (World Food Programme, 2008), the WFP argues that while food aid provides the calories needed to save hungry communities, this approach does not cover other complexities in settlements. By providing indirect access to food through different methods such as food subsidies, cash and voucher transfers or agricultural and livestock support, a food assistance approach not only provides calories and nutrients, but it also stimulates an economic development by empowering the population. Food assistance approaches create the possibility of camp markets where people can go and buy the food they want using not only their cash or vouchers provided by NGOs but also their resources made through other activities. This approach, however, requires a fully operational market and a context (economic, social and cultural) in which consumers have the means to buy and sell locally produced foods (Swartz, 2017). For this reason, it can be argued that food assistance solutions can only be utilized in rather long-term established camps assuming a system is in place.

2.4.3 Food distribution during an outbreak

In their model, Bögel (2020) experiments with a general food distribution of dry ingredients. The study assumes a monthly distribution that takes place in one day, sending one member of each household to stand in the queue at some point in the day to get their monthly feed.

From Bögel's results it was also observed that if no intervention is put in place, a single case of COVID-19 can lead to the total population being infected within 50 days. Moreover, Bögel identifies the food distribution as being a super-spreading event. It is therefore necessary to research policies to be applied at a food distribution level to reduce the COVID-19 infection risk associated with this event.

Distribution system options

In their Emergency Handbook (2015), UNHCR describes three distribution system options which differ on who is queuing up for the food. Fit for different phases of an emergency, these distributions suggest the use of representatives of groups to make the food distribution process easier, faster and cheaper. First, in the initial phase of an emergency, representatives of large groups are used. Then, according to the stage at which the emergency response is, representatives can slowly start representing smaller groups until the ideal situation is achieved - with heads of families attending the food distribution.

In Moria, before the fire, there were reports that people were queuing up to four hours (Nutting, 2019) every time they were going to pick food up. These long waiting times combined with the situation of misery in which refugees might live can justify high tensions experienced in these queues, which often lead to violence. Violence in queues is the cause of several injuries observed by doctors, together with feelings of panic, distress or even post-traumatic stress disorder experienced by refugees. In the context of a pandemic, violence, pushing and barging represent an added risk: by increasing the levels of contact between people, these actions can increase the infection risk of the individuals present in the queue (International Rescue Committee, 2020).

Overall, choosing different distribution systems will change some parameters of the queuing system. These changes can have the potential to reduce the time people have to spend queuing waiting to be served and, consequently, the potential to reduce infection risk. For this reason, it is concluded that it is worth it to test different policies and evaluate their potential in controlling the outbreak in the settlement.

2.4.4 Challenges

Finally, it is important to highlight the challenges associated with the food distribution in a refugee settlement. Some of these challenges include:

Duplication In refugee settlements, it is not unusual for inhabitants to not have documentation. This raises a challenge when distributing a scarce resource: it is difficult to keep track if a person has already obtained their ration and, consequently, some duplication might happen.

Storage Depending on the conditions of the camps, refugees might not have proper storage to keep their food. This needs to be considered when distributing food to refugees in order to avoid food waste or potential food poisoning.

Nutrition Different camps require different nutritional plans. Before deciding how to distribute food, it is necessary to identify what needs should be met. The food distribution method must be chosen accordingly.

Crowds When doing a distribution directly to each individual, it will often lead to crowds. It is necessary that such decisions take the overall context of the camp into account. Solutions such as targeting can help reducing the amount of people queuing up for food.

Accessibility However, when using targeting techniques, it is necessary to take into account that the food might not reach the final destination. When the head of a community picks up food to then distribute it can happen that certain households never have access to the food. This often means that the most vulnerable refugees are the ones not having access to food (often the sick and elderly refugees).

Re-sales If the food is not considered good enough, it can happen that refugees sell their food to get access non-essential goods (such as tobacco or alcohol) or other food products that are not distributed by NGOs.

Socio-political context Refugee settlements often have a quite specific socio-political context. As a measure to help people, GFD should be conducted in a way that does not increase tensions.

Costs Any implemented measure has associated costs: the cost of food, the supply chain costs, the staff helping and the infrastructure needed to proceed with the distribution. Budget constraints can often dictate what kind of options are viable or not.

2.5 Conclusions

In this chapter, three topics were covered: infectious diseases and its modeling, queuing behavior and food distribution in the humanitarian context. In each one of these topics, main key concepts were described and literature was reviewed.

From this literature review, it can be concluded that: 1) there is no agent-based modeling describing how people behave in a queue and how that influences the queue itself and 2) there is a need to look into food distribution solutions that balance the trade-off between fairness and accessibility of food while minimizing COVID-19 infection risk in these events.

Chapter 3

Research Formulation

This study aims to fill in the research gaps identified through the literature review. This chapter focuses on how the research is designed to do so and what steps are taken.

First, in Section 3.1, the main research question that guides this study is formulated. In this section the main research question is also broken down into different sub-questions that help guiding the research. Section 3.2 covers the flow of the study, the methods used and the motivation for these choices. Finally, Section 3.3 wraps up the content of this chapter.

3.1 Research question

Looking into a refugee settlement during an outbreak scenario, this study aims to provide insights on potential ways to minimize COVID-19 infection risk during essential activities such as food distribution. For this, it is first necessary to develop a model that represents human queuing behavior (and thus fill research gap 1). Then, this model can be used to evaluate how different policies influence the overall queuing dynamics and how this impacts the spreading of COVID-19 (research gap 2). This research goal can be formalized as the following research question:

> *What food distribution policies show robust performance under queuing behavior uncertainty while minimizing COVID-19 infections in the context of an outbreak in a refugee settlement?*

3.1.1 Sub-questions

Aiming to provide a modular composition for this thesis, the main research question can be broken down into different sub-questions. By answering these, the overarching question is answered.

1. What factors influence how people behave while waiting in a queue?
2. How is food access organized in a refugee settlement?
3. How to evaluate food distribution policies during a COVID-19 outbreak?
4. What are the drawbacks of using the chosen policies during food distribution?

3.2 Methodology

To answer the main research question, an exploratory modeling approach is suggested. This will be complemented with desk research and informal interviews to food actors working in Cox's Bazar (as an example of a refugee settlement where the COVID-19 hit). In this section the research flow is introduced. Then, the modeling approach is motivated. Finally, the XLRM framework is introduced as support to understand the overall context of the study.

3.2.1 Research Flow

First, an agent-based model is built to simulate the way people queue. Then, this model is integrated in the model developed by Bögel (2020), where policies are tested and the model dynamics are studied in scenarios with different queuing behaviors. Finally, the results will be discussed and policy recommendations are formulated based on the study insights. Figure 3.1 shows the flow of the study divided into ten steps and the methods used along the process.

Note that, although Figure 3.1 shows a one-directional flow, the real process of this study involved several step backwards mostly between the implementation and the conceptualization phase (in that order). This is because, along the implementation of the model in ABM, some questions come up that require a sharpened definition or adapted conceptualization. The same happens again when observing the first results produced by the model - while conducting verification tests in the model, problems are identified and the model is changed accordingly. Overall, it can be argued that the flow of this study is rather iterative instead of a one-directional flow.

3.2.2 Exploratory modeling: Agent-Based modeling

As highlighted in previous research (see sub-section 2.2.2), Agent-Based Modeling (ABM) is often the chosen method to study contagious diseases and their spreading. This is not only because this technique allows an analysis at an individual level (which can be argued to be key to study how to contain a disease that spreads through interactions) but also because it includes a behavioral component - citing Luke and Stamatakis, an ABM model uses "computer simulations to examine how elements of a system (agents) behave as a function of their interactions with each other and their environment" (2012).

Considering that the focus of this thesis is to understand the dynamics behind queuing and the spread of a virus (both highly connected to human behavior and interactions at the individual level), ABM seems to be fit for this study. With this technique it is possible to have active agents and integrate their perceptions and its influence in their individual behavior, allowing for an analysis of the macro behavior that emerges from individuals (Maidstone, 2012). In order to understand how different food distribution settings (schedules, locations, dynamics, etc.) influence the spreading of the virus but also how people change their actions according to these, an ABM approach will be used for this thesis. The choice for ABM can also be motivated by the uncertainty of human behavior in the queuing process and the

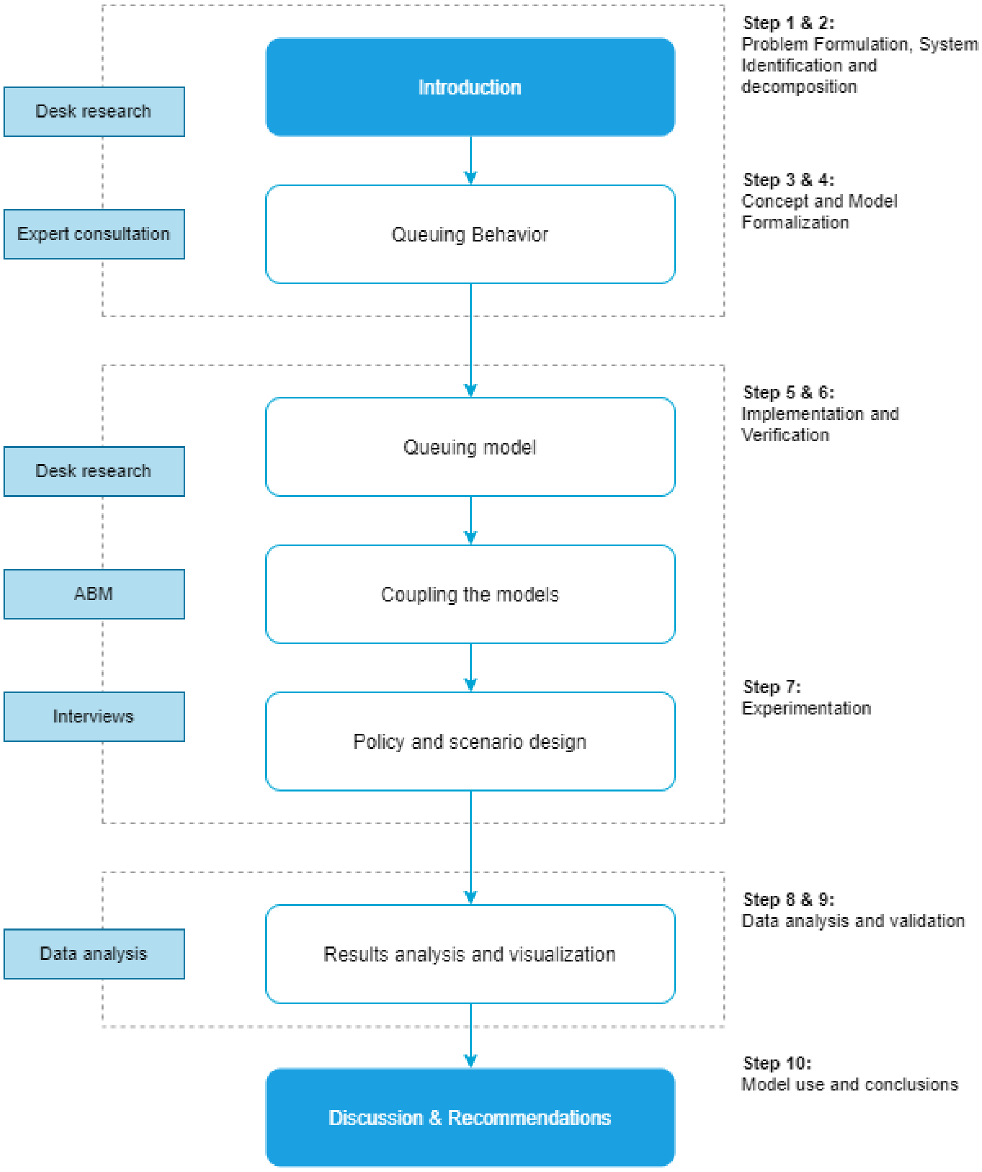


Figure 3.1: Research flow diagram

behavior heterogeneity that it allows to create. Finally, accounting for the uncertainty inherent to the problem and the system, this model will be used to explore different policies under different scenarios.

As this thesis uses a modeling approach, the steps of the research resemble those of the modeling cycle. In specific, the steps proposed by van Dam et al. (2013) are used as guideline.

3.2.3 XLRM framework

Introduced in 2003 by Lempert et al. (Lempert, Popper, & Bankes, 2003), the XLRM framework can serve as a support to organize relevant information in a study. This framework proposes the division of elements into four categories: policy levers ("L"), exogenous uncertainties ("X"), measures ("M") and relationships ("R"). Figure 3.2 provides a visualization of the XLRM framework and how the variables interact in the system.

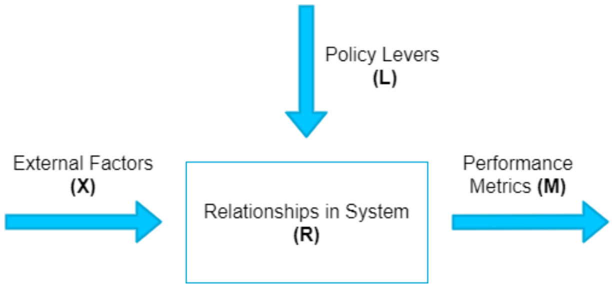


Figure 3.2: The XLRM framework as visualized by Kwakkel (2016)

Policy levers (L) This category represents the policies and strategies that decision-makers can apply to a system in an attempt to make it perform as desired;

Exogenous uncertainties (X) Factors that are outside of the control space of the decision-makers are placed under exogenous uncertainties. Even though decision-makers cannot influence them, they are relevant because the influence the system, playing a role on the success (or not) of the policy levers implemented. These variables are often integrated in the creation of scenarios in order to evaluate how strategies perform in situations with different values for these variables;

Measures (M) In order to measure the success of policies implemented, it is necessary to identify what variables to observe and evaluate. These variables are included in this category and are referred to as Key Performance Indicators (KPIs). After testing different policies, these KPIs are compared to rank the desirability of various scenarios;

Relationships (R) Finally, this category is composed by the relationships among the variables of the system. In socio-technical systems, these relations are rather complex. For this reason, these are often represented by a simulation model. Note that sometimes there are uncertainties within the relationships (R). These can be referred to as *structural uncertainties*.

Further identification of the variables that fit into each category is provided in Chapter 4 during the conceptualization phase of this study.

3.3 Conclusions

Picking up on the two research gaps identified in the literature review performed, this chapter translates this into a research formulation and a study structure. The main research question guiding the study can be formulated as:

> *What food distribution policies show robust performance under queuing behavior uncertainty while minimizing COVID-19 infections in the context of an outbreak in a refugee settlement?*

This research question is broken down into four different sub-questions. Together with literature review and interviews, this study will use an Agent-Based Modeling approach to answer the main question following the structure suggested in in Figure 3.1.

Chapter 4

Model Conceptualization

This chapter focuses on the conceptualization of the modeling process of this study. First, in Section 4.1, Bögel's model (Bögel et al., 2020) is introduced, alongside the main dynamics of its subsystems. Then, Section 4.2 follows with the conceptualization of the queuing model to be developed. After this, in Section 4.3, the XLRM framework is applied to the topic of this research to help understand the big picture of the system. Finally, a summary of the chapter is provided in Section 4.4.

4.1 Bögel's model

The base motivation of this research is to understand the infection risks of activities in refugee settlements and find solutions that minimize this. With the same objective in mind, Bögel (2020) developed an ABM of a prototypical refugee settlement and included epidemiological parameters to evaluate how COVID-19 spreads while refugees perform their main activities.

At a high level, Bögel's model consists of three subsystems as described in Figure 4.1. The *settlement layout & facilities* includes shelters and camp facilities. The *refugees* subsystem includes the agents in the model and their overall actions - their activities and behavior. Finally, the *COVID-19* subsystem includes the epidemiological parameters of SARS-COV-2 and the stages of progress of the disease.

Along a model run, there are several inter-system interactions and it can be argued that any change in either the settlement or the COVID-19 subsystems will influence the refugee one (and vice-versa). An obvious moment of interaction of the three systems are queuing moments: when several refugees want to use a facility of the camp, they line up and wait for their turn. If one of the refugees waiting in that line is infected with SARS-COV-2, then everyone around is potentially at risk of getting infected as well.

Identifying the risk of queues and specially the food distribution moment in a settlement (as suggested in Bögel's results), this thesis dives further into this moment. In specific, this thesis aims to get insights on how different policies can be implemented at the food distribution process and how they influence the spread of COVID-19, looking specifically at how they influence queue dynamics.

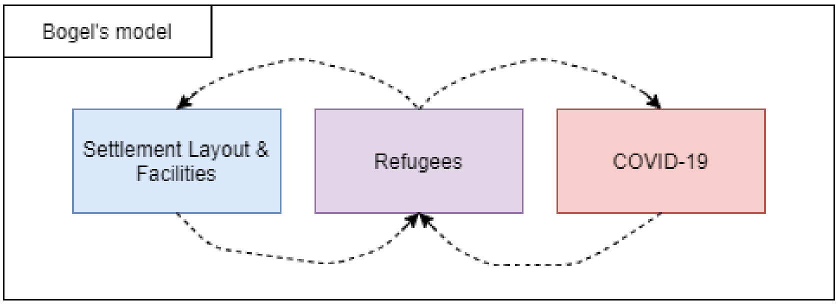


Figure 4.1: Subsystems of Bögel et al. (2020)

However, due to the simple behavior of agents when queuing for commodities, Bögel's model is considered to not be fit for this research as is. Identifying this limitation of the model, this thesis focuses on developing queuing dynamics in Bögel's work.

Before conceptualizing this process, however, it is necessary to understand the current model and its three subsystems.

4.1.1 Settlement layout and facilities

The model represents a medium-sized refugee settlement (with around 800 people) where people perform four activities: using latrines, fetching water, obtaining food from a distribution point or accessing healthcare facilities.

Bögel built a model with generic characteristics based on five major refugee settlements: Za'atari, Bidi Bidi, Cox's Bazaar, Kakuma and Moria. The study of these camps allowed to gather mostly demographic but also logistical data, such as the average size of a household or the number of facilities per capita. For this reason, Bögel's model represents a prototypical settlement rather than a representation of a specific camp.

Finally, because of some design choices, it can be argued that this model is more fit to be prototypical of a short-term (or in initial phase) refugee settlement than of a well-established one. One of these reasons is the random location of shelters (in contrast with the highly organized Kilis camp, for instance (Mcclelland, 2014)). Another reason is how the food system is conceptualized - the population is thought to be entirely reliant on a monthly general food distribution and not in the existence of markets or shops within the camp.

4.1.2 Refugees

When looking into the refugees, they can be narrowed down to two main concepts: refugees perform different activities during the day and they have behavior that influences what they do. However, this behavior is limited to whether they are compliant when a mobility restriction is implemented and if they perform or not activities (depending on their infection status). As mentioned before, refugees in the current model do not have any dynamic behavior when waiting in queues and they patiently wait for their turn to be served.

4.1.3 COVID-19

Finally, regarding the epidemiological subsystem of this model, it is worth mentioning two things: the disease progression and the difference between infection and perception.

Inspired by SIR model developed by Kermarck and McKendrick (1927), Bögel picks up on the idea of the compartmental modeling and adjusts it to COVID-19, overcoming some of the criticisms of the classical approach identified in the literature. This adaptation is done by, instead of only looking at the susceptible, infected and recovered stages from the typical SIR model, developing a more detailed disease path. This extension of the basic model also tackles the criticism of the non-inclusion of the variability of infectivity over time by creating several stages in the progression. A more detailed overview of this disease progression can be found in Appendix A.

Moreover, Bögel relaxes the often-made assumption that the probability of getting infected (and infecting others) is the same for everyone by adding a layer of detail to the agents regarding their age and assigning them different probabilities in the disease progression, slightly variating the path they follow when infected.

As mentioned before, one of the main challenges related to COVID-19 is the often-mild symptoms that infected people might have. This makes a considerable amount of people mistake their symptoms for a common flu instead of a COVID-19 infection. By not realizing they are infected, these individuals continue performing activities as if they were completely healthy, even if measures of isolation or quarantine are in place. Bögel's work implements this in a very interesting way. Added to their infection status, refugees have an extra attribute that related to their infection perception. By not always syncing these two variables, Bögel creates the wanted mismatch between an individual's health status and their perception.

4.2 Queuing model

The queue dynamics are developed in a separate queuing model. This section focuses on this standalone model, why it was done so and its conceptualization.

4.2.1 Queuing dynamics

In order to understand how people's behavior impact queues and how the characteristics of queues impact people's behavior, it is necessary to have a model that captures these dynamics. Moreover, to be able to evaluate how these dynamics impact further infections, it also needed to integrate epidemiological parameters of the virus in study. Figure 4.2 shows such a conceptualization. In this diagram it is possible to identify three main subsystems similar to Bögel's: the settlement, COVID-19 and refugee behavior. This last one, however, is highly focused on the way people might behave in a queue, based on the theory by Köster and Zönnchen (see Chapter 2). This is the component that will be further developed in a standalone model. As it is assumed that queuing behavior is dependent on the *personality* and *rationality* of each person queuing, an Agent-Based Modeling approach is used.

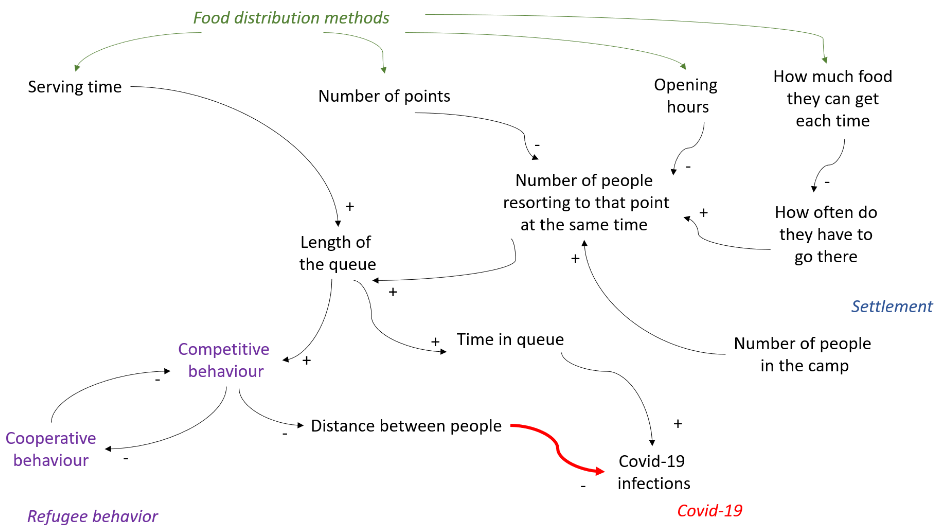


Figure 4.2: Causal loop diagram of the hypothesized queuing dynamics

4.2.2 Component-based modeling

Aiming for composability and to increase the utility of the work developed, the queuing behavior is developed in a separate model. This decision is motivated by the fundamentals of component-based modeling (Hofmann, 2004; Davis & Tolk, 2007): by modeling systems through different model components put together, one can increase the *flexibility* of the components and improve *maintainability* of these - by defining boundaries on what is part of each component, it is possible to develop each one individually. By making models a combination of smaller easier to handle models, it makes it easier to debug and reuse in other systems.

However, this decision entails some drawbacks: from deciding what is included in each component to different levels of resolutions, small modeling decisions can influence how easily models can be coupled. A trade-off can be identified in this decision: in order to make the code as clear as possible to this project, agents are called "refugees" and facilities are called "food distributions". This will facilitate coupling the model with Bögel's one as it follows the same logic and syntax. Nonetheless, this decision will limit the comprehensibility of the model when using it in other contexts (this is covered by writing it very explicitly in the beginning of the code).

4.2.3 Queuing attitudes: Cooperative vs Competitive

As conceptualized by Köster and Zönnchen (2015), people can have two different attitudes when queuing: *cooperative* or *competitive*.

Cooperative people, when faced with a queue for the service they want to use, identify who is the last person in line and patiently stand behind this person. Every time a person is served, this line moves a bit forward and people get closer to the service point. This type of behavior guarantees that a FIFO discipline is followed in the queue and is, consequently, the standard behavior in queues that are managed. Based on the principles of fairness and equality and social norms, this behavior is also often observed in self-organizing queues.

However, in self-organizing queues, there are people who might opt for a competitive behavior. These people, when faced with a queue, try to jump in the line and place themselves in a rather frontal position to minimize the time they have to wait. While some people might always approach queues this way and can therefore be argued to natural competitive queuers, others might be tempted to resort to this attitude due to the circumstances they are facing at the moment.

As discussed in the literature review (Chapter 2), Köster and Zönnchen model this switch of attitudes resorting to equations with a deterministic nature, not allowing the integration of the environment or rationality of agents when deciding to cut the queue. This limitation is highlighted by the authors - neither observations of the environment nor behavioral norms that may arise from the group play a role in the way people queue. This is developed further in this study.

Regarding the applicability of the theory by Köster and Zönnchen, it is relevant to keep in mind that this was developed in the field of pedestrian simulation and, hence, never thought to be applied at a refugee settlement level. Moreover, the authors clearly state in their limitations that the model does not include psychological nor cultural factors. When applying it to a refugee settlement, it can be argued that there are distinguishing contextual factors - the almost life-dependency on the good they are queuing for, for instance. However, this theory is still considered to be able to represent some of the dynamics in the queues at a refugee settlement. By leaving several variables flexible and to be adjusted by the user, it can be argued that the model is fit to represent any queuing situation once the values for the variables for each case are found. A reflection on how these could change according to the context being modeled can be found in Chapter 5.

4.2.4 Switching attitudes

As mentioned before, Köster and Zönnchen's model integrates the possibility of people switching between attitudes. The way they implemented it, however, does not take contextual factors into account to motivate this change.

In this study, some factors are integrated that make people adjust their behavior. Although several factors have been identified in literature as potential triggers (such as long lines, seeing other cutting the queue, urgency to be served, fear of scarcity, among others), this study will only include the first two.

To allow for this behavior, each individual is conceptualized to have a personal characteristic referred to as *tendency to competitiveness*. Each person in the model has their own value for this variable. Lower values mean that the person has a cooperative attitude and higher mean that the person is rather competitive. This value can be continuously updated when a person is queuing. This can happen at two different moments: if a cooperative person perceives the line as too long when joining, their tendency to competitiveness increases. When queuing, if a cooperative person observes people around cutting the line, they update their characteristic again. Once their tendency to competitiveness has crossed a certain threshold, their attitude is updated and their behavior will change accordingly. After being served, peoples' tendency to competitiveness returns to its initial value. This is based on the assumption that, while people might adapt their behavior depending on the circumstances and their surroundings, their personal nature is not changed. Finally, it is important to note that, while Köster and Zönnchen's consider the switch of attitudes possible both ways, this study only considers the possibility of a cooperative agent becoming competitive. Detailed explanation of the attitudes, the switch between them and related formulations can be found in Appendix B.

4.2.5 Behavior heterogeneity

The foundation of this study relies on differences of behaviors among people that translate into cooperative or competitive behavior when queuing. Another key point is that people can switch attitudes when queuing by perceiving the queue as being too long or by seeing other people cutting the line. However, this behavior is not black and white - not everyone has the same standards for what a long queue is or immediately becomes competitive when seeing a person cutting the line around them.

Another important feature that influences the behavior of people when queuing is the context of the distribution in place. It can be argued that, if NGOs are giving food to people who have not eaten in a couple of days, there will be a higher tendency to cut the line, fight and try to be served as soon as possible. However, if the distribution is of a good that people do not necessarily need to have right at that moment or know they will have access to in the next day, people who behave cooperatively will most likely do so during the entire distribution.

The way these two behavior heterogeneities are integrated in the model are explained in the implementation chapter (Chapter 5).

4.3 XLRM framework

In Chapter 3 the XLRM framework was introduced. By dividing variables into the four categories suggested by this framework, one can have an explicit overview of the system and understand the relations among the different components. The application of this framework to the problem can also support setting the scope of the study.

4.3.1 Policy levers

This study focuses on food distributions in refugee settlements. While these events move a lot of people around the camp and hence represent a risk during a disease outbreak, they are also necessary for the maintenance of the camp and the survival of its inhabitants. For this reason, it is essential to look into making these as safe as possible.

Representative-based policies

There are different approaches that can be taken to distribute food in a camp. Both the UNHCR's Emergency Handbook (2015) and the food guidelines of the Emergency Nutrition Network (2011) suggest three systems that are applied at different times in an emergency. Although these different policies are often used depending on the stage of development of the settlements, their potential to control an infectious disease outbreak has not been studied. For this reason, these will be the focus of the interventions of this thesis. These policies will be referred to as *representative-based* approaches.

At a high level, *representative-based* policies suggest the use of representatives to attend the food distribution and take on the responsibility of making the food reach the final beneficiary. This approach has several benefits. By having representatives picking up food for a part of the community, the interaction between NGO and population and the transfer of food becomes smoother and quicker, while the number of people waiting in line is highly reduced and, consequently, crowds are avoided. By reducing crowds, these policies have the potential to be beneficial during an outbreak.

However, resorting to the use of representatives can also result in some downsides. While serving each person will take considerably longer (as they are picking up food for a higher number of people), which can potentially increase the risk of infection if one of the people involved in the transaction is infected, this strategy can also sometimes lead to representatives not finishing their task and not distributing the food to everyone in need (risk of abuse and diversion). This often leads to vulnerable people of the community being left behind. Recognizing these downsides, NGOs often phase this into different stages, with representatives picking up food for less and less people along time until a system is in place in which the heads of each family can take on that responsibility (which is then maintained as the normal functioning of the camp). In some other camps, NGOs have to resort to daily distributions to each individual in the camp due to the lack of infrastructure to keep or cook food (example of the informal settlements in the north of France).

Timeslot-based policies

Another potentially promising policy is the introduction of timeslots for people to attend the food distribution. This technique is used in several places as a response to the COVID-19 pandemic to minimize crowds and queues in front of shops or services by strategically scheduling them along the service hours. This policy will be referred to as *timeslot-based* policy.

4.3.2 Exogenous uncertainties

As highlighted by Lempert et al. (2003), factors that are outside of the control space of decision-makers are called exogenous uncertainties.

In this system, two main uncertainties can be identified: the natural behavior of people living at a refugee settlement and the number of COVID-19 cases at the beginning of the implementation.

This study focuses on finding policies that can be beneficial *given* the uncertainty of human behavior when queuing. For this reason, this uncertainty will be the base for the scenario creation in the experimentation phase.

The number of COVID-19 cases at the beginning of the implementation of policies represents an added challenge. First, by having a very limited testing capacity available in settlements, there will most likely be a gap between the number of confirmed cases and real cases. On top of this, a certain stigma regarding being infected (and both uncertainty and fear on what happens if the test comes positive (2020)) makes people resort less to tests even if they think they might be carrying the virus. This increases the gap between the number of confirmed and real cases in a settlement. Identifying this lack of knowledge and the fact that there will most likely always be a gap plus time and resource constraints for this study, this uncertainty will not be used for scenario building. However, this will be used for a sensitivity analysis.

4.3.3 Measures

The underlying assumption in this study is that the way people queue has an influence in the way an infectious disease spreads. For this reason, it is relevant to take both the queuing and the outbreak dynamics into account when measuring the performance of the system. With this in mind, the following Key Performance Indicators (KPIs) are suggested to be used as metrics:

- **Average time in queue at the food distribution event**

  Including both the time waiting in queue and the time needed to be served, this metric is used to evaluate the queuing dynamics. One of the hypotheses is that the longer people queue, the more infections there will be. This metric allows the comparison of the average time in queue per policy in order to measure their impact on the system. This metric can also be looked at as related to one's individual utility (since competitive people want to maximize their utility, they cut the line to minimize their time in queue)

- **Cumulative COVID-19 infections**

  This metric is used to evaluate outbreak dynamics. By looking at the cumulative number of COVID-19 infections it is possible to assess the overall impact of policies and their impact in the spread of the infection. The steepness of this curve will also allow to understand when the outbreak starts taking off, giving insights on the temporal dimension of the spread.

Note, however, that these KPIs only represent one side of the story. The limitation of using these metrics to measure the performance of the system is discussed in Chapter 9.

4.3.4 Relationships

Finally, the R in XLRM stands for relationships. In other words, this can be considered as the model developed throughout the study - the model developed by Bögel (2020) including the queuing dynamics developed (i.e. the coupled model).

During both the process of model conceptualization and implementation, some decisions have to be made regarding the values of some parameters, the nature of some of these parameters and some relationships between variables. These can be called *structural uncertainties*. To evaluate their impact in the behavior of the system, a sensitivity analysis can be performed.

4.4 Conclusions

This chapter focuses on the conceptualization phase of this study. First, the existent model developed by Bögel and the logic behind it is analyzed. This allows to set a common understanding of the model and its dynamics. Then, the queuing model is conceptualized. By combining theories present in the literature in both pedestrian modeling and queue psychology, a narrative for the queuing model is put together and the dynamics are discussed. Finally, the XLRM framework is applied to the system in study, allowing a better view of the interventions, uncertainties, metrics and relationships taken into account.

Chapter 5

Model Implementation

This Chapter focuses on the implementation phase of this study. As indicated previously, the queuing behavior is modeled in a stand-alone model which is later on integrated in Bögel's prototype. For this reason, this section reporting on the model implementation is divided into two different topics: the queuing model (section 5.1) and coupling this model with the model developed by Bögel et al. (2020) (section 5.2). Then, the model is verified in Section 5.3. Finally, Section 5.4 provides a short recap of this chapter.

For detailed information on the software implementation of the queuing and the coupling of the two models see Appendix B and C, respectively.

5.1 Queuing model

This subsection covers the topics related to the implementation of the queuing model focusing on 6 main topics: modeling environment, model components, behavior heterogeneity, model interface, time, parameterization and model verification.

5.1.1 Modeling environment

To integrate queuing dynamics in the study, a queuing model was developed in Netlogo. Netlogo is a "multi-agent programmable modeling environment" designed by Uri Wilensky (Wilensky, 2019). Due to its free, open-source nature and ease of use, Netlogo is often the chosen environment in different settings ranging from education to scientific articles.

The main motivation for this choice of modeling environment is two-fold: both because the original model built by Bögel (2020) was developed in Netlogo and because of my familiarity with the environment. Moreover, Netlogo is also one of the most developed ABM tools, meaning that there is plenty of documentation available to support the model building process. Finally, and taking into account the importance of visualization to understand queue formation and spatial movement of agents, Netlogo's built in view of the developments of the system and its agents are a big advantage of the tool for the problem to be modeled.

It is, however, important to be aware of the limitations of this choice. Two of the limitations of NetLogo that are worth highlighting are its synchronicity and the slow computational performance. Due to its synchronous system, agents do actions one after another without true parallelism. This can have some implications for the problem at hand (e.g. some agents cutting the line in the radius of cooperative agents might be missed by them if they only cut the line after the cooperative agent has checked its surroundings). Further explanation on how to balance the effect of this synchronicity can be found under the paragraph regarding time. Moreover, the trade-off between ease of use and modeling performance (Shook, 2015) results in rather slow performance in NetLogo. A direct implication of this disadvantage is the time it takes to run experiments. Considering the time constraints of the study, this will limit the number of runs that can be performed. For this reason, the TU Delft server will be used during the experimentation phase of this thesis. Another drawback of using NetLogo is the lack of code testing tools to verify and debug the model. To overcome this disadvantage, meaningful print statements are used, together with giving colors and updating values of agents' attributes that can help identifying where problems come from.

Another point that is relevant to highlight is the appropriateness of the tool for the system and problem being modeled. If the ultimate goal of this study were to purely look into queue formation and proximity between people, a crowd simulation tool such as MassMotion would have been more appropriate. However, this thesis aims to look at a bigger picture problem in which different systems interact, integrating behavioral changes while they do so. For this reason, ABM and the specific choice of NetLogo are considered fit for this study.

5.1.2 Model components

The queuing model focus purely on the queuing process when refugees pick up their food. For this reason and in order to abstain from further complexity, this model only has two types of agents: *refugees* and *food distributions*. Further information on these components can be found in Appendix B.1.

An important thing to note is the adaptability and purpose of the model. Although the queuing model was developed specifically to be integrated in Bögel's one, the model can be used in any situation in which a queue can be observed. Although at the moment the model agents are called refugee and food distribution, these can easily be changed to a broader names (such as citizen and service, for instance).

Refugees

Represented by agents in a human shape, refugees are the active component of the model. These agents have a list of attributes that are supportive to their behavior and actions. While some of these are key to define the behavior of the agent, some are supportive and are used as a solution to store information and share it across functions. Two attributes that are worth noting are the *tendency-to-competitiveness* and the *attitude*, which will dictate the behavior of each agent.

When created, each agent gets a value for their tendency to competitiveness (which is stored as *natural-tendency*). This value can vary between 0 and 100 and will dictate the attitude of the agent (between cooperative, if the value is low, and competitive, if they have a high value).

In their normal state, refugees move around the world (NetLogo syntax) with no defined direction. This is implemented using a random walk algorithm. At some point, these agents get the task to get food (depending on their *preferred-fooddistro-time*). When so, and independently of their queuing attitude, they face the food distribution point and walk towards it. What happens next depends on the attitude of each individual: cooperative agents queue behind the last person in line, while competitive people place themselves in a frontal position to be served quicker.

Based on the literature from Köster and Zönnchen (2015), there are two main types of agents: *cooperative* and *competitive*. By default, the whole population is initialized as cooperative. To add competitive people it is necessary to adjust the value of "percentage-competitive" in the interface. These two attitudes will dictate how agents behave in a queue. Cooperative agents, when faced with the queue to join, identify how long it is. If the queue is longer than a certain acceptable threshold, then they adjust their tendency to competitiveness (initialized as *natural-tendency*) by increasing its value (storing it as *tendency-after-queuing*). While they wait in the queue, they also check their surroundings - if there are competitive person jumping the queue in their vision, they increase their tendency to competitiveness (storing it as *tendency-to-competitiveness*). If the value of a cooperative agent's tendency to competitiveness surpasses the threshold that separates the two attitudes, these agents remove themselves from the position in which they were placed and jump a few places in line. To guarantee that these agents who changed attitude are identifiable, their new attitude is named *new-competitive*. Competitive agents, on the other hand, immediately join the queue in a place that is not the last one in the queue (breaking the possibility of a FIFO dynamic).

For a more comprehensive overview of this behavior, please see Appendix B.2. The appendix also covers how this is implemented in the software and the spatial placement of agents.

Food Distribution

The other model component is the food distribution point. This is a simple static point represented by a truck with only four main variables: the location, the service-time (time needed to serve an agent), schedule (both when it open and when it close) and waiting-list (explained below).

As NetLogo does not necessarily have a built-in way of dealing with queues, these were modeled by using lists. This also allowed to use the information in the list to guarantee that each person waited in a place relative to the person who was queuing before them. This is quite straight forward for cooperative agents. However, one of the challenges was guaranteeing that agents who are not physically in the queue (the competitive and new-competitive agents) still have their turn to get food. This was solved by using two different queues: the *physical-waiting-list* and the *serving-waiting-list*. While the first is composed purely by cooperative agents and is used to model the actual queue, the second dictates the order by which the server is going to give food to the refugees - i.e. while some cooperative agents might be in the second spot in the physical queue, there might be competitive agents who have managed to sneak in in front of them and will be served first (consequently be placed first in the *serving-waiting-list*).

When an agent reaches the first place of the *serving-waiting-list*, they stay there for a time equivalent to the *service-time*. Once this time has passed, the refugee has been served. This triggers two events: the served refugee leaves the queue and returns to their random walks and everyone else in the queue updates their position by changing both their queue related attributes and stepping forward.

A more detailed mapping of these sequences of interactions between the food distribution and the agents can be found in Appendix B.2.

5.1.3 Behavior heterogeneity

As mentioned in the conceptualization, there is always heterogeneity of behavior in a group of people. This heterogeneity can be associated to two main sources: individual personality and the context. Both of these are integrated in the model as follows.

The most accurate way to account for each agent's reaction to the same situation (e.g. their personality) would be to have individual attributes with an agent's own value for certain variables (such as *impact-seeing-cutting*, *impact-long-queues* and *acceptable-length*) which are now global variables. However, this would lead to the creation of too many variables and increased complexity while not being the focus of this study (and a source of uncertainty). A simplified solution to this was used by creating agents with different (random) tendency-to-competitiveness values (stored as *natural-tendency*). This means that, if the *natural-tendency* of agent A is 40 and agent B's is 20, it will take more people cutting the line to make agent B turn competitive.

To account for the context of the distribution and how this might influence people's behavior, the threshold that distinguishes cooperative from competitive is provided in the interface as a slider and hence taken as an input and not a fixed parameter. In a situation in which there is a clear fear of scarcity, this *threshold-to-competitiveness* can assume values around 20, for instance. This means that any agent that has a tendency to competitiveness above 20 will behave competitively. A quiet and non-essential distribution can have a higher threshold. For example, if the threshold is set at 80, it takes a lot to turn naturally cooperative people into competitive ones. Another variable that can be used to describe the context of the distribution is the *percentage-competitive*. If the situation being modeled is one of a culture where queues are respected or extremely managed, the percentage of initially competitive people can be set to a low value. If the population being modeled does not follow queues by nature, this variable can be set to a high value. Finally, a third variable that can be used to describe the behavior of the population is the *distribution-pick-up*. This variable will determine each agent's preferred time to attend the food distribution (*preferred-fooddistro-time*) and can be argued to be a way of describing different situations. For example, if there is food scarcity and no guarantee that each person can have access to goods, it can be argued that agents will try to attend the food distribution as early as possible. In this case, a Poisson distribution with a positive real number (represented by *poisson-mean*) of 1 can be argued to be the best representation of refugee behavior. However, if the context is a very warm summer day, it can be argued that refugees will try to avoid the warmest hours of the day, attending the food distribution later in the day. To simulate this behavior, a distribution with a later peak is needed.

5.1.4 Model interface

As mentioned before, one of the advantages of using NetLogo is its built-in visualization of the system developments. Since the model is used to simulate a queue, being able to observe how agents queue and what they do is an important feature to verify the model.

For illustration purposes, Figure 5.1 shows the user interface of the queuing model. This interface has four main components: the function buttons (in grey), the user input parameters (in green), the monitors (in beige) and the world (in black). The function buttons are the ones one has to press to run the model. The user input parameters include contextual variables that help characterize both the population being modeled and their environment (such as the number of agents, the distribution of the time they pick up food, etc.), uncertain parameters but also the policies that can be implemented. The monitors simply show the state of the system (such as the time, broken down into days, hours and minutes). In the world, it is possible to distinguish three types of agents: the food distribution point (represented by the pink truck) and two types of refugees. The two colors of refugee agents represent their natural attitude, with the orange agents being the cooperative ones and the cyan the competitive ones.

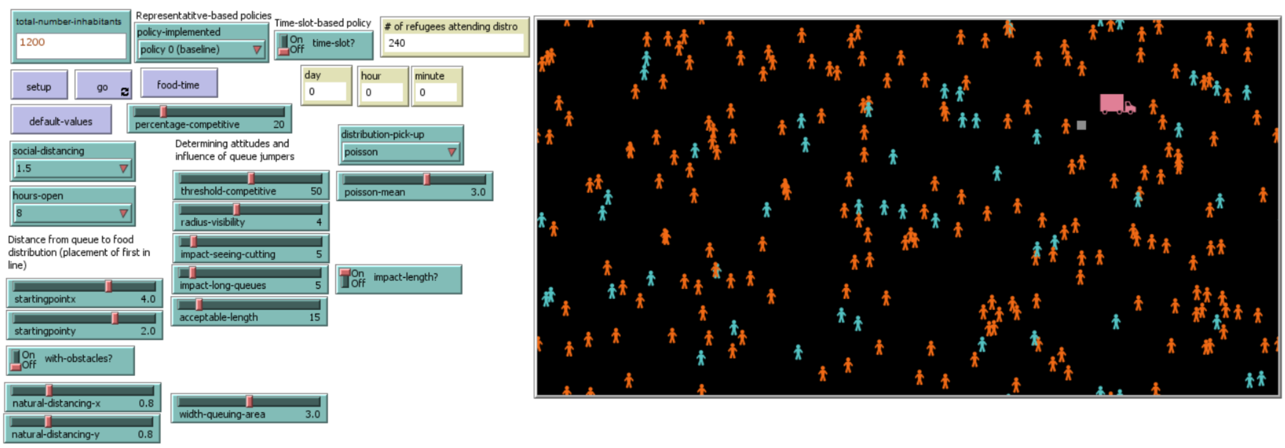


Figure 5.1: Interface of the queuing model

5.1.5 Time

Real queues, their formation and interactions of people while queuing occur in a continuous real time space. This means that agents can act parallelly and multiple things can happen at the exact same time. However, this level of similarity to reality is not possible to obtain in computer-based models. By working with timed instruction clocks and performing rounds of operations within each time step, conventional computers and any models developed in those are bound to this *discrete* nature (van Dam et al., 2013). This means that, instead of having true parallelism of actions, actions happen sequentially (as highlighted before as one of the limitations of NetLogo in subsection 5.1.1). This can lead to some unwanted consequences - for example, in this queuing model, it can happen that someone cuts the line *after* the cooperative agent has checked their surroundings, making the second agent not consider the first one's transgression when calculating their tendency to competitiveness. Although this is a rather simple example that might seem to have little to no impact in the bigger picture, the repetition of this throughout runs can highly influence the results obtained.

A way of balancing this is by randomising the iteration order of agents at each step (van Dam et al., 2013). NetLogo does this by randomising the agents when working with agent-sets. By doing this, NetLogo guarantees a certain variability between runs that can guarantee there is not a constant benefit to one agent or that leads the model in a certain direction. This leads to the point of *reproducibility*. During the initial experimentation and verification phase of the model, it is important to have a fixed seed set up to guarantee that the randomisation is the same throughout runs. This is done by setting up a *random-seed* which generates a pseudorandom number generator's number sequence in its turn. This sequence ensures that all the stochastic processes of the model generate the same value throughout runs. Note that it is necessary to remove this fixed seed when running multiple replications of the same experiment, otherwise the value of running several replications is gone.

Finally, it is necessary to discuss the time dimension of the model. As mentioned above, running models means having a sequence of time steps at which different actions happen. This time step can also be referred to as *time tick*. While the concept of a time step is a purely modeling one, trying to translate it to a reasonable equivalent in the real world can help interpretation and making sense of results. For this reason, the choice of the time step and its granularity is highly dependent on the system to be modeled. As queues and queuing dynamics happen rather fast, it is necessary to have a certain time granularity to allow for the caption of these interactions. For this reason, a time tick is thought to represent around one minute.

5.1.6 Parameterization

To run the model, it is necessary to find values for each one of the model variables. When possible, these were based on literature about queuing. However, this was not always the case as some of the variables were conceptualized for this specific study. For these variables, choices had to be made. These choices are explained in Appendix B.3. Moreover, the variables that describe the mix of the original attitudes of the population are sampled and used to build scenarios.

5.1.7 Model Verification

When building a model (and before using it to run experiments), it is important to evaluate if the model was correctly implemented. This step is called *model verification*.

As the model was constantly tested and altered, it can be argued that model verification was done in an iterative way. Verification tests included observing individual agents, printing error statements and extreme-condition testing.

When performing multi-agent testing and testing the model for a highly competitive population (represented by 40% of the population being naturally competitive), the model produced unexpected results with a lower average waiting time across all queuing agents than when tested with 30%. While this is an unexpected result, it can be justified by the simplification made that people who cut the line only do it once. Although this simplification does not play significant role when evaluating populations with a higher tendency to follow queues, it can be argued that it will limit the model's capability of capturing desired behavior in a highly competitive population. For this reason, it can be concluded that the final version of the model is verified to represent populations with a low natural competitiveness. However, it should not be used to model populations with a percentage of naturally competitive agents higher than 30%. A more detailed discussion on this limitation can be found in Chapter 9. More information on how the verification tests were performed can be found in Appendix B.6.

5.2 Model coupling

In this section, coupling the queuing model and the model developed by Bögel (2020) is reported upon. The coupling of these two models is essential in order to get insights on how different policies applied at the food distribution level can affect the number of COVID-19 infections in a settlement based on the queuing attitude of people.

5.2.1 The coupling process

As mentioned before, Bögel modeled a refugee settlement where agents perform daily activities. As the focus of this study is to observe the relation between queuing dynamics and the number of COVID cases resulting from the food distribution event, it is necessary to integrate the queuing behavior developed in the model when refugees attend food distribution. The coupling process targets this: coupling the two models is done so that refugees picking up food in Bögel's model follow the more complex queuing behavior simulated by the queuing model. At a high level, this means that the queuing model needs to be integrated in Bögel's model as suggested in Figure 5.2. A more detailed diagram on the coupled model flow can be found in Appendix C.

The actual process of coupling the models can be done in two different ways: by creating a NetLogo library with the queuing model or by integrating the queuing model code in the original model. To simplify the process and due to the lack of familiarity of NetLogo libraries, the second option was chosen. This allowed for a quick integration which was highly valued due to time constraints. However, the creation of a NetLogo library continues to be a potential further step in this work in order to make the queuing model widely available for future use.

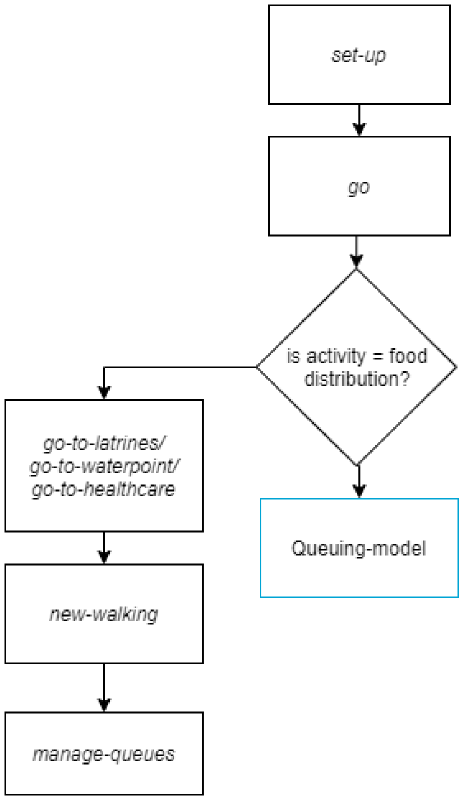


Figure 5.2: High-level dynamics of coupling the queuing model and Bögel's work

5.2.2 Challenges

Coupling models developed by different authors often represents a challenge. Obstacles can rise due to different levels of detail between models, the model logic or simply due to syntax used in the code. A way to minimize obstacles to this process is to know the main model in a high-level of detail. For this reason, a strong focus was put into understanding the model developed by Bögel and its dynamics. This was done through carefully reading the documentation of the work, reading and making sense of the code and by asking Bögel for some clarifications directly. One clear model choice made to facilitate the coupling of the models was the decision of taking a time tick as a minute. By creating two models with the same temporal granularity, it is easier to guarantee a rational development of time and events along runs. For more information on the coupling challenges, see Appendix C.1.1.

5.3 Model verification

The coupling process was done by integrating a verified model (the queuing model) into another verified model (developed by Bögel). However, to test if the coupling process was correctly done, the coupled model was subjected to extra verification tests. After performing these, it was concluded that the coupled model is also verified (with the previously mentioned limitation of not being fit for representing populations with more than 40% of naturally competitive individuals). More information regarding these tests can be found in Appendix D.

5.4 Conclusions

This chapter focuses on the model implementation in NetLogo. Due to the scope of the study, this chapter has a dual focus: the queuing model and the coupling of the queuing model with the original by Bögel (2020). First, the queuing model and its components are discussed. Then, the coupling process and its challenges were mentioned. Finally, the coupled model was verified. Detailed information about the software implementation of the models can be found in Appendix B and C. The coupled model is used for running experiments in the next chapter.

Chapter 6

Design of Experiments

This section focuses on the Design of Experiments (DoE) phase of this study. Experiments are combinations of specific model parameters and sets of policies used to analyze model behavior and get insights on the system being modeled. This section focuses on the experiments used in this study, their logic and their design. Note that these experiments are conducted in the coupled model (i.e. Bögel's model with the more complex queuing behavior) and are designed to answer the main research question.

The DoE is rooted in the XLRM framework introduced in Section 3. The objective of the experiments is to observe how the **M**easures (i.e., Key Performance Indicators) that quantify **R**elationships in the system (i.e., model / infection dynamics) behave and respond to changes in e**X**ogenous factors (scenarios) and **L**evers (policies). This chapter is therefore divided accordingly into four parts. First, in Section 6.1, the policies are introduced and formalized in terms of values to be used in the model. Then the Key Performance Indicators are reviewed (Section 6.2). After this, in Section 6.3, the scenarios in which the model is simulated are introduced. Finally, the experiments to be conducted are outlined in Section 6.4, together with their formalization.

6.1 Policies

The main motivation of this study is to understand how the process of distributing food in a refugee settlement can be made safer during an outbreak. This is done by evaluating how infections spread and how this spread changes depending on the policy implemented at a food distribution level.

As mentioned in Chapter 4, two different types of policies will be implemented: *representative-based* and *timeslot-based* policies. Table 6.1 and Table 6.2 show the breakdown of these policies, respectively.

As shown above, the policies vary either the number of representatives that attend a food distribution event (i.e., representative-based policy) or the use of timeslots for food distribution (i.e., timeslot-based policy). We omit consideration of the policy in which food distribution events are eliminated entirely. Such a policy is unrealistic given that food distributions often represent the only reliable source

Table 6.1: Breakdown of the *representative-based* policies

	Policy	Size of the represented community
P0	Distribution to the head of each household (Baseline)	5 people (size household)
P1	Distribution to large groups	50 people (10 households)
P2	Distribution to medium groups	25 people (5 households)
P3	Distribution to small groups	15 people (3 households)

Table 6.2: Breakdown of the *timeslot-based* policy

	Policy	Explanation
P4	Timeslot for distribution	Timeslots are given to people in order to spread visits to the food distribution point uniformly over the day

of food for the population of a temporary settlement. It is assumed that refugees are dependent on food distribution events for subsistence and that such events must continue even in a pandemic.

To be able to evaluate the impact of different policies, it is necessary to have a baseline for the system. The baseline is selected as the situation in which each head of household picks up food for the household (previously identified as policy **P0**). This choice is made given the wide-spread implementation of this policy in real life, as noted in literature on food distribution and interviews conducted with food actors in different camps.

6.1.1 Policy Formalization

To able to implement the policies as parameters to use in the model, it is necessary to consider how these policies differ from each other and how they can be translated into model inputs. Table 6.3 shows the formalization of the *representative-based* policies and Table 6.4 of the *timeslot-based* policy.

Representative-based policies entail community representatives attending food distribution events for food collection. The community representative represents multiple households, in contrast to having each head of household attend a food distribution event. These policies are differentiated in terms of two components: (i) the percentage of total population attending the food distribution, which can be calculated from the number of people every representative is picking up food for and (ii) the total amount of time needed to serve each person in line.

Based on the logic that picking up food for more people will require additional time, it can be argued that the larger a community a representative represents, the larger the amount of time needed to serve that representative. However, it is challenging to select precise values that represent the actual time needed and to determine how these values differ according to the size of the community represented. Based on personal experience at a refugee settlement coordinating daily food distributions to individuals, I estimate that the serving time is around one minute per person. From interviews with food actors currently working in Cox's Bazar where food is distributed once every month to the head of the family (i.e., the baseline in this study), the serving time is around four minutes. Note that this is dependent on how often food distribution occurs and consequently how many days' worth of food are being distributed.

All *representative-based* policies are broken down into quantified values in Table 6.3 which can be input into the model.

Table 6.3: Formalization of the *representative-based* policies

Policy	**% of the population that attends food distribution**	**Service-time (minutes)**
P0 (Baseline)	20	4
P1	2	10
P2	4	7
P3	7	6

The *timeslot-based* policy can be introduced in conjunction with any *representative-based* policy or by itself. This policy can be implemented in the model by changing the distribution of times in which community representatives pick up their food (Table 6.4). Instead of using the distribution chosen in the interface (*distribution-pick-up*), implementation of this policy results in a uniform distribution of all representatives attending the food distribution across the opening hours of the food point. This results in a uniform distribution for the values of *preferred-fooddistro-time* in the model.

Table 6.4: Formalization of the *timeslot-based* policy

Policy	**Distribution of people attending food distribution**
P4	Uniform

It is important to note that these policies are implemented while there is a constant "keep 1.5m" general rule in queues - only respected by cooperative agents (see model assumptions 9.1).

Due to time and resource constraints of this study, the range of policies to be tested is quite limited. However, the results will show if it is a relevant direction to go further in. If so, it is recommended that more time is put into developing policies and seeing their potential effect in the system. For this reason, this study should be looked at as a starting development in the direction of making food distribution safer during an infectious disease outbreak and not as a plan on how to act.

6.2 Key Performance Indicators

In applying the XLRM framework to the topic of this study, the Key Performance Indicators (KPIs) are used to represent measures of the model, and are described as follows:

- Average time in queue at the food distribution event
- Cumulative COVID-19 infections

6.3 Scenarios

Experiments are used to compare the performance of policies across different scenarios. Considering this problem is defined by a certain uncertainty inherent to some of the system variables, it is not straight forward to come up with scenarios to test policies on. In cases like this, techniques for deep uncertainty modeling can be used to test policies under a wide range of possible scenarios. However, such techniques are also known for being time consuming and computationally expensive.

Given time and computational constraints, the decision to test policies across a defined set of scenarios was made. Considering the scope of this project, these scenarios were based on the mix of attitudes in the initial population (i.e., agents being cooperative or competitive by nature). These scenarios are formalized through differences in the *percentage-competitive* variable in the model, which will take the values of 0%, 10%, 20% and 30%. These scenarios are referred to as **S0, S1, S2** and **S3**, respectively (Table 6.5).

Table 6.5: Breakdown and formalization of the scenarios

	Scenario	**percentage-competitive (%)**
S0	The whole population starts off as cooperative	0
S1	10% of the population starts off as competitive	10
S2	20% of the population starts off as competitive	20
S3	30% of the population starts off as competitive	30

6.4 Experiments

A potential approach for analyzing model behavior and the influence of different policies under different scenarios is to sample all the policies across all the scenarios previously identified. However, given the computational constraints of running the model, a fractional factorial design approach was implemented by dividing the experiments into smaller batches. This approach simulates only a portion of the possible combinations of model parameters, therefore yielding model outputs in a more timely manner and enabling quicker identification of errors in the model or experimental setup.

Table 6.6 outlines the conducted experiments. For each experiment, the implemented policy, the range of scenarios in which the policy is tested and the overall focus of the experiment is outlined.

Table 6.6: Design of Experiments

Experiment	Policies	Scenarios	Focus of experiment
E0	P0	S0 S1 S2 S3	Baseline policy in each scenario
E1	P0 P1 P2 P3	S0	Effect of each policy when 0% competitive
E2	P0 P1 P2 P3	S1	Effect of each policy when 10% competitive
E3	P0 P1 P2 P3	S2	Effect of each policy when 20% competitive
E4	P0 P1 P2 P3	S3	Effect of each policy when 30% competitive
E5	P0 (P0 + P4) (P3 + P4)	S1 S3	Effect of timeslot policy in each scenario

Note that, to account for the stochasticity of the model, each combination of policy and scenario was run with 10 replications. All the experiments were set to run until 90 000 time ticks (which is equivalent to approximately 62 days in the model, considering each time tick is 1 minute).

The values of the remaining variables are maintained as constant throughout all the experiments. The values used for these variables can be found in Appendix C.2.

6.4.1 Server

The high time granularity of the model (leading to a high number of ticks needed to simulate 62 days) makes running of the model computationally intensive and time-consuming. Additionally, the computation time required per time tick increases after infections begin to spread (i.e., at approximately time tick 72 0000). For this reason, a single full run of the model requires extensive computational power and time and represents a major constraint on the flexibility of model use in the experimentation phase.

To address this challenge, a cluster server was used to perform the experiments described in this chapter. The cluster server at TU Delft contains numerous cores, which enabled simultaneous execution of multiple runs of the model. This access to additional computational capacity made possible additional runs and replications of the experiments, which allowed closer evaluation of the impact of stochasticity on model results, thereby increasing the robustness of the analysis.

Given that the model must be run headless (i.e., without a Graphical User Interface), a script for executing the experiments on the server was developed. More information on the scripts used to run the model in the cluster can be found in the GitHub repository of this project.

Chapter 7

Sensitivity Analysis

Along the process of this thesis, both during the conceptualization and the implementation phase, abstractions and assumptions had to be made. Moreover, the model simulates a highly uncertain system with parameters for which the value is not fully known. It is, for this reason, useful to perform a Sensitivity Analysis (SA) to understand the impact of these decisions and the scenarios on the final results of the model. By sampling the input parameters across a certain range of values, a sensitivity analysis can provide a better understanding of the model and its results. Ultimately, the goal of the sensitivity analysis is to understand how robust the conclusions taken from model use are and which inputs the model is more sensitive to.

First, in Section 7.1, the sensitivity analysis approach is explained. Section 7.2 and Section 7.3 cover the input parameters and the outcomes of interest, respectively. Then, Section 7.4 provides the results of the analysis and their implications. Finally, Section 7.5 summarizes the conclusions of the chapter.

7.1 Global Sensitivity Analysis

There are three types of sensitivity analysis: global, regional and one-factor-at-a-time. Considering that the model developed is non-linear and dynamic, it is considered that a one-factor-at-a-time analysis is not the best approach because it focuses on the impact of changes in one input at a time (Saltelli et al., n.d.). For this reason, a global analysis is performed. When performing a global SA, the inputs are sampled at the same time instead of individually. This allows to identify situations in which inputs have an impact in combination with other inputs (interaction effects), which would be ignored when conducting a one-at-a-time sensitivity analysis.

The sensitivity analysis is performed through feature scoring. Feature scoring is a machine-learning alternative to the more traditional global sensitivity analysis techniques (Kwakkel, 2017). This was chosen due to the time and computational constraints that make a Sobol analysis challenging to perform (as they need a higher number of scenarios in order to provide useful insights, leading to a number of runs that would take weeks to perform with this model) and its ease of use. By resorting to feature scoring, it is possible to identify the relative importance of different input parameters for specific outcomes.

This analysis is divided into five steps. First, the parameters to sample and the outcomes of interest were specified. Then, BehaviorSpace (NetLogo experimentation tool) is used to sample the parameters and perform the necessary runs. Then, the data generated by BehaviorSpace is restructured to have the correct shape for analysis. After having the data structured, the sensitivity analysis is performed by using the feature scoring functionality of the Exploratory Modeling and Analysis (EMA) workbench (Kwakkel, 2017). Finally, the feature scoring results are visualized in a matrix. Since the model is too computationally expensive to run on a normal computer, the BehaviorSpace step was performed on the TU Delft cluster. This allows for the use of more cores and, consequently, a faster running time of the experiments all together. From these runs, an output file of 33GB was generated, making its analysis and handling an added challenge. For this reason, the process of structuring the data was divided into two steps: i) reducing the size of the csv file outputted by the experiments in order to be able to work with it and ii) processing it to only contain needed data to input for the EMA analysis. Both the scripts involved in this process can be found in the GitHub repository of this project.

7.2 Input parameters

In order to maintain the number of runs within a reasonable order of magnitude, four different parameters are varied in the sensitivity analysis. The rest of the model input parameters are left constant and assume the values used during the experimentation phase. The varying parameters are as outlined in Table 7.1 and cover different parts of the model. The *impact-long-queue* represents the impact that seeing a long queue has in an agent, which is a variable created during the conceptualization part of this study. The *threshold-competitive* represents an equally conceptual parameter: this is the value from which agents start behaving competitively (once their tendency-to-competitiveness exceeds this threshold, agents start behaving competitively when in the queue). The *initial-covid-cases* (equivalent to the initial-corona-number variable in the model) represents the number of COVID-19 infected people at the beginning of the simulation (day 0). Finally, the *service-time* is the time that it takes to serve an agent in the food distribution process. These parameters are varied over a range of +- 50% of their default value used in the experimentation phase, as suggested by Kwakkel and Pruyt (2013) (except for the *initial-covid-cases*, which was varied between 1 and 5).

Table 7.1: Input parameters for sensitivity analysis

Parameter	Value
impact-long-queue	[3, 4, 5, 6, 7]
threshold-competitive	[30, 40, 50, 60, 70]
initial-covid-cases	[1, 2, 3, 4, 5]
service-time	[2, 3, 4, 5, 6]

Considering the sampling values of these parameters, this results in the simulation of 625 scenarios. To account for the stochasticity of the model, 10 replications of each scenario are conducted, leading to a total of 6250 runs to be conducted. These are tested under the baseline (where the head of each household attends the food distribution) and under scenario 1 (where 10% of the population is naturally competitive when queuing for food). Due to the extensive time needed to run the model, it was decided that the sensitivity analysis simulates 30 days (instead of the 60 days of the rest of the experiments). Even with the runs shortened and using the TU Delft cluster, the 6250 runs took 60 hours to be simulated.

7.3 Outcomes of interest

Finally, it is necessary to decide which are the outcomes of interest to be evaluated in the sensitivity analysis. These are the outcomes of which sensitivity is relevant to be evaluated in order to analyze the model. Given the dual focus of the model (both the queuing and the COVID-19 dynamics), three outcomes of interest were decided for each. To study the impact of the uncertainty in the input parameters on queuing dynamics, the average time in queue, the maximum queuing time and the minimum queuing time are chosen. For the COVID-19 dynamics, three moments in time are chosen to be evaluated: the cumulative number of cases before the first food distribution (in day 7), the cumulative number of cases after the first food distribution plus an incubation period (in day 13) and the cumulative cases in day 30 (which in this experiment matches with the end of the run). Note that the food distribution occurs at day 8. By choosing these days, the number of infections occurring at the food distribution can be focused on and the impact of the input parameters in this can be evaluated.

7.4 Results

After performing the sensitivity analysis, the feature scoring matrix in Figure 7.1 was generated. From this analysis, it is possible to observe two main drivers of the model - the *service-time* for the queuing related outcomes and the *initial-covid-cases* for the infection related outcomes. The sensitivity of these outcomes to these input parameters was expected and they highlight the importance of looking into these two parameters.

The overall little relative impact of the *service-time* in the variability of the number of cumulative cases along time can be related to the limited difference of the values that this variable was sampled over (Table 7.1). From this, it can be said that taking six minutes to serve a person instead of four minutes does not play a big (relative) role in the evolution of the outbreak (but it heavily does in the queuing dynamics and the time people spend queuing).

From the matrix, it is clear that the *initial-covid-cases* has the main and dominating effect in the development of the outbreak along time. However, it is also possible to observe that the relative impact of the *initial-covid-cases* considerably decreases between the total number of cases before and after the food distribution (*total-infected-beforedistribution* and *total-infected-afterdistribution*), increasing again in day 30 *total-infected-day30*. This implies that, although the parameter stays the main driver of the infection outcomes over time, after the food distribution event

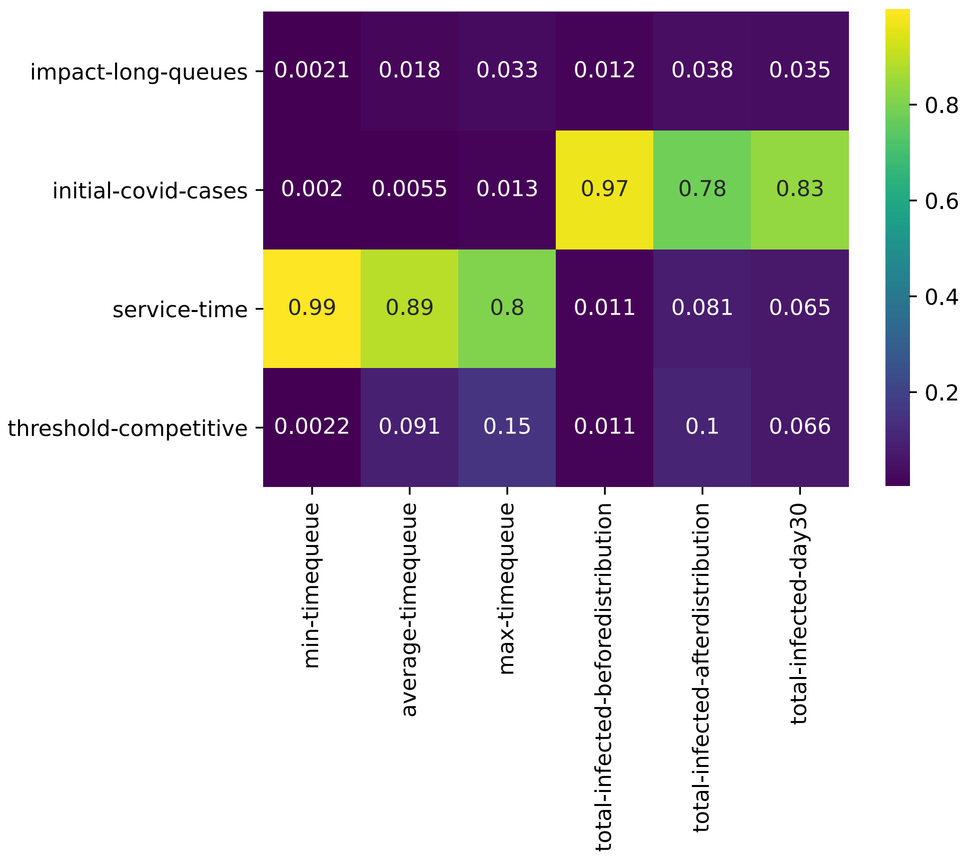


Figure 7.1: Sensitivity Analysis: Feature Scoring matrix

there are other parameters that are partly responsible for the variability of the number of cases. From the matrix, it is possible to observe that both *service-time* and *threshold-competitive* have a higher impact after the food distribution than they have during in other moments of the run. This variation suggests that, although the queuing process seems to have little relative impact on the number of cases at the end of the run, it plays a larger role at after the food distribution. Specifically, and taking into account the difference between the impact of the two parameters, this suggests that, more important than the time in queue (*service-time*) is the behavior in queue (*threshold-competitive*).

From the analysis of sensitivity of the number of total cases after food distribution (*total-infected-afterdistribution*) it can also be observed that the *threshold-competitive* plays a bigger role than the *service-time*. This means that, when looking into queues and how to make them safer, it is more important to control the behavior of people and aim for a cooperative behavior than to speed the serving process. The impact of the *threshold-competitive*, however, seems to reduce over time (in specific at day 30). This goes in line with the results obtained before and the converge of the system into a near-total infection across all scenarios. Finally, it is possible to observe that none of the outcomes of interest is relatively sensitive to changes in the *impact-long-queues*.

Overall, Figure 7.1 suggests that the infection model is extremely sensitive to the size of the outbreak by day 0. Although this is an expected outcome that highlights the necessity of quick action when trying to control an infectious disease

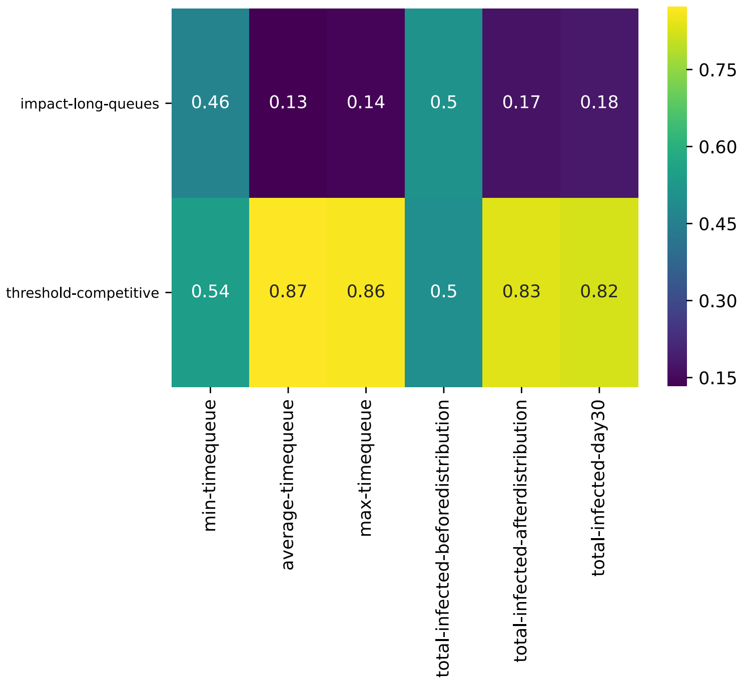


Figure 7.2: Sensitivity Analysis without key sensitivity analysis: Feature Scoring matrix

outbreak, this is a parameter that decision-makers have little control over (other than constantly testing and being aware of the state of the system at all times, which can be argued to be extremely challenging). For this reason, and considering that the feature scoring matrix shows the relative importance of parameters, a second sensitivity analysis is performed without considering the key sensitivities (*initial-covid-cases* and *service-time*).

Not considering the key sensitivities identified previously, a second sensitivity analysis was conducted with the two variables that showed the lowest values in the first analysis. Figure 7.2 shows the feature scoring matrix for the second sensitivity analysis performed. From these results, it is possible to conclude that the *threshold-competitive* is a larger driver of almost all outcomes of interest than the *impact-long-queues*. These parameters are connected, with the *impact-long-queues* being connected to the competitiveness agents have that can, or not, pass the *threshold-competitive* and make them behave competitively. However, this sensitivity analysis shows that, between these two variables, when making decisions at a food distribution level, the focus should lie on increasing the threshold that makes people behave competitively than on their interpretation of long queues. Techniques to increase the threshold to become competitive can include clear communication, increasing confidence in the system, among others. This will be further discussed in Chapter 9.

It is important to mention that this analysis was conducted while maintaining the natural competitiveness of a population on 10% (S1) and with policy 0 (baseline) (P0) implemented. By maintaining these parameters fixed, potential interaction effects could have been missed and the sensitivity analysis could lead to other results if conducted under different conditions.

When designing policies, a sensitivity analysis can be performed first to explore what factors influence the system and understand their relative importance. With this information, one should reflect on which factors one can have an influence in and design policies accordingly. These policies can then be tested again in a sensitivity analysis to evaluate the scenarios in which they are successful. As this analysis often provides insights on the dynamics of the system, it should be used iteratively and as a way of guiding the decision-making process in deep uncertainty. However, due to the time constraints of this project and the late execution of a sensitivity analysis, this was not the direction of steps of this study.

7.5 Conclusions

This chapter covered the sensitivity analysis performed on the model. The sensitivity analysis showed that the initial number of COVID-19 cases in the beginning of the simulation is the main driver of the epidemiological model and has a high influence in the number of cases over the run. This highlights the need to act quickly to contain outbreaks as a higher number of cases in the beginning highly influence the number of total infections along time. Similarly, the analysis also shows that the time it takes to serve each person is the main driver of the queuing related outcomes (maximum, average and minimum queuing time).

Finally, the analysis suggests that, although the queuing parameters seem to have barely any (relative) impact on the number of infections at the end of the run, they play a larger role when evaluating the number of infections after the food distribution event. This suggests that influencing the queuing process can be a way of reducing the number of infections happening during the food distribution event and, consequently, the number of total infections in the days following this event (considering the incubation period).

Chapter 8

Results

After setting up the experiments for the model (see Chapter 6), these were defined in BehaviorSpace in NetLogo. Each experiment resulted in a spreadsheet file with highly granular data (per time tick) and multiple text files containing variable values at the end of the run. These model outputs were pre-processed and visualized in Python, using packages such as Matplotlib and Seaborn. The results from this analysis are reported upon in this Chapter.

First, in Section 8.1, the system as is and the dynamics involved are explored. Then, Section 8.2 will focus on the implementation of both representative and timeslot-based policies. Finally, Section 8.3 provides a summary of the Chapter.

Additional comments on the data preparation and visualization can be found in the GitHub repository of this project and in Appendix E, respectively.

8.1 Model Behavior

To understand the impact of different policies, it is important to first observe the model outcomes with no policy in place. As mentioned before, due to the importance of food distribution in a settlement, the baseline scenario is not a lack of food distribution, but rather the typical occurrence whereby the head of each household attends food distribution once every 28 days (also referred to as **P0**). Note that this is also how Bögel conducted their experiments.

This baseline case was simulated across the four scenarios introduced in Chapter 6: with 0%, 10%, 20% and 30% of the population adopting naturally competitive behavior when queuing (**E0** from Table 6.6).

8.1.1 Key Performance Indicators

Average time in queue at the food distribution

In terms of queuing dynamics, Figure 8.1 shows the average time in queue across all queuing individuals per scenario. It was observed that a clear trend between the competitiveness of a population and the average time in queue exists. This figure shows that, on average, it is highly beneficial if the whole queue behaves cooperatively as this quickens the queuing process for everyone.

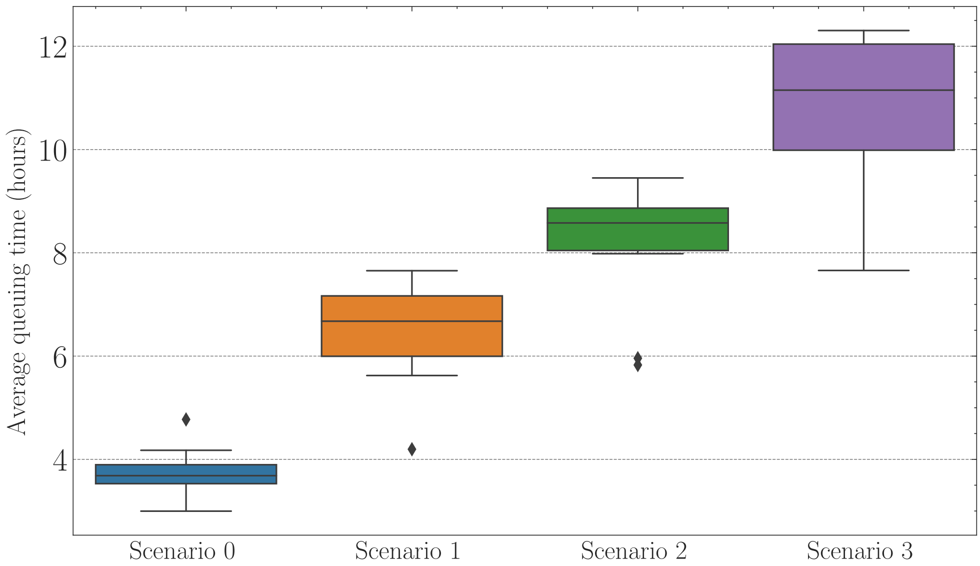


Figure 8.1: Average time in queue at the food distribution across all queuing agents: Baseline in each scenario (E0)

Cumulative infections

Figure 8.2 shows the cumulative infections across scenarios in the baseline. From this figure, it is possible to observe that 95% of the runs follow the behavior identified by Bögel that, in case of an outbreak (in day 0) in a refugee settlement, most of the population is infected by day 60, regardless of the scenario.

As it is difficult to observe the differences between scenarios in Figure 8.2, Figure 8.3 shows the cumulative number of infections per scenario at five key time steps (day 10, day 20, day 30, day 40 and day 50). From this figure, it is possible to observe that, although all scenarios converge to a similar number of infections by the end of the run (as was observed before), the number of cumulative cases between the selected time steps varies across the scenarios. This suggests different speeds at which the outbreak spreads in the settlement across scenarios. This relation is not linear, in that it is not possible to claim that the more competitive a population, the quicker the spread of an outbreak in a settlement. Neither is it possible to directly correlate the speed of an outbreak with the average wait time in a queue (from Figure 8.1). However, the results do indicate that the varying queuing behavior in a population plays a role in how the infection spreads. As the different behavior is only implemented when individuals are queuing for food, this suggests that looking into the food distribution event might be a direction to follow when studying how to control outbreaks.

From the sensitivity analysis performed, it was possible to observe that the relative importance of the queuing parameters in the number of total infections by day 30 was very reduced. However, it was also possible to observe that, over time (specifically after the food distribution), these parameters were of higher impact. This suggests that, although different queuing dynamics do not seem to have an impact in the number of infections after a long time, they do have the potential to influence the development of an outbreak at some point. This is consistent with the results from Figure 8.3 and the difference between scenarios.

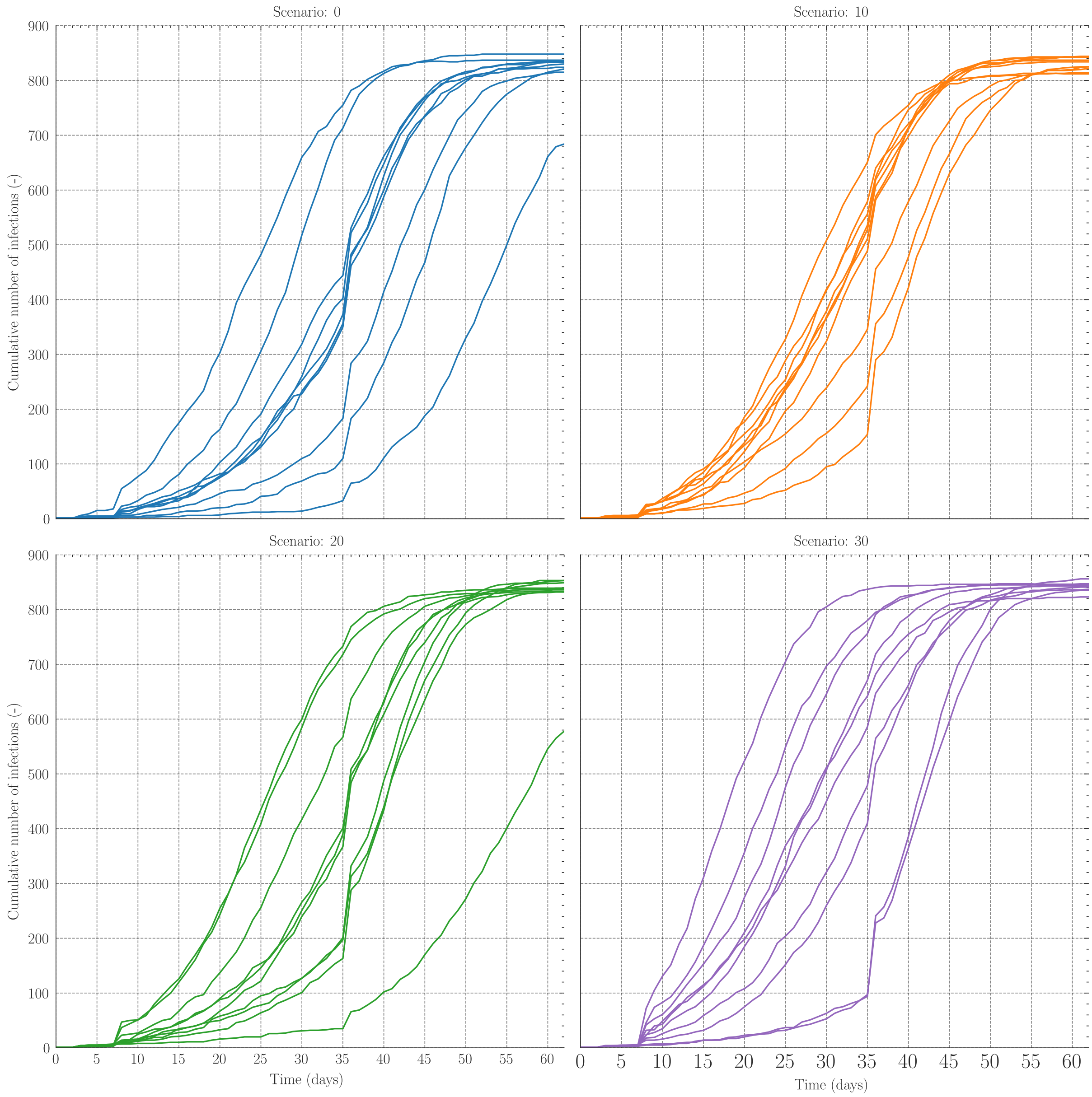


Figure 8.2: Cumulative infections: Baseline in each scenario (E0)

Moreover, although the number of cumulative cases (both in the sensitivity analysis as well as in Figure 8.2 and 8.3) are disaggregated over time, they are aggregated over population and locations of infections, potentially not showing all relevant dynamics for a complete analysis. For this reason, and taking into account the computational constraint of repeating a new sensitivity analysis, this section will explore more of the model dynamics than focusing only on the Key Performance Indicators previously identified.

8.1.2 Attitude exploration

In order to understand how different attitudes play a role in the dynamics of the model, this section focuses on the disaggregation of results per attitude. For clarity purposes, this section will only look at two scenarios of interest: one with a lowly competitive population (**S1**) and one with a highly competitive population (**S3**).

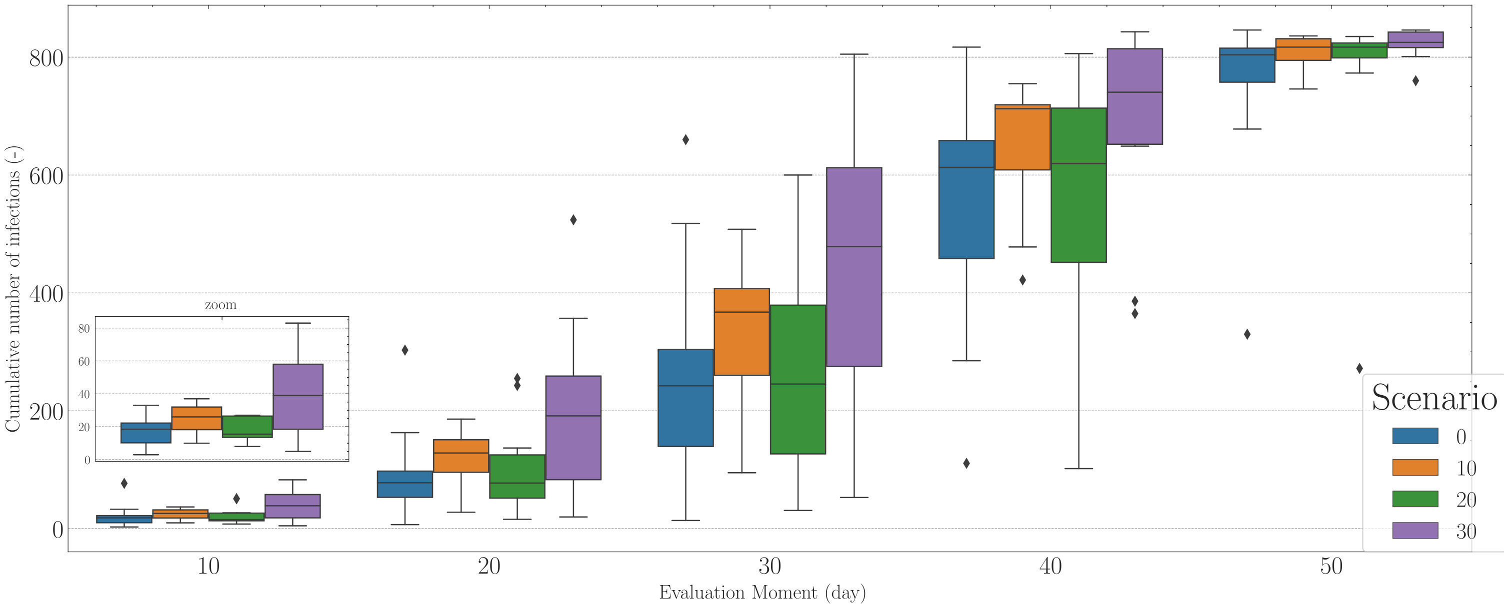


Figure 8.3: Cumulative infections: Baseline in each scenario (E0)

Considering that, in the model developed, the attitude of a person only affects the way they queue at the food distribution, this section will focus solely on this event.

Average time in queue at the food distribution per attitude

Figure 8.1 shows that adding competitive people to a queue will increase the average waiting time across all queuing individuals. Based on this, it can be concluded that it is beneficial for the common good if every queuing individual follows queuing rules, joining the queue at the end of the line and waiting for their turn to be served. However, it was not observed how the time in queue varied per attitude. Figure 8.4 shows the disaggregation of the data per attitude.

Figure 8.4 shows that, by cutting the line, competitive individuals have a clear benefit in terms of time saved. The figure also shows that competitive individuals minimize their own time in queue at the expense of the waiting time of cooperative individuals. Moreover, it is also possible to observe that, while competitive people cut the line with the motivation of minimizing their own time in queue, the more competitive people there are in a population, the more they have to wait as well. This creates a counter-productive situation in which everyone is worse off (as already suggested by Figure 8.4).

Finally, it is also important to note the high range of average waiting time for cooperative individuals in scenario 3 and the high waiting time for new-competitive individuals. As the latter are individuals who initially join the queue cooperatively (due to their natural attitude) but who change behavior because of the circumstances around them, they are always at a disadvantage relative to the naturally competitive (who immediately cut the line when they arrive). Consequently, new-competitive individuals are more likely to wait longer.

In addition, among the 10 replications of scenario 3, there is a high variation in the number of people who switched behavior and turned new-competitive. This

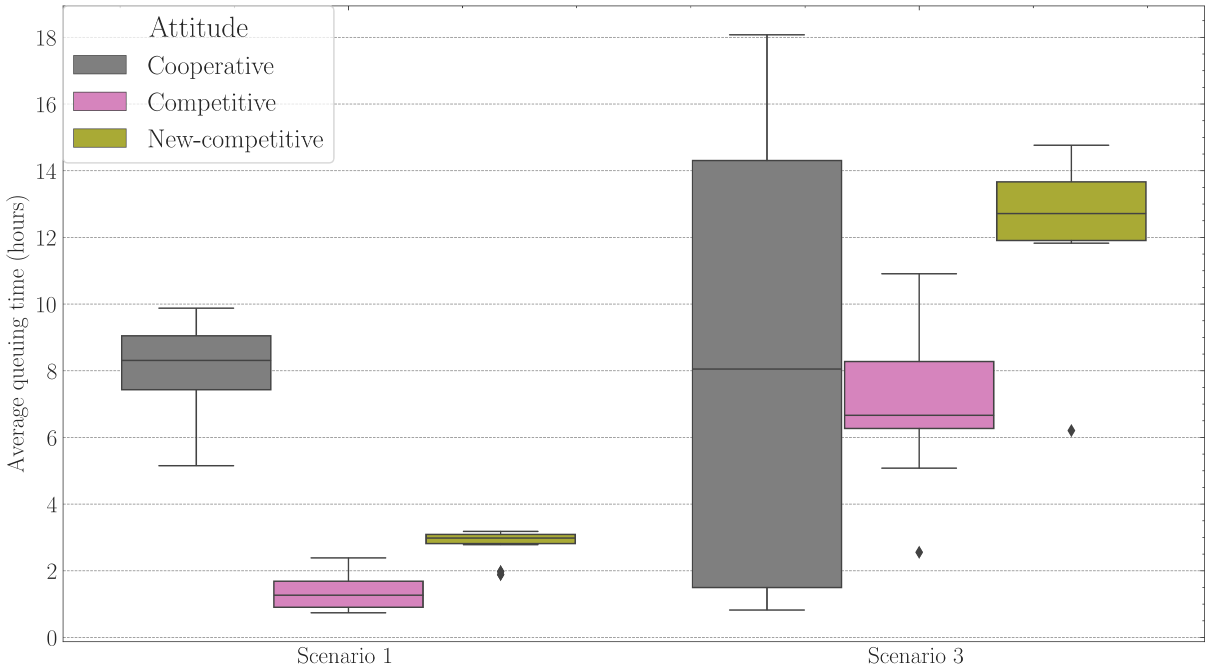


Figure 8.4: Average time in queue at the food distribution: Baseline in each scenario (E0)

depends on several factors: the time of day at which they attended the food distribution (and consequently how long the queue was then), how many people they observe cutting the line around them and their natural tendency to become competitive. However, it is interesting to observe that the number of people who turned new-competitive in scenario 3 always takes values of either around 110 or 35 (see Figure 8.5). The non-existence of values in between shows an interesting behavior reinforcing loop, whereby the more people are influenced to cut the line, the more others will be influenced to do so too, creating a snowball effect. This circumstantial behavior results in either low (below 40) or rather high numbers (110) of people turning new-competitive.

However, with a sufficiently low initial number of competitive individuals in the queue, the competitive behavior does not seem to propagate. For reference, the number of people who turn new-competitive in scenario 2 always mostly takes values around 35. However, there is one exception of a run in which 51 people turned new-competitive. Yet, as the number of naturally competitive people is lower (20% of the population, per definition), the surrounding circumstances did not lead to the snowball effect observed in scenario 3, resulting in better overall results. This dynamic suggests the existence of a tipping point from which a snowball effect can be observed onward. As a trend can also be observed between the runs where more people switch behavior leading to higher queuing times, this dynamic represents a possible place to implement a policy in order to stop this effect, control the number of people switching behavior and, consequently, reducing waiting times.

Likelihood of getting infected at the food distribution per attitude

By cutting in line, competitive agents reduce their waiting time in a queue, thereby maximizing their personal utility. However, while doing so, they do not

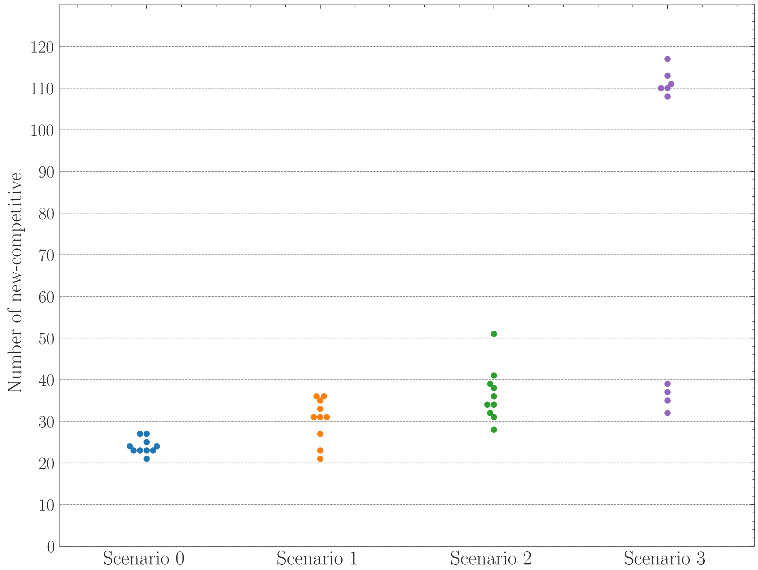


Figure 8.5: Number of people switching behavior when waiting in the queue for food distribution: Baseline in each scenario (E0)

comply with 1.5m social distancing requirements, potentially putting themselves (or others) at risk of infection. To evaluate this, Figure 8.6 shows individuals' *likelihood to get infected* during both food distribution events. This likelihood is calculated as the number of people of a certain attitude who were infected at the food distribution event divided by the total number of people with that attitude who attended the event. Figure 8.6 shows that, regardless of the scenario, competitive people are more likely to get infected when they attend the food distribution than they would if they were to follow the queuing rules.

The figure also suggests that individuals who first join the queue but then decide to cut the line (identified as new-competitive) highly reduce their risk of infection by doing so. This could be justified by the shorter time they wait by cutting the line. However, it should also be noted that individuals that were infected while they were still following the queuing rules and then decided to cut the line will contribute for the likelihood to get infected of cooperative individuals. As the number of cooperative people who got infected includes these cases and is divided by the number of people who were cooperative when they left the queue, it could be argued that the values of likelihood to get infected of cooperative agents have lower values than suggested in the figure (and, consequently, the values for new-competitive are higher than suggested here).

Between scenarios, it is not possible to observe a significant difference. Note, however, that the likelihood is calculated across both queuing events and that the number of susceptible people at the second food distribution event is somewhat dependent on how many people were infected in the first and the time in between. Regardless, it is possible to observe that competitive agents are more likely to get infected during a food distribution event.

The increased likelihood of infection of individuals who behave competitively when joining a queue shows one down-side to this behavior. Although people with this attitude benefit in terms of reduced waiting time spent in a queue, they increase their risk of getting infected.

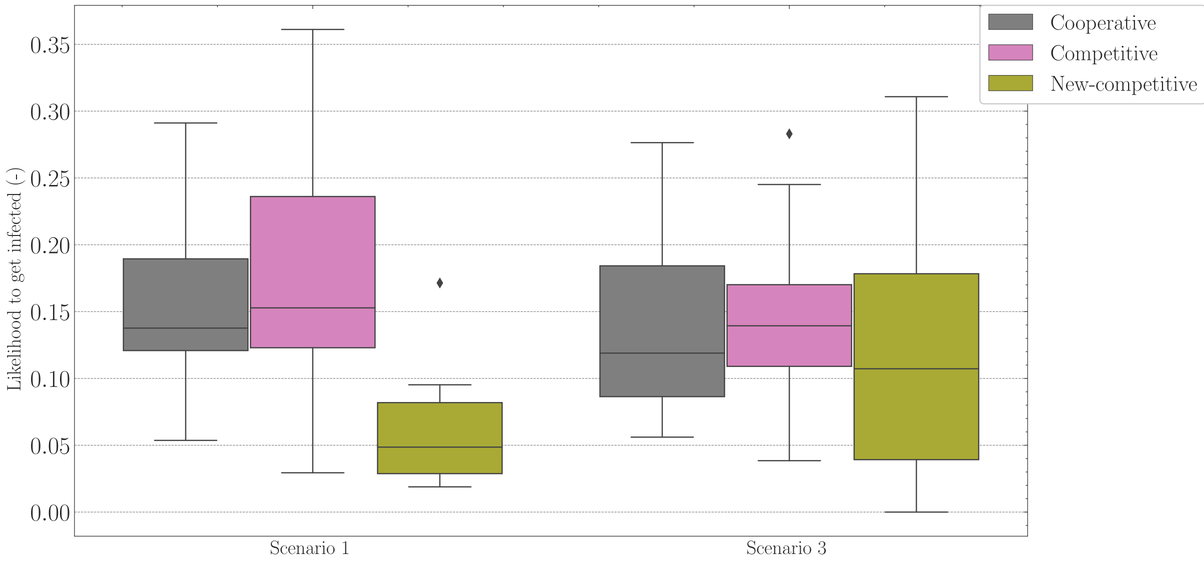


Figure 8.6: Likelihood of getting infected at the food distribution per attitude: Baseline in each scenario (E0)

Likelihood of infecting others at the food distribution per attitude

After establishing the higher risk involved in competitive behavior, it is also relevant to compute the risk that this behavior represents for individuals around. This likelihood is defined as the ratio between the number of infections caused by competitive people at the food distribution events and the total number of infected competitive people who attended the event. Due to the lack of data on the number of infected people attending the event and their attitudes, a proxy indicator had to be used.

Making use of available data, the *likelihood to infect others* is calculated as the number of infections caused by people with a certain attitude in the food distribution divided by the product of the total number of people with that attitude and the total number of infectious people with that attitude in the settlement at that moment. Although this is not necessarily the same as the initially suggested way of calculating the likelihood, by multiplying the number of people of a certain attitude who were served and the total amount of infectious people with that attitude, a proxy of the number of infectious people with that attitude attending the food distribution can be calculated. Due to a lack of data, this will not be calculated for the new-competitive individuals and will focus only on people who joined and left the queue with the same behavior

In terms of the likelihood to infect, Figure 8.7 shows a similar dynamic to the likelihood of getting infected, with higher likelihoods for people not following the queuing rules.

From Figure 8.6 and Figure 8.7, we observe that, in scenario 3, competitive agents are not only more likely to get infected during the food distribution, but they are also more likely to infect others. This heightened risk is logical considering

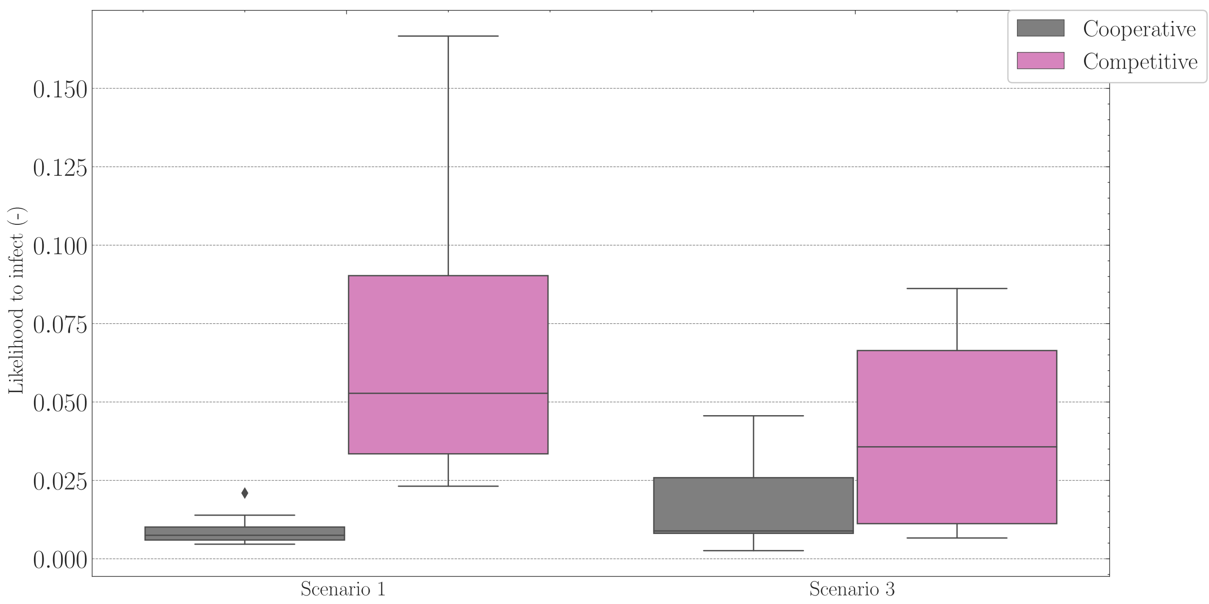


Figure 8.7: Likelihood of infecting during the food distribution per attitude: Baseline in each scenario (E0)

that infection dynamics in the model rely on the same factors: proximity to other individuals and the duration of close-proximity contact.

It can then be concluded that, regardless of the number of competitive people in a population, competitive individuals reduce their queuing time by cutting the line. However, by doing so, they put both themselves and others at a higher risk of getting infected. By being more likely to get infected at this event, and considering both that their behavior in the rest of the model is independent of their queuing behavior (and hence identical to the cooperative population) and that there is no possibility of isolation within a household (assumption), it can be concluded that competitive agents will play a more important role in the spread of the outbreak throughout the settlement, specifically in the days following the incubation period after each food distribution event.

8.1.3 Location exploration

As suggested before, disaggregating model outputs by location of infection can be beneficial to understand both the role of each location but also the impact of the competitiveness of a population on the dynamics of the infection model. Similarly to the attitude exploration, this section will focus on both scenario **S1** and scenario **S3**, representing a population with low and high competitiveness, respectively.

As observed in Figure 8.2, independently of the competitiveness of a population, all model runs converged to a near-total outbreak. Nevertheless, it was also possible to observe some variation in the steepness of the curves, representing different outbreak rates. To allow for a more detailed analysis, this section will focus on four moments of evaluation. As the focus of this study is the food distribution and its influence, the four moments of evaluation were chosen as follows:

- **Day 7:** The day before the first food distribution takes place;

- **Day 13:** The day of the first food distribution plus five days to account for incubation period;
- **Day 35:** The day before the second food distribution takes place;
- **Day 41:** The day of the second food distribution plus five days to account for incubation period.

Figure 8.8 shows the identification of these moments of evaluation against the development of the outbreak, represented by the number of cumulative cases.

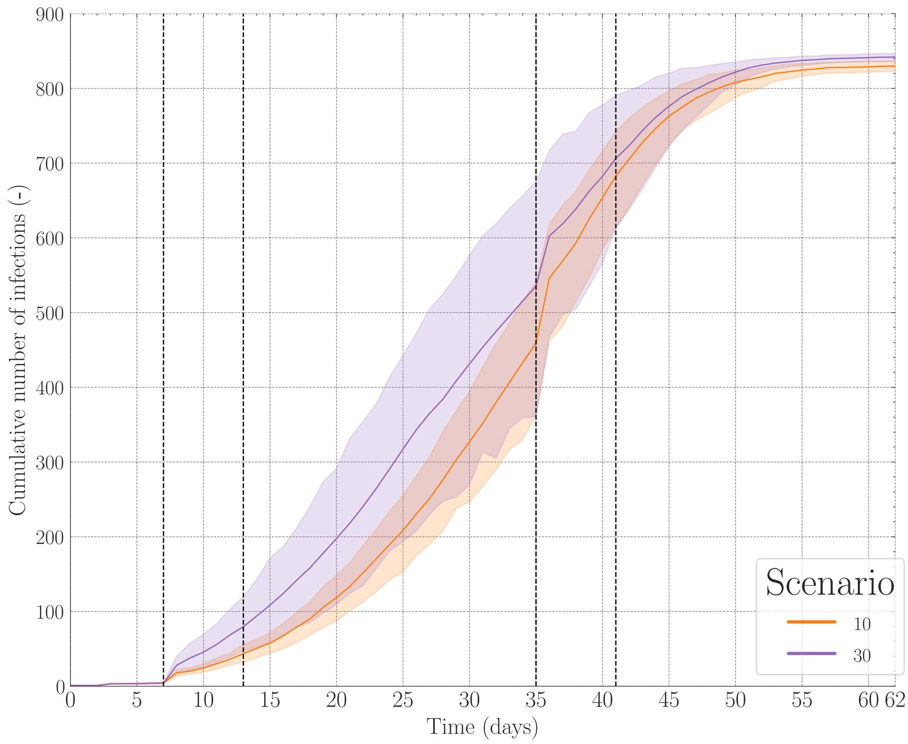


Figure 8.8: Cumulative infections: Identification of the moments of evaluation in the baseline (E0)

Cumulative cases per moment of evaluation

By zooming into the four moments of evaluation and the cumulative cases in these two across the two scenarios of interest, Figure 8.9 shows that, although the number of infections in day 7 is similar in both scenarios, there is a bigger increase in scenario 3 after the food distribution (day 13). This effect propagates over time, with scenario 3 having considerably higher cumulative infections by day 35. By day 41, however, the median of both scenarios converge, as suggested in Figure 8.2.

Distribution of infections per location per moment of evaluation

Although Figure 8.9 shows the evolution of number of cases per scenario across the four moments of interest, it still does not show the role of each location in the spread of COVID-19.

With this purpose in mind, Figure 8.10 shows the number of infections per location at the four moments of evaluation per scenario. Note that the locations

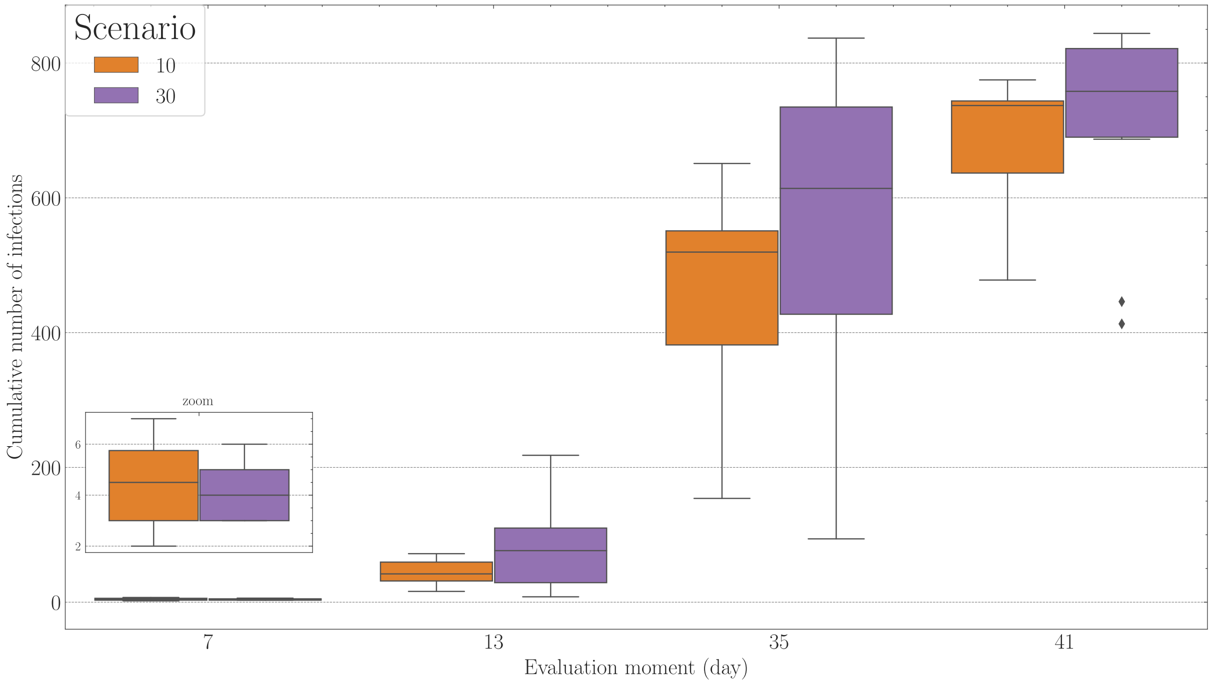


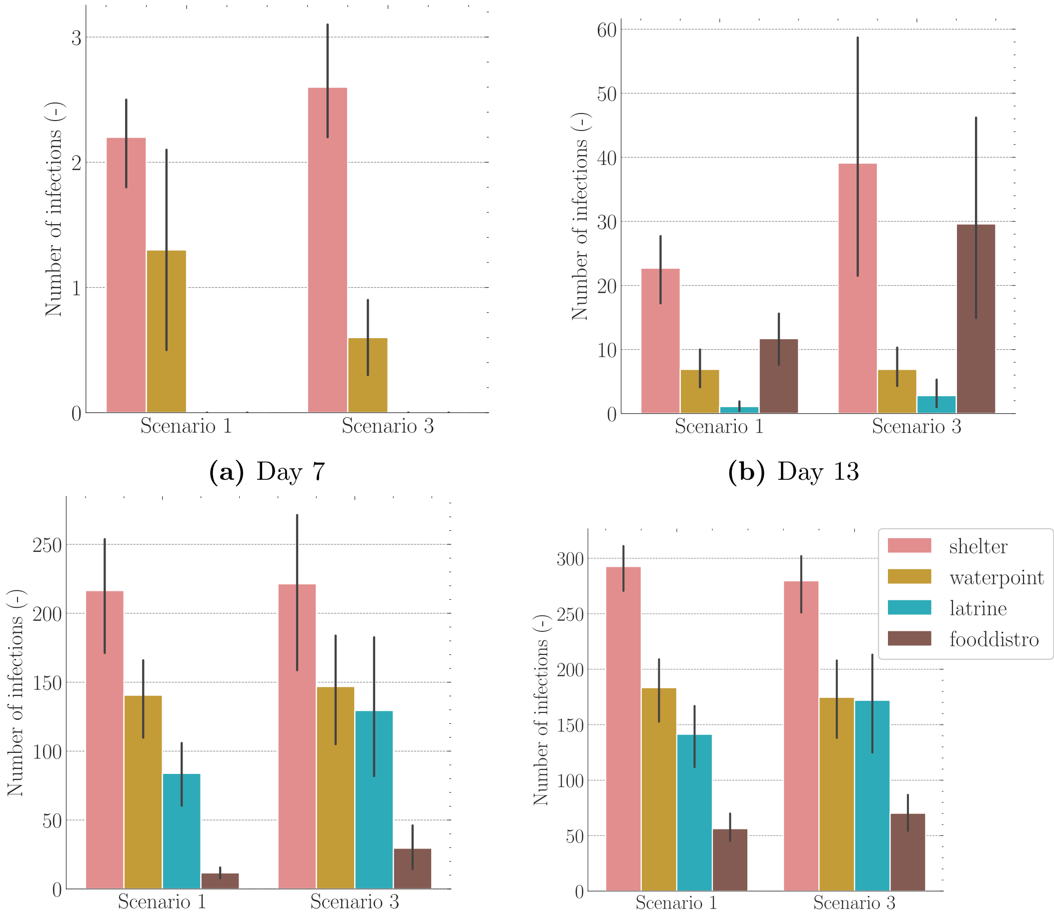
Figure 8.9: Cumulative infections: Baseline in each scenario of interest per moment of evaluation (E0)

correspond with the four activities in the camp: fetching water (waterpoint), using a latrine, attending a food distribution (fooddistro) and visiting a healthcare facility (hc-fac). A fifth location in this figure is the shelter, which represents individuals infected while at home.

Figure 8.10 shows that the shelter represents the place where most of the infections occurred by day 41. This relates to one of the main assumptions of the model which is that it is impossible to isolate infected people within a shelter, leading to many infections occurring within shelters. After the shelter, both the waterpoint and the latrines are locations of high importance regarding the number of infections taking place there, followed by the food distribution location. It was found that the healthcare facility does not host any infection until day 41 in either scenario.

Although the food distribution location is not a hotspot of infections in either scenario, it is possible to observe that the competitiveness of the population influenced the number of infections happening at the food distribution by day 13.

Moreover, it is important to note that, even though Figure 8.10 suggests that the total number of infections happening at the food distribution location is relatively low, the food distribution activity is performed only twice in the whole run (i.e., day 8 and day 36), while individuals visit the other locations (shelter, waterpoint and latrine) every day of the run, multiple times per day. This disparity between the frequency of event and number of infections occurring at that location indicates the importance of looking into the food distribution and how to make this process safer in order to control an outbreak in a refugee settlement.



(a) Day 7 **(b)** Day 13

(c) Day 35 **(d)** Day 41

Figure 8.10: Cumulative infections per location: Baseline in each scenario of interest per moment of evaluation (E0)

Relative importance of the food distribution as a source of infections at other locations

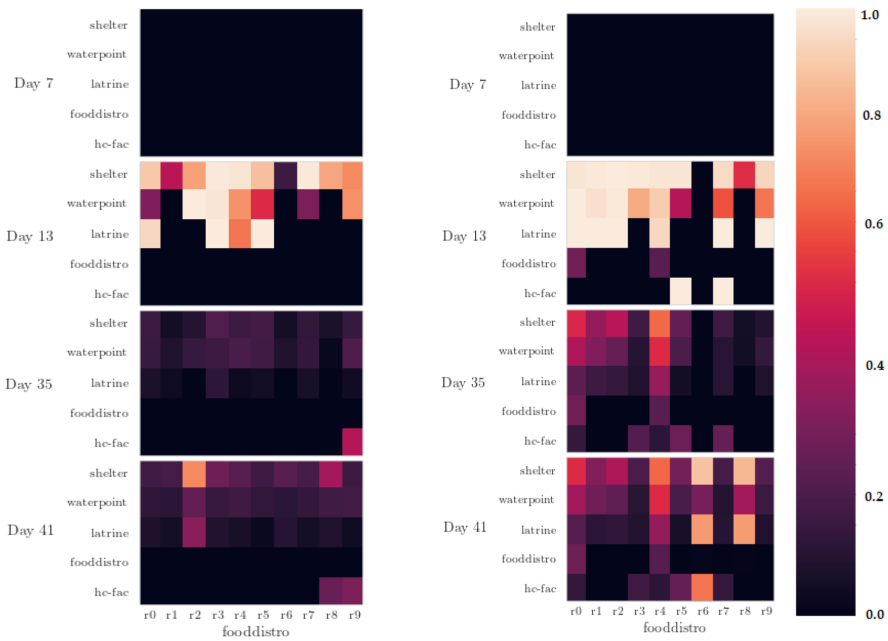
Figure 8.10 showed the (especially with a low event frequency in mind) relative importance of the food distribution in terms of number of infections that occurred during a food distribution event. However, the figure does not show the number of infections that subsequently occurred at other locations as a result of an infection initially occurred at the food distribution event (cause by someone who was originally infected while queuing for food). To further understand the importance of a location in the development of an outbreak, one can explore the role the location takes in the *chain of infections*.

With this aim in mind, the relative importance of the *links* between locations was analysed by means of a heatmap representing these links. These matrices' values represent the number of infections that occurred at a particular location versus the location where the infector was *previously* infected. Due to the significant role of stochasticity (see section 8.1.4), replications are explicitly represented in this matrix. As a result, the analysis has been done with a large 40 (a. two scenarios, b. four evaluation moments, c. five locations) × 60 (a. six locations, b. ten replications). In the Appendix E the full visualization can be found. Next, the most essential take-aways are discussed.

Figure 8.11 shows a part of the heatmap focusing on the role of the food distribution location as the source of infections that occurred by the different evaluation moments. Along the vertical axis, the location where the infection of the *infectee* happened is present, for every moment of evaluation (indicated with Day X). In the horizontal axis, the location where the *infector* was infected is outlined (note that this is only showing the results for infections originating from the food distribution). Along this axis, it is also possible to observe the results for each one of the 10 replications conducted. Finally, the heatmap is divided per scenario 1 (with 10% of competitive people) on the left and scenario 3 (with 30% of competitive people) on the right.

By normalizing the number of infections regarding the number of infections in each particular replication, this heatmap indicates the relative importance of food distribution as a source of infections at other locations.

The lighter colors for Day 13, 35 and 41 (that is, days after which food distribution events have taken place) in the right figure can be related to a relatively higher importance for the food distribution in the infection chain. This coincides with scenario 3 when compared to scenario 1. Hence, the graph suggests that an increase in the number of competitive people in a population (scenario 3 versus scenario 1) can be related to a more important role of the food distribution event. Thus, it can be concluded that scenario 1 and 3 correspond, respectively, with a less and more important role - directly (as seen in Figure 8.10) as well as indirectly (Figure 8.11) - of the food distribution event in the development of an outbreak in a refugee settlement.



(a) Scenario 10 **(b)** Scenario 30

Figure 8.11: Relative contribution of the food distribution in the infection chain for 10 replications and the two selected scenarios (S1 and S3)

Notwithstanding this, a highly significant variation *per replication* can be observed. Such a variance shows that a constant scenario specification (and correspondingly constant input variables) can still result in different model dynamics. In short, this can be explained by the large contribution of stochasticity, often inherent to modeling infectious diseases (Oli et al., 2006). By exploring two representative (i.e. contrasting replications) examples, the next chapter will further discuss the role of stochasticity.

8.1.4 Stochasticity exploration

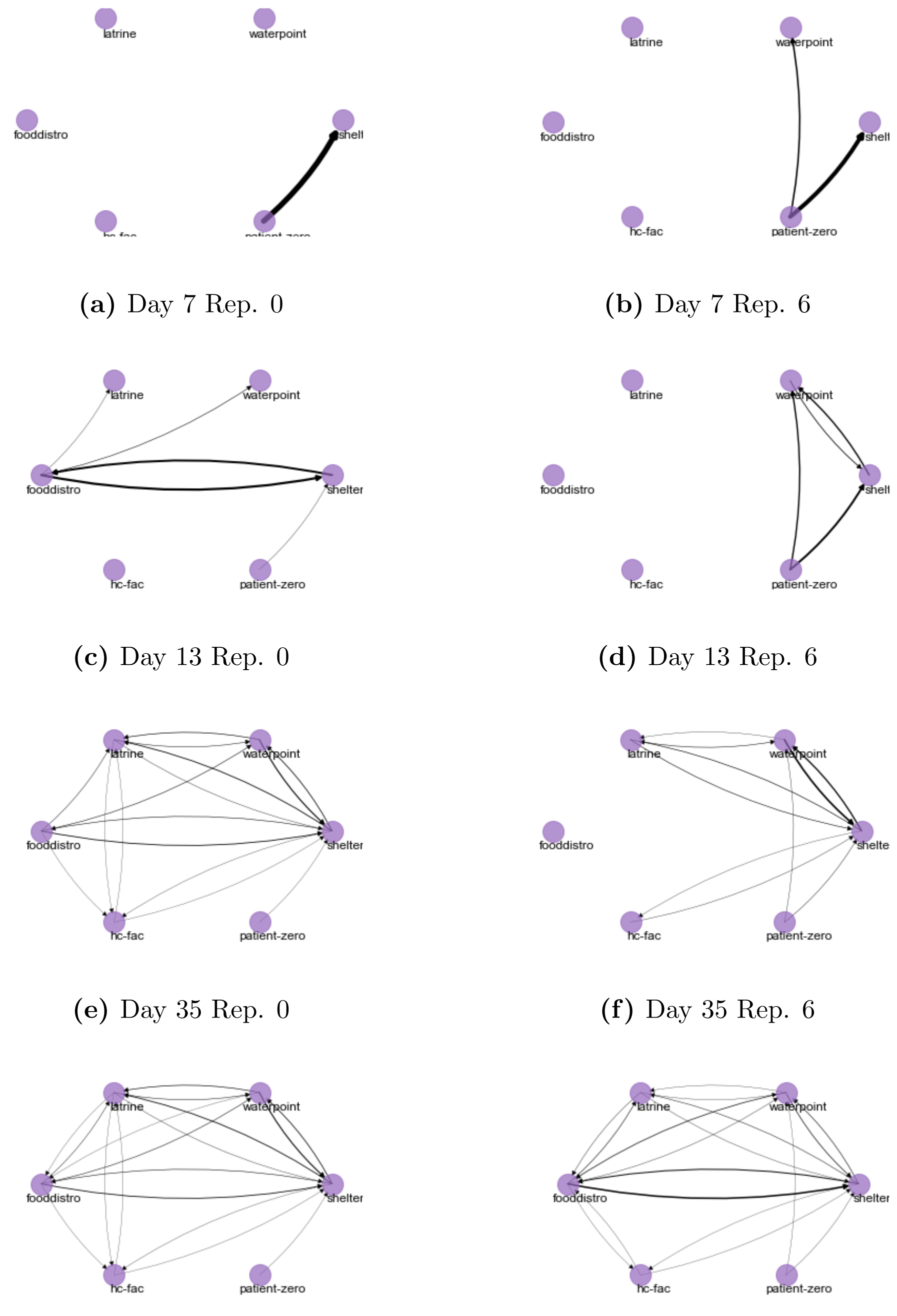
From the analysis of Figure 8.11, it is possible to observe replications with the same input parameters that result in very contrasting results.

Using the whole heatmap (Figure E.11) as a guide, it is possible to identify replications that do not follow the trend observed in the rest of the runs. An example of these outliers is replication 6 of scenario 3. In this replication, it is possible to observe that, at day 13, the normalised number of infections resulting from infections that occurred in the food distribution are absent. This stands as clear contrast to all the other replications of the same scenario, which all highlight the food distribution as playing a crucial role by then.

Replication 0 of the same scenario can be identified as following a quite regular trend when compared to the rest of the replications. To visualize the differences between these two runs, Figure 8.12 shows the infection chain at each moment of evaluation for both replication 0 and replication 6.

On the left side of Figure 8.12, the network of replication 0 is divided into the four moments of evaluation. Similarly, the right side represents the same but for replication 6. Note that these are both replications of scenario 3, implying constant input parameters. Adding to the locations previously identified (shelter, waterpoint, food distribution, latrine and healthcare facility), *patient-zero* is included as a node. As the first infection in the camp is placed randomly, it is neither relevant (nor possible) to include where this infection comes from. However, it is relevant to include this patient in the nodes in order to understand their impact in the network to fully understand the range of their contagiousness and cases resulting directly from this patient zero. Note also that the links are bidirectional, with the connection *latrine-to-shelter* indicating an infection occurring in the shelter that resulted from someone previously infected in the latrine, and the connection *shelter-to-latrine* indicating the opposite dynamic. In all networks, the weight of the links between nodes is the relative importance of the link compared to the number of total infections represented in the graph. Finally, it is important to note that links between the same location (such as *shelter-to-shelter*) are not present in the network graph.

Figure 8.12 shows a clear difference in the infection network of replication 0 and 6, with the most striking contrast being the network of day 13. As the chosen input parameters and scenario are the same across these two replications, this variation of behavior can only be attributed to the stochasticity of the model. This suggests that the, although the queuing behavior shows a clear overall impact in the importance of the first food distribution event in the chain of infections, under some circumstances, it is also possible to observe that this event plays no role at all (for example in replication 6). This sensitivity to stochasticity also explains some of the outliers



(a) Day 7 Rep. 0

(b) Day 7 Rep. 6

(c) Day 13 Rep. 0

(d) Day 13 Rep. 6

(e) Day 35 Rep. 0

(f) Day 35 Rep. 6

(g) Day 41 Rep. 0

(h) Day 41 Rep. 6

Figure 8.12: Infection network: Identification of two baseline runs in the same scenario (S3) that lead to different dynamics

and the high ranges of variance observed in the results.

Finally, one should be aware of this sensitivity when evaluating the impact of policies - as there are some parameters that are not included in the experimental design but have the potential to highly determine the development of the outbreak, results observed after policy implementation should not be entirely associated to the effect of the policy itself, as they can be the result of an underlying dynamic. Further implications of this finding are discussed in Chapter 9.

8.2 Policy implementation

As described in the previous section, although not the most important location in terms of total number of infections, the dynamics involved in the food distribution process contribute to the spread of infectious diseases in a refugee settlement when there is an outbreak. Moreover, when there is no policy implemented to alter the food distribution process, the model suggests an almost certain convergence to a near-total outbreak within 60 days of the first COVID-19 case.

In this section, the impact of policies implemented at the food distribution level is evaluated. As introduced before, these policies can be described as *representative-based* and *timeslot-based* depending on their approach. For this section, the results from experiment **E1** to **E4** are used. These policies are tested in two scenarios: with a lowly (**S1**) and a highly (**S3**) competitive population. Finally, in this section, only the figures that show something relevant are included. Full visualization of the results of policy implementation are included in Appendix E.

8.2.1 Representative-based policies

Representative-based policies resort to the use of representatives of communities to attend the food distribution event instead of sending the head of each household to the queue. Although this means sending less people to the queue, the time needed to serve each representative is adjusted accordingly to the number of people it is representing. These policies are implemented as formalized in Chapter 6. The motivation of resorting to representatives is two-fold: by sending less people to the queue, it is expected that people have to wait less time to be served and that there is a smaller concentration of people in these queues. By reducing these two factors, it is expected that the risk of infection at the food distribution is reduced.

Average time in queue at the food distribution

Figure 8.13 shows the average waiting time in queue across all queuing agents when each one of the three representative-based policies is implemented. From this figure, it is possible to observe that resorting to representatives highly reduces this value, bringing the average waiting time across all queuing agents to an order of minutes (except for Policy 3, which can go to values up to 2 hours), instead of the nearly 7 and 11 hours suggested in Figure 8.1.

When policy 1 is implemented, Figure 8.13 suggests that, given a certain competitiveness of the population, a higher percentage of competitive people is beneficial to the system, reducing the average waiting time of all queuing agents. This dynamic was never observed before in the baseline, nor it is observed when policy 2 or policy 3 are implemented. By looking into the dynamics and outcomes from Policy 1, it was possible to observe that, by implementing this policy, virtually no cooperative agent switches to a new-competitive attitude. This near-total elimination of the dynamic of changing behavior had never been observed in other runs and suggests a beneficial effect for the overall group even when there is a bigger naturally competitive part of the population. However, these results could also be related to the stochasticity of the model. Due to the low number of replications, conclusions should not be made without further analysis. Further investigation should include

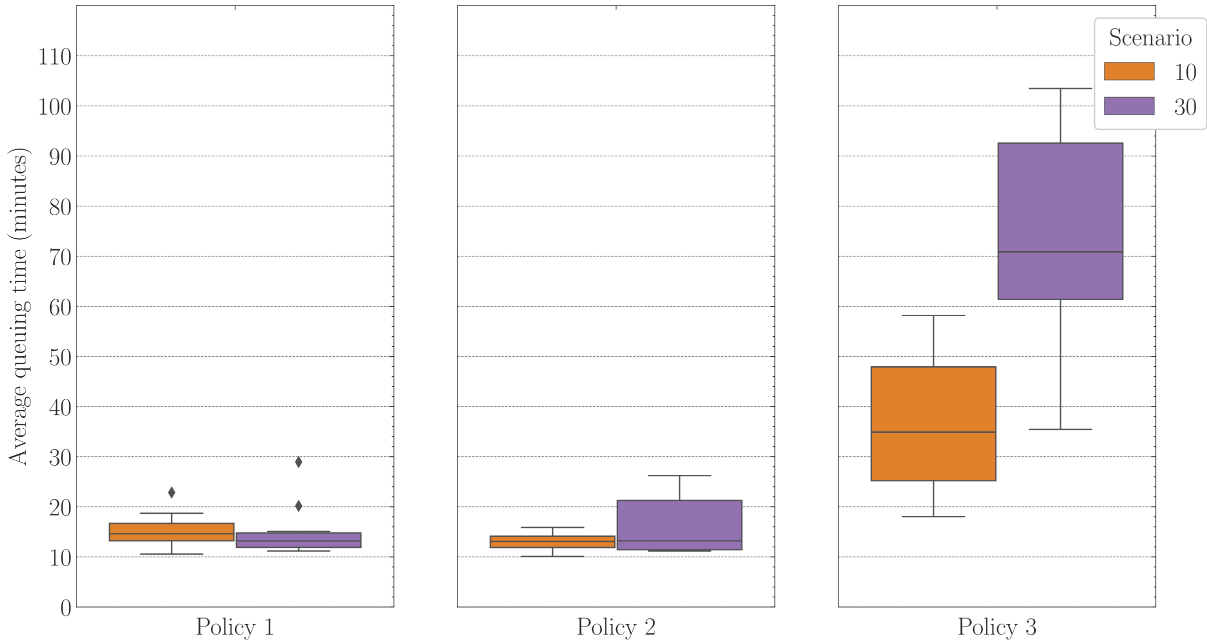


Figure 8.13: Average time in queue at the food distribution: Implementation of representative-based policies (P1, P2 and P3) in Scenario 1 and Scenario 3

running new experiments with only naturally competitive people and no mechanism of behavior change but also a closer investigation of the model runs in which this happens.

Average time in queue at the food distribution per attitude

From the implementation of policy 1 it is also possible to observe that the time competitive people save by cutting the line is minimum (in Figure 8.14). This can mostly be associated to the constantly short sizes of the queue and the quick turnover of people waiting. This shows that, when queue sizes are maintained low, having a competitive approach does not highly influence the time waiting and, consequently, the total time saved. For this reason, it could be argued that shorter lines result in less motivation to behave competitively and not follow the rules.

Likelihood of getting infected at the food distribution per attitude

Another interesting dynamic that arises when implementing representative-based policies is the switch in the likelihood of getting infected. While in the baseline it was concluded that competitive people were more likely to get infected, when Policy 1 is implemented, it can be observed that cooperative people are now reaching higher likelihood values. By looking into the time people spend in queue, a potential reason is identified - by cutting the line, competitive people reduce their time in queue to values of less than 15min; by doing so, they also reduce the likelihood of getting infected, as virus transmission is dependent on the time of interaction between infected and susceptible individuals (with a considerably lower chance of getting infected if the interaction is shorter than 15 minutes). This parallelism is, however, not observed in the likelihood to infect others, with competitive people always scoring higher than cooperative people. As policy 1 resorts to a considerably

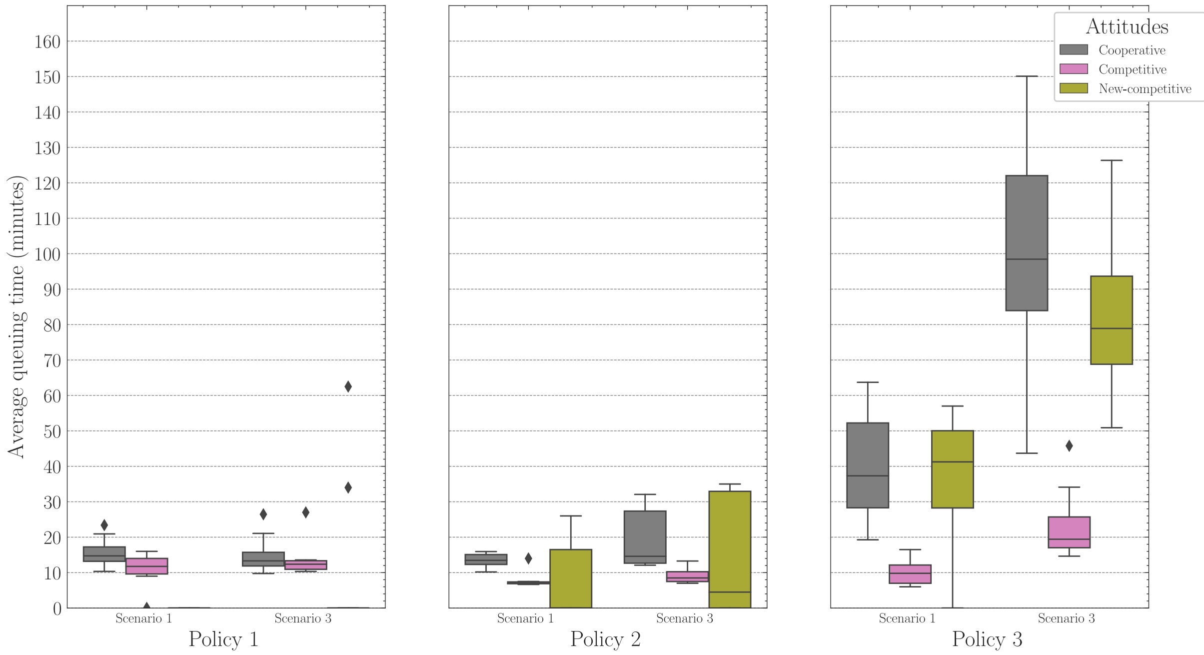


Figure 8.14: Average time in queue at the food distribution per attitude: Implementation of representative-based policies (P1, P2 and P3) in Scenario 1 and Scenario 3

low number of people attending the food distribution, it can be argued that the results are highly dependent on who gets chosen and their infection status. Moreover, both the fact that the likelihood of infecting others is based on a proxy and that only ten replications were conducted, no conclusions can be drawn from this dynamic.

Cumulative infections

Figure 8.15 shows the cumulative infections in Scenario 1 and Scenario 3 when representative-based policies are implemented. From this figure, it is possible to observe that some of the runs have a fully controlled outbreak. This had not been identified in the baseline case. However, when looking into what happened in one of these runs that lead to the spread dying out, it was possible to observe that this happened before the food distribution. For this reason, this successful containment can not be associated to the policy put in place but rather to the stochasticity of the model. As a fixed seed was not set across experiments, stochastic processes do not take the same values, making it impossible to directly compare runs from policy implementation and the baseline. This will be covered more in depth in Chapter 9.

Regarding the cumulative cases at the end of the run, although all policies show the potential to slow the disease onset down and postpone the moment in which nearly the whole population has been infected, none of them fully controls the spread. This suggests that representative-based policies can be used to slow the spread and give more time to camp managers to react and implement other policies. However, when used alone, these policies are not enough to control the outbreak and simply have delaying effects.

Moreover, Policy 1 is the only policy that does not suggest a convergence to a near-total outbreak by day 60. Conclusions regarding the further development

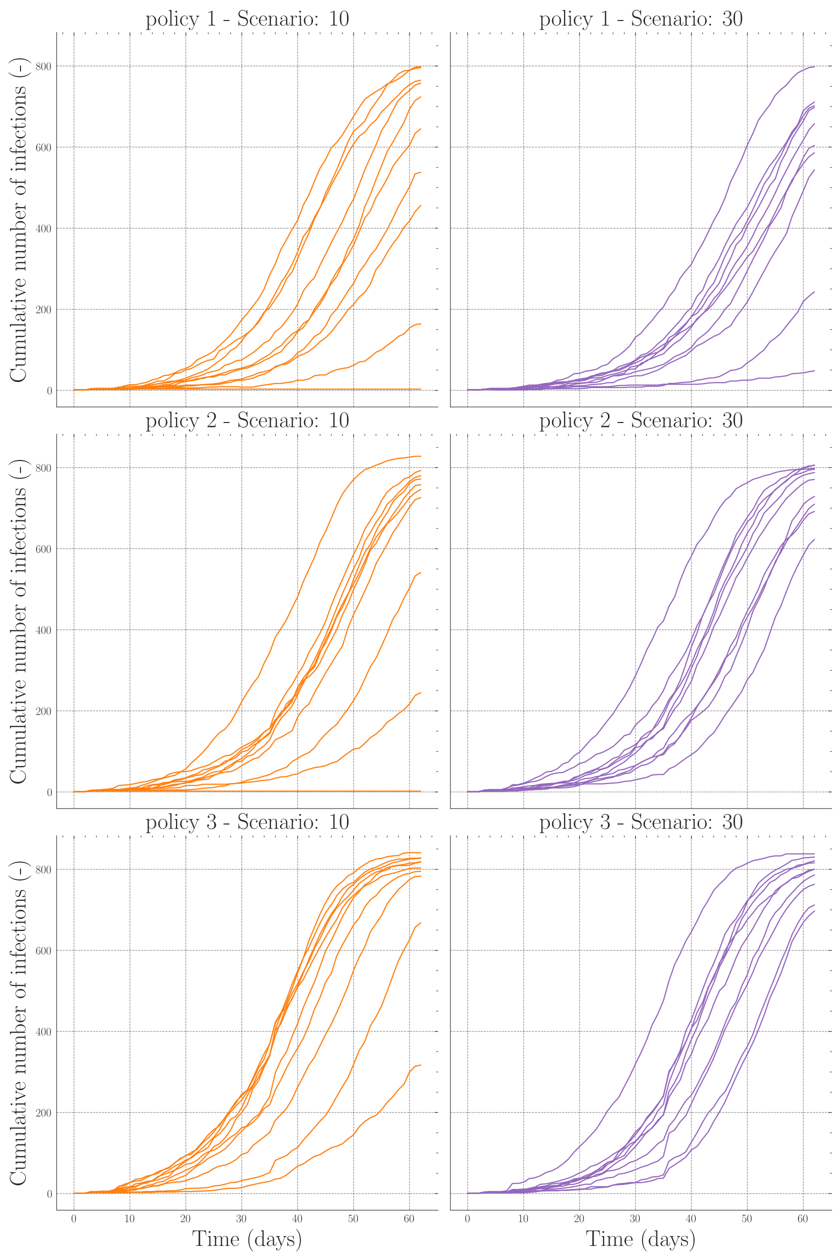


Figure 8.15: Cumulative infections: Implementation of representative-based policies (P1, P2 and P3) in Scenario 1 and Scenario 3

of the outbreak and the possibility of never reaching a near-total outbreak are not possible to be made with the current results. However, by analyzing the number of active cases at the end of the run, one could have deeper insights on the trend observed and the *expected* behavior after day 60. This is recommended as further research.

Distribution of infections per location by day 41

Finally, Figure 8.16 shows that, when applying any of the representative-based policies, the total number of infections happening at this location highly decreases, reducing the infection risk of this event. However, as these policies do not influence anything regarding behavior in shelter, latrines or waterpoints, the infections continue happening at these locations. This goes in line with the result observed before that, although representative-based policies have the potential to slow the onset down by reducing the number of infections happening during the food distribution, they are not enough to control the outbreak and other locations continue to represent a risk.

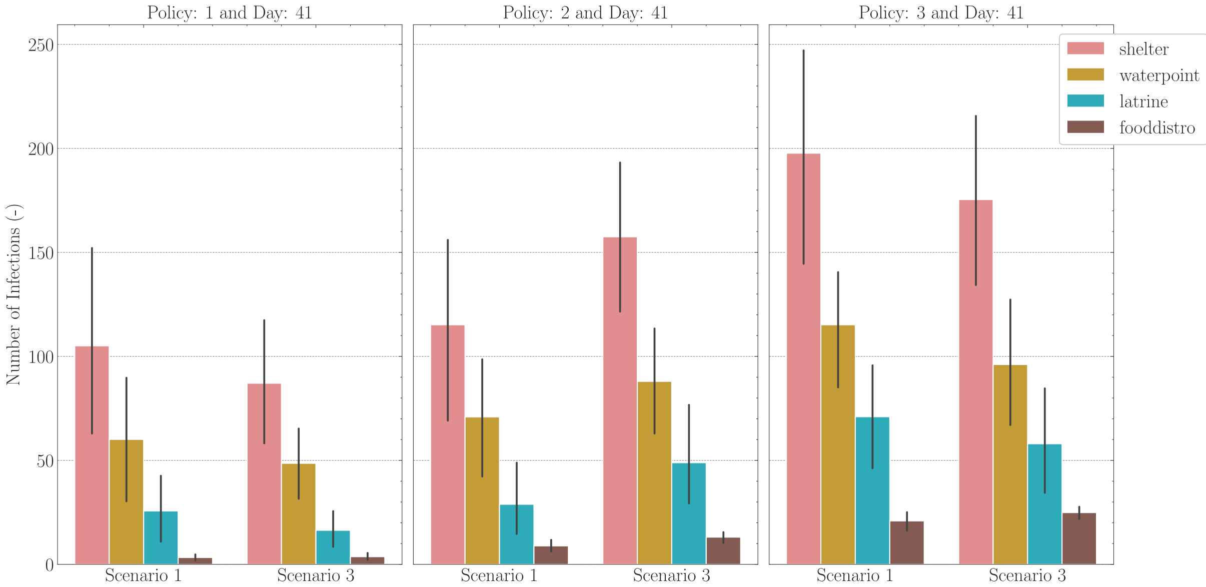


Figure 8.16: Distribution of infections per location by day 41 when representative-based policies are implemented

8.2.2 Timeslot-based policies

Timeslot-based policies resort to the implementation of timeslots for people to attend the food distribution instead of leaving the decision on what time to attend entirely to the individuals. For more details on the policy formalization, please see Chapter 6.

The motivation to this type of approach is to spread the demand throughout the day to reduce pressure of the system and avoid both highly quiet and highly busy periods. Finally, by implementing it, the same effect as with representative-based policies is expected: reduce averaged waiting times and smaller concentration of people in the queue. By reducing this, it is expected that the risk of infection at the food distribution is minimized.

Timeslot policy implemented alone

When resorting to the implementation of timeslots alone, it is possible to observe that the impact in the average waiting time for the food distribution event is negligible (with values rounding 6 and 11 hours (Figure 8.17), instead of the 7 and 11 hours observed in the baseline).

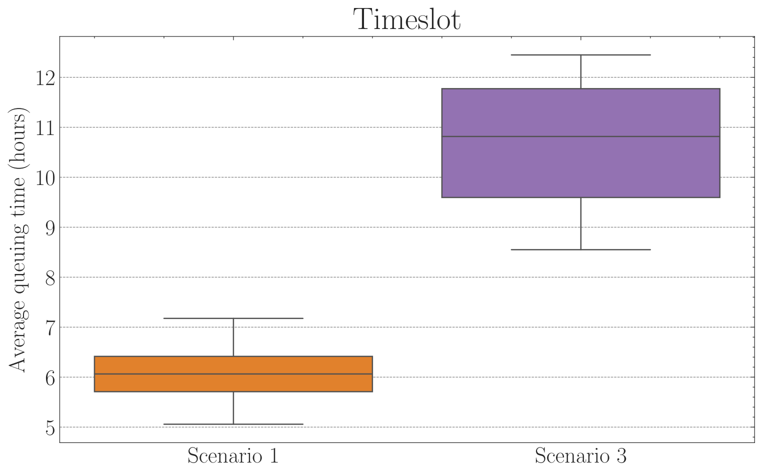


Figure 8.17: Average time in queue at the food distribution: Timeslot policy implemented in Scenario 1 and Scenario 3

Regarding the cumulative infections, Figure 8.18 shows that the implementation of timeslot policies alone show no relevant impact in the development of the outbreak and still show a trend to converge to a near-total outbreak by the end of the run.

This figure also shows one run in which the infection was controlled by day 35 and no further infections were observed. Again, as direct comparison between runs in the baseline and runs in different experiments is not possible due to the lack of a fixed seed across experiments, it is not possible to determine if this behavior is a consequence of the implementation of the policy or stochastic processes in the model (or the interaction effect of both). Further experimentation is needed in order to allow for this comparison.

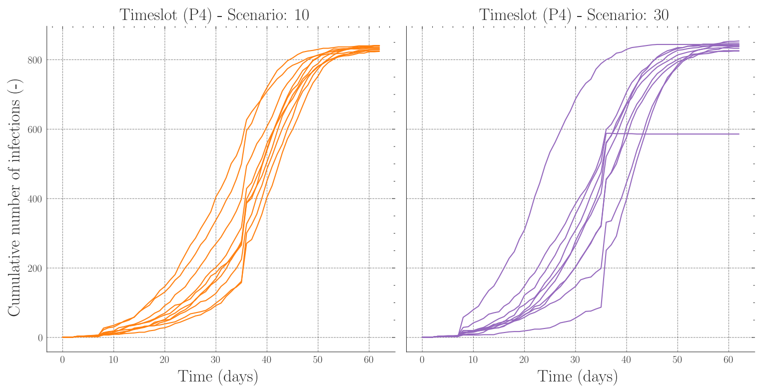


Figure 8.18: Cumulative infections: Timeslot policy implemented in Scenario 1 and Scenario 3

From the rest of the analysis of the implementation of timeslot policies alone, no relevant insights or different dynamics were observed.

This lack of impact shows that, contrary to expected, dividing the demand of the food distribution throughout the day of the event is not a solution to reduce neither queuing times nor risk of infection. This lack of impact, however, can be associated with the constant existence of a queue at the food distribution. This suggests a bigger capacity problem with a clear shortage of enough service points to deal with the demand, invalidating any effort of spreading the demand over the day.

Timeslot policy implemented in combination with Policy 3

To evaluate the impact timeslots can have when there is no such shortage of capacity, the timeslot policy was combined with policy 3. With this combination of policies, Figure 8.19 shows that the average waiting time across all agents is reduced in both scenarios (comparing to the implementation of policy 3 alone). This shows potential of using timeslots to reduce the average waiting time at the food distribution when there are no evident capacity shortages, moving to a more efficient process.

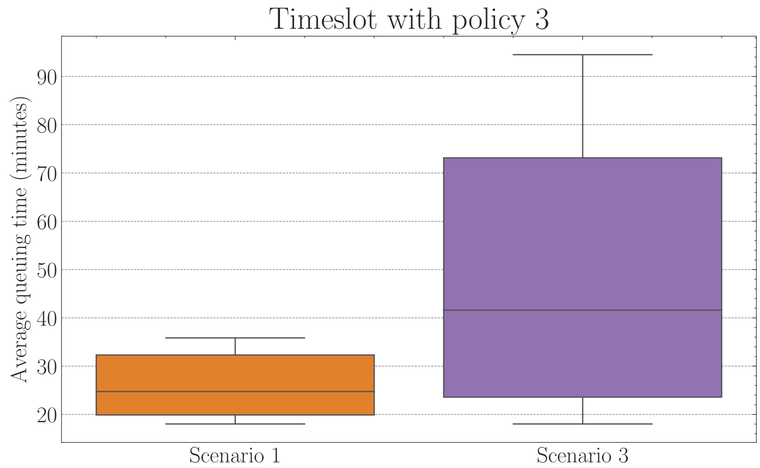


Figure 8.19: Average time in queue at the food distribution: Timeslot policy implemented in combination with Policy 3 in Scenario 1 and Scenario 3

Figure 8.20 shows that the combination of policies is not only successful at reducing average waiting times in the queue but also has some (limited) effect in delaying the speed of spread down. However, similarly to the implementation of policy 3 alone, the combination of policies still suggests a trend to a near-total infection by the end of the run.

8.3 Conclusions

In this chapter, the results from the experimentation phase were visualized and commented upon. First, this baseline and the model dynamics were discussed by disaggregating results per attitude and location. In this section, focus was also given to the stochasticity and the model sensitivity to this. Then, the impacts of implementing policies were visualized: first the representative-based policies and then the timeslot-based policy (both alone and in combination with a representative-based policy).

Several conclusions can be taken from this chapter. From the study of the model

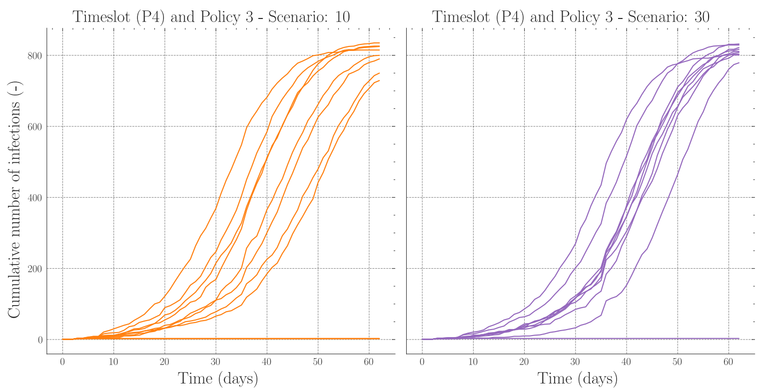


Figure 8.20: Cumulative infections: Timeslot policy implemented in combination with Policy 3 in Scenario 1 and Scenario 3

in the baseline, it was possible to observe consistently high average waiting times at the queue for the food distribution. Regarding infections, a convergence to a near-total infection trend was also identified. When disaggregating the results per attitude, it was possible to see that, while competitive people save time by cutting the line, they are also more likely to get infected and to infect others. Finally, from the location disaggregation it was possible to see that the shelter is the location where most of the infections take place. However, although less important, it was possible to observe that (given its low frequency) the food distribution plays a quite important role both in terms of the number of infections happening there as well as the source of further infections.

From the implementation of representative-based policies, it was possible to conclude that these have high impacts of reducing average waiting times at the food distribution and of slowing the infection spread down. However, all policies but policy 1 continue suggesting a convergence to total infection by the end of the run. It can be concluded that although representative-based policies have the potential to slow infection down, they are not enough to fully control the outbreak.

By implementing the timeslot policy alone, no relevant change is possible to observe. This highlights a bigger problem from the system, suggesting a high shortage of capacity that spreading the demand throughout the day is not able to fix alone. However, timeslot policies can be used together with representative-based policies to reduce the average waiting time. The implementation of this policy combination, though, is not very successful at reducing the number of cases by the end of the run, still suggesting a convergence to a near-total infection.

Finally, two extra conclusions can be taken from this chapter. By analyzing two different replications within the same scenario in isolation, it is possible to observe a relatively big difference of model behavior. This suggests that the model is extremely sensitive to stochasticity and unknown input parameters. This is extremely important to keep in mind when using this model for decision-making, as it suggests that the implementation of a policy can be undermined by some unknown dynamics that are now represented by stochastic events. From the analysis of these two runs it was also possible to observe that one of the runs in which the first food distribution did not lead to any cases still resulted in a near-total outbreak mostly due to a higher number of infections at the second food distribution. This raises the point that a low number of infections in the first two evaluation moments do not necessarily mean a controlled outbreak.

Chapter 9

Discussion

This chapter focuses on the analysis of the results and their interpretation. First, in Section 9.1, the main assumptions of the model and some of their implications are discussed. Then, Section 9.2 discusses the model's validity. After this, in Section 9.3, the implication of the findings is covered. From the analysis of the results, policy recommendations are drafted in Section 9.4. Finally, the chapter is summarized in Section 9.5.

9.1 Main assumptions

During the model building process, several assumptions were made. Complete lists of these assumptions regarding the queuing and the coupled model are enumerated in Appendix B.4 and Appendix C.4, respectively. From these, the ones with the main influence in the model and its dynamics are as follows:

- **Refugees in settlements are dependent on food distributions;**

  In this study, it is assumed that there is no other source of food in the settlement and, for this reason, the organization of at least one food distribution event per month is deemed necessary for the survival of the population. Moreover, as refugees are dependent on this distribution, all of them (or their representatives) will attend the event when it happens. The total number of people attending the food distribution is consequently fully dependent on the policy implemented (i.e. the functioning of the camp) and not by personal decision. Although this assumption might not be realistic in normal functioning of settlements with often the existence of camp markets and interactions with the host community, several camps implemented a full lockdown during the COVID-19 crisis, making refugees fully dependent on the distributions organized by the NGOs.

- **There is enough room to create a long queue for the food distribution;**

  In order to allow all cooperative agents to queue while keeping a distance from each other, it is assumed that there is enough room for the queue. Different queuing settings such as zig-zag lines are not considered in the model. This assumption has two main implications: while it guarantees that people who want to queue and maintain a distance are able to do so, it also leads to agents quickly having the perception of long queues happening (while zig-zag queues could be a strategy to trick people into perceiving the queue as shorter than it actually is). This assumption highly depends on the settlement and their geographical boundaries and it might not always hold truth. When this is not the case, the model should be slightly changed and other queue organizations should be included.

- **Refugees queuing up for food can have two main attitudes: cooperative or competitive;**

  Refugees are assumed to naturally have one of the two main attitudes. Cooperative refugees who follow the rules can switch behavior into competitive and cut the line when their surrounding environment influences them to do so. This implies that the decision of cutting or not the line is purely decided according to the personality of the refugees and the factors of seeing other people cutting or perceiving the line as too long. This simplification was necessary in order to be able to build a narrative and conceptualize potential behaviors. However, by doing so, behaviors as joining their friends in the queue, leaving the queue before being served or forming groups are not considered.

- **Cooperative refugees respect social distancing measures applied, competitive refugees do not;**

  When joining a queue, cooperative people are assumed to respect the social distancing rules applied and keeping that distance among each other. On the other hand, competitive refugees who decide to cut the line do not follow neither the queuing nor the distancing rules. This will influence the distance people keep from each other when queuing, consequently impacting their risk of getting infected while waiting in line. By assuming this, it is considered that competitive people do not take the outbreak and the risk of getting infected into account when joining the queue. As mentioned by Epstein et al. (Epstein, Parker, Cummings, & Hammond, 2008), potential dynamics driven by a *fear* of getting infected could influence the behavior of people when queuing. Further research is advised to include this dynamic and observe its impact in the model.

- **It is is assumed that competitive refugees only cut the queue once and that cooperative agents allow this to happen;**

  This simplification will influence the dynamics happening when there are a lot of people cutting the line. As mentioned in the verification, this results in unexpected results when simulating a population with a high percentage of competitive people (40% or more). This assumption will consequently limit the suitability of the model and should only be used when looking into populations with a lower percentage of competitive people.

- **It is assumed that no one other than representatives attends food distribution if a policy is implemented;**

  When resorting to the use of representative of communities, it is assumed that there is a full compliance to this rule. This results in the number of people attending the food distribution being exactly the number dictated by the camp management and policy. This assumption excludes potential behavior such as people trying to get food twice or not respecting the rules.

- **Vaccination programs are not considered - COVID-19 immunity can only be achieved through previous infection;**

  This assumption means that, at the beginning of the run, the whole population is susceptible to the virus. This is a very permitting environment for the virus to spread as it will not find natural barriers to infect people. This means that the model is fit to simulate a first outbreak in a settlement. However, if a second wave is to be modelled, changes are necessary.

- **It is assumed that infected people always return back to their shelters and do not have the possibility to isolate from their household;**

  By assuming that people cannot isolate from infected members within the same shelter, the chance of getting infected after one of the household members gets infected is very high. This will inherently lead to the shelter taking an important role as location of infections, which can be argued to be similar to the normal dynamics of COVID-19 and the infections at home. Further discussion about this topic is provided in the policy recommendation section.

- **After the first case appears in the settlement, it is assumed that no one enters or leaves the perimeter.**

  This means that the settlement is put under lockdown when the first case appears. Due to this assumption, all cases observed in the model runs can always be traced back to patient zero. If the infection ever dies out, then there is no mechanism for it to reappear. This assumption leaves potential interaction between refugees and their host communities out, which could be sources of extra infections along time.

Further implications of these assumptions will be discussed in the limitation section in Chapter 10.

9.2 Model validation

After having verified if the model behaves as intended, it is necessary to validate it. This step involves evaluating if the model can be taken as an accurate representation of the system being studied and if it is fit to answer the research question.

Again, as the model involves two major components (epidemiological and queuing dynamics), this test could be divided into these two sections as well. However, it is important to note that this concrete study only developed the queuing process, leaving the rest of the model as was developed by Bögel (Bögel et al., 2020). For that reason, this section will focus mostly on the validation of the infection component of the model. The validation of the queuing component of the model relies mostly on comparing it to literature and interviews with food actors in refugee settlements.

Regarding the queuing implementation, it is important to first understand the motivation of this study. Looking into the queuing behavior was decided not only because of the literature gap but also by Norwegian Refugee Council's suggestion. Highlighting that at some camps where they are active in there is a high discrepancy of attitude in a queue that is connected to individual's nationalities, the theory chosen to model queuing behavior (Köster & Zönnchen, 2015) is a good fit to simulate the system described by NRC. By using this theory, it is concluded that the model is fit to represent the dynamics suggested by NRC.

When adding competitive agents to the initial mix of behaviors or introducing mechanisms to change behavior (cooperative people turning new-competitive), it is possible to observe that the average time in queue increases. This goes in line with the study done by Kingman (1962) that concluded that the variance of waiting time is minimum when customers are served in order of arrival.

To validate some of the main assumptions made that guide both the model and the policy building process, interviews with food actors in Cox's Bazar were conducted. The decision to make the food distribution service time in the baseline equal to four minutes came from these discussions, as it resembles the system implemented at the camp at the moment. Similarly, the policies of using representatives to pick up food for communities were validated by the food actors at Cox's Bazar. Resembling their *majee* system, introducing community leaders that are responsible for some of the logistics of the settlement is a normal practice used by the Bangladeshi government. This leads to the next assumption validated by these food actors: the representatives (when using policies) are chosen randomly from the population. This is backed up by the idea that, in Cox's Bazar, these community leaders (majees) are chosen by the government instead of being elected. In 2011, the UNHCR proposed that the majee system would be replaced by a more democratic alternative (Kiragu, Rosi, & Morris, 2011). This alternative has the potential to guarantee that representatives all share a cooperative attitude when queuing (assuming that the community will vote for a rule abiding resident). If this is the case, the model can be slightly adjusted to guarantee this. Moreover, one of the interviewees, when asked about the queuing dynamics, mentioned that the impact of people cutting the line because they see others doing so is clear in and specially at the distribution of rare (or scarce) goods.

Regarding results produced, most of the runs in the baseline (see Figure 8.1) suggest that the average waiting time is somewhere between 3 and 11 hours (depending on the scenario). Although these numbers sound extremely high at first, they go in line with reports of Moria of waiting lines of an average of four hours to get one meal (Nutting, 2019), leading to totals of 8 waiting hours per day (Harlan, 2020). As the time needed to serve people their rations for one month is higher than the time needed to serve meals, it is considered that the values fall within reasonable ranges.

Regarding the infection component, a very brief validation to test if the model produces reasonable results is conducted. This validation will focus on the value of R and its evolution in the baseline. At the first food distribution event, R takes values in the range 5-10. This goes in line with the number suggested by Kochanczyk (2020) regarding super-spreading events. In the rest of the run, R takes values of less than 1. If this were the case throughout the entire run, it would be expected for the infection to die out. However, as there are two distribution events with higher R values in the middle of the run, most of the replications show a continuous infection.

Note, however, that perfectly validating this model's behavior is a difficult task - by dealing with uncertain factors such as COVID-19 and human behavior, it is extremely challenging (even impossible) to build a model that perfectly recreates the system being modeled. However, the goal of this study is to integrate dynamic behavior in a queue and understand how this can affect the spread of an infectious disease. For that reason, the interesting outcomes of this thesis are not the exact quantified values of the KPIs but rather the differences between them and how to influence trends in the desired direction (decreasing time waiting and decreasing infections, in specific).

With this in mind and given that it is a prototypical model that does not represent one specific settlement with a certain context, it is concluded that the model is valid for the purpose of answering the research question of this study.

9.3 Implications of the findings

The implication of the findings is divided into three main sections: what the results of this study show and what this study does not include but should still be taken into account.

9.3.1 Analysis of the results

From the analysis of the results presented, a few topics were raised. These are discussed below.

***Status quo* is undesirable**

When evaluating the behavior of the system in the baseline, it is clear that, in most of the replications, when no policy is implemented, there is a convergence to most of the population being infected 55 days after the first case appears in the settlement.

Looking at the food distribution, regardless of the scenario, there are high average waiting times for a service that takes around 4 minutes, always leading to the creation of queues. This suggests a high discrepancy between demand and supply, indicating a shortage of capacity to deal with the amount of people attending the food distribution. Moreover, a clear relation between the competitiveness of a population and the average waiting time can be observed - the more competitive people there are in a population, the longer the process of queuing takes on average.

Cutting the line: *a personal dilemma*

Observing competitive individuals and their behavior when queuing during the food distribution, it is possible to see that, by adopting this attitude and not following the queuing rules, they can reduce their waiting time. This is a clear benefit of this attitude which might make this behavior appealing.

However, it is also possible to observe that, by behaving competitively, these individuals have a slighter higher likelihood to get infected and, consequently, higher likelihood of bringing the virus home and infecting the rest of their household, putting their families at risk. This raises a personal dilemma for competitive people and what they value more: saving time waiting in a queue or the health of themselves and their loved ones.

At the moment, this personal dilemma is not introduced in the model and its dynamics and, consequently, does not influence decisions. However, it could be integrated by creating a mechanism of naturally competitive people switching to a cooperative attitude due to their fear of getting infected (or infecting) (Epstein et al., 2008). By knowing there is a higher risk resulting from the attitude they have when queuing, some individuals might reconsider their actions and wait in queue even if they normally (in a non-outbreak situation) would not.

An interesting exception emerges when queues and (consequently) average waiting times are kept short (as seen when Policy 1 is implemented). By reducing their average waiting time to less than 15 minutes, competitive agents go through the queuing process quickly enough to reduce their likelihood to get infected. This suggests that, in short queues, there is no personal dilemma for competitive agents, leaving both quicker and safer from the food distribution.

Cutting the line: *anti-social behavior*

As mentioned before, by increasing competitive behavior in a queue, average waiting times quickly go up. Moreover, by having a higher likelihood to infect others, competitive behavior puts people around at higher risks. One could hence argue that people cutting the line have a certain anti-social behavior and only look at their own benefit when making decisions.

If the rest of the community does not accept this behavior, extra dynamics might emerge and people might behave differently when confronted with someone cutting the line.

Cutting the line: *tragedy of the commons*

As just noted, by increasing competitive behavior in a queue, average waiting times quickly go up. Although this is mostly at the expense of cooperative people, competitive people are also worse off if there are a lot of people cutting the line.

Moreover, by having higher likelihoods to both get infected and to infect others, it could be argued that competitive people play a higher role in the infection spread. This raises an interesting dynamic in the model that could be framed as a tragedy of the commons - by taking their own utility (time spent in queue) into account when making decisions, competitive people are making the system worse for everyone both in terms of average waiting times but also by increasing the spread of the outbreak.

Snowball of behavior change

Among the runs of scenario 3 it was possible to observe an interesting dynamic with the number of naturally cooperative people adopting competitive behavior due to the circumstances of the queue either staying consistently low (below 40) or extremely high (around 110). This suggested the existence of a snowball effect that, once the number of people switching behavior reaches a certain number, a chain of other people switching behavior follows.

By looking into the specific runs where this happened, it is possible to observe that the higher waiting times coincide with the runs where there were high numbers of people switching behavior.

This suggests that, by influencing a number of people to not turn competitive, a bigger effect might be accomplished and the whole snowball can be avoided.

Food distribution: a super spreading event

Although the absolute number of infections happening at the food distribution is relatively low among all runs when comparing to other locations, it is possible to observe that the food distribution plays an important role in the outbreak spread in two ways: as a super-spreader event and as the source of subsequent infections in other locations. This is mostly connected to the high waiting times in queue (increasing potential risks of infection if there is an infected person around and the high concentration of people (which is not observed in any other event in the model)).

Given this role, making the food distribution a safer event by reducing the risk of infection can represent a way of slowing the infection spread down, giving more time to react and prepare for the management of an outbreak.

Infections at the shelter: the risk of home

Across all runs, shelters were consistently the main hotspot of infections in the settlement. In order to effectively control an outbreak in a settlement, focus should be put into making isolation at home a possibility (or equivalent solutions).

Using representative-based policies

Representative-based policies have a clear impact in reducing the average waiting time in queue with policy 1 and 2 leading to similarly low values (below 20 minutes) and policy 3 maintaining them between 20 and 105 minutes (with the higher value corresponding to the scenario with higher competitiveness in the population). Considering that the difference between policies is both the number of people attending the food distribution (which increases per policy) and the time needed to serve each person (which decreases per policy), it is not possible to identify what are the tipping-point values for these variables that make the difference nor the exact impact of changing each one of these variables. Moreover, it is possible to observe that policy 1 has a shorter range of variance for average queuing time, suggesting more robustness to different scenarios. This can also be justified by the almost non-existence of people switching behavior when this policy is implemented, suggesting that Policy 1 resembles a perfect FIFO dynamic with no line cutting.

Regarding the infection component, however, it is possible to observe that policy 1 is the only one that does not suggest a convergence trend into a near total infection by the end of the run. It was also identified that the number of total infections happening at the food distribution was lower when comparing to Policy 2. As the time spent in queue is similar under the two policies, this difference can be related to the number of people attending the food distribution. As policy 1 resorts to less people attending the event, there is a lower probability of sending someone who is infected.

Finally, it is important to note that, even though Policy 1 is the only one that does not show a convergence to a near-total infection by day 60, this policy does not have the capacity to control the spread either and should only be looked at as a way to slow the onset down, giving the settlement more time to prepare and implement other policies.

Using timeslot-based policies

When applied alone, resorting to timeslots in the food distribution has a limited impact in the average queuing time. This confirms that the main reason of long waiting times at the food distribution in the baseline is not only related to the existence of busier periods but rather to the lack of capacity to deal with all the demand and the constant presence of a queue.

When applied in combination with policy 3, however, timeslots have a high potential of reducing the average time in queue, bringing the average waiting time almost always to less than one and a half hours.

Delaying an outbreak is not enough

From the analysis of some individual model runs, it was possible to observe that in some of the cases where the first food distribution did not lead to a high number of infections the model still converged to a near-total outbreak by the end of the run. By postponing the moment in which the spread starts to take off, the number of susceptible people at the second food distribution event is higher and consequently leads to a higher number of infections at this day.

Although delaying the onset of an outbreak can be beneficial to have more time to prepare, one should be aware that it is not enough and should not be looked at as a final goal. Moreover, as this often leads to a higher number of infections happening at a later stage, it could be argued that, if people need medical assistance, this puts the medical facilities under higher pressure if the number of cases is concentrated in the same week.

Role of stochasticity and uncertainty

As observed in the results, the model shows quite a high sensitivity to stochastic processes which sometimes have the potential to fully dictate the development of the outbreak, regardless of scenarios or policies implemented. For this reason, it is highly important to be aware of the sources of stochasticity in the model and their implications.

There are several dynamics that resort to stochastic processes in the model. One of the sources of stochasticity is a common one to all ABMs given their iterative nature. From this model in specific, for example, the first infection in the settlement is a source of considerable stochasticity - all the attributes of patient zero will influence how they behave: if child, adult or elderly (which can determinate which activities they conduct), their course of infection (if they develop symptoms or rather overcome the infection quite quickly), the time they attend activities, their attitude when attending the food distribution event (if they queue or not). Another relevant place where stochasticity can be found is in the time people attend the food distribution event and their attitude. If a cooperative person with a low tendency to become competitive attends the food distribution at peak times, it might never turn competitive. However, if a person with a cooperative nature but with high tendency to become competitive attends the event, this person can switch behavior immediately with the smallest trigger. As noted before, this switch of behavior can then trigger a snowball effect, resulting in considerably different overall dynamics.

Moreover, when implementing representative-based policies, the role given to stochasticity is considerably higher, as the selection of these representatives is based on a random process itself, which can highly vary the attitude these people have and their current infection status.

This role of stochasticity has a main implication - one should never analyze results of one replication, as they can vary immensely. In this model this is very clear - if the results from one replication where the total outbreak had 2 cases and then died out were used for analysis, one would be massively undermining the potential effects of an outbreak and would see no use in preparing for it.

One solution to overcome this is by repeating several replications, increasing statistical significance of the results. However, due to the trade-off between a higher sample size and the time constraints of running more replications (especially relevant once a model reaches high running times like it is the case), ten replications were used throughout all the experiments conducted. As observed in the high range of outcomes, it can be argued that 10 replications are not enough for this model. For this reason, further analyzes of results with more replications is suggested.

9.3.2 Scope of the study

Before formulating policy recommendations, it is important to understand the boundaries of this study and its scope. This thesis focuses on the event of food distribution from the NGO to the beneficiary in a refugee settlement during an infectious disease outbreak. To control the outbreak and avoid a near-total infection, the study analyzes the impact of policies that can be implemented at the food distribution level and their potential to influence the outbreak development.

It is, however, necessary to highlight that the model does not simulate the further distribution from the representatives to the final beneficiaries. If there are infected people involved in this process, this second distribution can lead to further infections. Potentially, if the representative is an infected (and infectious) agent, this further distribution could lead to a high number of infections, undermining the effort of using representatives in the first place. This is discussed further in the policy recommendations.

Moreover, the study does not look into the consequences of using representatives.

If these do not follow up on their entire set of tasks and do not distribute the food to the final beneficiaries, it is possible that people who are not representatives try to attend distribution even if they are not supposed to be there. This could lead to more people attending the food distribution than modeled, leading to different dynamics than the ones simulated in this study. Further discussion regarding the use of representatives is provided in Chapter 10.

Finally, it is important to keep in mind that different transmissions probabilities and different values for parameters can result in quite different developments of outbreaks. Until these parameters are more accurately known and adjusted accordingly, this model should be used to test relative differences among policies and not to accurately predict the development of the outbreak.

9.4 Policy Recommendations

Some policy recommendations can be formulated based on the results from this study. These are covered in this section.

Rethinking the food distribution and increasing capacity

Two main problems can be identified with the food distribution in the baseline: the high queuing times and its super spreading nature in case of an outbreak. These two problems can be associated to the same cause: a inherent shortage of capacity to deal with the necessary demand, leading to the creation of long queues every time there is a food distribution event.

Given this, it is recommended that the food distribution process is rethought in order to make it both more accessible and safer. As seen in the results, sending representatives and implementing timeslots are two techniques with a certain potential to reduce waiting times. However, other solutions could be considered.

By creating more distribution points, the population could be divided through different food distribution events. Highly reducing the number of people attending each event, this situation would resemble the current Policy 1 but performing even better by having lower service times (since people would still pick up food for their household and not for a community). Moreover, by reducing the amount of people attending each point, the number of interactions a potential infected person could have at the food distribution would be highly reduced. Finally, increasing capacity would lead to shorter lines. As short queues are more time efficient, there is a lower motivation to behave competitively and cut the line. This would also minimize the number interactions and potentially make a competitive population behave cooperatively more often.

Extending serving hours and allowing refugees to pick up their food when they want and need by means of a food ATM or multiple food distribution events per month could also be a direction to take.

Downsides of each of these policies are, however, the organizational and resources constraints, as they would need more staff and equipment, respectively. Moreover, behavioral components other than the queuing behavior could play a role in this situation, with people potentially wanting to attend certain distributions rather than other, leading to potential further mismatches in capacity and demand. These points should be taken into account when deciding what solution to implement.

Bringing awareness to the consequences of competitive behavior

A generally cooperative population joining food distribution has the potential to form a queue following a FIFO discipline. If this is the general behavior in camp's queues, the average time in queue can be highly reduced, making the whole process of getting food considerably quicker. With this in mind, it is recommended that refugees are encouraged to maintain a cooperative attitude when queuing for food.

Moreover, by analyzing the results it was found that having people with a competitive behavior when queuing also leads to higher number of infections happening at the food distribution event. While it is expected that everyone knows that, by not following the queuing rules, they are putting others in worse positions regarding time, they might not be aware of the increased health risk of this decision during an outbreak.

For this reason, it is recommended that there are awareness campaigns during which people are alerted to the risks of their behaviors. As it could be argued that people who behave competitively do not care about the risk they put others under, a strategy could be to make it clear that their safety (and their families') is also at risk when they behave competitively. By making it clear that cooperation leads to a better situation for everyone, it is expected that some of the naturally competitive people do resort to queuing. If this strategy is deemed to not be enough due to certain population or environment characteristics, highly controlled queues and sanctions for misbehavior could be resorted to.

Promoting certainty, information and security

From field experience in a refugee settlement in Calais, I have observed the different dynamics that can emerge when the same group of people queue. During my work there, I was part of both the food distribution process as well as the clothing one. During the food distribution, the environment was always very relaxed with people patiently waiting for their turn and being respectful to one another. On the other hand, the exact same group of people would behave very differently when there was a distribution of clothes, sometimes leading to dangerous situations and the abrupt cancelling of further distributions.

Although the group present in both distribution was the same, there were key differences that justify this contrasting behavior: the food distribution happened every day around the same time and there was always plenty to eat while the distribution of clothing happened at random moments in time (depending on the existing supply), often after weeks of bad weather and with refugees thinking that there was no guarantee that everyone queuing would be able to be served (even when we had enough material to distribute).

For these two distributions different techniques were used: while the food distribution simply relied on people queuing up, the second resorted to the use of tokens to guarantee that everyone would only be served once. However, even with the token process, often happened that the same person would try to be served twice at different times (with two different tokens). Moreover, a trend could also be seen among these people coming twice - they often had the best sneakers, the best jacket and the best jeans in the group, suggesting some underlying dynamics happening and the abuse of the system in order of their own benefit.

Techniques to promote cooperative behavior in a queue can range from information campaigns with constantly updated queue expected time (Aksin, Gencer, & Gunes, 2019) and appealing to inhabitants for a joint effort to make the process smoother to everyone. Guaranteeing that there is enough for everyone lining up is also a way of keeping people more cooperative and avoiding situations similar to panic buying (or the behavior observed in the clothing distribution). Although providing security, certainty and information in these environments can be difficult, its successful use can lead to dynamic changes and smoother queuing processes.

Although these policies might not be 100% successful and might not stop naturally competitive people from cutting the line, they might be enough to make cooperative people not change behavior, avoiding the previously identified snowball effect that can lead to a chaos behavior.

Resorting to representatives

This study demonstrates the potential of using representatives of communities to minimize crowds at the food distribution and, consequently, to slow the onset of an outbreak. However, it does not look into the further distribution from the representatives to the final beneficiaries and infections resulting from this interaction. To guarantee that the use of representatives does not represent a higher risk than the one of sending the head of each household to the service point, it is recommended that representatives are regularly tested and, if positive, that alternatives are set up. After prioritizing the most vulnerable to COVID-19 (which in refugee settlements are a small minority, due to the demographics of these environments), the inclusion of representatives in the priority list of a vaccination rollout program can also be discussed. By prioritizing these agents both for tests and for vaccines, the chances of the representative being healthy and not a carrier of the virus can be increased, hopefully minimizing further spreading during the rest of the distribution while not having to spend the very limited resources in the whole population.

If representative-based policies are implemented, decision-makers should be aware of the possible downsides of this decision. Drawbacks of resorting to representative-based policies can range from simple ones such as the limited engagement of the community but can also be considerably bigger. In case the representative of a community is dishonest and diverts the food that should be distributed further, potential side-effects can happen. These could range from people who did not get their food trying to attend the food distribution even when they are not supposed to be there (creating a certain chaos and, in case of an outbreak, potentially higher risks of infections), unfair access to food with vulnerable people more likely to be deprived of their rights or the creation of unbalanced power dynamics which could lead to consequences such as the creation of black markets, debts and gang formation.

Before implementing such policy, decision-makers should have a clear understanding of the group behavior and the likelihood of these side-effects happening.

Potential ways of minimizing these risks could be by using a democratic system to elect the representatives of each community and, if necessary, keeping a strict control on these. Alternatives such as implementing guarantee of final delivery or switching roles can also be considered.

Finally, as most of the representative-based policies suggest a simple delay of the spread onset and not necessarily its total control, it is extremely important that this is combined with further policies. As delaying infections can lead to higher number of cases occurring per day later on, one should be aware that policies that only have delaying effects cannot be implemented alone.

Increasing COVID-19 awareness, monitoring and acting quickly

From the analysis, it was possible to observe that the system is highly sensitive to the initial number of COVID-19 cases. As each case can potentially lead to several others, it is clear that the earliest measures are implemented, the most successful these efforts can be. Moreover, by implementing policies early on, the onset of the spread can be delayed, giving camp managers more time to prepare and adapt.

In order to increase knowledge of the current situation of the outbreak, awareness campaigns should be organized to inform the population of the COVID-19 symptoms and prevention techniques. Due to the high prevalence of respiratory diseases in refugee settlements (Bellos et al., 2010), COVID-19 symptoms can often be mistaken for other diseases and, consequently, not given enough attention. By making testing accessible, it is not only possible to better control the development of the outbreak, but households can also make better decisions when it comes to deciding who should attend the food distribution event or fetch water. By increasing testing, the probability of someone carrying the virus attending these common facilities can be reduced, consequently reducing risks of infections.

As discussed, relatively low numbers of infections during the first days can still lead to near-total outbreaks. For this reason, it can be concluded that decisions should be adjusted in response to the settlement's situation and should not be planned once for the entire period. For this, it is recommended that there is a constant monitoring of the situation and that both camp managers and the population are kept updated of the current figures in order to allow for timely action and behavior adaptation.

Uncertainty and preparing for worst-case scenario

From the analysis of the results it was possible to conclude that, under some unknown parameters (resulting from the stochasticity of the model), the model shows an extremely wide range of outcomes for the same policy and the same scenario. This highlights that, although some policies might show a high potential to control the outbreak in most scenarios, some unknown combination of other factors might make the implementation of this policy unsuccessful.

Given this sensitivity of the system and the high consequences linked to uncontrolled outbreaks (number of deaths, pressure on the healtcare system, etc.), it is recommended that policy-making is focused on the *worst-case scenario*. Although less frequent than the others, there is a combination of unknown factors that lead to these results, making this scenario unusual but *possible*. In order to be prepared to any possible development, policy-making should consider this potential scenario, try to understand which factors lead to it and how to avoid it.

Looking into other solutions, communicating and adapting

From the implementation of policies at the food distribution and subsequent evaluation of their impact, this study found that, although these show some potential to reduce the speed of the virus spread, they are not enough to fully control it. For this reason, it is recommended to look into other ways of minimizing contacts within the settlement and implementing different sets of policies.

In specific, this study highlights the role of the shelter as the most important location in terms of number of infections happening across all runs. This can be justified by the difficulty of isolating infected people inside an often one division shelter.

Identifying this challenge, the Bangladesh Government implemented a relocation policy consisting of sending COVID-19 positive people to an island in order to avoid an outbreak. However, the unclear communication and lack of transparency in this process led to the creation of rumors that people who tested positive would be taken away or even get killed (Mainul Islam & Yeasir Yunus, 2020), making people avoiding tests and hiding their symptoms. This situation raises an important point: due to poor implementation, what started as a policy to control the outbreak, turned out to have such negative side-effects that undermine the implementation of the policy in the first place.

For this reason, it is recommended that the process of developing policies to contain an outbreak includes not only the camp-managers but also some inhabitants. In an environment as fragile as a refugee settlement, it is important that the interventions implemented are culturally accepted by the population. If this is not the case, it is likely that people do not follow the measures and these consequently do not have the effect intended.

9.5 Conclusions

This Chapter focuses on the discussion of the results obtained and previously visualized. To do so, the main assumptions guiding the model behavior are identified and their impact in the model is outlined. Then, by comparing the results obtained with other studies, the validation of the model is discussed.

Then, a deep discussion about the implication of the findings is conducted by analyzing the results and identifying key points and insights obtained. Finally, these key points are used to formulate policy recommendations with different strategies in order to control the spread of COVID-19 in a refugee settlement. Although it is not possible to summarize all these insights in a short conclusion, a key point to keep in mind is the need to look into further policies to control an infectious disease outbreak rather than only looking at the food distribution event and how to change it.

Chapter 10

Conclusion

This chapter concludes the study conducted on the risks associated with food distribution during an outbreak in a refugee settlement. First, the sub-questions proposed in the beginning of the study are revisited and answered in Section 10.1. After this, the main research question is answered in Section 10.2. Then, in Section 10.3, the limitations of both the model and the study are discussed. Section 10.4 and Section 10.5 cover the contributions of this study at both an scientific and societal level, respectively. Finally, the study wraps up with suggestions for further research in Section 10.6.

10.1 Answering the sub-questions

After identifying the research gaps in the literature, this study proposed to answer a main research question. Breaking down this question into smaller steps, four sub-questions were formulated. The first sub-question aims to help conceptualizing how people wait in a queue and what factors influence their behavior when doing so. The second sub-question refers to how food systems are organized in refugee settlements. The third sub-question refers to measuring the performance of policies implemented in the food distribution in the context of an infectious disease outbreak. The fourth sub-question reflects on the drawbacks of using the policies proposed to manage the food distribution in a refugee settlement. Answering all these questions allows to formulate an answer to the main research question proposed in the study, which will be answered in the following section.

1. What factors influence how people behave while waiting in a queue?

Queues are, per nature, places where people stand and interact. For that reason, queues can be the source of infections during an outbreak. After highlighting that the food distribution in refugee settlements often leads to long queues where a part of the population spends a couple of hours, it was decided that this study would focus on these queues and simulating interactions during them. For this reason, it was necessary to understand how people behave in a queue and what factors can influence this behavior.

There are different theories that conceptualize people's behavior when waiting in a queue. Due to the similarity with the case described by the NRC - that while some refugees respect the queue and wait for their turn, others decide to cut the line - the theory developed by Köster and Zönnchen (2015) was chosen. This theory divides people's attitude when waiting in a queue in two different ones: *cooperative* or *competitive*.

When faced with a queue for the service they want to attend, *cooperative* individuals identify the last person in line and wait behind them. On the other hand, *competitive* people aim to go to the service point as fast as possible and try to position themselves closer to it, ignoring most of the people waiting in the queue. While people might have a cultural (or personal) predisposition to have one of the attitudes, this theory also defends that people can switch between strategies - an individual who joins the queuing process with a cooperative attitude switch to a competitive one and vice-versa.

However, Köster and Zönnchen do not specify what factors could influence individuals to switch between attitudes. From complementing literature, it was noted there were two main factors that make people cut a queue:

1. When people perceive the queue as being too long and do not want to wait;
2. When people see others not staying in the queue and cutting it instead.

There are other factors that could influence the attitude of a person when joining a queue such as the fear of scarcity of the good to be served. However, these are not considered in this study.

2. How is food access organized in a refugee settlement?

At a political level, refugee settlements are often looked at as a temporary solution in an overall context of migration flows and conflict. This means that their layout and set up is often the result of uncoordinated decisions made by different groups (either refugees or NGOs) along time rather than a planned, coordinated and well-designed structural effort. Lacking a structure where people can restart their lives and quickly gain economic and structural independence, it can be claimed that NGOs provide a crucial support in maintaining essential systems of the camps. An example of such a system is food.

To provide access to food to the population of a refugee settlement, NGOs have two main approaches: *food aid* and *food assistance*. While food assistance aims to stimulate economic development through subsidies, cash, voucher or agricultural or livestock support while creating a food market in the settlement, food aid resorts to the direct transfer of food from the NGOs to the beneficiaries and has an only goal to feed a population.

During the COVID-19 outbreak and due to lockdowns implemented in camps that hinder the in and out movement of food and goods, several camps put their food assistance programs on hold and resorted entirely to food aid. For this reason, the focus of this study was on *food aid* and, in specific, monthly distributions. These are events that occur once a month where (often dry) ingredients are handed out to the population. In most of the camps (and when possible), this distribution is done by giving rations for the whole household to the head of the household. However, when it is not possible (often in the initial phases of development of the settlement), NGOs can resort to the use of representatives of communities. By doing so, the food distribution process is broken down in two steps: from NGO to representative and from representative to final beneficiary.

3. How to evaluate food distribution policies during a COVID-19 outbreak?

In this study two types of food distribution policies are considered: *representative-based* and *timeslot-based* policies. While the first ones are a direct integration of the distribution methods suggested by the Emergency Nutrition Network (2011) and UNHCR (UNHCR, 2015), the second represents the widely used approach of introducing timeslots to distribute the number of people attending the food distribution across the day of the event.

The focus of this study is both the queue and the outbreak dynamics. Moreover, it is assumed that people who choose for a competitive approach to do in order to increase their individual utility and aim to spend less time queuing. For these reasons, the policies implemented at the food distribution are measured by the following Key Performance Indicators:

1. Average time in queue during the food distribution event;
2. Cumulative COVID-19 infections.

Given the high level of these policies, further disaggregation was conducted both at an attitude and location level. These extra metrics help understanding the model and its dynamics and are as follows: the average waiting time in queue per attitude, the number of people switching behavior, the likelihood of getting infected at the food distribution, the likelihood of infecting others at the food distribution, the distribution of infections per location and the infection chain.

4. What are the drawbacks of using the chosen policies during food distribution?

While the study briefly looks into the potential of timeslot-based policies, the focus lies more on the *representative-based* policies. This is justified by both their real use in the humanitarian world but also by the results yielded when testing the policy in the model developed.

However, although the *representative-based* policies result in desirable outcomes in the KPIs considered in this study, it is important to not lose sight of the fact that they can have considerable drawbacks. These drawbacks are a common concern discussed in the literature and were also mentioned during the interviews with the two food actors from Cox's Bazar when discussing their *majee* system.

Drawbacks of resorting to *representative-based* policies can range from simple ones such as the limited engagement of the community but can also be considerably bigger. In case the representative of a community is dishonest and diverts the food that it should distribute further to other inhabitants, potential side-effects can be observed. Among these, some are as follows:

- People who did not get their food attending the food distribution even if they are not supposed to be there;
- Unfair access to food with vulnerable people more likely to be deprived of their rights;
- Distrust in the system, potentially causing tensions and riots among the population;
- Potential creation of black markets where the representatives could sell their reserves and famished people have to resort to when desperate;
- With the creation of black markets further consequences such as prostitution, high debts and gangs can rise.

Although these side-effects were not integrated in the study due to the difficulty to quantify them and the complexity involved, these should be kept in mind when considering the implementation of the policies.

10.2 Answering the main research question

The foundation to answer the main research question is laid by answering the four sub-questions proposed in this study. To recall, the research question guiding this study is as follows:

> *What food distribution policies show robust performance under queuing behavior uncertainty while minimizing COVID-19 infections in the context of an outbreak in a refugee settlement?*

To answer this question, a modeling approach was conducted. This was complemented with desk research and (informal) interviews to actors working in Cox's Bazar. The flow of this study is visualized in Figure 3.1.

After having developed the queuing model, this was coupled in the model developed by Bögel (2020). Then the scenarios in which the model would be used were developed. These scenarios were created by sampling the variable responsible for the percentage of competitive individuals at the beginning of the run.

Then, a baseline was tested to evaluate the performance of the system under no extra policies and to understand the dynamics of the system. This baseline represents the case when the head of each household attends the food distribution and was tested across all scenarios. As this experiment showed a high number of infections across all scenarios and considerably high waiting times at the food distribution event, it was concluded that there is a need to implement policies at this event in order to minimize these.

After, both the *representative-based* and the *timeslot-based* policies were tested across two scenarios: one with a relatively lowly competitive population and one with a highly competitive population.

From the results obtained, a couple of insights can be drawn. First, when no policy is implemented, a trend to a near-total infection by day 60 is observed across all scenarios. It was also observed that there is a clear relation between the competitiveness of a population and the average waiting time in queue, with a lower competitiveness resulting is lower waiting times. From the baseline, a clear relation between the competitiveness of a population and the speed of infection spread could not be drawn. Finally, it was possible to observe a trend between the competitiveness of a population and a higher role of the food distribution event in the infection chain.

Secondly, it is possible to conclude that there is a clear impact of the use of *representative-based* policies in the average waiting time in queue and the speed of the outbreak onset. From the low impact of the implementation of *timeslot-based* policies on its own on the average waiting time at the food distribution it was observed that there is a clear shortage of capacity to deal with the demand in a settlement.

Across all scenarios, policy 1 (resorting to representatives of 50 people) seems to yield the best results. However, considering that this policy is the one that relies the most on the use representatives (and less of them), it is also the policy that has the highest potential to result in side-effects according to other metrics not taken into account in this model (see answer to sub-question 4). Moreover, it is important to consider that the variation between the policies is done by adjusting the number of representatives used and the time it takes to serve each one of them. For that reason, it can be claimed that potential improvements in the time it takes to serve each representative might be enough for another policy to perform better.

During model exploration, it was possible to identify certain runs under the same scenario (and consequently assuming the same input parameters) with distinctive behavior. This was also identified in the implementation of policy 1 and raises an important point - under some unknown conditions, there is still a small chance of near-total infection of the settlement when policy 1 is implemented. As this is a result of some of the stochastic components of the model, this study does not identify the parameters that lead to these outcomes. However, as they might undermine the successful implementation of policy 1, it is recommended that this is given further attention. By preparing for the worst-case scenario, the robustness of the implementation of policy 1 can be increased.

Finally, it is important to highlight that none of the policies tested in this study were enough to fully control the outbreak. This is not a surprising result, as refugees continue performing other activities in the settlement even if they do not attend the food distribution and end up being infected at later stages. For this reason, it is highly recommended that policies are implemented at other levels and not only at the food distribution. This study drafts other policy recommendations and suggests further research into the development of other policies.

10.3 Limitations

Models are abstractions of the real world. And to build such abstractions, decisions have to be made regarding the boundaries of the system being represented, what to integrate and the level of detail included. Moreover, there are also uncertainties on some of the dynamics to represented or some unknown components. For these reasons, choices and assumptions had to be made throughout the process of this study, resulting in natural limitations. Although these do not undermine the value of this thesis, it is important to be aware of them when reading the conclusions of the work. In this section, limitations are divided in model and study limitations. Further discussion on how these can be overcome can be found in Section 10.6.

10.3.1 Model limitations

The model focuses on three main components: COVID-19, queuing and food distribution in a refugee settlement. For this reason, the limitation section will be divided accordingly, with an extra subsection focused on the model performance.

COVID-19

Regarding the COVID-19 component, the limitations of the model are mostly associated with the epidemiological parameters and their accuracy. As a pandemic caused by a recently discovered virus, the COVID-19 crisis was initially characterized by uncertainty. As time passes, more people get infected with the virus and scientific methods improve, scientists and medical staff gather more and more information regarding the SARS-CoV-2 virus, how it spreads and how it develops in different people. The COVID-19 component of this model was developed by Bögel and, due to a different focus for this study, was not updated with more recent parameters. It is thus important to be aware that this study uses epidemiological parameters from June 2020. By doing so, it is likely that the model is overestimating the risk of outdoor activities and that the results suggest worse outcomes than the ones to observed in case of an outbreak. In fact, current reports from settlements have not described major outbreaks yet, contrary to the chaos expected at the beginning of the pandemic. This can be justified by the relative isolation of the camps from host communities (reducing probability of the first case to appear), the strict lockdown policies implemented but also by potentially the lack of testing and identification of cases. The reduced amount of deaths can also be associated with the demographics of such settlements, where the average age is considerably lower than in urban settings (Egeland, 2021).

The epidemiological parameters used are based on observations in urban settings. However, as respiratory infection rates in refugee settlements are considerably high (Bellos et al., 2010), it can be claimed that new infections are more difficult to detect. In this model, this would increase the mismatch between infection and infection-perception, leading to more refugees performing activities without knowing they were carrying the virus if isolation or quarantine policies are put in place.

In line with the previous consideration, it should be highlighted that the concept of individuals being super spreaders was not integrated in this study. The probability of infecting other individuals is dependent on the age of the infectious agent and not in an attribute whether the agent is a super spreader or not. Similarly, the progression and effects of the virus in individuals is also not dependent on anything else other their age group (children, adult or elderly). This means that the level of detail to which the COVID-19 spread was modeled does not include underlying medical conditions that could make individuals have more severe complaints when infected.

Finally, regarding COVID-19, it is worth noting that parameters are not static variables and that the constant emergence of new strands represents a challenge in having a model that is always up to date.

Queuing

The queuing component of the model is highly based on the theory by Köster and Zönnchen (2015). This is only one theory behind queuing dynamics, existing other ones that could be implemented as well. According to this theory, people have a natural attitude when queuing: they either cooperate or they cut the line. People who initially cooperate can also be motivated to cut the line if they see other people cutting or if they perceive the queue as being too long. This theory hence attributes the cause of people becoming competitive to only these two reasons. By doing so, the theory does not include people who are queuing cooperatively but are forced to cut the line because of urgent reasons (i.e. after getting a call and realizing they cannot wait until their turn) or people who cut the line because they see a relative or a friend further ahead in the queue. Similarly, the theory does not include people who become tired of waiting too long and decide to leave and come back at a later time nor people who could have a priority for being served (elderly, e.g.).

If the only goal of this thesis were to model a queue and how people wait for their turn to be served, a queuing or crowd management software should have been used. However, as the queuing process is only a part of the whole dynamic of this study, NetLogo was used instead. This choice of software limits the potential of properly simulating queues and crowds. However, this was deemed not relevant enough to invalidate the use of the software. An example of such a simplification made due to the software (and the limited skills in using it), is that competitive agents only cut the line once. This limits the use of this model in an extremely competitive environment where crowds are rapidly formed as this cannot be simulated by the model as it is now. For this reason, this model is more fit to represent an environment where people are more likely to be cooperative and competitive agents are the exception. This simplification directly results in less interactions in the queuing process than modeled. For that reason, it can be assumed that when there are higher numbers of competitive people, the actual number of infections is higher than what the model suggests.

Moreover, the integration of dynamic queuing behavior is only implemented when refugees queue for food and not for the rest of the activities in the settlement. Similarly, food distribution is the only event refugees walk to instead of being immediately transported to. By applying this behavior into other queues in the settlement, it is expected that the number of infections increases.

Food distribution

Regarding the food distribution, there are a few limitations to be highlighted. As mentioned before, this model focuses on the main food distribution from NGOs to the refugees and assumes that the population is highly dependent on this event for survival. However, refugee settlements can have other food sources. Among these, there are settlements that have shops, markets or where inter-shelter trade happens. Other camps also are in relative proximity with other civilizations where the population can go to in order to find food (creating an in- and out- flow within the settlement). This model is not fit for the representation of these camps as it is assumed that there is no movement in and out of the camp and that the food distribution is the only food source.

Moreover, the policies implemented at the moment at the camp are quite simplistic - either resorting to representatives of communities or timeslots to attend the food distribution. A further limitation relates to the use of representatives: as the model only focuses on the distribution of food from the NGO to the refugees (whether they are representatives or not), further distributing between representatives and the final beneficiary is not modeled.

Finally, regarding the use of representatives, the model considers a total trust in the representatives. In other words, this means that, if there is a policy in which representatives are being used, the rest of the population accepts this and does not attend the food distribution.

Computational limitation

A model related limitation is directly connected to the performance of the model developed for this thesis. As the model integrates a high number of agents and has an infection component, the running speed of the model increases throughout runs. This results in a technical limitation to run the model which consequently impacts the number of replications used throughout the study.

Finally, another limitation originates from a mistake made during the setup of the experiments. By not having fixed a seed, it is not possible to compare replications across different experiments. For this reason, some of the results obtained during the policy implementation cannot be directly related to the implementation of the policy but can be the result of a combination of stochastic elements that had not been seen before. Such an example are the model runs that suggest a total containment of the outbreak - by observing them, it is possible to note that the containment happened even before the first food distribution, showing that neither the policy nor the scenario were the drivers of such a dynamic. By not having fixed a seed, the fact that this result did not appear in the baseline is justified.

10.3.2 Study limitations

While some limitations are direct consequences of the modeling approach and modeling decisions, the scoping and conceptualization of the study also result in some limitations.

First, this study simplifies activities in a refugee settlement down to four ones: picking up food, fetching water, using latrines and visiting healthcare facilities. This is an obvious simplification of the daily routine at a camp, but these activities represent the main dynamics that cannot be put on hold even if there are COVID-19 preventive rules in place. However, a discussion about the importance of schools and social contact can be raised, together with population relying on support from other shelters or administration work that should also not be stopped.

Second, this study focuses on a prototypical settlement and not a specific one.

This means that some variables (such as the number of people per shelter, number of facilities per population, among others), the location of facilities and the type of facilities is rather general and not particularly representing any camp.

Another limitation is directly connected to the policies being studied. The policies suggested in this study are quite simple ones and only target the food distribution event in the camp. In case of an outbreak in a settlement, more policies should be tested, targeting different components of the camp.

Moreover, it is important to consider the downsides of such policies to fully evaluate their impact. This study focuses purely on the personal utility (time in queue) and the COVID-19 infections. However, implementing policies almost always leads to unwanted consequences that should be taken into account to properly evaluate them.

This study has representative-based policies as the main studied solution. However, when discussing the use of representatives, a common concern of diversion of food is often mentioned. This was noted both in the documents related to food distribution but also in the interviews with food actors from Cox's Bazar about their majee system. In case the representative of a community is dishonest and mishandles the food that it should distribute further to the final beneficiaries, potential side-effects can be observed.

These side-effects were not integrated in the study due to the difficulty to quantify them and the complexity involved. On the same line of reasoning, this study does not take any other social or economic factors as metrics to evaluate the performance of the system. Nonetheless, such factors should never be forgotten when deciding to implement policies and can be integrated through a qualitative study, for instance.

Having highlighted the limitations of this study, it is important to conclude that, although the model can be used to support decision-making and obtain insights about some important dynamics, one should never forget its limitations and should not take it as a unique source of information.

10.4 Scientific contribution

This study picks up on an refugee settlement infection model developed in 2020 (Bögel et al., 2020) and develops it further by adding more dynamic behavior to the refugees queuing for food. By doing so, it increases the range of experiments that can be conducted in the developed model and the insights that can be taken from it. Specifically, it allows the integration of heterogeneous behavior in queues and understanding how effective policies to control the spread of an infectious disease can be.

This study comes to fill in the gap of the lack of representation of queuing models using ABM techniques. By implementing a queuing theory into an ABM model, this study represents a step forward in the behavioral study of queues. Moreover, by developing the queuing process in a separate stand-alone model, this study provides a queuing model that can easily be plugged in any other model. This allows for a quick integration of dynamic queuing behavior in other situations where looking at the way people queue is relevant.

To the extent of my knowledge, this study represents the first one combining queuing dynamics during an outbreak in a refugee settlement, expanding the literature in this area. By doing so, this is the first study showing the effects of having competitive people in a population and the role that they play in the infection spread during a queuing event. This study also shows the trade-offs of such a behavior and the overall impact a higher percentage of competitive people in a population has in the number of infections happening during a food distribution event.

Finally, the model built in this study is publicly available and fully documented. By sharing these developments, the queuing model can be used for Operations Research and how to optimize queues *given* that people do not stand in line and patiently wait for this turn. By integrating such a model in OR, solutions to make the queuing process quicker can be tested and their impact evaluated.

10.5 Societal contribution

Standard recommendations to stay safe during the COVID-19 outbreak are as simple as keeping a distance and avoiding crowds. However, such a simple thing can be extremely difficult for refugees. Often living in overcrowded camps with shared facilities, refugees represent a vulnerable part of the world population during this pandemic.

Due to structural differences between the settings where refugees (and other persons of concern) live, modeling the way an infectious disease spreads needs to take these factors into account. Moreover, the same differences need to be considered when looking into policies to be implemented. For these reasons, it is necessary that some of the research focuses on these specific settings instead of applying take-aways achieved from urban studies.

This study represents another step in the direction of prioritizing the humanitarian world and including it in research. By simulating a refugee settlement, this model can be used to test policies that are not only relevant but also feasible in a humanitarian setting.

Moreover, the idea of looking into queues and how to keep people safe while queuing is also very relevant for the (hopefully) near future. When vaccination programs in refugee settlements start taking off, queues will form. Being aware on how to keep these queues to limited numbers and making them as safe as possible must be a priority. However, for these, other policies must be designed as the use of representatives is not a possible solution to avoid crowding.

Finally, as the number of displaced people around the world has been steadily increasing since 2012 and seem to continue so for a while, studies that focus on people in these conditions are more and more urgent in order to not only provide NGOs with data-driven policy recommendations but also to increase awareness on the topic. In addition, studies in this topic can accelerate the achievement of the Sustainable Development Goals.

10.6 Further research

As mentioned before, this study represents a step in the field of modeling humanitarian settings and prioritizing vulnerable people who are displaced from home in research. However, as with any study, it represents only a small step and it is far from being complete. Due to time and resource constraints, the scope of this project was limited. While working on it, I often came across potential directions or additions that I would have enjoyed including but had to be left behind. Taking these ideas and the limitations of the study into account, some further research is suggested.

The first direction of further research relates to the wide range of outcomes observed in the result section. As was previously mentioned, replications under the same scenarios can lead to completely different outcomes. This suggests that, when implementing a policy, the success of its implementation is not only dependent on the scenario but also on some other combination of unknown parameters which are now guided by stochastic events in the model. To to understand the impact of policies under these particular situations and allow a full comparison to the baseline, a seed should have been fixed among experiments. However, as this was not the case, it is suggested that the experiments are repeated with fixed seeds so that different results can be attributed to the policy implementation. Moreover, in order to discover what parameters are leading to these outcomes, further exploration of these circumstances and uncertainties is recommended. One potential direction could be to turn some of the stochastic events into input parameters of the model (who gets infected as patient zero, for instance). Then, by running the model using deep uncertainty techniques, a more extensive scenario sampling can be created, allowing for an examination over the total scenario space. This could help understanding the necessary conditions to increase robustness of the policies.

10.6.1 COVID-19

First, some suggestions are made regarding the epidemiological component of the model. To better simulate the current outbreak, it is recommended that the COVID-19 related parameters (regarding the incubation period, the period in which individuals are infectious, percentage of asymptomatic, among others) are updated. Developments could also be made by adding an extra layer of detail to the model and including underlying health conditions that can make individuals have different COVID-19 experiences and adjusting the epidemiological parameters accordingly. This could show interesting results by, for example, showing that if refugees in settlements have different health status than people living in a city, the outbreak shows different outcomes (not only less casualties since there is less elderly at a camp than in a city but also less obese individuals, for instance). Expansion to include different variants and their own epidemiological parameters could also be interesting - potentially different variants need different policies to be controlled, for instance.

As time goes by, discoveries are being made and people start getting vaccinated for COVID-19. By changing the way people get immunity in the model it is possible to include a possible vaccine rollout and observe the adjusted outbreak dynamic considering that an increasing number of the population can achieve immunity without being previously infected.

Regarding infections, relevant experiments can be conducted by changing the number COVID-19 cases in day 1 or by seeing the impact of different people being infected. For example, it would be interesting to observe how the outbreak would have developed if the initial case were from the NGO member responsible for the process of the food distribution.

Policies including the capacity of testing can be included in the model. This would reduce the gap between the infection attribute and the infection perception, which would hence reduce the number of infected agents attending communal facilities and infecting others when quarantine policies are implemented.

By implementing policies with a merely delaying effect, one can be increasing the total number of cases happening per day at a later stage. This can be argued to be putting the healthcare facilities under higher pressure instead of spreading the medical demand throughout time. For this reason, further analysis on the effect of policies in the number of active cases per day is suggested.

10.6.2 Queuing

Then, regarding the queuing component of the model, some further directions can be suggested. Regarding the behaviors being modeled, right now the model is highly based on the theory developed by Köster and Zönnchen (2015). However, this theory limits the types of behavior people can have into only two different ones. While modeling something as essential as a food distribution, other behaviors could be considered. For example, a priority system where certain type of people (elderly or disabled people, for instance) do not have to wait in a line to be served and can just join the queue in a frontal position. Behaviors like balking and reneging could also be integrated when developing the queuing behavior.

Moreover, the spatial component of the queuing is now highly dependent on choices made during the modeling process. Further research on where people queue and why they choose those positions is recommended. This can be done by performing some field research and observing queuing formation.

In this study, the dynamic queuing behavior was only implemented when refugees wait for food. However, similar behavior could be observed in any queues in the camp. For this reason, it is recommended that further developments in this model include integrating this dynamic behavior in the queues for WASH or healthcare queues. Once camps start with a vaccination program, there will be queues for this as well. However, none of these queues could be managed by resorting to representative-based policies. For this reason, it is important to understand the risks of the queue to make sure people do not get infected while waiting for their vaccine.

Finally, regarding the flexibility and applicability of the queuing model, it is relevant to note that the coupling now is done in a hard way. However, a further step could be to create a library from this model so that it can be more easily plugged into other models and used in other studies. For this it would first be necessary to fix some things such as the location where they wait (tweak this a bit) and syntax differences.

10.6.3 Adjusting it to a camp

In this study, the model is used as a prototypical model that combines information from different settlements. This means that data such as the demographics and the number of facilities per population is taken as an average from different settlements. Another implication of its prototypical nature is that several parameters are left as an interface choice in the model.

To use this model for policy making support in a specific settlement, it is recommended that the model is adjusted to represent the settlement. This can be done by adjusting the demographic data, the facilities and the spatial layout, for instance. When focusing on the food system, this adjustment should also consider the existence of other food sources such as markets, own creation or shops.

Regarding behavior, tailoring the model to represent a specific settlement can also be done by adapting the behavior to the one in that settlement and consider its contextual factors. For example, if there is scarcity of food or an unstable food distribution system, it is normal that people behave more competitively or that people try to attend the distribution more than once. Another interesting contextual parameter related to the distribution of the time people prefer to attend the food distribution. If the camp being modeled is one where the middle of the day has extreme peaks of heat, it is possible that the peak of people attending the distribution happens early in the morning or in the evening. Similarly, if the food distribution coincides with a religious festivity, for instance, maybe trends of people attending the distribution before or after religious events can be observed. By including these variances the model can be shaped to represent a specific settlement as much as intended. Moreover, instead of simply varying the percentage of competitive agents in the initial population, meaningful scenarios can be created with these variables. Such low-level details on the behavior of people can be difficult to find in literature. For this reason interviews and field work can represent a best approach to achieve this.

Finally, adjusting the model to a certain settlement can also open the possibility of integrating a relevant social network layer. Settlements are often divided in communities with certain cultural factors making people belong (or not) to a certain community. It can also be assumed that contact among people from within the same community is higher than with outsiders. In a context of a disease outbreak, social networks and interactions are a key factor in the development of infections. By integrating a social network level to the model the impact of these can be studied and policies can be made taking these into account (for example, it could be interesting to look up the effectiveness of policies that allow movement but only within communities).

Finally, the use of this model to simulate other settings where facilities are shared and home isolation is not easily guaranteed could be considered. Examples of such places are Brazilian favelas or slums. Although the main assumptions of this model and the queuing behavior theory could easily be adjusted to these settings, the assumption that there is no in or out movement from the setting is a more debatable one. If this assumption remains valid for these settings, it is believed that this model could be used.

10.6.4 Development of policies

Regarding policies, it is first important to understand the simplicity of the policies considered in this study. Most the policies studied, the *representative-based* policies, are implementing by simply adjusting the number of people attending the food distribution (representatives) and the time it takes to serve each person. However, the model does not look into the further distribution from these representatives to the final beneficiaries, not fully simulating the total amount of interactions needed for the food distribution process and, consequently, not picturing all the potential infections that can happen in the process. Integrating this distribution is the first step that should be taken if the study of the potential of these policies is to be continued.

Similarly, these policies have been noted by several actors to entail in some downsides. Such downsides can go from as little as the lack of community engagement to tension between population when a representative fails to give the food to the final recipient. The gap between the access to food by different individuals can also lead to the creation of a hierarchical system and less transparent food transactions potentially resulting in power dynamics that can take over the settlement. In this study, none of these consequences is measured by any metrics. Due to the extent of these consequences and the complexity this would add to the model, these were left out of scope. Whole behavioral concepts related to power dynamics, trust and corruption can be integrated in this direction, creating a whole range of possible topics for further studies.

While the range of policies considered in this study is very limited, the model offers the opportunity to test different policies with completely different targets. These policies could range from information campaigns that inform people on how long the wait is at each line in an attempt to make them more informed and less likely to turn competitive but also could involve more distribution points or more days, for instance. Nonetheless, to develop more meaningful policies and policies that are feasible in a settlement setting, the policy development should be the result of a conversation between food actors and members of the population of refugee settlements. By understanding the needs from each side and their perspective on the system maybe better compromises can be achieved and more effective policies can result from it.

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Appendices

Appendix A

Epidemiological modeling

Figure A.1 shows the COVID-19 progression as implemented in Bögel's model (Bögel et al., 2020).

Note that the epidemiological parameters used in the model were updated with data from June 2020, which might not represent the current knowledge on COVID-19.

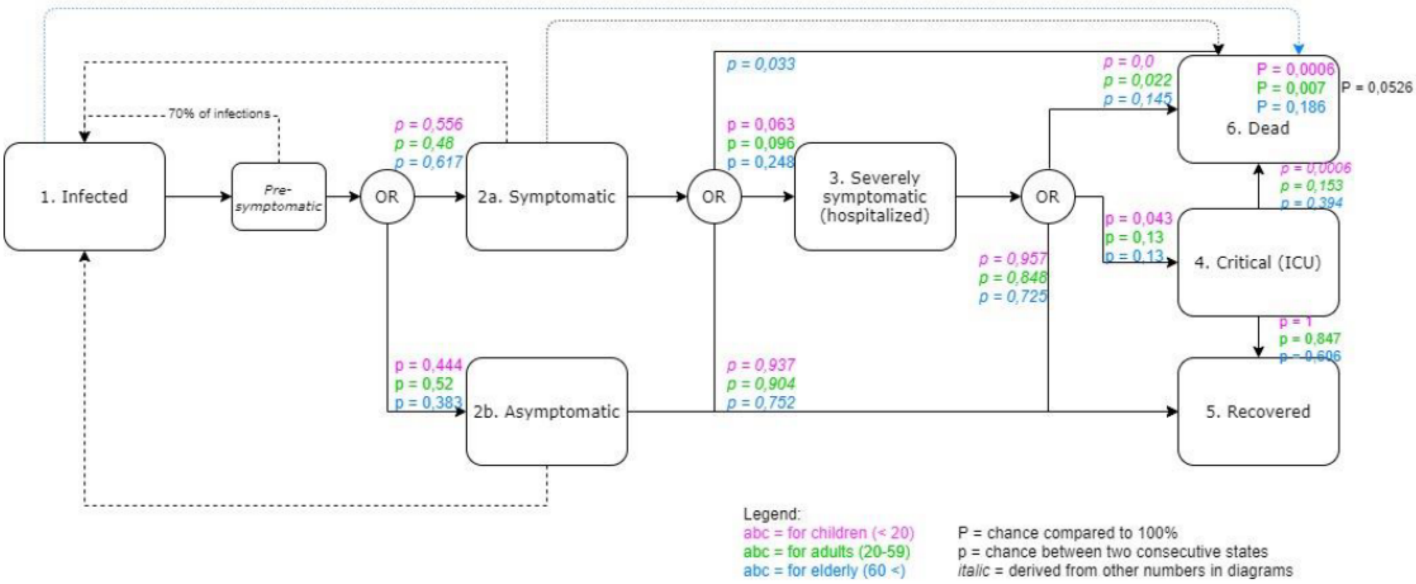


Figure A.1: COVID-19 progression as implemented in (Bögel et al., 2020)

Appendix B

Queuing model

This appendix covers the software implementation of the queuing model in order to complement the information already included in the main text. It will first focus on the model agents (section B.1), the general reasoning of the model in the form of a diagram (section B.2), parameterization (section B.3), model assumptions (section B.4), technical limitations (section B.5) and model verification (section B.6).

B.1 Agents attributes & behavior

In order to simulate a queuing process, a model was built. This model has two main components: the food distribution point and the refugees. In this section the model is broken down to understand the variables and the attributes and behavior of the agents.

B.1.1 General variables

There are two types of global variables in the model: the ones defined in the interface and the ones defined in the code.

Table B.1 provides an overview of the interface variables of the queuing model, while Table B.2 outlines the rest of them. There are also extra variables that are used to keep track of the performance of the model that are not included in these tables.

Table B.1: Interface variables of the queuing model

Level	Variable	Explanation
Levers	*policy-implemented*	which policy is implemented at the moment
	timeslot?	if a policy of using timeslots is being used (boolean)
	social-distancing	distance people following social-distancing keep from each other
	hours-open	how many hours the food distribution is open for
Context	*percentage-competitive*	percentage of the population that starts up as competitive
	threshold-competitive	tendency to competitiveness threshold to turn competitive
	total-number-inhabitants	variable that keeps track an agent's current tendency to become competitive
	distribution-pick-up	variable that keeps track an agent's current tendency to become competitive
	poisson-mean	variable that keeps track an agent's current tendency to become competitive
Structural	*radius-visibility*	the visibility of agents (used to influence some agents when they see people cutting the line around them)
	impact-seeing-cutting	impact seeing a person cutting the line has in the competitiveness of an agent
	impact-long-queues	impact seeing a long queue has in the competitiveness of an agent
	acceptable-length	maximum length of queue that people still accept
	startingpointx	defining the beginning of the queue (x coordinates)
	startingpointy	defining the beginning of the queue (y coordinates)
	width-queuing-area	to decide how far from the queue new competitive can go
	natural-distancing-x	natural distance people keep from each other without a COVID social distancing measure (x coordinates)
	natural-distancing-y	natural distance people keep from each other without a COVID social distancing measure (y coordinates)

Table B.2: General variables of the queuing model

Variable	**Explanation**
patchespertick	To control how much they can move every timetick (sort of speed)
freeRefugees	This is an agentset of refugees that are not busy getting food
firstInLine	This is an agentset of the refugees that are the first in line
distanceFirstToFood	This is the distance from the first refugee in line to the food distribution point
supportive	Supportive variable for placements (can be -1 or 1)
day	To keep track of time
hour	To keep track of time
minute	To keep track of time
middle_distribution_time	Calculates the hour that is the middle of the distribution time
num-refugees	Number of refugees attending food distribution (depends on policy implemented)
frontal_position_min	Position in serving queue of the first agent to be in the frontal zone
medium_position_min	Position in serving queue of the first agent to be in the medium zone
medium_position_max	Position in serving queue of the last agent to be in the medium zone

B.1.2 Food distribution

The food distribution agent is a rather simple one with only five different attributes. These are outlined in Table B.3.

Table B.3: Attributes of the food-distribution agents

Attribute	Explanation
service-time	time it takes to serve an agent
opening-time	time the facility opens
closing-time	time the facility closes (calculated as opening-time + hours-open)
physical-waiting-list	list to place agents in a queue (only for cooperative people)
serving-waiting-list	list to serve agents (includes competitive and new-competitive)

B.1.3 Refugees

This subsection focuses on three main topics related to refugees: their attributes, their attitudes and their spatial placement.

Attributes

Table B.4 shows the main attributes that the refugee agents have in the model, together with their meaning.

Attitudes

Based in the literature, agents are created with two main attitudes: *cooperative* and *competitive*. This attitude is defined by their *natural-tendency* with lower values representing a cooperative person and higher values a competitive one.

1. Cooperative

Cooperative agents, when faced with a queue, identify the last person lining up, head towards them, queue behind this person and wait for their turn. This is done by adding themselves to the last position in both the *physical-waiting-list* and the *serving-waiting-list*.

2. Competitive

Competitive agents, on the other side, when faced with a queue, try to place themselves in a rather frontal position to minimize the time they have to wait to be served.

This happens as follows: they get close to the queue in the same as cooperative agents. However, when they are faced with it, they consider the 80% first spots (closer to the service point) as attractive places to join instead of joining in the back. The place where they force themselves depends on their current *tendency-to-competitiveness* - the more competitive they are, they more frontal they will put

Table B.4: Attributes of the refugee agents

Type of Attribute	**Attribute**	**Explanation**
General	*destinationx*	X coordinates of their next destination
	destinationy	Y coordinates of their next destination
	current-task	task they are currently busy with
	preferred-fooddistro-time	time each agent prefers to go pick up their food
Attitude	*natural-tendency*	natural characteristic of a person that shows how competitive they are
	tendency-to-competitiveness	variable that keeps track an agent's current tendency to become competitive
	tendency-after-queuing	value of their tendency to competitiveness after checking the length of the queue
	attitude	attitude they have: cooperative, competitive or new-competitive
	list-influencing	list of agents that influence one to become more competitive
	currently-influencing	list of the influent people (see explanation above) around a refugee at a given time
Placement & Queue attributes	*number-in-physical-queue*	their position in the physical queue
	number-in-serving-queue	their position in the serving queue
	before-me-queue	only for cooperative: the turtle that is before them in the physical queue
	before-me-x	only for cooperative: the X coordinates of the person before them in the (physical) queue
	before-me-y	only for cooperative: the Y coordinates of the person before them in the (physical) queue
	time-spent-food	how much time they already spent with the process of getting food
	time-remaining-service	time left to be served when in the first place of the line
	tracking-time-in-queue	how much time agent has been in the actual queue
	start-tracking-time	boolean to check if they have already started tracking the time
	first-destination	only for competitive: the first destination they join in the queue
	first-jump	only for competitive: boolean to help me keep track if agent hasn't cut the line yet

themselves. Considering F as the place where they manage to join the queue, this is calculated as follows:

$$\textit{desirable-area} = \textit{length-of-the-waiting-list} \times 0.8 \tag{B.1}$$

$$F = \textit{desirable-area} \times (100 - \textit{tendency-to-competitiveness} \times 0.01) + 1 \tag{B.2}$$

Once calculated F, the agent places themselves in position F in the *serving-waiting-list*. Note that it is assumed that these agents can never force themselves in the first place in the queue because this is the only place that is monitored (by the person serving). This is the reason why the + 1 is included in the previous equation.

3. New-competitive

Köster and Zönnchen's (2015) theory defends that cooperative people can become competitive due to their environment. This has been narrowed to two different events: by seeing other cutting the line or by thinking that the line is too long. This is implemented in the model by constantly adapting each agent's *tendency-to-competitiveness* according to the following formula:

$$\textit{tendency-to-competitiveness} = \textit{natural-tendency} + E + L \tag{B.3}$$

With E and L being the result of seeing other people cutting the line and of seeing a long queue, respectively. These are calculated as follows:

$$E = \textit{number-of-people-cutting-the-line} \times \textit{impact-seeing-cutting} \tag{B.4}$$

(with the number-of-people-cutting-the-line being the number of people who do so within the agent's visibility)

and

$$\begin{array}{ll} L = 0 & \text{, if } 0 \leqslant \textit{length} \leqslant \frac{1}{3}\textit{acceptable-length} \\ L = \textit{length} \times \textit{impact-long-queues} \times 0.05 & \text{, if } 1/3 \times \textit{acceptable-length} \leqslant \textit{length} \leqslant \textit{acceptable-length} \\ L = \textit{impact-long-queues} & \text{, if } \textit{length} \geqslant \textit{acceptable-length} \end{array}$$

The final value of *tendency-to-competitiveness* is bounded between 0 and 100 by setting lower and upper limits, respectively.

Ultimately, an agent's *tendency-to-competitiveness* will dictate their attitude (Table B.5). The creation of the third attitude (*new-competitive*) instead of using the normal *competitive* was a decision in order to keep track of who is behaving competitively because of the circumstances and not because of their nature.

If the *tendency-to-competitiveness* of an agent is now bigger than the *threshold-competitive*, the agent is now a *new-competitive* and will cut the line to place themselves in a better position. In order to do so, the agent first removes themselves from both waiting lists. Then, it calculates a better position to be placed at in the

Table B.5: Refugee's queuing attitude based on their tendency-to-competitiveness

	Attitude
if *tendency-to-competitiveness* $\leqslant$ *threshold-competitive*	cooperative
if *tendency-to-competitiveness* $>$ *threshold-competitive*	competitive (or new-competitive, depending on the *natural-tendency*)

serving-waiting-list. Considering M as the new position where the agent will place themselves, this is calculated as follows:

$$M = INT((\textit{number-in-serving-queue}-1)\times(100-\textit{tendency-to-competitiveness})\times 0.01)+1 \tag{B.5}$$

Similarly to *competitive* agents, their placement is dependent on their competitiveness and can never be the first place. Note, however, that this calculation is not exactly the same as of the first agents. This is because *new-competitive* agents were already placed in the *serving-waiting-list* and will then have to place themselves in a position that is better than the one they initially had.

Spatial Placement

The placement of agents in the model is not directly connected to their position in the queue. For that reason, it is important to cover how this was implemented.

1. Cooperative

As cooperative agents follow the unspoken rules of queues, their spatial placement is directly related to the position of the person before them in the queue. Their behavior is rather simple: if they are the agent is the first one in the queue, it sets the start of the queue as its destination. If not, it gets coordinates of the person before them in the physical queue, heads there and places themselves at a distance (*social-distance*) behind of them. Every time a cooperative agent is served, the queue moves forward and so does every element of the *physical-waiting-list*.

2. Competitive

After solving how to introduce competitive agents in the food distribution and guarantee that they are served without perturbing the spatial location of competitive agents (using the two different waiting-lists), another challenge arose. This challenge was related to the spatial placement of these agents when they are waiting for their turn.

This was done by imagining three zones: frontal, medium and far. These are all created with the in-cone function and with a certain distance to the food distribution and the placement of agents in each one of these zones depends on the position they have in the *serving-waiting-list*. Competitive agents who occupy positions between 1 and 3 in the list are placed in the frontal zone. Agents that have positions between 3 and 40 in the list are placed in the medium zone and agents placed further wait in the far zone. Note that the values mentioned above can be changed by altering *frontal_position_min*, *medium_position_min* and *medium_position_max* (that now have the values of 1,3 and 40, respectively). If the competitive agent occupies position 0 in the *serving-waiting-list* (indices begin from 0 in NetLogo and not from 1), it is placed in the patch where the food distribution occurs.

Every time there is a change to the serving list (i.e. an agent jumps in or a refugee is served), the agents update their positions. This can mean agents moving backwards if the changes in the list were such that they are not place in the frontal or medium zone anymore.

3. New-Competitive

Placing *new-competitive* agents represented another challenge. The way it is implemented in the model now was developed before introducing the frontal, medium and far zone for the *competitive*. Further developments should look into the spatial placement of agents and the placement of these agents should be perfected.

The placement of these agents is dependent on the person before them in the *serving-waiting-list*. For their x coordinates, *new-competitive* agents take the position of the person before them in the serving list minus *how-close-x*. Their y positioning is similar to the one from the person before them minus (or plus) *how-close-y*.

Time to attend food distribution

Each refugee has a *preferred-fooddistro-time* attribute that defines the time they attend the food distribution. Note that this is the time they start heading to the food distribution point and not the time they arrive there. For that reason, the possible values for this attributed are limited to between the opening time of the food distribution and one hour before it closes to guarantee that agents have enough time to reach it.

In the interface the user can set how this distribution looks like by choosing between normal and poisson. The first one was used by default since it shows a distribution with a peak in the middle of the day (which is often observed in supermarkets). Note that it is capped in order to not give values close to infinite values that are common to a normal distribution. A poisson distributed is complemented with the *poisson-mean* value to describe where the peak is.

B.1.4 Implementation of policies

In this thesis there are two types of policies to be studied: *representative-based* and *timeslot* based policies.

The first type is implemented by creating only a certain percentage of the agents in the simulation (*num-refugees*) and adapting the *service-time* of the food distribution accordingly. This is possible because in this simulation agents are only created for this (i.e. there are no families, other activities nor epidemiological factors).

Implementing the *timeslot* based policy is done by setting up the *preferred-fooddistro-time* as a uniform distribution instead of a poisson or normal one.

B.2 UML

Figure B.1 describes the flow of the queuing model, with the different steps taken by agents during a run.

B.3 Parameterization

This subsection focuses on the parameterization of the variables in the queuing model. When possible, the values of these variables are based on literature. However, some concepts are novel of this study and are not present in literature. This poses a challenge for parameterization. Due to time limits, choices and assumptions were made. These are explained in this subsection. It is important to note, though, that the variables can be changed in the model interface in case one deems necessary, increasing model flexibility for application in other studies.

Another important point to highlight regarding parameterization is the purpose of the model. The queuing model is utilized to study queuing dynamics and the impact of different policies in *relative* changes in the system. For this reason, it can be argued that the *absolute* impact of a measure is not the focus but rather how it differs from the impact of a different one. For instance, it is more relevant to know that a policy reduces the waiting time to half rather than the actual time people have to wait with given policy. It can be argued that the choice of a value for certain parameters merely serves to be able to compare model behavior under different initial conditions and to evaluate the relative impact of the implementation of policies. To evaluate the impact of the choices made, a *sensitivity analysis* is recommended.

B.3.1 Threshold to become competitive

In this model, every agent has an inherent and individual tendency to become competitive. This value is adjusted throughout their queuing experience and, once it has overcome the threshold to become competitive (*threshold-competitive*, in the model), the attitude of the agent turns to competitive as well (*new-competitive*). Inspired by other ABM studies, this variable was conceptualized for this study and is not present in literature.

Changing this value, however, can be used to represent different settings and scenarios. For instance, in a scenario where there is food insecurity and people are not sure whether there will be food when it is their turn to be served, people might turn competitive more easily. This can be represented by a lower threshold. Contrarily, in a culture where queuing is more respected, a higher threshold is needed for one to become competitive (for instance in Japan).

The focus of the queuing model experiments is, however, to look into the impact of different policies in scenarios that differ on the initial attitude of the agents. For this reason, the choice of a threshold serves merely to be able to compare model behavior. After several tests, the value for the threshold to become competitive was set to 50 since it resulted in reasonable behavior of the system and it provides a medium ground for a variable that can vary from 0 to 100.

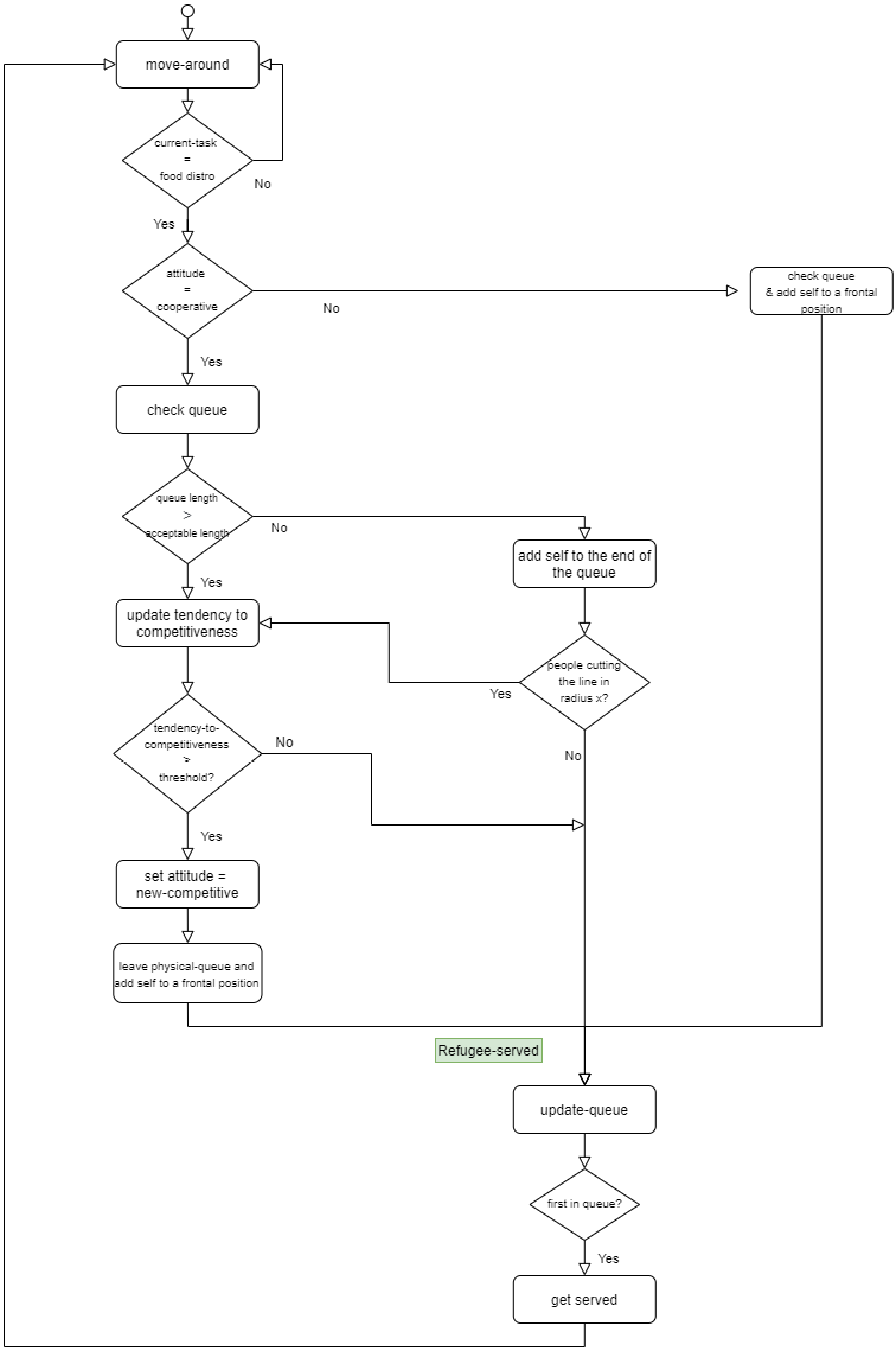


Figure B.1: Flow of the queuing model

B.3.2 Distribution on how they go pick up their food

When setting up the agents, each one gets an attribute that corresponds to their preferred time to join the food distribution queue (*preferred-fooddistro-time*). The combination of these variables across the entire population of the agents in the model can be described as the time distribution on when agents go to pick up their food. Similarly to the threshold to become competitive, this variable influences the behavior of people and can be tweaked to represent different situations. However, because the focus of the experiments with the queuing model are the relative differences between policies and not the absolute impact of these, it can be argued that maintaining the same distribution across experiments is sufficient.

To allow for a somewhat realistic depiction of the arrival of agents to a queue setting, a normal distribution with a standard deviation of 2 is used. Because of the unbounded nature of normal distribution, it is necessary to guarantee that agents do not arrive before nor after the opening times. For this, the values are capped between the opening and closing time of the food distribution. This decision leads to a distribution of people joining the queue along the day, with a peak in the middle of the day (i.e. in the middle of the functioning time of the food distribution). Several studies argue that customer arrival is better modeled through a Poisson distribution. This also has the benefit of allowing to switch the peak along the range of the distribution - for example, during summer lunch time might not be the most popular hour because of the strong heat and the risks of insulation. A Poisson distribution would allow to switch the peak of the arrival either to the morning or evening, for instance. Another potential scenario is that, due to a certain fear of scarcity, the majority of people will go as soon as possible with lower numbers going in the afternoon. These two situations can be modeled by choosing a Poisson distribution instead. However, due to the discrete nature of the Poisson distribution, a normal distribution was used for this study instead - by allowing to have agents with preferred times that differ by the minute, it is considered that a normal distribution is a better fit to describe the arrival of agents to the queue.

If a situation as the ones mentioned above (peak before the heat time, peak as soon as the doors open, among others) is to be modeled, a Poisson distribution is then a better fit. Note that, if this distribution is chosen, it is necessary to add the value of the mean in the interface in order to fully describe the distribution. Furthermore, a technical solution might be needed to overcome the discrete limitation of the Poisson distribution (potentially by adding a random integer to compute the final value).

B.4 Assumptions

To be able to build the model, several assumptions had to be made. These assumptions highly impact the way agents behave and, for this reason, are critical in order to understand the results obtained.

They are as follows:

- People can have two attitudes when queuing: cooperative or competitive.
- Each person is born with a natural tendency to become competitive. Although

Table B.6: Parameterization of model variables of the queuing model

Variable	Value	Range
radius-visibility	4 (m)	[0;6]
distribution-pick-up	normal	[normal; poisson]
acceptable-length	70	[0;500]
threshold-competitive	50	[0;100]
poisson-mean	3	[0.2;5]
impact-long-queues	5	[0; 20]
impact-seeing-cutting	4	[0; 20]
hours-open	8	[4; 8]
impact-length?	on	[on; off]
initial-corona-number	1	[1;5;10;15;20]

their tendency to become competitive might change in one queuing event because of their environment, their natural characteristic does not change (this is guaranteed by making the tendency to competitiveness equal to the natural tendency after the agent has been served).

- Time to attend food distribution - each person has a preferred time to go attend food distribution and it stays constant along runs: morning people will always be morning people, night people will always be... doomed.
- Once in the line for getting food, refugees always wait to be served before they leave;
- Both competitive and new competitive people only cut the line once - once they place themselves in a frontal position, they will way for their turn to be served
- It is assumed that everyone who attends food distribution will be served (i.e. it might happen that people with a late preferred time to pick up food are still in the queue past the closing time. Those will be served anyway).
- It is assumed that there is enough food for everyone (there is no shortage of food - everyone who lines up is served).
- Cooperative people follow social distancing while competitive and new-competitive people don't.
- The number of hours a food distribution center is open can be altered but it will always open at the same time (set to 9am).
- The more competitive one is, the more frontal it will place themselves in the waiting list.
- Queue manager (person serving) will not allow someone jumping to the first position.
- Other than to the first place (see assumption above), no one objects to people cutting in line.

- Two things can make people increase their tendency to competitiveness: the length of the queue and seeing other people cutting the line.
- People queuing only see people cutting the line if this happens in front of them.
- There is sufficient room to queue for food (In the model it is done in a long queue. However, this could also be done in a zigzag queue and it can be assumed that it will not highly influence the cases because cooperative people would still be distanced - given that there would be instructions to do so)

B.5 Technical Limitations

This section outlines some technical limitations of the queuing model. These are as follows:

- The preferred time agents get to attend the food distribution is actually the time they leave their shelters and start heading to the food point, not the time they arrive at the food location. Moreover, these values range between the opening time (and hence it can happen that the food point opens at 9 in the morning and no one is there yet) and one hours before its closing. This latter boundary is an attempt to guarantee that everyone arrives to the food distribution before it is closed. However, it could still happen that someone arrives after the closing time has passed (and it will still be served).

  This could be fixed either by tweaking the preferred time to get food or by introducing a mechanism in which the food distribution point only manages waiting lists (and hence serves people) between opening and closing, potentially leaving people in the queue and not serving them. In a real situation, having these not served people will probably result in distress and people returning to the queue with a more aggressive approach. However, that is not within the scope of this study;
- As the poisson distribution is a discrete one, it only returns integer values. These are then multiplied by 60 (to turn into minutes), giving very big differences between possible outcomes (60, 120, 180, etc.). However, by multiplying by 60 before doing the random process, it will give values in a very short range instead of spreading them throughout the hours during which the distribution is open. For this reason, the distribution used for the experimentation phase is the "normal". However, the poisson solution is implemented in the model and could be used if wanted;
- At the moment, the placement of cooperative refugees in a queue is dependent on the placement on the one in front. If there is a computing error placing one of the cooperative agents, this error will propagate to every cooperative agent standing behind in the queue. This is more of a design error due to inexperience in NetLogo. However, this error was never observed when running the model and observing the behavior. This could be fixed by setting the spatial placement of agents depending on their position in line instead of connecting it to the person in front. With this solution, in case there is a a computing error placing one of the agents, the error won't propagate;

- In one run, only the change of attitude cooperative to competitive can happen, not the other way around. For that reason, policies such as keeping people informed about the waiting time to make them stay as close to 0% as possible cannot be implemented in the middle of a run and would have to be included before. If so, then the impact of such a policy should be integrated by adjusting the values agents get for their *natural-tendency*.

B.6 Model verification

This section focuses on the verification tests performed in the queuing model. The aim of these tests is to evaluate whether the model behaves in the way it is intended and that no implementation errors occurred while writing the code. If the model passes these tests, then it is considered as a verified model that can be used for experiments and later on go through validation tests.

Note that the process of verification was a rather iterative one - when performing tests and realizing that the model was not behaving as intended, the model was adapted and the verification test performed again. This was done until the model passed all the conducted tests and could be considered verified.

To ensure reproducibility of results and that different runs can be compared during the verification, a seed was set to a fixed value.

B.6.1 Tracking agents

To verify agent behavior, agents were carefully tracked along some runs. This subsection focuses on three techniques used for this.

Coloring agents

After performing different actions, agents change their color to a different (pre-defined) one. This allows to observe the development of the model and understand where problems are coming up.

Changing attributes

Similarly to the color technique, agents were given odd but specific numbers to some attributes after performing different actions. When identifying an agent that is behaving in a non-desired way, this solution allowed to identify the path the agent followed before giving an error or deviating from the normal behavior. By understanding the path and functions that the agent conducted, it was easier to find the functions where the errors were.

Printing error statements

The integration of *output-print* statements along the code was also used. By printing the ID of each agent that performed some actions it was possible to identify errors and agents that were following functions that they should not.

Individually inspecting agents

Finally, a more time intensive approach was used when necessary. By individually inspecting some agents it was possible to identify some deviant behavior. All the problems that were found during this process were fixed once found.

B.6.2 Testing parameters

Another approach to verification tests is to evaluate the parameters used in the model. Again, this was done iteratively along the process and will not be reported one by one. For these tests different values were given to some of the interface parameters such as the *percentage-competitive* and the *threshold-competitive*. By changing the first variable it is expected that the number of competitive agents created when setting up the model changes accordingly. This was verified. The change of the threshold has a twofold impact: the result of this change should be seen in the values agents have for their *natural-tendency* when created but it should also impact the value of *tendency-to-competitiveness* needed to change attitude. Both of these changes were positively verified.

B.6.3 Extreme-condition test

After this, an extreme-condition test was performed. Again, the whole process followed will not be reported because it is too extensive and slightly redundant. For this test two different and interesting examples can be reported. The first deals with the *percentage-competitive*. By setting this value to 0% it is expected that no one joins the queue with an immediate competitive attitude. This was verified. Similarly, no one behaves cooperatively when this variable is set to 100% (for this scenario, please read Section 10.3 over the limitation of using this model in an extremely competitive setting). However, it is important to note that, when *percentage-competitive* is set to 0%, some agents along the run turn into *new-competitive* and choose a rather competitive approach. This is also validated as there are still mechanisms set for these agents to be influenced by their environment. The situation is as described: the whole population is cooperative; for this reason, they all wait in a queue when wanting to pick up food; this results in a high number of people waiting and, consequently, very long queues; by looking at these long queues, some agents get influenced (an amount equal to *impact-long-queue*) and, for some, this is enough to cross the threshold and become competitive (or more accurately *new-competitive)*; when with this new attitude, people cut the line, impacting others around. This sequence of events leads to people leaving the physical queue and cutting the line, but all with a *new-competitive* approach. To test a scenario in which no one naturally acts nor is influenced to act as competitive, all the *percentage-competitive*, *impact-long-queues* and *impact-seeing-cutting* variables are set to zero. In this situation, it is expected that no one at all diverts from the normal behavior of waiting in line. This is observed as expected.

B.6.4 Multi-agent testing

Finally, when testing the entire model with all the agents wanted as intended for the experimentation phase, undesired results were obtained. In specific, when increasing the percentage of naturally competitive people to 40% (*percentage-competitive = 40*), the average queuing time across all queuing agents resulted in a lower value than when this variable was set to 30%. Although this is an unexpected result, it can be easily justified by the simplification made in the modeling process that people who cut the line only do it once. While this simplification will not heavily impact the dynamics when the percentage of competitive population is maintained in lower values (from 0% to 30%), it can be argued that this represents the boundary for which the model can be used to represent the real system. In an environment where a big part of the population does not respect queues and decides to cut the line instead, it can be argued that a whole dynamic of cutting and pushing can emerge, which this model can not reproduce. Moreover, this could even raise a discussion if this environment can be included in *queuing* modeling or if it is a switch to *crowd chaos*.

After having performed the verification tests explained above and given the limitation referred in the last paragraph, it was considered that the queuing model is verified and behaves as intended when applied to a population with 30 or less per cent of competitive individuals. However, this model should not be used when wanting to simulate the queuing process of a population with 40% competitive individuals.

Appendix C

Coupling models

This appendix covers the implementation component of coupling the two models. First, it will focus on the actual coupling process and its challenges (Section C.1). Then, the parameterization of the model variables (Section C.2). Finally the assumptions of the coupled model are enumerated (Section C.4).

C.1 Coupling process

Figure C.1 shows the flow of the coupled model. This diagram shows mostly the flow of the model developed by Bögel and the place where the queuing model is integrated (in blue). From then on, the model follows the logic of the queuing model explained in Figure B.1.

As the queuing model was originally developed with the final intention of using it in this study, design decisions when developing the model were already fitted to the problem. For example, although the model represented any queuing event, agents were purposely called *refugees* and *food distribution*. Coupling the models was done through a direct integration of the code responsible for the queuing process in Bögel's code. In order to achieve this two main things were done: first, Bögel's model was studied to a very extended detail in order to understand the reasoning of the model and make the process of integrating the codes easier; then the model was integrated by mostly add a test checking the agent's current activity - if this activity was food distribution, then make sure they follow the queuing process with the new code. In order to make the models consistent and guarantee their functioning, it was necessary to change the name of the *refugee* agents to *tents*.

C.1.1 Challenges

When coupling models developed by different authors, challenges can arise from differences of reasoning or simply from different syntax. Overcoming these represents the majority of time spent coupling models. Some of the challenges faced during these process were:

- The way Bögel developed the model, refugees are conceptualized as a unique shelter (i.e. household) represented in the model as a tent. Once it is time to

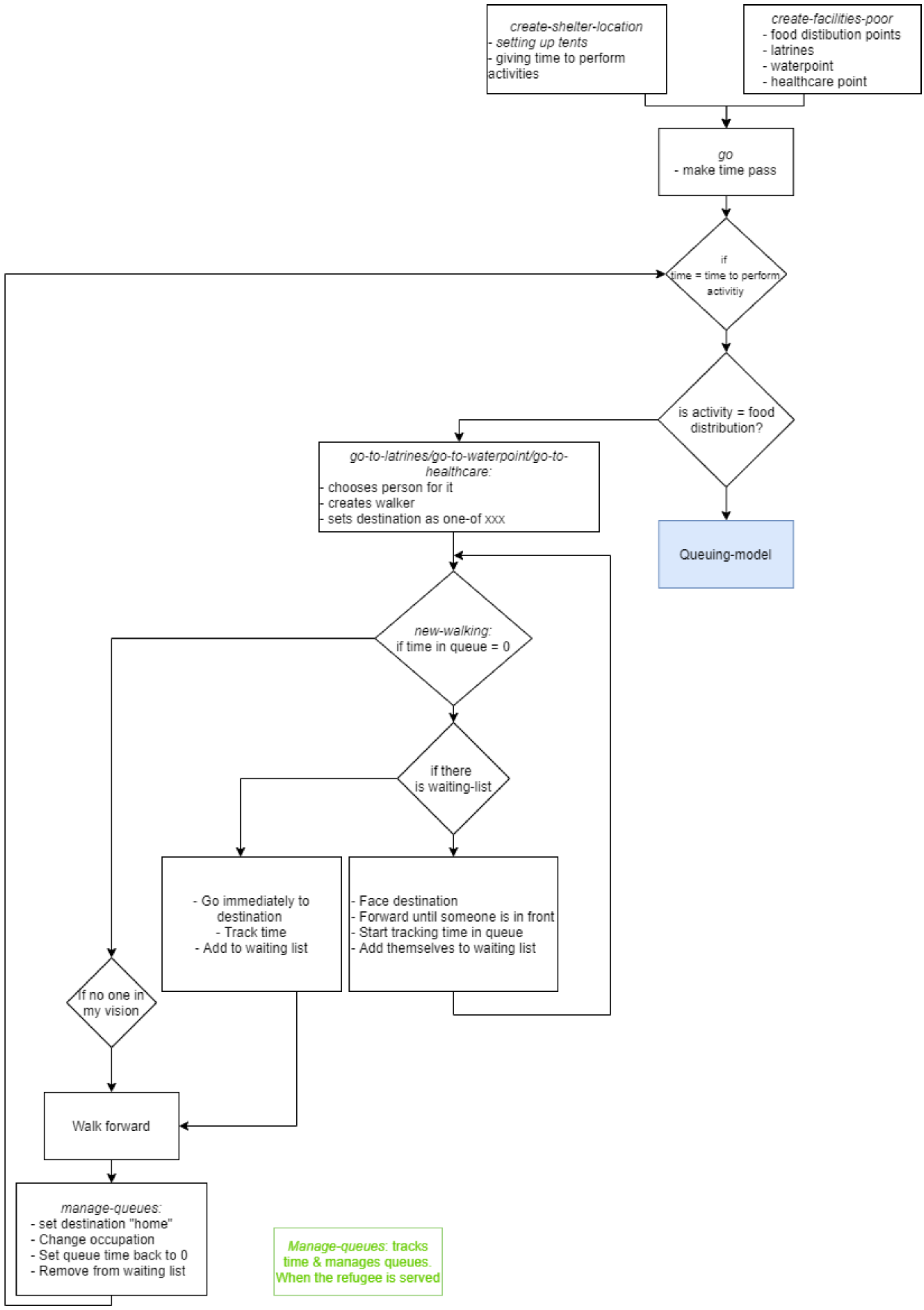


Figure C.1: Flow of the coupled model

conduct an activity, these tents create *walkers* to perform these activities. This raised a challenge for the implementation of the representative-based policies. In order to overcome this challenge, an agent set called *representatives* was created and only these agents attend food distribution

- Another challenge rose from the modeling decision that agents could just move to a location instead of walking there. In order to correctly simulate a queue, it is necessary to have agents that walk step by step. As the focus of the study is the process of distributing food, the model was slightly adjusted to make refugees walk when they attend food distribution but not to other activities (as this is considered outside of the scope).

- Extra challenges rose from the spatiality of the model. If everyone behaves cooperatively but too many people attend the food distribution (in the baseline, for instance), a very long queue can form. To avoid the queue reaching the boundaries of the world and agents pilling on top of each other (leading to a lot of infections since no distance is kept), an extremely large world was created (see Figure C.3). Instead of a long queue a zigzag queue (also known as serpentine queue) could have been used. This, however, is assumed to not make a relevant difference since the big gap between various layers in these would avoid transmission between people who queue at the same x coordinate but different y coordinates. For this reason, the decision of going for an extremely large world was made. This had as implication that the other facilities are placed very far from the camp. However, that is considered to not be a problem since agents are transported there (use *move-to*) instead of (*go-to*).

C.2 Parameterization

As the coupled model is just a combination of Bögel's model and the queuing one, the parameters involved in it are also a combination of these. The only addition made was the creation of a variable *initial-corona-number* that represents the size of the outbreak (number of infections) in day 1, which is set by default to 1. For that reason, further explanation of the motivation of the parameter values is not needed (considering the one given in Bögel's work (2020) and Section B.3). Table C.1 summarizes the values for each one of the variables and the range they can be varied within.

Note that this table only includes the interface variables that are not used for policy implementation (*policy-implemented* and *time-slot?*) nor scenario creation (*percentage-competitive*).

C.3 Model interface

Figure C.2 and Figure C.3 C.3 show the interface of the coupled model. These figures depict the model interface and the world, respectively. Note that, as mentioned in the coupling challenges, the world of the coupled model had to be adjusted to allow people to queue behind each other. Although this increases the time needed to run the model, the benefit of allowing people to queue cooperatively behind each other is deemed to be a sufficient reason to do this.

Table C.1: Parameterization of model variables in the coupled model

Level	Variable	Value	Range
Original model	*compliance*	100 %	[0;100]
	transmission-probability	5 %	[0;100]
	social-distancing	1.5 (meters)	[0.5;1;1.5]
	factor-asymptomatic	1	[0.5;2.0]
	food-delivery-day	8 (day)	[1;27]
	mask-usage	yes	[yes;no]
	mask-effect	50 %	[0;100]
	household-size	5 - 10% elderly	[5-10% elderly; 5-20% elderly; 7]
	plotsize-shelters	12.5 (m2)	[12.5;25;50;100]
	mobility	free	[free; quarantine; isolation; no-elderly]
	poor-conditions?	on	[on;off]
	block-size	120	[60;120]
Queuing model	*radius-visibility*	4 (m)	[0;6]
	distribution-pick-up	normal	[normal; poisson]
	acceptable-length	70	[0;500]
	threshold-competitive	50	[0;100]
	poisson-mean	3	[0.2;5]
	impact-long-queues	5	[0; 20]
	impact-seeing-cutting	4	[0; 20]
	hours-open	8	[4; 8]
	impact-length?	on	[on; off]
	initial-corona-number	1	[1;5;10;15;20]

C.4 Assumptions

Similarly, the assumptions over which the model relies on are a combination of assumptions initially made by Bögel and assumptions made during the process of this thesis. For that reason, please refer to Section B.4 for the queuing related assumptions.

From Bögel's work (2020), the following assumptions remain true:

- Agents perform four types of activities: use of latrines, obtaining food and water and visiting healthcare facilities;
- Facilities have set opening times and are located on two edges of the settlements (except for the food distribution);
- Every household performs the activities with the following frequency: visit latrines (7x per day), obtain food (once every 28 days), obtain water (1x per

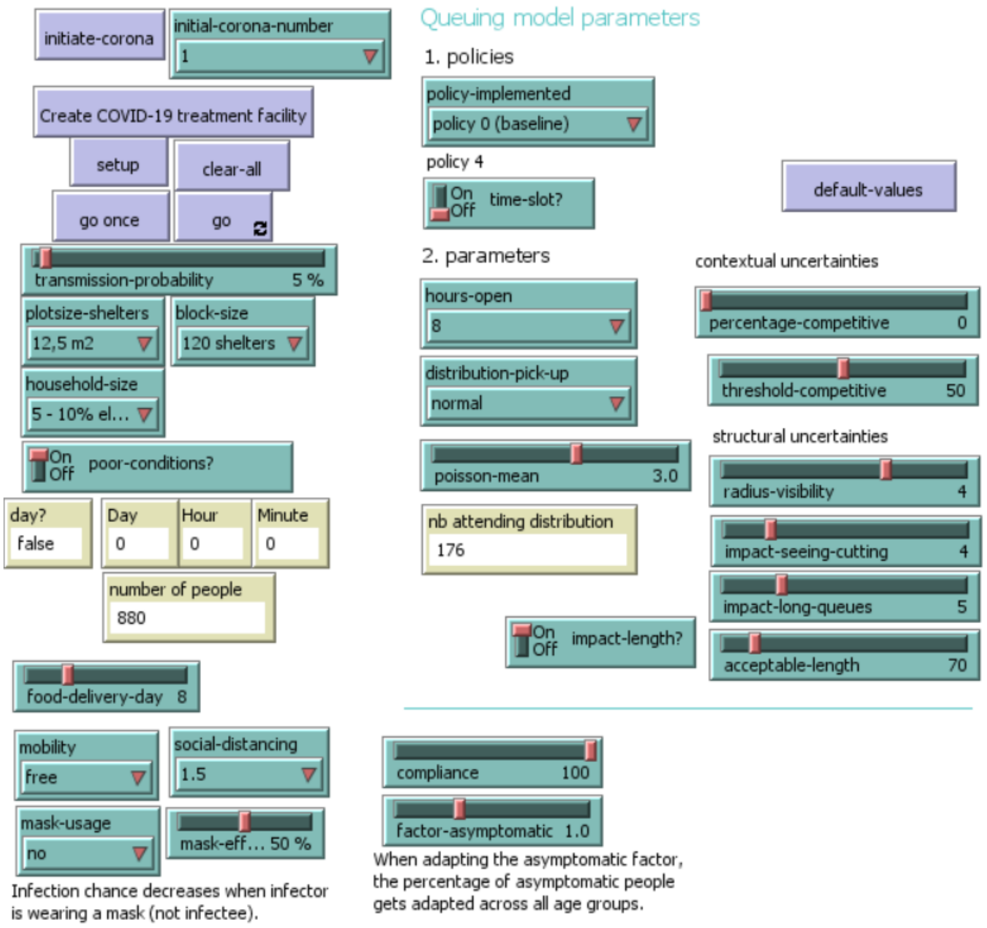


Figure C.2: Interface of the coupled model - Inputs

day) and visit healthcare facility (when sick);

- Service time of each facility is as follows: latrine (2 minutes), water point (15 minutes) and healthcare (10 minutes);
- Food distribution service time depends on the policy in place (i.e. depends on how many people the agent is picking up food for)
- All households obtain food at the same day and it must be done by an adult or elderly;
- Food and water are, if possible, obtained by a healthy household member;
- People arrive at a facility instantly (i.e. they don't walk there) - this is for all activities except food distribution;
- After an activity, a person returns to its shelter instantly;
- COVID-19 infection can occur when agents are within 1.5 meters distance of an infectious person;
- After being infected, people become immune to COVID-19;
- COVID-19 progression follows the flow presented in Appendix A;
- COVID-19 progression is different from children, adults and elderly;

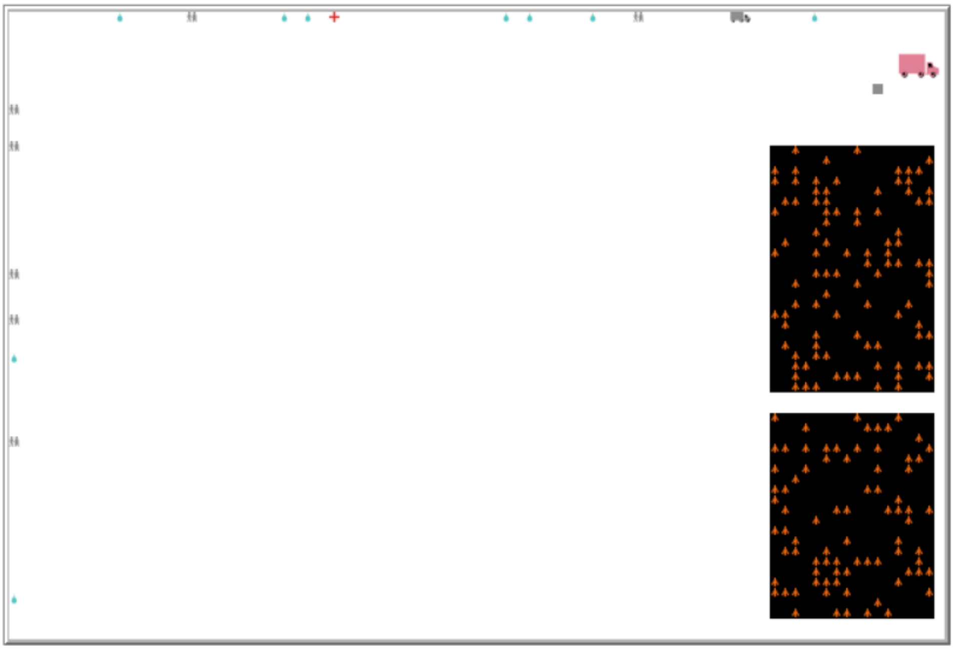


Figure C.3: Interface of the coupled model - World

- Children have a lower probability of getting infected but, once sick, they have a similar chance of infecting others;
- Elderly are more likely to develop severe symptoms and therefore have a higher Case Fatality Ration (CFR);
- Children are less likely to develop severe symptoms and therefore have a lower CFR;
- COVID-19 infection perception can differ from actual infection status;
- 10% of all infected people immediately suspect they are infected (and consequently set their perception to infected). When they become asymptomatic, their perception changes to healthy again;
- Time between consecutive stages is equally distributed among the different age groups;
- Disease progression only moves in one direction: people cannot go back to symptomatic anymore once they have become severely or critically ill.

Other assumptions made but not specifically identified by Bögel are the following:

- It is assumed that shelters do not offer the possibility of infected refugees to isolate from the rest of the household;
- Vaccination programs is not considered - immunity can only be achieved through previous infection;
- After the first case appears in the settlement, it is assumed that no one enters or leaves the perimeter.

From the further development of this study (and excluding the queuing assumptions mentioned before), the following assumptions are considered:

- There is enough room to create a long queue in the settlement;
- Refugees are dependent on food distribution and their functioning for survival;
- The service time to give a refugee food for their household is around 4 minutes;
- The serving capacity of the food distribution is maintained constant;
- The representatives (when implementing policies) are randomly chosen from the population;
- It is assumed that no one other than representatives attends food distribution if a policy is implemented.

The reasoning for some of the assumptions and the implication of others is further discussed in Chapter 9.

Appendix D

Model verification

This appendix focuses on the verification of the coupled model. As mentioned in the main text, the coupled model results from a hard integration of a verified model (the queuing model) into another verified model (developed by Bögel (2020)). The verification tests performed in each one of these models can be found in Appendix B.6 and in Bögel's report, respectively.

In order to test if the coupling process was correctly done, the coupled model was subjected to extra verification tests. After performing these, it was concluded at the coupled model is also verified. Note that the previously mentioned limitation regarding the competitiveness of a population maintains. For this reason, it is concluded that the coupled model is verified to be used under the same circumstances as the queuing model (and, consequently, not for a population with tendency to behave competitively in a queue).

Attending the (right) food distribution

In order to have enough room for the food distribution, a different food point was set up. This can be found between the camp and the boundaries where the rest of the model facilities are found. The main change when integrating the queuing model in the model developed by Bögel is that refugees should attend the new food point. This was verified and works as expected.

Tracking agent behavior

Similarly to the tests reported for the queuing model, the verification procedure of the coupled model also involved tracking agents and their behavior. The same techniques were used for this, together with a bigger focus on tracking individual agents. After fixing the problems found along the process, it is considered that the model is working as intended.

Verification of policies

Finally, it is important to refer back to the process of implementing policies in the model. While in the queuing model this was done by simply reducing the number of total agents in the model (as the model's unique purpose was to simulate queues this does not affect the overall logic of the model), the same approach could not be taken for the coupled model. In other words, even if representatives are used and less people attend the food distribution, the rest of the model integrates the whole population of the camp.

As a solution to this problem, an agent set called *representatives* was created. The agents that are part of this agent set are the ones who are supposed to attend the food distribution. The number of agents in this set should depend on the policy implemented. In order to guarantee that these are the only people attending food distribution, the *go* function only checks if it is food time for this agent set. By checking the number of representatives in different set ups with different policies implemented, this integration can be verified as well.

Overall, the model is considered to behave as intended. In other words, it can be argued that the coupled model is verified.

Appendix E

Model results

This appendix contains all the results generated in this study. Explanation on the figures will not be provided in the Appendix as it can be found, if relevant, in the main text.

E.1 Model behavior in the baseline

Average time in the food distribution queue across all queuing agents

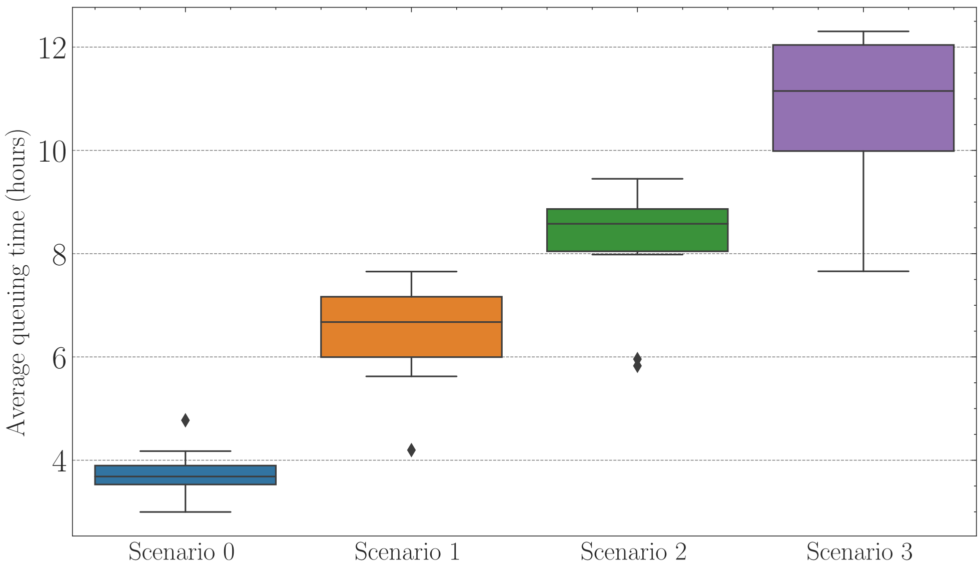


Figure E.1: Average time in queue across all queuing agents: Baseline in each Scenario (E0)

Cumulative cases over time

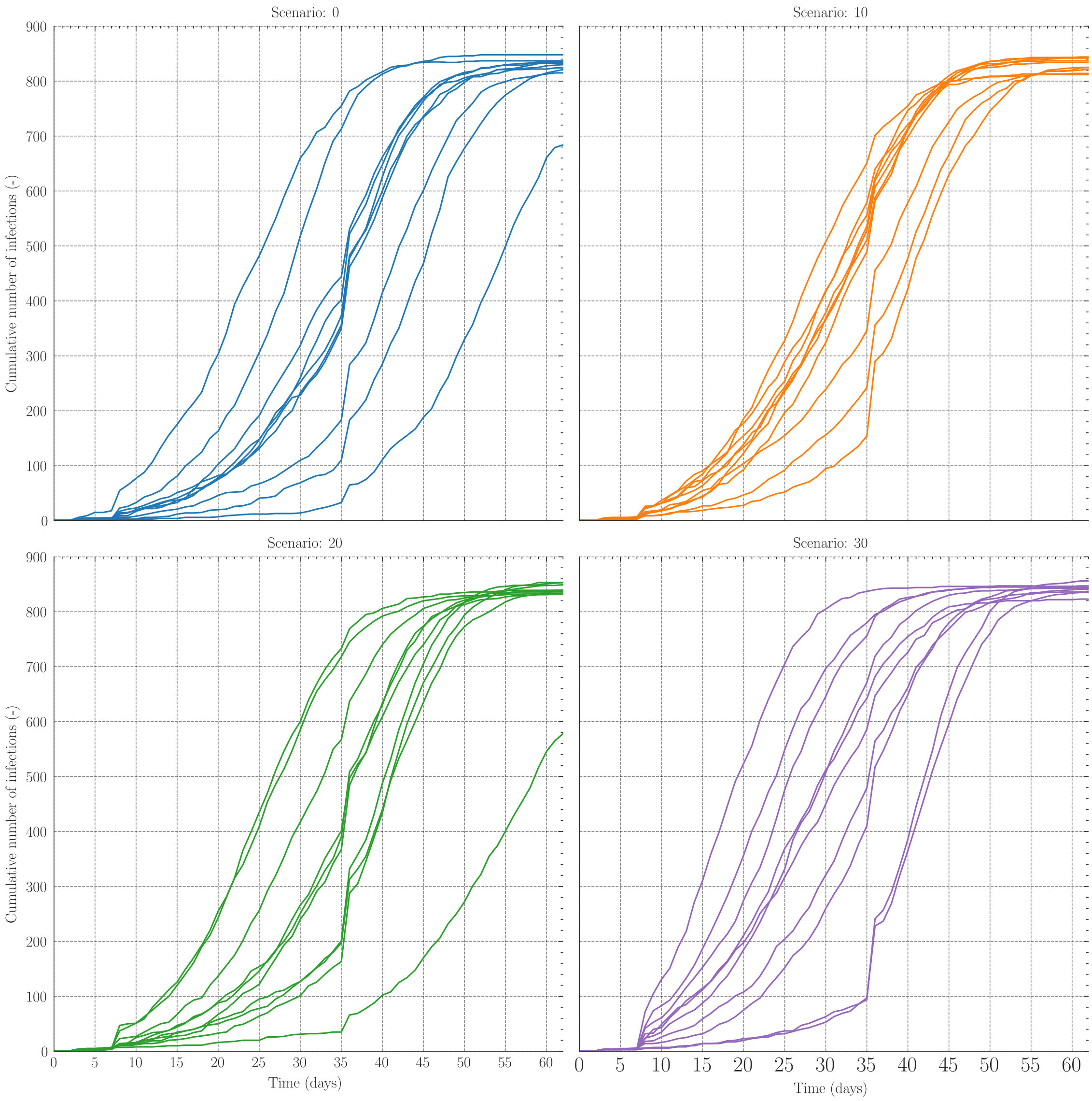


Figure E.2: Cumulative infections: Baseline in each Scenario (E0)

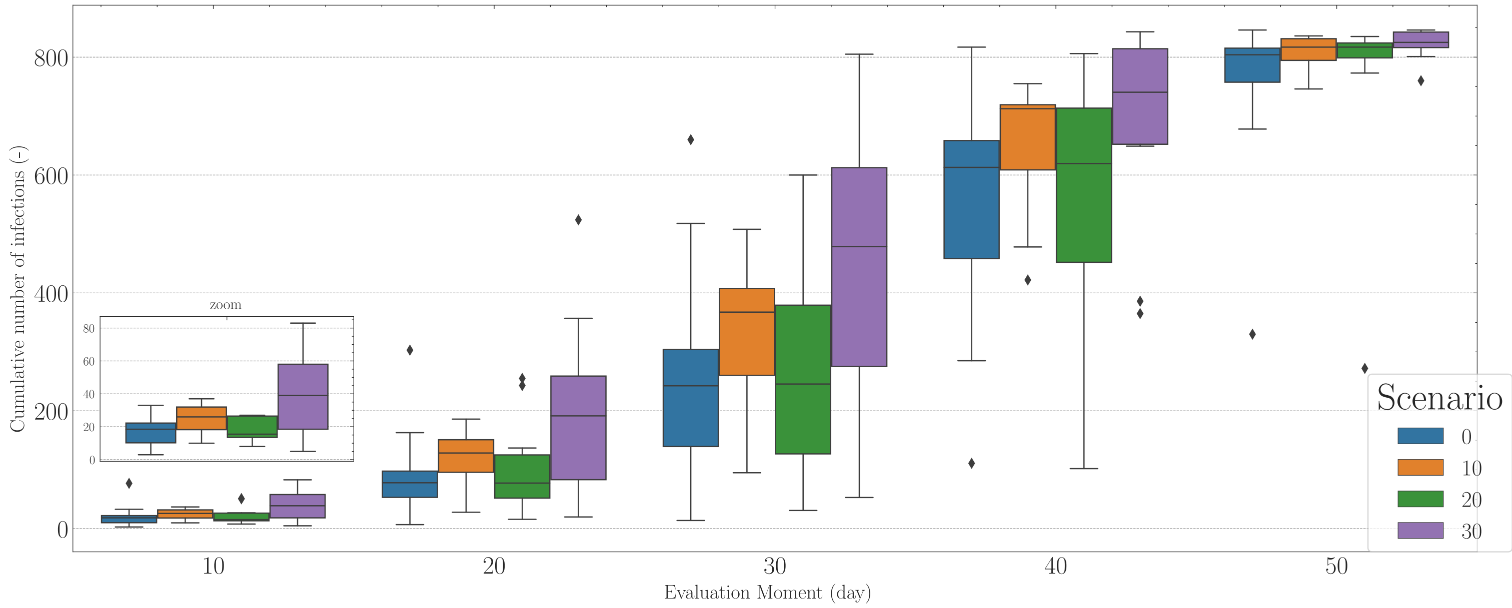


Figure E.3: Cumulative infections: Baseline in each Scenario (E0)

Average time in the food distribution queue per attitude

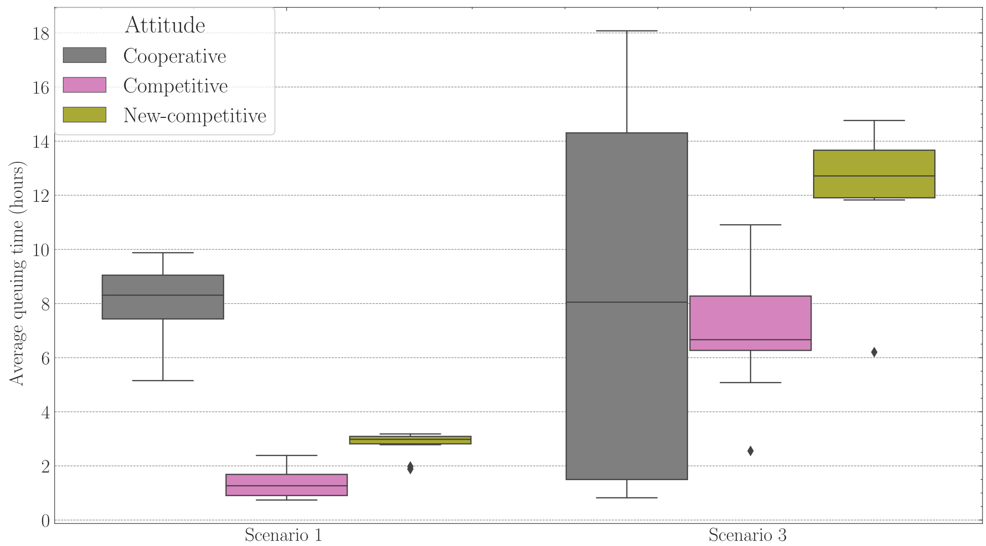


Figure E.4: Average time in queue per attitude: Baseline in each Scenario (E0)

Number of people switching behavior

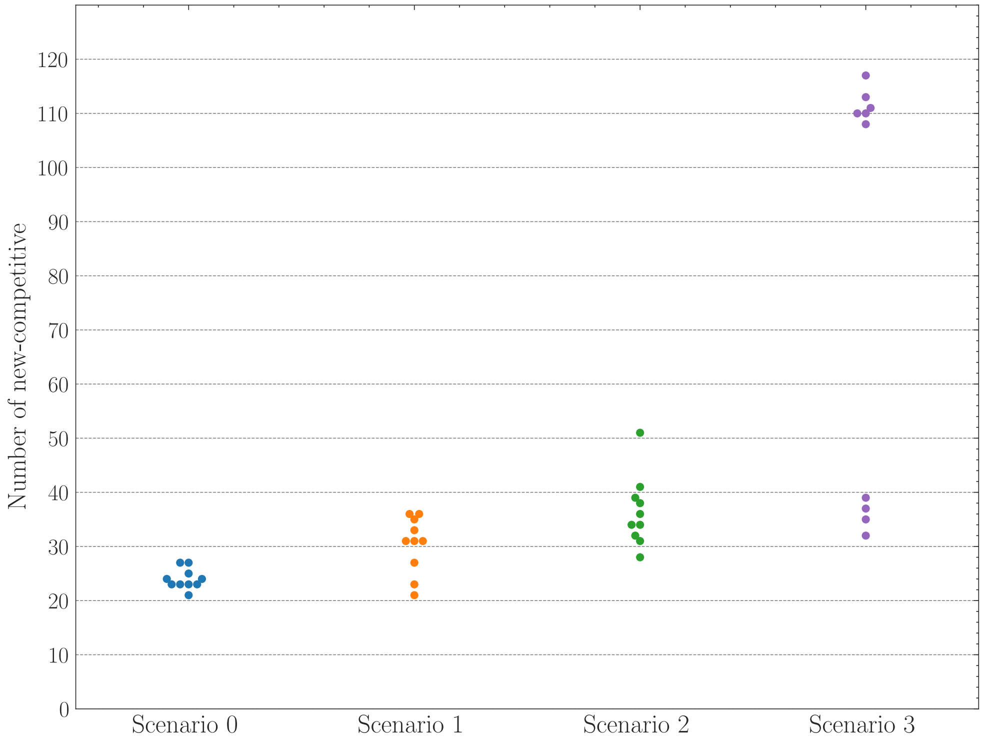


Figure E.5: Number of people switching to a competitive behavior: Baseline in each Scenario (E0)

Likelihood of getting infected

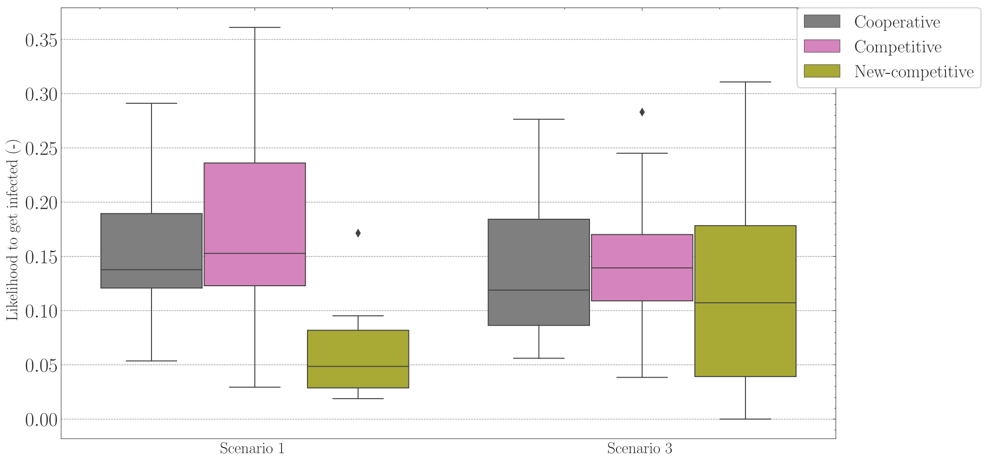


Figure E.6: Likelihood of getting infected at the food distribution per attitude: Baseline in each Scenario (E0)

Likelihood of infecting

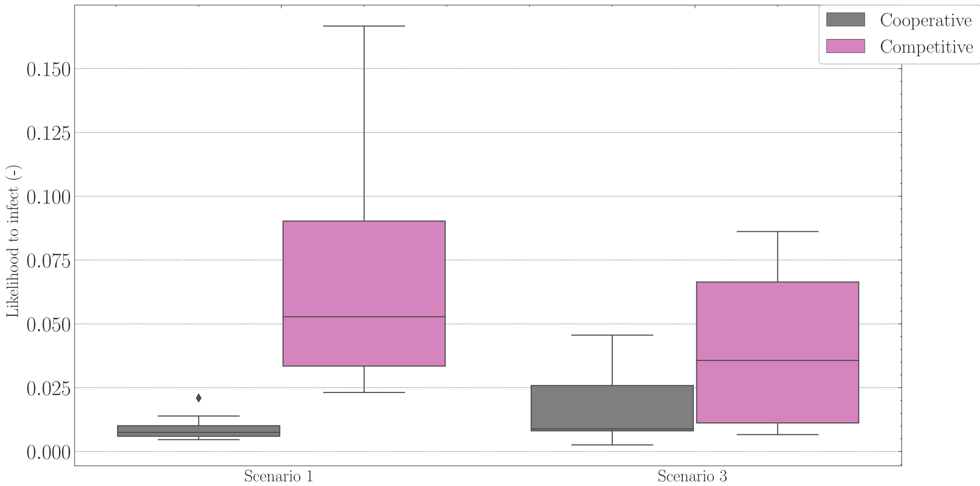


Figure E.7: Likelihood of infecting during the food distribution per attitude: Baseline in each Scenario (E0)

Identification of points of interest

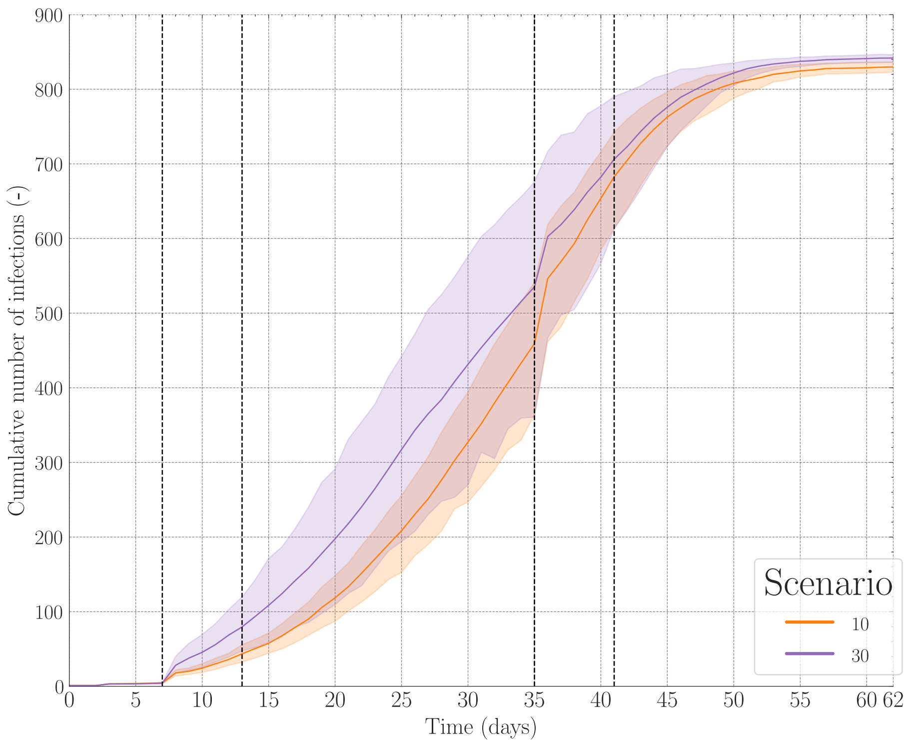


Figure E.8: Cumulative infections: Identification of the moments of evaluation (E0)

Cumulative cases per moment of evaluation

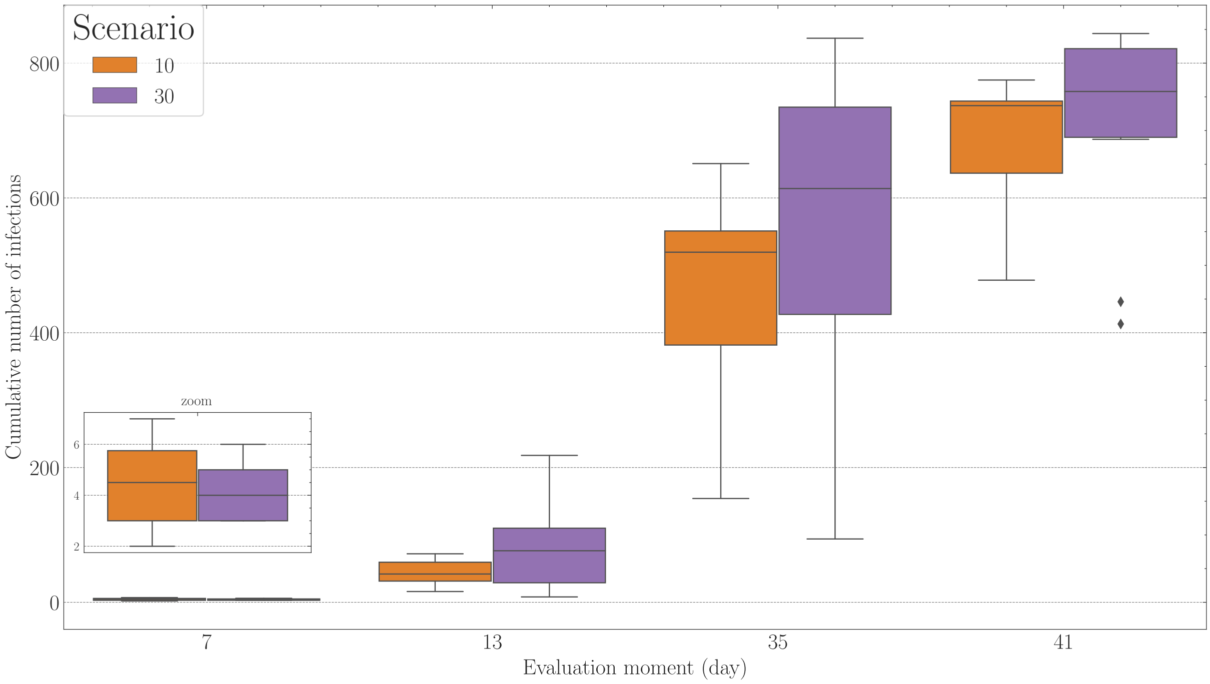
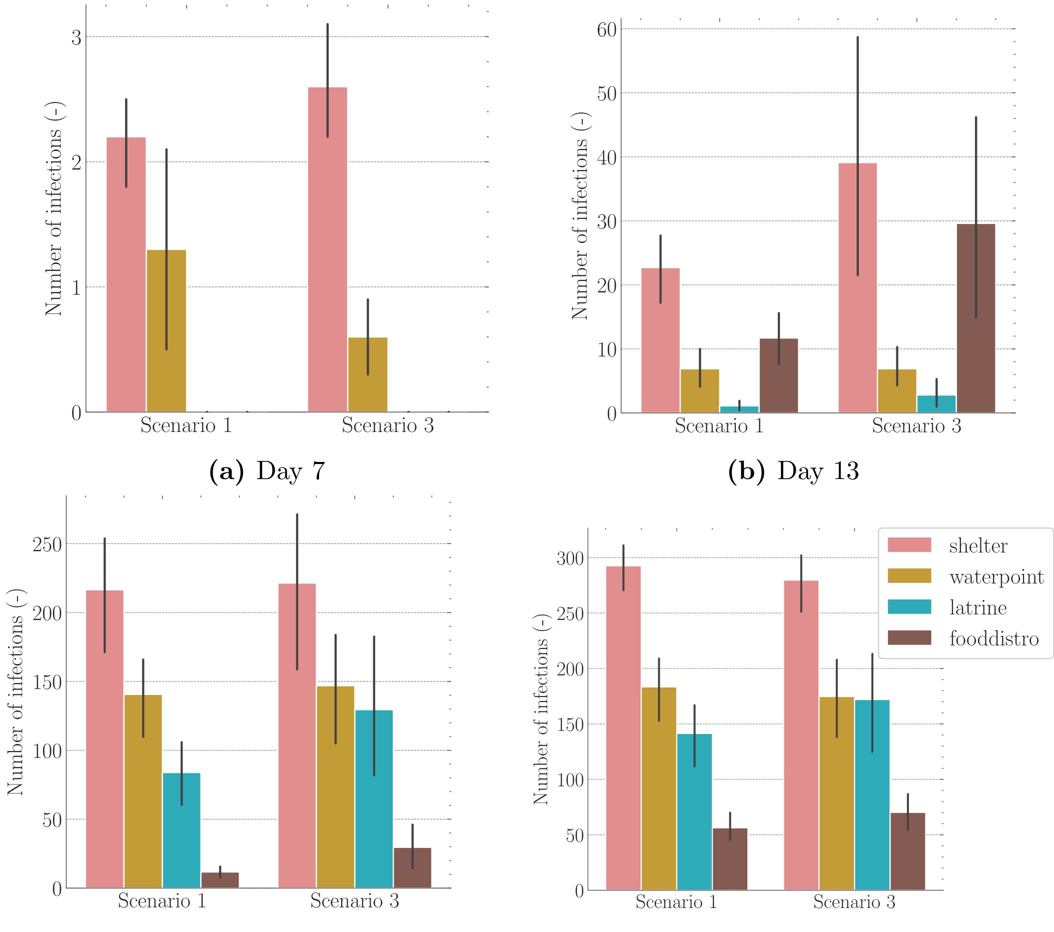


Figure E.9: Cumulative infections: Baseline in each Scenario of interest per moment of evaluation (E0)

Distribution of location per moment of evaluation



(a) Day 7

(b) Day 13

(c) Day 35

(d) Day 41

Figure E.10: Cumulative infections per location: Baseline in each Scenario of interest per moment of evaluation (E0)

Visualization of the relative impact of each location in the infection chain

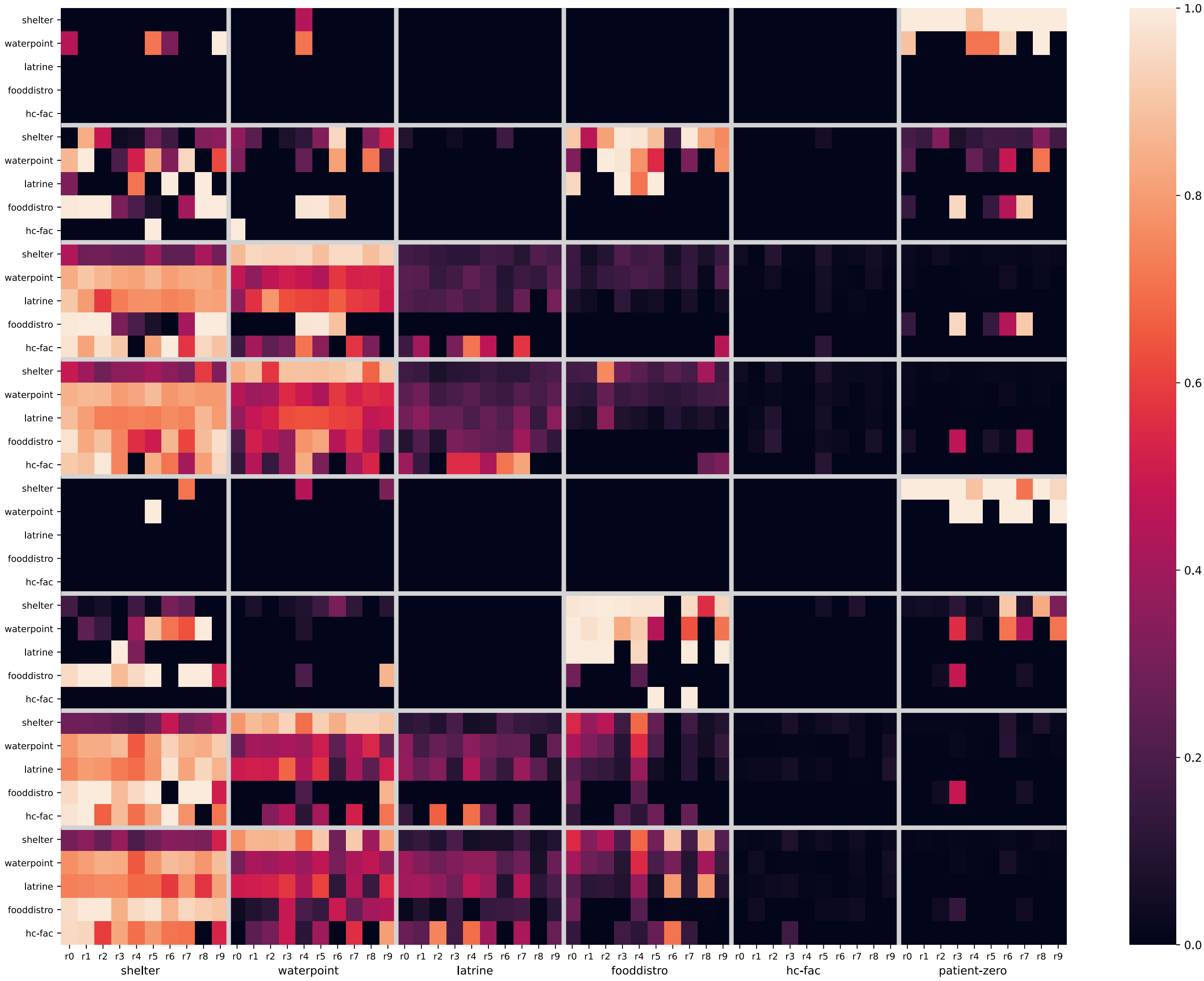
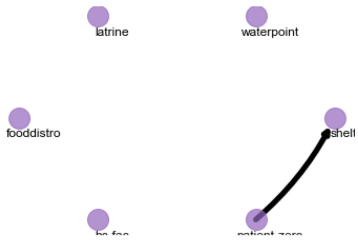
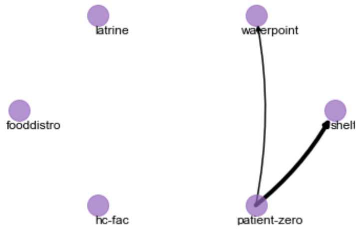


Figure E.11: Visualization of the relative impact of each location in the infection chain: this heatmap shows the variation between replications in both scenarios of interest (S1 and S3) in the four moments of evaluation (7, 13, 35 and 41). The first four rows are representative of scenario 1 and the bottom four are scenario 3. The y-axis show the place where the infection occurred while the x-axis shows the place where the infector was infected in the first place. In the x-axis it is also possible to see the number of the replication

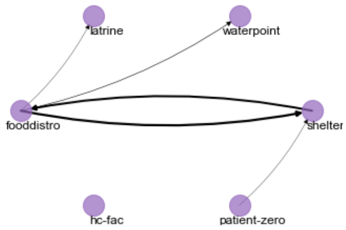
Visualization of two runs of scenario 3 with different behavior - role of stochasticity



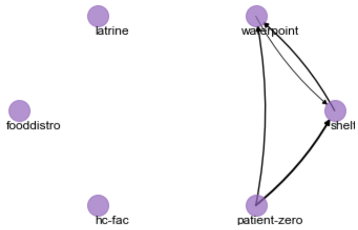
(a) Day 7 Rep. 0



(b) Day 7 Rep. 6

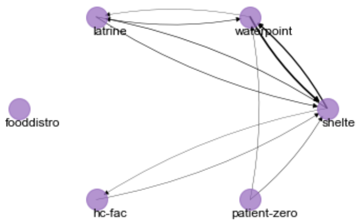


(c) Day 13 Rep. 0

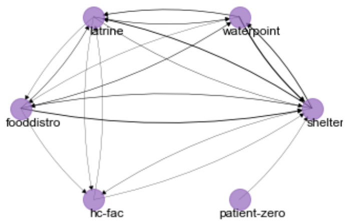


(d) Day 13 Rep. 6

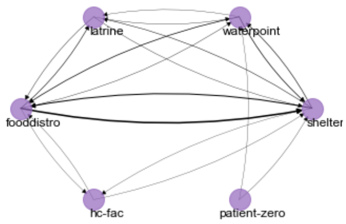
(e) Day 35 Rep. 0



(f) Day 35 Rep. 6



(g) Day 41 Rep. 0



(h) Day 41 Rep. 6

Figure E.12: Infection network: Identification of two baseline runs in the same scenario (S3) that lead to different dynamics

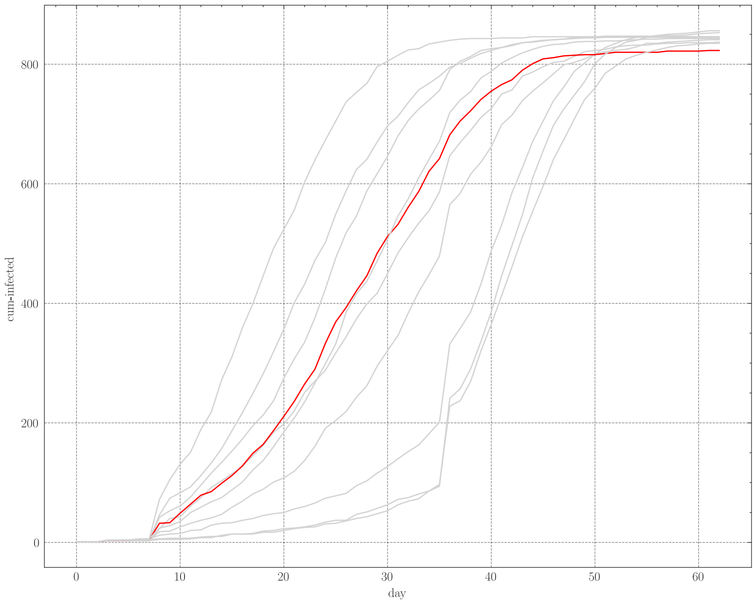


Figure E.13: Cumulative number of infections: Observation of replication 0 of scenario 3

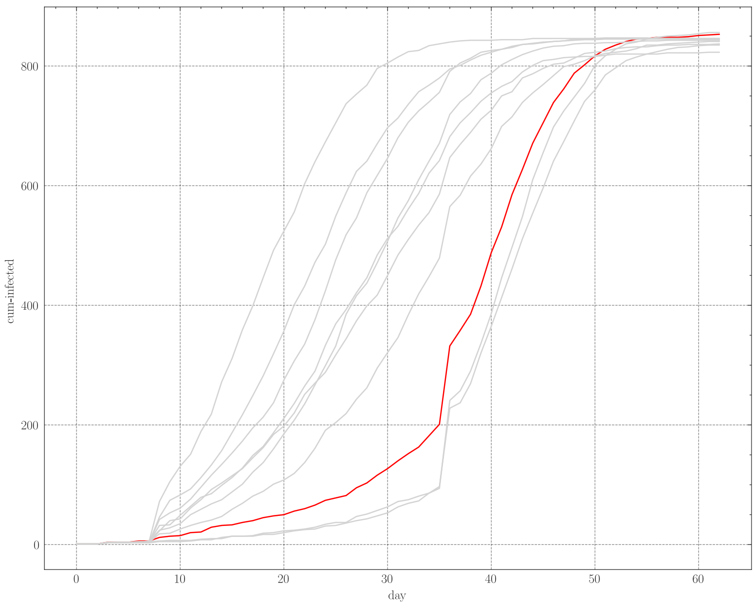


Figure E.14: Cumulative number of infections: Observation of replication 6 of scenario 3

E.2 Representative-based policies

Average time in the food distribution queue across all queuing agents

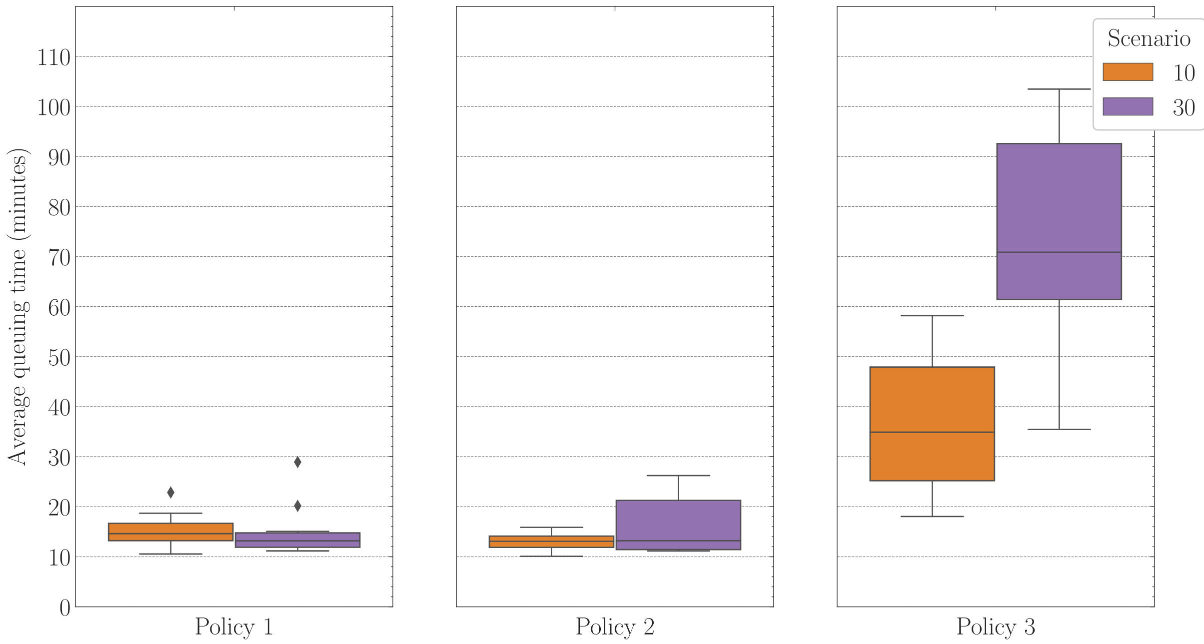


Figure E.15: Average time in queue across all queuing agents: Implementation of representative-based policies (P1, P2 and P3) in Scenario 1 and Scenario 3

Average time in the food distribution queue per attitude

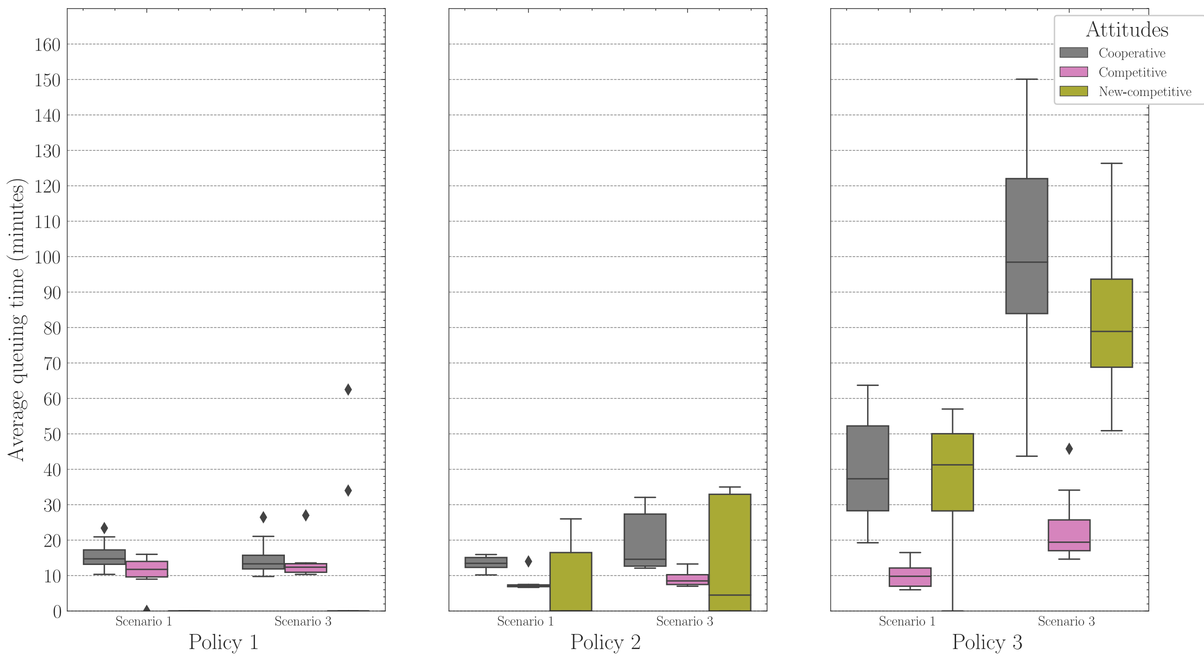


Figure E.16: Average time in queue per attitude: Implementation of representative-based policies (P1, P2 and P3) in Scenario 1 and Scenario 3

Number of people switching behavior

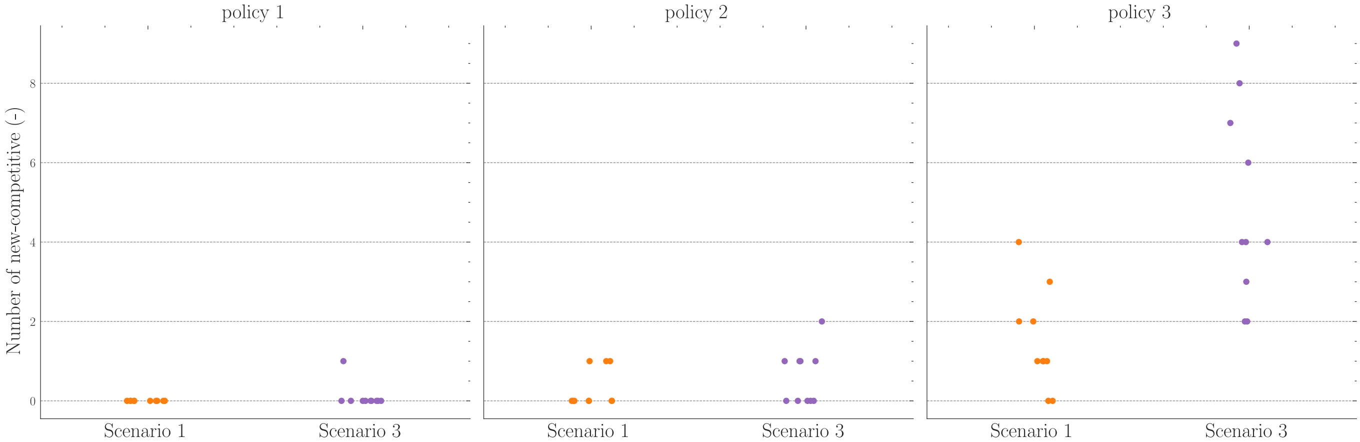


Figure E.17: Number of people switching to a competitive behavior: Implementation of representative-based policies (P1, P2 and P3) in Scenario 1 and Scenario 3

Cumulative Cases

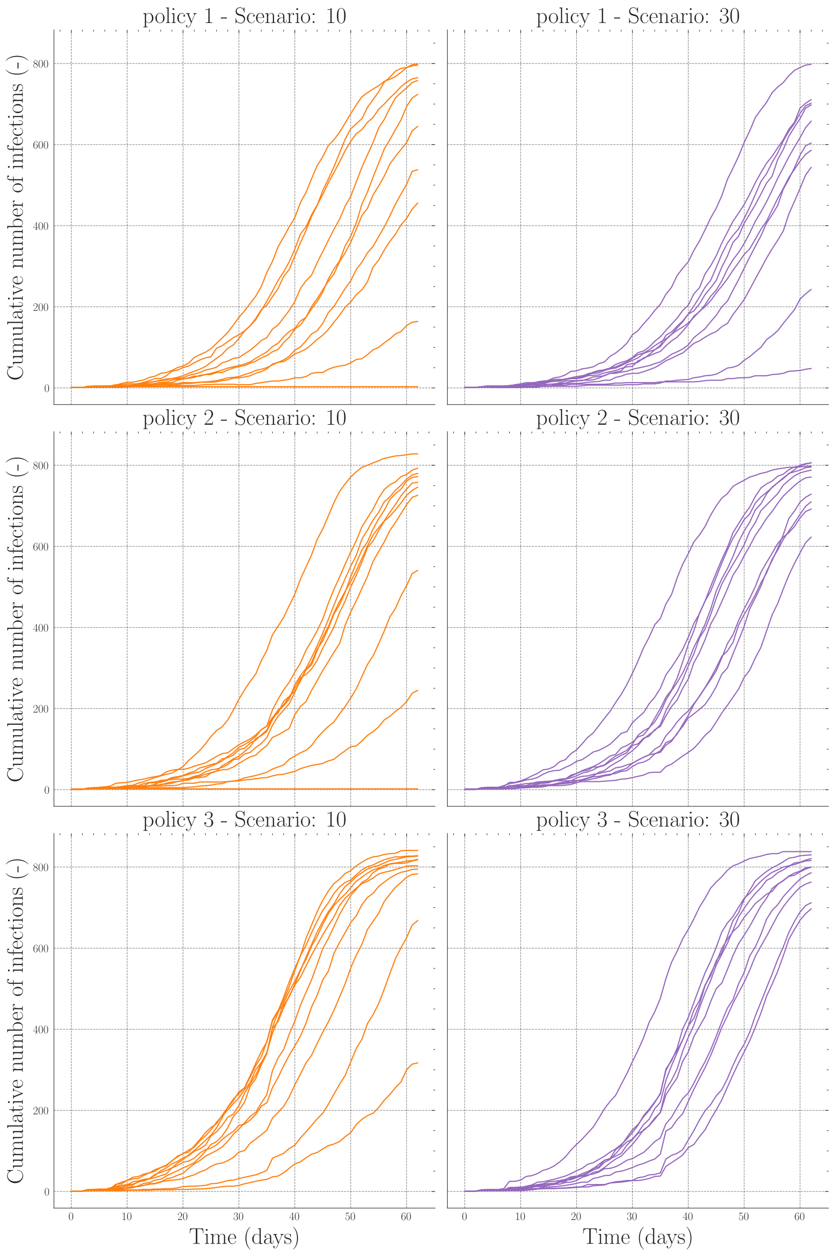


Figure E.18: Cumulative infections: Implementation of representative-based policies (P1, P2 and P3) in Scenario 1 and Scenario 3

Likelihood of getting infected

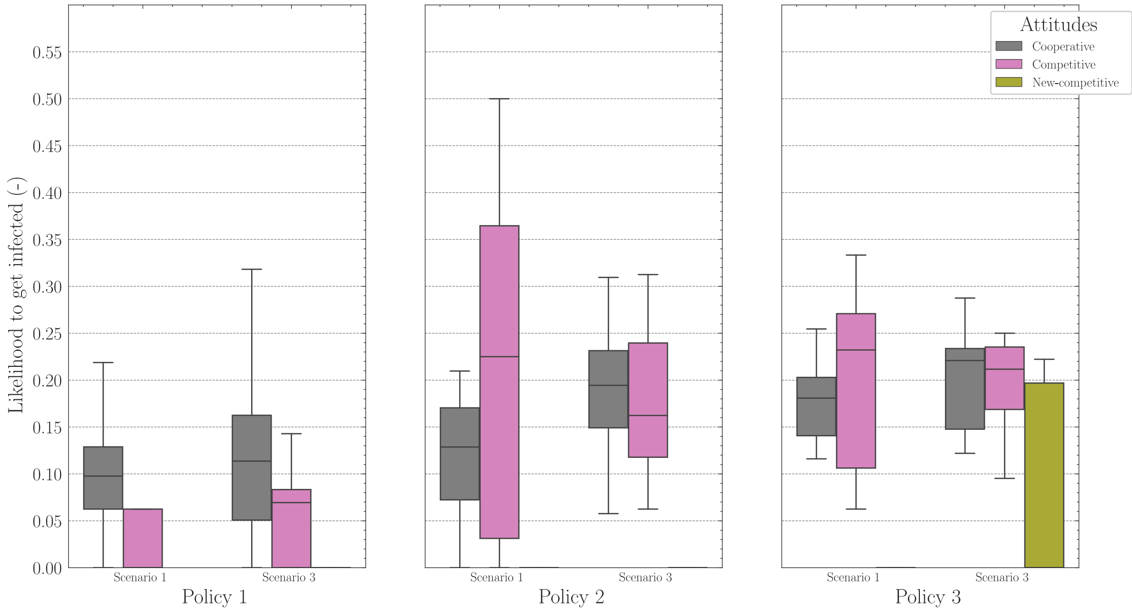


Figure E.19: Likelihood of getting infected: Implementation of representative-based policies (P1, P2 and P3) in Scenario 1 and Scenario 3

Likelihood of infecting

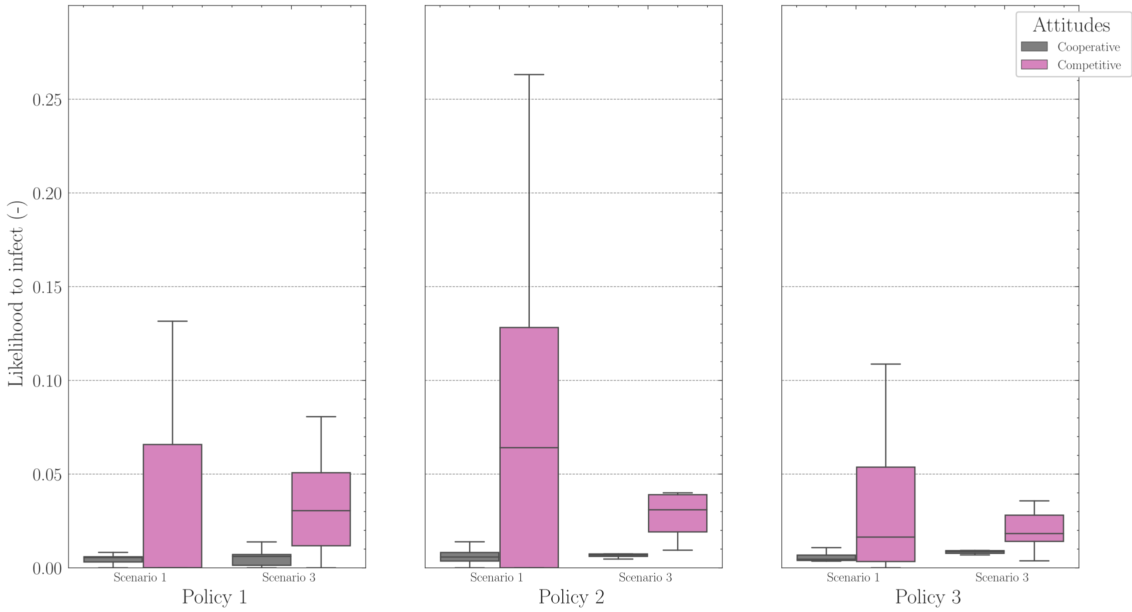


Figure E.20: Likelihood of infecting: Implementation of representative-based policies (P1, P2 and P3) in Scenario 1 and Scenario 3

Distribution of location per moment of evaluation

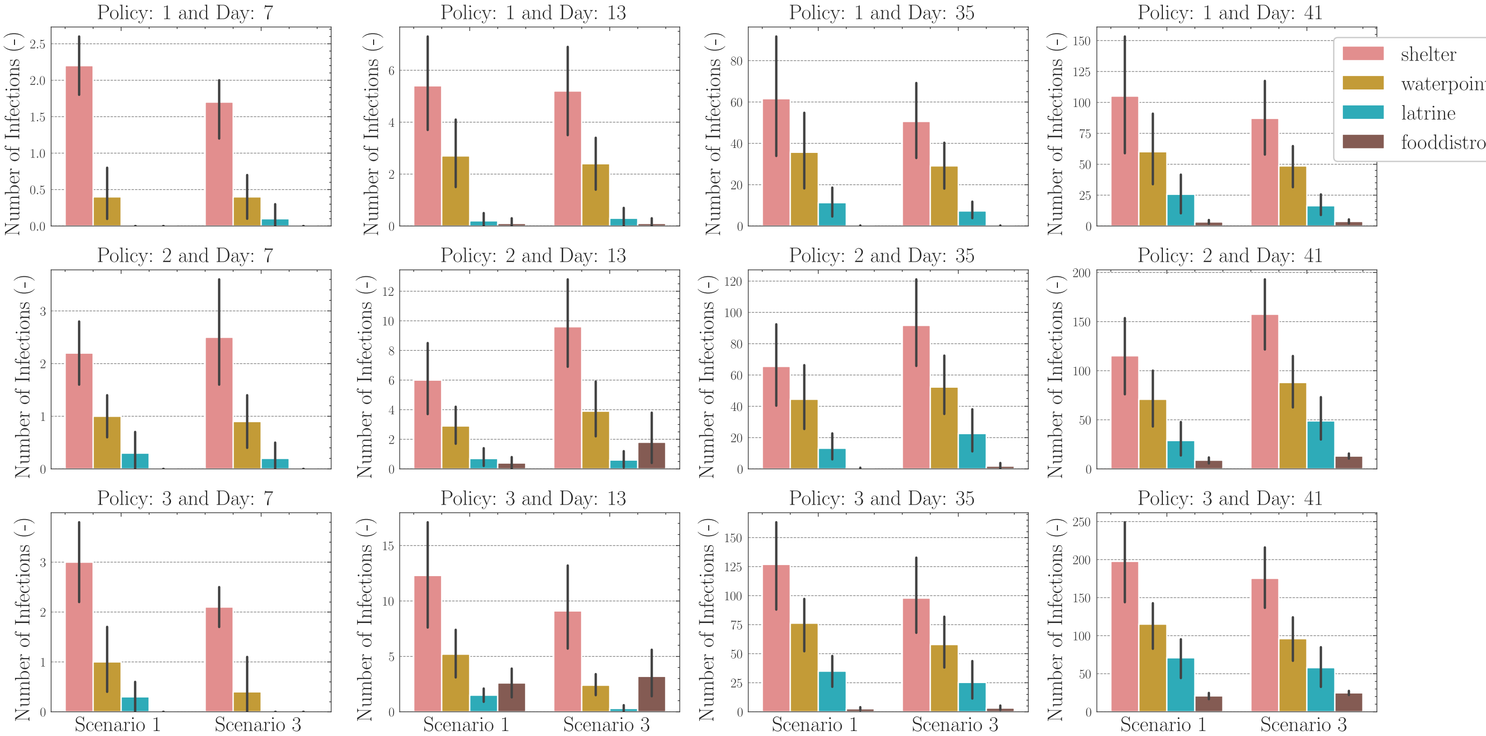
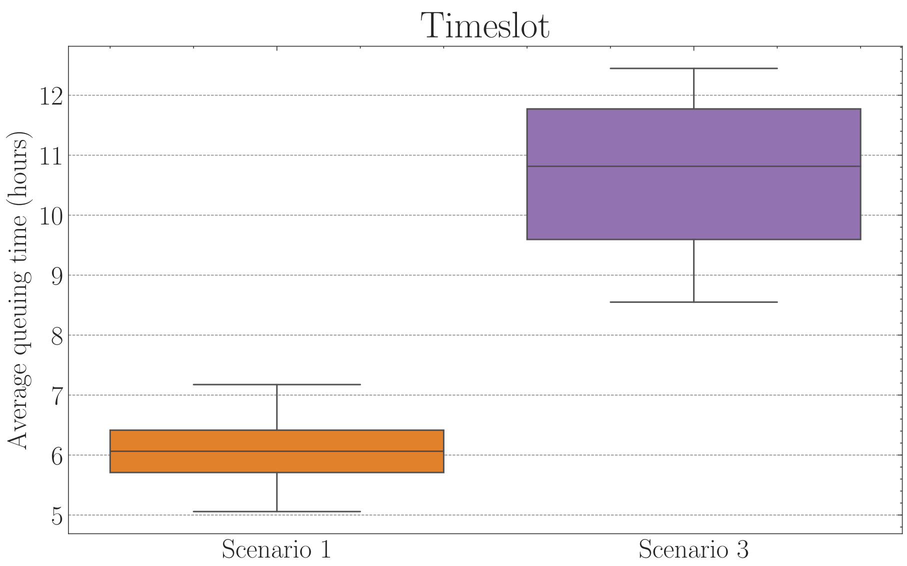


Figure E.21: Distribution of infections per location per moment of evaluation: Implementation of representative-based policies (P1, P2 and P3) in Scenario 1 and Scenario 3

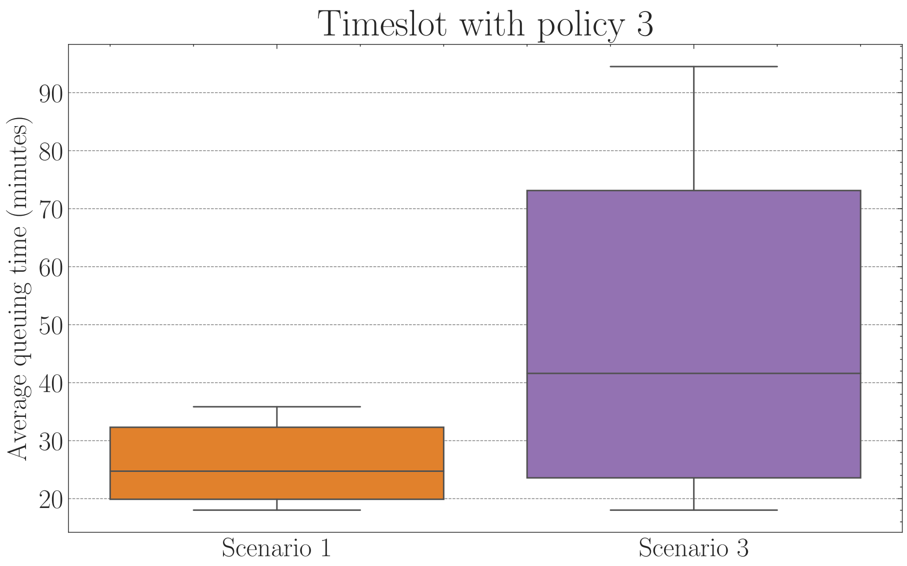
E.3 Timeslot-based policies

In this section both the results of the implementation of the timeslot alone and the combination of the timeslot and policy 3 are included.

Average time in the food distribution queue across all queuing agents



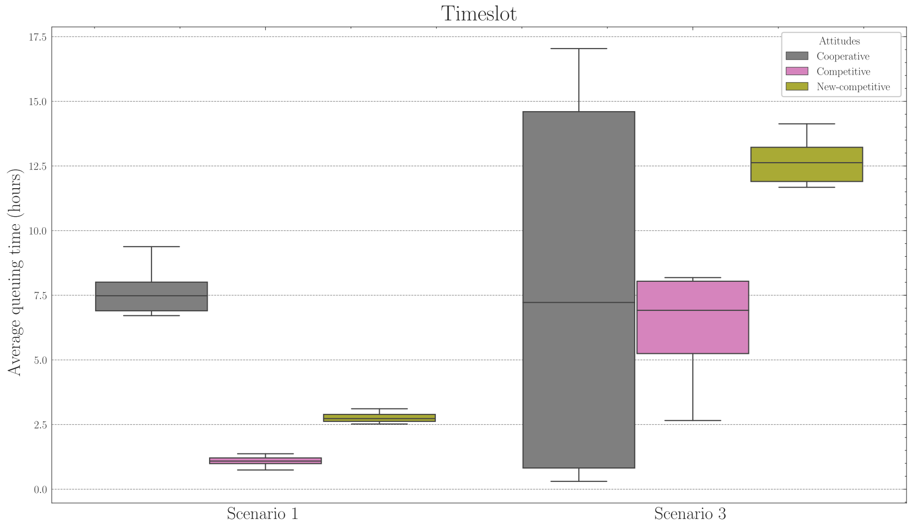
(a) Timeslot (P4)



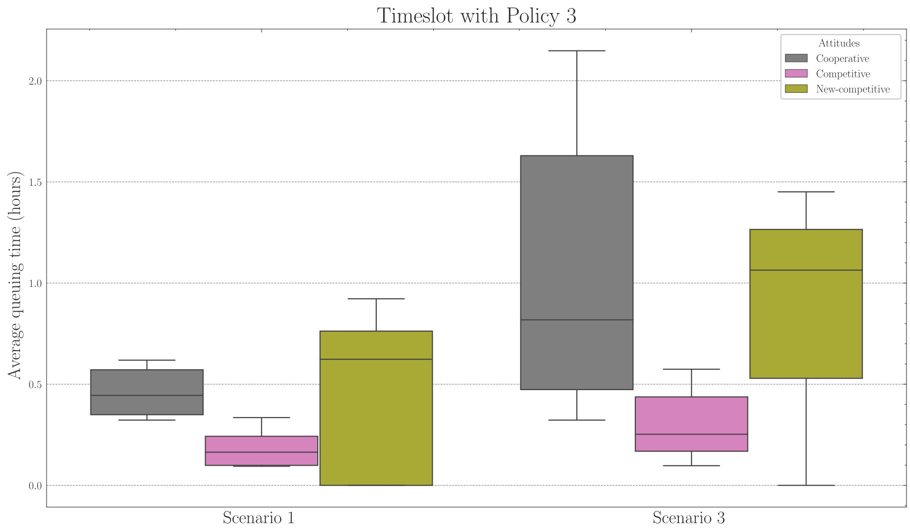
(b) Timeslot (P4) + P3

Figure E.22: Average time in queue across all queuing agent: Timeslot implemented in isolation and in combination with Policy 3 in Scenario 1 and Scenario 3

Average time in queue per attitude



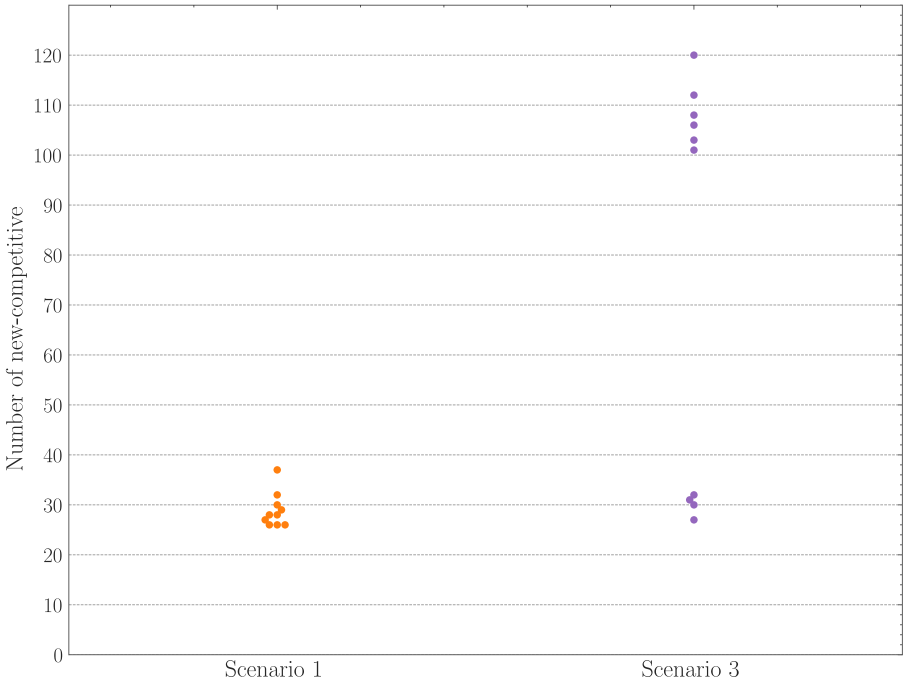
(a) Timeslot (P4)



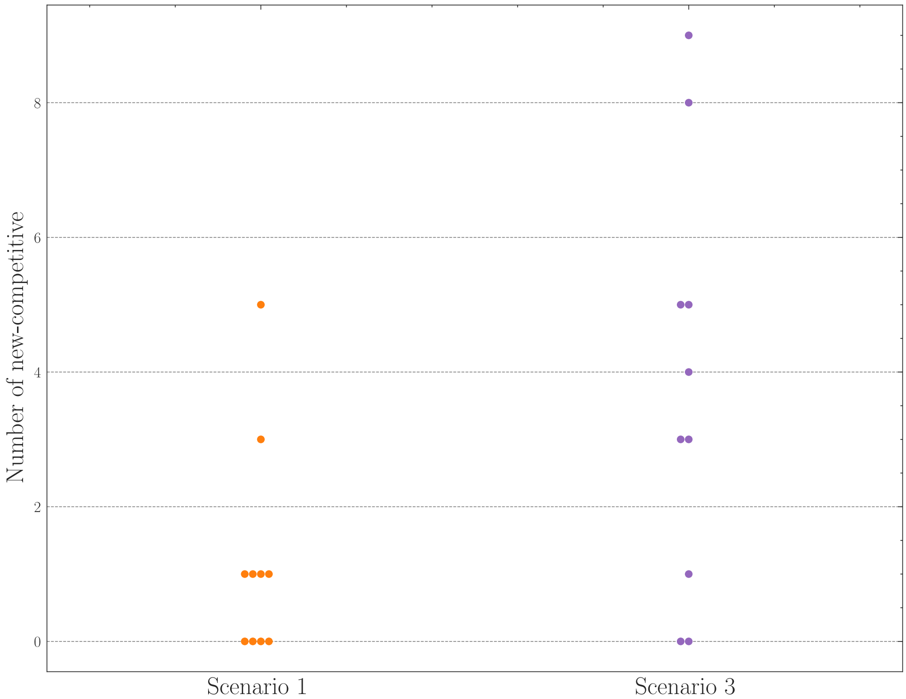
(b) Timeslot (P4) + P3

Figure E.23: Average time in queue per attitude: Timeslot implemented in isolation and in combination with Policy 3 in Scenario 1 and Scenario 3

Number of people switching behavior



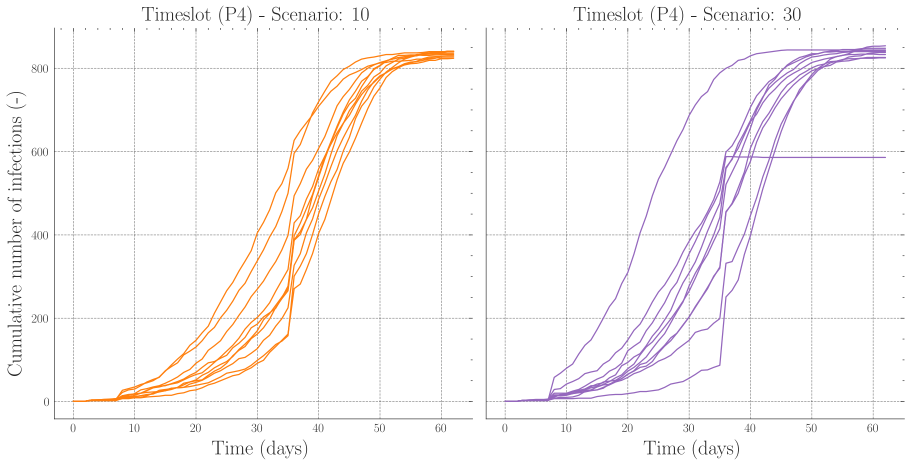
(a) Timeslot (P4)



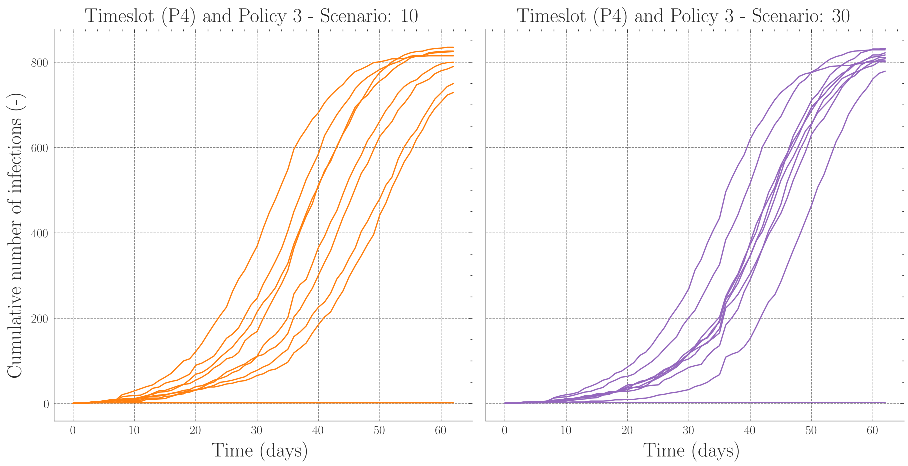
(b) Timeslot (P4) + P3

Figure E.24: Number of people switching to a competitive behavior: Timeslot implemented in isolation and in combination with Policy 3 in Scenario 1 and Scenario 3

Cumulative Cases



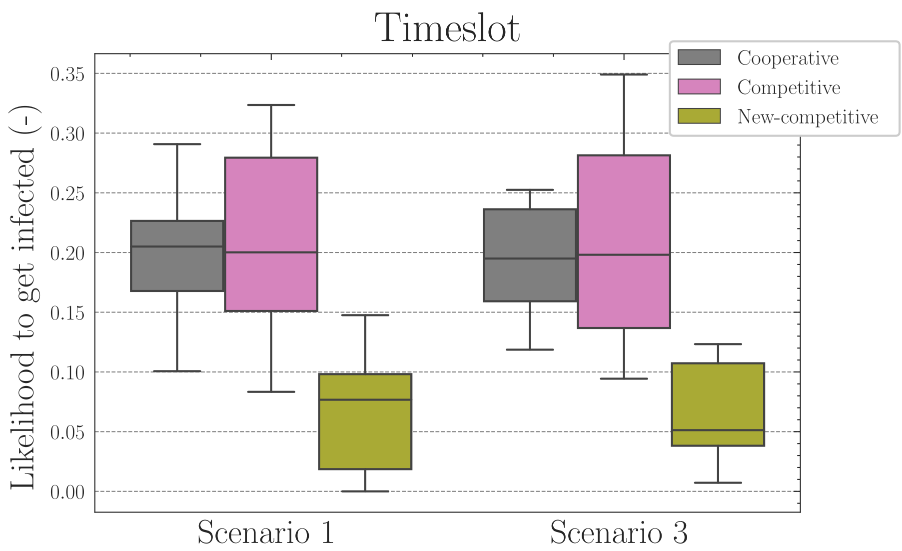
(a) Timeslot (P4)



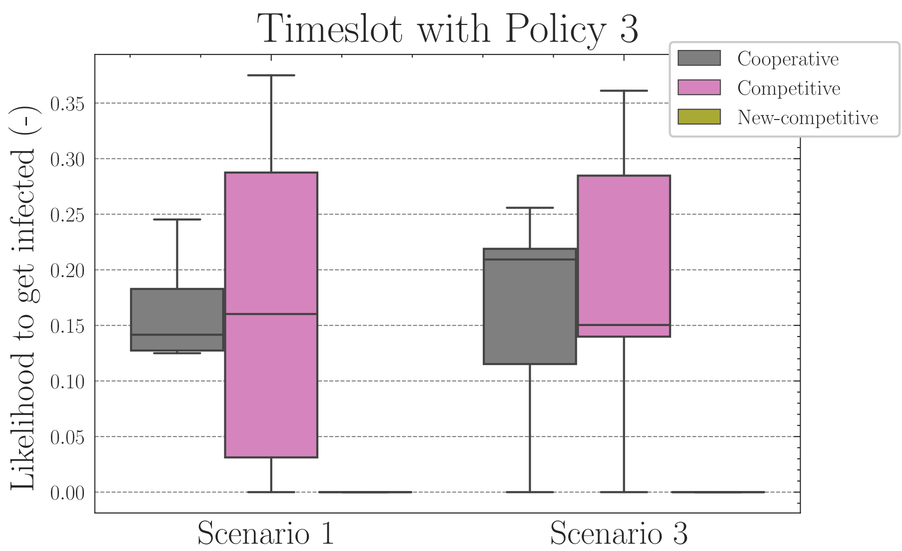
(b) Timeslot (P4) + P3

Figure E.25: Cumulative infections: Timeslot implemented in isolation and in combination with Policy 3 in Scenario 1 and Scenario 3

Likelihood of getting infected



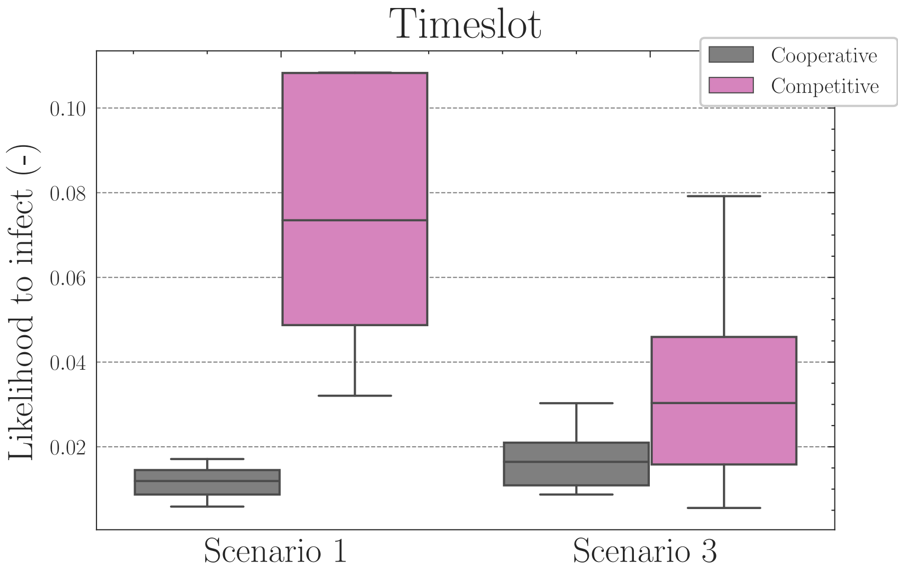
(a) Timeslot (P4)



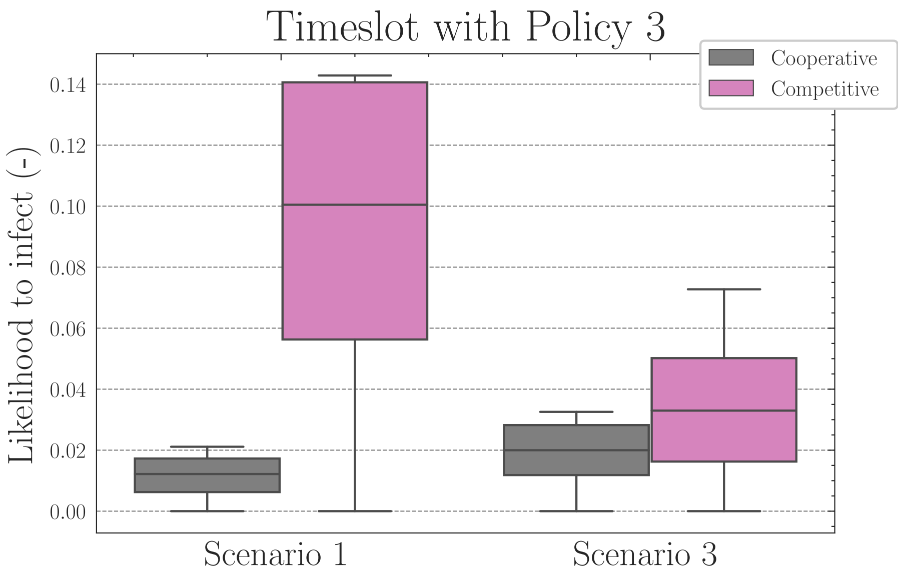
(b) Timeslot (P4) + P3

Figure E.26: Likelihood of getting infected: Timeslot implemented in isolation and in combination with Policy 3 in Scenario 1 and Scenario 3

Likelihood of infecting



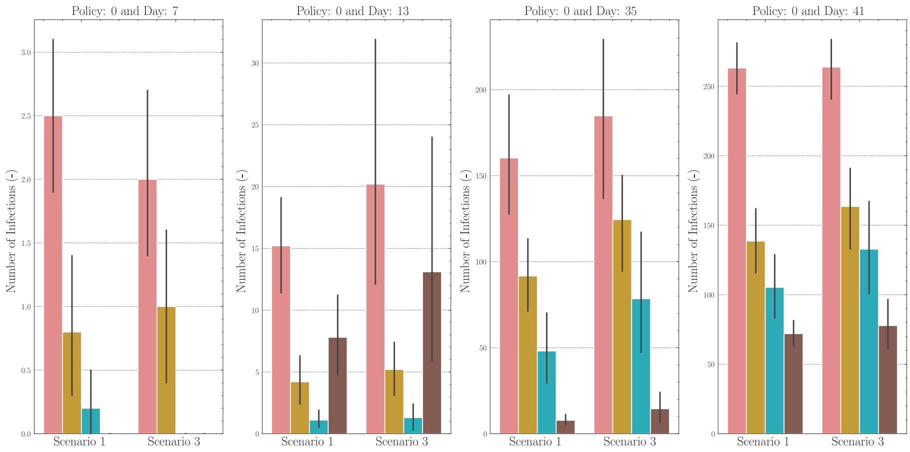
(a) Timeslot (P4)



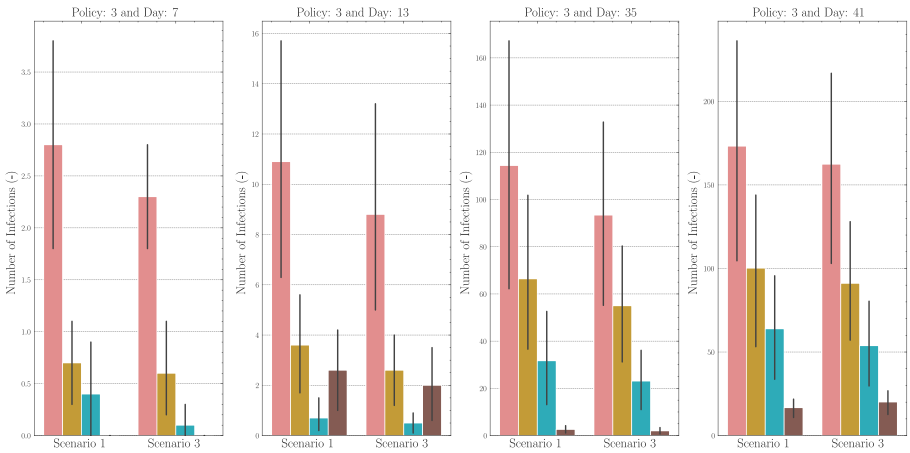
(b) Timeslot (P4) + P3

Figure E.27: Likelihood of infecting: Timeslot implemented in isolation and in combination with Policy 3 in Scenario 1 and Scenario 3

Distribution of location per moment of evaluation



(a) Timeslot (P4)



(b) Timeslot (P4) + P3

Figure E.28: Distribution of infections per location per moment of evaluation: Timeslot implemented in isolation and in combination with Policy 3 in Scenario 1 and Scenario 3

Appendix F

GitHub

All the scripts, models and notebooks used along this thesis are published in the GitHub repository. These can be divided into 5 main sections

- **Model and running**
  1. Queuing Model
  2. Coupled Model
  3. Script to run NetLogo headless for experiments
- **Supportive Conceptualization**
  1. Flowchart queuing model
  2. Flowchart Model Bogel
  3. Flowchart coupling process
- **Results (both .csv and text files**
  1. Experiment 0 - Baseline across all scenarios
  2. Experiment 1 - Scenario 0 with all representative-based policies
  3. Experiment 2 - Scenario 10 with all representative-based policies
  4. Experiment 3 - Scenario 20 with all representative-based policies
  5. Experiment 4 - Scenario 30 with all representative-based policies
  6. Experiment 5 - Scenario 40 with all representative-based policies
  7. Experiment 6 - Timeslot-based policy implemented in the baseline in scenario 1 and scenario 3
  8. Experiment 6 - Timeslot-based policy implemented in combination with policy 3 in scenario 1 and scenario 3
- **Data preparation, analysis and visualization (Jupyter Notebooks)**
  1. Notebook Baseline - Queuing dynamics
  2. Notebook Baseline - Infection dynamics

3. Notebook Representative-based policies

4. Notebook Timeslot-based policies

- **Sensitivity Analysis**

  1. Model used for the Sensitivity Analysis (slight variation to include specific outputs)

  2. Script to run NetLogo headless for SA

  3. Pre-processing script to reduce size of the SA .csv

  4. .csv file from Sensitivity Analysis

  5. Notebook Sensitivity Analysis

Cover Picture: Cox Bazaar, Bangladesh- 31 October 2017: Rohingya refugees queue for a food supplies distribution at the refugee camp
Credits: Mickey5/Sthutterstock.com